International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 17 (2025) pp. 704-729
© Cerebration Science Publishing
https://doi.org/10.70917/ijcisim-2025-0043
Article

AI-Enabled IoT System for Real-Time Indoor Air Quality Monitoring to Safeguard the Health and Safety of Industrial Workers

Dina Djeghar [1,]*, Karima Aksa [1], Ahcène Bounceur [2] and Mounir Aouadj [1]

[1] Laboratory of Automation and Manufacturing, Department of Industrial Engineering, Faculty of Technology, University of Batna 2, Mostefa Ben Boulaïd, Batna 05000, Algeria
[2] College of Computing and Informatics, University of Sharjah, University City, 27272, Sharjah, UAE
* Correspondence author: d.djeghar@univ-batna2.dz

Received date: 3 January 2025; Accepted date: 12 November 2025; Published online: 31 December 2025

Abstract: The rapid advancement of technological innovations has led to the pervasive digitization infiltrating every aspect of modern life, often termed as Industry 4.0. This transformative paradigm incorporates digital technologies within professional environments, engendering the emergence of “smart factories” and fundamentally altering conventional manufacturing methodologies. Consequently, the establishment of robust Occupational Health and Safety (OHS) protocols has become imperative in the digital era to ensure the welfare of the workforce. Indoor Air Quality (IAQ) assumes a pivotal role in OHS, given that substandard air quality presents considerable health hazards to individuals in occupational settings. This paper describes the RDSA (Risk Detection and Safety Assistance) system, an integrated framework that leverages the Internet of Things (IoT) and artificial intelligence (AI) to monitor hazardous conditions in real time and proactively assess risks. The RDSA system combines cost-effective IoT sensors with cloud-based dashboards to aggregate and clarify environmental data, while machine learning algorithms predict indoor air quality (IAQ) levels and facilitate early identification of pollution spikes. In addition, a convolutional neural network (CNN) is used for instant face mask detection to promote compliance with safety measures. Among the models examined for IAQ prediction, logistic regression, decision tree, and random forest classifiers showed the highest effectiveness, each achieving 99.9% accuracy on the evaluation dataset. In the context of face mask detection, the CNN model achieved an accuracy of 0.99. The proposed system demonstrates strong performance for all classifiers and significantly improves workplace safety by promoting data-driven decision-making. The empirical results validate the effectiveness and scalability of the RDSA system for practical industrial implementation.

Keywords: occupational health and safety (OHS); Industry 4.0; Internet of Things (IoT); artificial intelligence (AI); indoor air quality (IAQ); industrial safety

1. Introduction

Digitization has become a fundamental aspect of the remarkable progress made by technology, extending its influence across all aspects of life. Virtually every aspect of modern life is influenced by it, promoting innovation, efficiency, and connectivity, while presenting new opportunities and challenges in the digital age [1]. The emergence of the fourth industrial revolution (Industry 4.0) refers to the integration of digital technologies into industrial processes to create “smart factories” and replace traditional manufacturing methods. The latter has fundamentally transformed the nature of work environments in multiple industrial sectors. This transformative change encompasses the assimilation of cutting-edge technologies, including Internet of Things (IoT), Artificial Intelligence (AI), Big Data Analytics and Automation, into various aspects of industrial operations [2]. The transformation of occupational health and safety (OHS) practices is a necessary step in the context of digitization and technological advancement [3]. It is essential for ensuring the health, safety, and well-being of workers in the digital age. OHS, as a proactive and multidisciplinary field, plays a critical role in protecting workers from occupational hazards and promoting a safe and healthy work environment. By identifying risks, implementing control measures, ensuring compliance, and fostering employee involvement, OHS professionals contribute to the well-being and productivity of workers across industries. The main objectives of occupational health and safety (OHS) programs are to prevent occupational injury and illness, anticipate and recognize hazards, evaluate and control them, fit workers to suitable work, prevent professional diseases and injuries through proper control of working conditions, conserve worker health through medical supervision and education, and restore the health of workers suffering from diseases or injuries [4]. Exposure to pollutants, toxic compounds, and gases is one of the most significant occupational hazards faced by workers in various industries. This exposure poses a significant threat to the health and safety of workers, and requires robust measures to mitigate these risks. Especially in high-risk industrial environments like oil and gas plants, refineries, and chemical industries, the risk to workers' health and safety is more pronounced. In closed workplaces, the concentration of hazardous substances can accumulate, exacerbating the potential dangers to workers. In manufacturing facilities, warehouses, and confined spaces, the importance of indoor air quality becomes paramount. Indoor air quality (IAQ) is a critical aspect of occupational health and safety, and poor air quality can have severe effects on workers' health, ranging from headaches and dizziness to asthma, cardiovascular diseases, cancer, and even death [5]. Harnessing the capabilities of advanced technologies from Industry 4.0, including IoT, Smart Personal Protective Equipment (PPE), AI, and sensor networks, can significantly enhance OHS initiatives [6]. By using these technologies, industries can create a robust system for real-time monitoring and detection of hazardous conditions in the workplace. Early detection of toxic gases, particulate matter, low oxygen levels, and elevated CO_2 concentrations enables timely interventions to protect workers' health and safety. Additionally, AI-driven analytics enhance the accuracy and effectiveness of hazard detection, allowing industries to proactively address air quality concerns and prevent workplace accidents and injuries. In this article, we explore the transformative potential of IoT and AI in revolutionizing toxic substance monitoring and control systems in industrial environments. We delve into the capabilities of IoT-enabled sensors to provide real-time insights into environmental conditions, coupled with the analytical prowess of AI algorithms to identify patterns, detect anomalies, and predict potential hazards. Furthermore, we examine how these technologies enable early warning alerts, rapid response actions, and data-driven decision-making, empowering organizations to safeguard worker safety and well-being.

This article is organized as follows. Section 2 discusses the Related Work; Section 3 presents the selection of air quality parameters and their indices; Section 4 describes the architecture of the System; Section 5 provides the Methods and Implementation with a detailed explanation of each method in the proposed architecture. In Section 6, the experimental results are discussed; Section 7 concludes with limitations and considerations of future work.

2. Related Work

These works aim to ensure the safety and well-being of workers by maintaining healthy indoor environments. In this section, we describe both IoT and AI proposals for monitoring risks in the workplace. Firstly, we present systems that use IoT technologies to prevent and/or identify risks related to environmental conditions in workplaces. Secondly, we introduce proposed systems that utilizes both IoT and AI. The studies have been selected based on a similarity criterion with the proposal of this work regarding the technologies. The work conducted by authors in [7] addresses critical safety concerns in high-risk workplaces, particularly those where exposure to toxic compounds poses a threat to human health. Their approach involves the implementation of a distributed sensing system to monitor air quality. This system is designed to measure the concentration levels of various hazardous gases including CO, NO_2, Oxygen, and CO_2. In sum, the key aspects of their system include Sensor Utilization (the system employs commercially available low-cost sensors), Monitoring Scope (sensors are strategically deployed to monitor the presence of toxic compounds both indoors and outdoors), and Targeted Monitoring (specifically, the system focuses on monitoring the emissions from a melting furnace). Continuous Monitoring (The system operates continuously, providing real-time data on gas concentrations) and data Analysis and Trending (the system offers capabilities for long-term data analysis and trending).

The authors in [8] proposed an IoT-based indoor air quality monitoring system designed to ensure the health and safety of office environments, particularly during the COVID-19 pandemic. The system employs a BME680 air quality sensor, a NodeMCU ESP-12 microcontroller, and ThingSpeak IoT cloud platform to track real-time air temperature, humidity, pressure, IAQ index, carbon dioxide levels, and

VOCs. The data is accessible through a web application on computers or smartphones, allowing remote monitoring from anywhere at any time, the proposed system is not designed for industrial workplaces. Another system presented by authors in [9] a complete air quality monitoring infrastructure based on the monitoring of IoT systems in industrial environments, which includes the development of two highly precise compact devices to facilitate the real-time monitoring of the concentrations of particles and pollutants in the air. Machine learning techniques, specifically Gaussian Process Regression, have been applied to the collected data to predict safety levels and improve accuracy. The results show that Gaussian Process Regression has the highest accuracy among the air quality data sets gathered by the devices. This is an excellent system that can be applied to indoor industrial workplaces.

The system proposed by authors in [10] offers a practical solution for monitoring air quality in industrial settings by leveraging IoT technology. The device's ability to measure temperature, humidity and carbon dioxide levels, as well as $PM_{2.5}$ and PM_{10} particles, makes it a comprehensive tool for assessing environmental conditions. The NodeMCU (ESP8266) serves as the controller and a printed circuit board (PCB) for integrating all hardware components to ensure efficient operation and compact design. One of the notable advantages of this system is its low power consumption, which is crucial for continuous monitoring applications. The authors make a case for scalability and widespread adoption of their proposed solution by utilizing affordable and readily available hardware components. This affordability factor could allow the deployment of sensors in various workstations within a factory environment, facilitating comprehensive air quality monitoring.

The research conducted by authors in [11] proposed a prototype of an intelligent helmet designed to monitor environmental conditions in workers' surroundings and conduct a near real-time assessment of risks. By integrating sensors into the helmet, such as those measuring temperature, humidity, air quality, and possibly other relevant parameters depending on the specific application, the device provides valuable data to both workers and supervisors. This device aims to protect operators from impacts while simultaneously monitoring light, humidity, temperature, atmospheric pressure, gas presence, and air quality. Alerts are conveyed to the operator through sound beeps, while an LED strip on the helmet uses color codes to indicate environmental anomalies.

A real-time surveillance helmet for mine workers using IoT technology introduced by authors in [12]. The proposed prototype is designed with a three-tier architecture. The initial tier utilizes Arduino Uno and various sensors to assess health and environmental metrics such as temperature, humidity, gas concentration, dust level, heartbeat, and fire incidents. The second tier is comprised of a fuzzy classifier that sorts environmental circumstances based on the parameters from the first tier. Lastly, the third tier produces the health status report of the miner and is in charge of notifying the monitoring and rescue team during emergencies. Furthermore, a built in GPS tracker is included to aid in monitoring the current location of the worker. The three-tier architecture combines sensor technology, data processing, and communication systems to create a comprehensive surveillance and safety solution for mine workers, improving their protection and allowing a timely response to potential hazards or emergencies.

The authors in [13] presented the development of a low-power scenario for an IoT-based indoor air quality monitoring system in the workplace. The system measures parameters such as CO, CO_2, PM2.5, temperature, and humidity, and sends the data wirelessly via IEEE 802.11 b/g communication. Sensor nodes are designed to send data periodically to reduce power consumption, and can also handle emergencies such as fire. The results show that the controlled transmission interval can decrease power consumption and allow effective monitoring of air quality remotely through a web application.

The authors in [14] present the development of an indoor industrial environment monitoring system using wireless sensor networks (WSN) for a digital assembly plant in Kenya. The system utilizes sensors, Zigbee, Raspberry Pi, and Arduino Uno to collect data on environmental parameters such as carbon monoxide, temperature, humidity, and dust. The collected data is transmitted to the Raspberry Pi, which acts as a base station and then displayed on a GUI. The system employs Zigbee technology for the transmission of SMS and email notifications to registered users. Extensive testing was performed on the newly implemented system across multiple plant sectors, ultimately leading to the successful identification of specified parameters. Consequently, alerts were sent out through email and SMS to update users on the findings.

A proposed monitoring system aimed at improving the safety of workers in factories, described by authors in [15]. The system utilizes a NodeMCU microcontroller connected to three sensors: a temperature and humidity sensor (DHT sensor), an ultrasonic sensor (HC-04), and a smoke sensor (MQ-2 sensor). These sensors continuously monitor the working environment and transmit the data to the Losant IoT Platform. This platform facilitates data visualization and analysis, offering information on workplace safety conditions. Implementation of such a system can aid in averting mishaps and safeguarding the well-being of employees in industrial settings.

The authors in [16] proposed an IoT-based system that monitors and controls industrial environments using sensor and control units, where the control unit is based on the NodeMCU development kit. The sensor unit incorporates gas and temperature sensors for assessing toxic gas concentrations and temperature levels. An integrated buzzer facilitates alerts in hazardous situations. The system automates air conditioning and fan systems based on measured parameters. A mobile application on the Blynk platform allows authorized personnel to wirelessly monitor and control the environment. The IoT system provides both automatic and manual control capabilities, thereby enhancing overall monitoring and control in industrial environments.

The authors in [17] aimed to develop and validate a predictive model for respirable dust (RD) using low-cost sensors and AI algorithms. Various low-cost sensors are integrated into an RD sensor module and installed on a portable aerosol monitor for a duration of two weeks. The best performing model, random forest regression, demonstrated robust prediction capability and was validated against traditional sampling methods, yielding closely aligned results with a strong positive correlation. The developed sensor module showcased exceptional predictive performance, data stability, and accuracy, making it well suited for exposure assessments in workplace environments.

The authors of [18] presented a real-time air pollution monitoring and forecasting system designed for the chrome plating industry, using IoT sensors and AI technologies. It constantly detects dangerous pollutants, like hexavalent chromium and volatile organic compounds (VOCs), which are a big health risk for workers. With its real-time data analysis and forecasting capabilities, the system improves the ability to effectively monitor indoor air quality, enabling rapid response to protect the health and safety of industrial workers in highly polluted work environments.

The authors of [19] have presented an IoT-based real-time air quality monitoring system designed to protect the health of industrial workers. System uses an ESP32 microcontroller (MCU), an MQ-135 gas sensor, an SDS011 optical dust sensor, a BME280 sensor to monitor pollutants such as sulfur dioxide, carbon monoxide, and particulates. It assesses the AQI and displays the results on the ThingSpeak platform. If harmful gas concentrations exceed predefined thresholds, the ESP32 activates fans to maintain safe pollution levels, improving worker safety in industrial environments.

Authors in [20] examines air quality monitoring in automotive workshops to improve occupational health and ensure regulatory compliance. This paper presents an environmental monitoring system based on IoT and AI using DHT11 and MQ-135 sensors to measure temperature, humidity, and toxic gases. Data is transmitted in real time to the ThingSpeak platform via the MQTT protocol. Machine learning models (linear regression, decision trees, and SVM) analyze the data to calculate an air quality index using Gaussian functions. System effectively detects pollution spikes and sends automatic alerts, thereby improving workplace safety. The system's implementation has led to better regulatory compliance and reduced occupational risks. The case study demonstrates that integrating IoT and AI offers a practical and scalable solution for environmental monitoring in industrial settings.

In addition to the literature review, this paper also presents a comparative analysis of representative systems based on IoT and AI mentioned in the literature is presented in Table 1 below. These overview systematically reviews representative IoT and AI based systems mentioned in the literature, focusing on their technological frameworks, application domains, monitoring environmental parameters, algorithmic approaches, user interfaces, integration level, functional strengths, and identified limitations. Including this comparative overview allows for a critical evaluation of existing methodologies and places the proposed Risk Detection and Safety Assistance (RDSA) system in the broader context of contemporary researchers. RDSA stands out in particular for its integration of multiparameter, machine learning based air quality prediction, computer vision for mask compliance monitoring, and cloud storage with real-time visualization, offering a low-cost, scalable platform for industrial safety applications.

Table 1. Overview and Comparison of Intelligent Air Quality Monitoring Solutions in Industrial Contexts.

Study	**Techno-logy**	**Application Domain**	**Parameters Measured**	**AI/ML Models**	**Dashboard / Control**	**Integration Level / Multi-service System**	**Key Strengths**	**Limitations**
[7] Parri et al. (2023)	IoT	High-risk industrial	CO, NO_2, CO_2, O_2	None	Local visualization	*No-integrated (IoT sensing only)*	Continuous sensing; trending	No AI integration

[8] Uddin et al. (2022)	IoT	Office	IAQ Index, VOC, CO_2, Temp, Humidity	None	Thing-Speak Cloud, web	*Partial (IoT + remote visualization)*	Remote monitoring; low-cost	Not for industrial settings
[9] García et al. (2022)	IoT + ML	Industrial	PM, pollutants	GPR	Local display	*Partial (IoT + ML analytics)*	Precise sensors; ML prediction	Limited scope
[10] da Costa et al. (2022)	IoT	Industrial	$PM_{2.5}$, PM_{10}, CO_2, Temp, Humidity	None	PCB integrated	*Partial (IoT + embedded design)*	Low power; scalable	No AI or alerts
[11] Campero-Jurado et al. (2020)	IoT	Wearable industrial	Temp, humidity, pressure, gas	None	LED & beeps	*Partial (IoT + real-time alerts)*	Safety helmet; real-time alerts	No centralized control
[12] Singh et al. (2022)	IoT + fuzzy logic	Mining	Temp, gas, humidity, fire, heartbeat	Fuzzy Classifier	Alerts, GPS	*Integrated (IoT + AI + location tracking)*	3-tier logic; worker location	Complex design
[13] Panghurian et al. (2018)	IoT	Workplace IAQ	CO, CO_2, $PM_{2.5}$, Temp, Humidity	None	Web GUI	*Partial (IoT + periodic data)*	Low power; periodic data	No ML/AI
[14] Rotich (2021)	IoT	Digital assembly plant	CO, dust, Temp, Humidity	None	SMS + GUI	*Partial (IoT + notification system)*	Sector alerts; Zigbee-based	Simple analytics
[15] Kodali et al. (2017)	IoT	Factory	Temp, smoke, ultrasonic	None	Losant IoT	*Partial (IoT + real-time alerts)*	Real-time alerts	Few parameters measured
[16] Jaber et al. (2019)	IoT	Industrial control	Toxic gases, Temp	None	Blynk App	*Integrated (IoT + control automation)*	Automation & manual override	No forecasting
[17] Chang et al. (2023)	IoT + AI	Workplace	Dust (RD)	RF	N/A	*Partial (IoT + AI prediction)*	High prediction accuracy	Focused on RD only

[18] Ramadan et al. (2024)	IoT + AI	Chrome factory	VOCs, Chromium	Forecasting AI	Real-time dashboard	*Integrated (IoT + AI + forecasting)*	Pollution modeling	Narrow application
[19] Veeramanikandasamy et al. (2024)	IoT	Industrial IAQ	SO_2, CO, PM, Temp, Humidity	None	ThingSpeak Cloud, auto fan	*Partial (IoT + automatic actuation)*	Affordable & effective	No AI used
[20] Mariano et al. (2024)	IoT + AI	Auto workshop	CO, toxic gases, Temp, Humidity	SVM, LR, DT	ThingSpeak Cloud + alerts	*Integrated (IoT + AI + alerting)*	Alert system; AQI calc	No deployment tested
RDSA System	IoT + AI	Industrial zone-based	$PM_{2.5}$, PM_{10}, CO_2, Temp, Humidity, Facemask	KNN, RF, SVM, LR, DT (AQ); CNN (Facemask detection)	ThingSpeak Cloud real-time, web/mobile app dashboard, HVAC + alerts	Fully Integrated (IoT + AI + control + computer vision)	High prediction accuracy; end-to-end AI; mask detection; low-cost; extensible; open dataset	Deployment in live industry pending; potential privacy constraints

3. Air Quality Parameters

The subsequent sections outline the reasons for selecting the key parameters crucial for assessing Indoor Air Quality in industrial workplaces.

3.1. Particulate Matter

Particulate matter is composed of minuscule solid and liquid particles that are dispersed in the atmosphere, as described by the United States Environmental Protection Agency [21]. Although some particles, such as dust, are visible to the naked eye, others require a microscope for observation. These particles vary significantly in size and shape and originate from various sources, including direct emissions such as fires, unpaved roads, and industrial activities.

Particulate matter is generally categorized by aerodynamic diameter into:

- PM_{10}: particles with an aerodynamic diameter ≤ 10 µm (micrometers),
- $PM_{2.5}$: particles with a diameter ≤ 2.5 µm.

These pollutants are typically measured in micrograms per cubic meter (µg/m³), which quantifies the mass of particles present in one cubic meter of air. Fine particles like $PM_{2.5}$ can penetrate deep into the lungs and even enter the bloodstream, increasing the risk of respiratory and cardiovascular diseases.

Many studies have utilized monitoring systems to track particulate matter (PM), encompassing $PM_{2.5}$ and PM10 concentrations across various industries [22-26]. The measurements conform to established indoor and outdoor air quality regulations regarding particulate matter pollutants, with exposure to PM identified as a significant risk to the health of workers [27-32].

3.2. Carbon Dioxide

Carbon dioxide (CO_2) is a colorless gas formed from the combination of one carbon atom and two oxygen atoms. Its production stems from the metabolic processes of aerobic organisms as they break down carbohydrates and lipids, alongside emissions from geological phenomena like volcanoes and hot springs. As a predominant constituent of the atmosphere, CO_2 is vital to maintain various forms of life. Additionally, its diversity extends to a wide range of industrial applications, making it an important resource in industrial processes. Moreover, elevated indoor carbon dioxide levels correlate with diminished work performance and increased health symptoms [33]. According to the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) recommend maintaining the concentration below 700 ppm as shown in Figure 1. While excessively high CO_2 levels can lead to loss of consciousness and even death, lower concentrations can still induce dizziness and sleepiness, adversely affecting work efficiency [34].

Figure 1. Levels of CO_2 and their Effects on the human body.

3.3. Thermal comfort

According to (ASHRAE Standard 55-2017) standard [35], thermal comfort is defined as the level of satisfaction with the ambient thermal conditions, assessed subjectively based on individual perceptions. It is influenced by several factors, such as clothing, air temperature, relative humidity, and air movement. In addition, occupant expectations play an important role in shaping their thermal experience. Improving indoor air quality in workplaces not only enhances productivity but also fosters a healthier environment [36]. Therefore, maintaining the indoor environment within acceptable temperature and humidity levels is crucial to controlling indoor air quality. ASHRAE guide lines [35] suggest maintaining a relative humidity (RH) of 30% to 60%, along with specific temperature ranges, for optimal indoor comfort. In winter, the recommended temperature range is between 68°F and 74°F (approximately 20°C to 23°C), while in summer, it's between 72°F and 80°F (approximately 22°C to 27°C).

3.4. Indoor Air Quality Standards

Indoor quality standards for the levels of CO_2 (carbon dioxide) and PM (particulate matter) in the workplace can vary depending on organizations or jurisdictions. Table 2, presents a comparison of indoor air quality (IAQ) standards for permissible concentrations of $PM_{2.5}$, PM_{10}, and CO_2 as defined by four major organizations: ASHRAE, OSHA (Occupational Safety and Health Administration), EPA (Environmental Protection Agency), and WHO (World Health Organization). These organizations were selected because of their authority and global influence in setting occupational health and environmental standards. ASHRAE provides technical guidelines for acceptable IAQ in buildings, OSHA sets regulatory exposure limits for workplace safety in the United States, EPA offers guidance on environmental and public health issues, and WHO provides internationally recognized public health references. However, we opted for the updated version of general guidelines provided by ASHRAE Standards 62.1 and 62.2 are the recognized standards for ventilation system design and acceptable indoor air quality (IAQ). Expanded and revised for 2022, both standards specify minimum ventilation rates and other measures in order to minimize adverse health effects for occupants [37]. Which recommends maintaining CO_2 levels below 700 parts per million (ppm) for high-level comfort, 65 μg/m^3 for $PM_{2.5}$, and 150 μg/m^3 for PM10 for a 24-hour average.

Table 2. IAQ standards of PM and CO_2 by ASHRAE, OSHA, EPA, and WHO.

$PM_{2.5}$	PM_{10}	CO_2	Organization	Ref
0-65 µg/m³ (for a 24-h average)	0-150 µg/m³ (for a 24-h average)	No more than 700 ppm	ASHRAE 62.1-2022	[37]
0-5000 µg/m³ (for an 8-h average)	0-150 µg/m³ (for a 24-h average)	600-1000 (preferred)	OSHA	[38]
60 µg/m³ (for an 8-h average)	0-150 µg/m³ (for a 24-h average)	800ppm (Acceptable)	EPA	[39]
0-25 µg/m³ (for a 24-h average)	0-50 µg/m³ (for a 24-h average)	1000 ppm	WHO	[40]

4. Architecture of the RDSA System

4.1. Overview of the System Architecture

This section introduces the architecture of the proposed system named the Risk Detection and Safety Assistance (RDSA) system. Designed to enhance occupational safety in industrial workplaces, the RDSA system combines IoT and AI technologies to enable IAQ monitoring and face mask compliance detection. The system comprises two key components: the IoT-Environmental Node for environmental sensing and the IoT-Facemask Node for visual compliance monitoring. Data collected from each workplace zone is transmitted via the MQTT protocol to a ThingSpeak cloud dashboard for centralized analysis and real-time alerting. Figure 2 depicts the global architecture of the system.

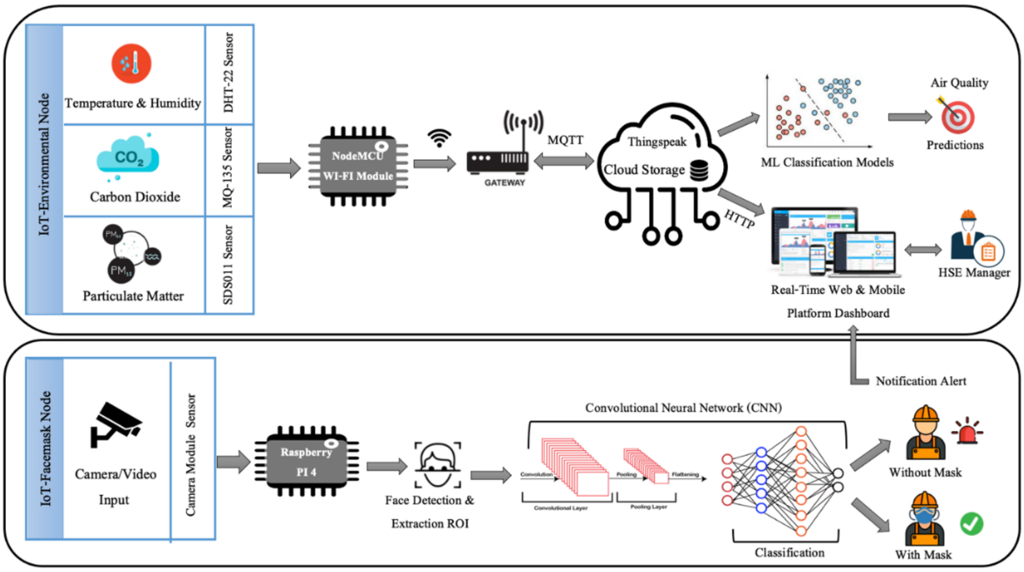


Figure 2. General Architecture.

4.2. Division of Industrial Zones

To enable localized monitoring and intervention, the industrial environment is divided into distinct zones. Each zone is equipped with its own IoT-Environmental Node and IoT-Facemask Node, allowing the system to independently monitor and respond to conditions in different work areas. This zone-based design enhances scalability, precision, and responsiveness in managing safety risks.

4.3. IoT-Environmental Node

1. SDS011 PM Sensor (Nova Fitness Ltd.) Principle: Laser scattering (optical detection).

Operation: A fan maintains airflow; a photodiode detects scattered light, and an MCU converts pulses into $PM_{2.5}$/PM_{10} mass concentrations (range: 0.0-999.9 µg/m³, min. particle size: 0.3 µm) [41,42].

2. MQ-135 Gas Sensor

Detects: NH_3, benzene, CO_2, smoke, and nicotine.

Interface: Analog (PPM output) and digital pins (TTL 5V). Validated for reliability in [43].

3. DHT22 Temp/Humidity Sensor

Mechanism: Capacitive humidity sensor + thermistor.

Range: 40°C to 80°C (temp.), 0-100% (humidity). Operates at 3.3-6V; widely used in IoT.

4. NodeMCU (ESP8266) Microcontroller

Features: Wi-Fi connectivity, low power, programmable via Arduino IDE/Lua/MicroPython.
Role: Aggregates sensor data and transmits to the cloud via MQTT (lightweight IoT protocol)

4.4. IoT-Facemask Nodes

The proposed system for facemask detection uses the Raspberry Pi 4 Model B which is a highly versatile single-board computer renowned for its compact form factor and robust performance. Equipped with a Broadcom BCM2711 quad-core Cortex-A72 processor running at 1.5GHz, it offers significant processing power for a wide range of applications. The Raspberry Pi 4 supports dual displays with resolutions up to 4K and features multiple USB ports, Gigabit Ethernet, dual-band wireless networking, and Bluetooth connectivity.

• The Camera Module V1.3: specifically designed for Raspberry Pi boards, enhances the system's capabilities by enabling high-quality imaging and video capture. With a fixed-focus lens and a resolution of up to 5 megapixels, this camera module is ideal for computer vision projects.

• Local Processing: The system uses Face Detection and Extraction ROI for computer vision techniques to locate faces within the image/video feed and isolate them as Regions of Interest (ROI) Classification Convolutional Neural Network (CNN): A specialized deep learning model analyzes the facial ROIs and classifies them as "With Mask" or "Without Mask".

4.5. Cloud Platform

The NodeMCU collects environmental data from sensors and transmits it to the ThingSpeak cloud service over Wi-Fi. This service stores the data in graphs and numerical values, enabling it to be viewed instantly and analyzed in real time. In addition, the data can be exported to an Excel spreadsheet for data analysis. ThingSpeak was selected for this project due to its open-source nature and advanced IoT functionality. It offers an intuitive dashboard for viewing data and enables live analysis of information collected by devices connected to the cloud. In addition, a single API key makes it easy to upload millions of data to the ThingSpeak cloud.

4.6. Data Analysis

The IoT environmental node was successfully used to gather IAQ measurements, and after that, raw data were downloaded from the cloud, labeled and ready for modeling and prediction using machine learning classification models to understand the indoor environment.

4.7. User Interface and Notifications

Web and Mobile Platform Dashboard offers an interface to visualize:

- Current air quality conditions in each zone.
- Mask compliance status;
- Historical data and potential predictions
- HSE Manager: The primary user interacts with the dashboard and receives critical alerts.
- Notification Alert: The system proactively issues alerts (email, SMS, or push notifications) about dangerous air quality levels and instances of cases of non-compliance with the use of masks.

5. Method and Implementation

The goal of the Risk Detection and Safety Assistance (RDSA) system is to enhance occupational health and safety in industrial workplaces by monitoring indoor air quality and enforcing mask compliance in real time. In line with this objective, our research focuses on developing an integrated web platform and mobile application for visualizing environmental data collected from IoT sensors. This interface simplifies complex datasets, supporting informed decision-making and improving worker well-being. Furthermore, AI-based models are implemented to perform real-time face mask detection and classify air quality levels, enabling proactive safety measures.

The global hardware connectivity of the system and components are illustrated in Figure 3. The system integrates multi-sensor modules (SDS011, MQ-135, DHT22) with a NodeMCU (ESP8266) microcontroller, which serves as the central hub for data acquisition and wireless transmission. Additionally, the Raspberry Pi 4 processes video streams for mask detection.

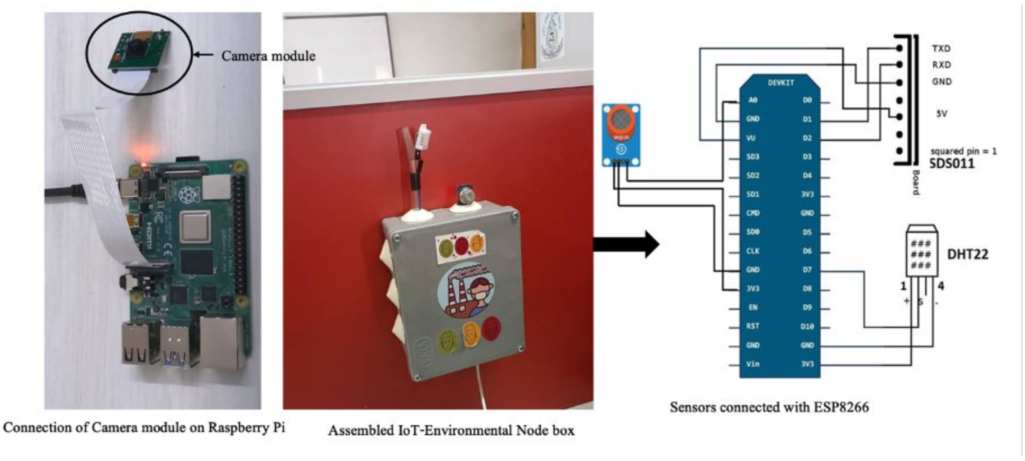


Figure 3. Connection of hardware components.

5.1. Development of Web Platform and Mobile App for Data Visualization

Our idea is to install the hardware system in different industrial zones (ZONE 1, ZONE 2, ZONE 3, ZONE 4, etc.) as it is illustrated in Figure 4. Currently, during preliminary laboratory tests, one remote module was employed to control only ZONE 2.

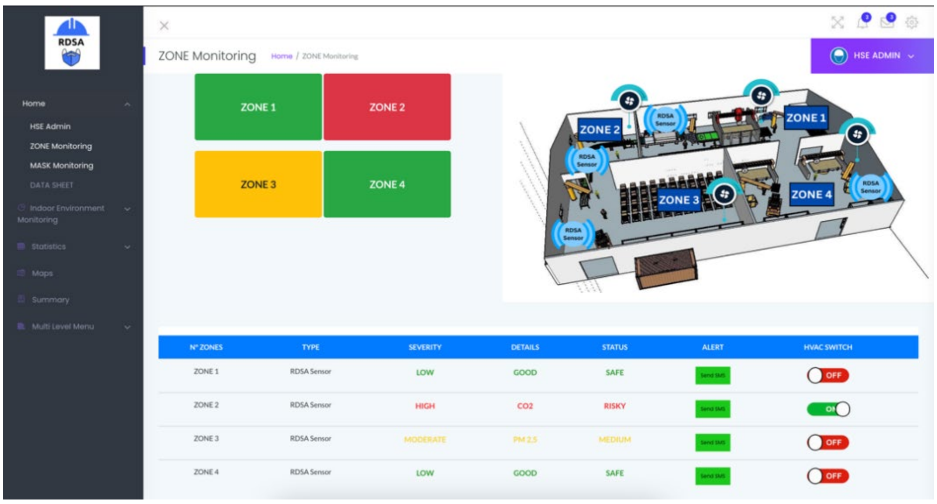


Figure 4. Industrial Zone Monitoring via Web Platform.

The developed Web Platform (RDSA) aimed to enable HSE managers to monitor air quality and face masks, the fundamental application infrastructure running on the local server that managed all incoming data from the IoT nodes. Real-time data management and visualization is the primary focus of web platform development. As illustrated in Figure 5, this involves representing incoming data from ThingSpeak cloud storage using a variety of information graphics of various air quality characteristics. Although ASHRAE Standard 62.1-2022 provides recommendations on acceptable thresholds for indoor pollutant concentrations, such as keeping $PM_{2.5}$ below 65 µg/m³, PM_{10} below 150 µg/m³, and CO_2 below 700 ppm on average over 24-hours, as shown in Table 2, these limits are primarily intended for assessing long-term exposure. Furthermore, the proposed RDSA system is designed for real-time monitoring and risk classification, which requires a more detailed understanding of short-term variations in indoor air quality. Therefore, to improve immediate interpretability and enable proactive intervention, color-coded hazard levels have been implemented on the ThingSpeak dashboard as shown in Figure 5, based on the IAQ index thresholds referenced by the US EPA [44]. In addition, in Figure 4, the color-coded values displayed in each zone area visually represent the real-time air quality status: green for (Good), yellow for (moderate), orange for (unhealthy), and red for (very unhealthy). These visual cues facilitate rapid identification of air quality deterioration and support real-time decision-making.

Furthermore, it is useful to access the raw values to get a detailed view of all the parameters reported by the system. In addition, the Web platform is designed to receive notification alerts regarding instances of compromised if poor air quality is detected and instances where workers are found not wearing face masks, as shown in Figure 6.

Upon detection of such incidents, the HSE manager is empowered to activate the HVAC (Heating, ventilation, and air conditioning) system and send SMS alerts directly from the mask monitoring web page to the respective workers in question to a smartphone, as shown in Figure 6, and Figure 7. Thus, ensuring timely intervention and adherence to safety protocols.

Moreover, in Figure 8, a mobile application is developed for workers/HSE to display the data in real-time with some supportive info-graphics.

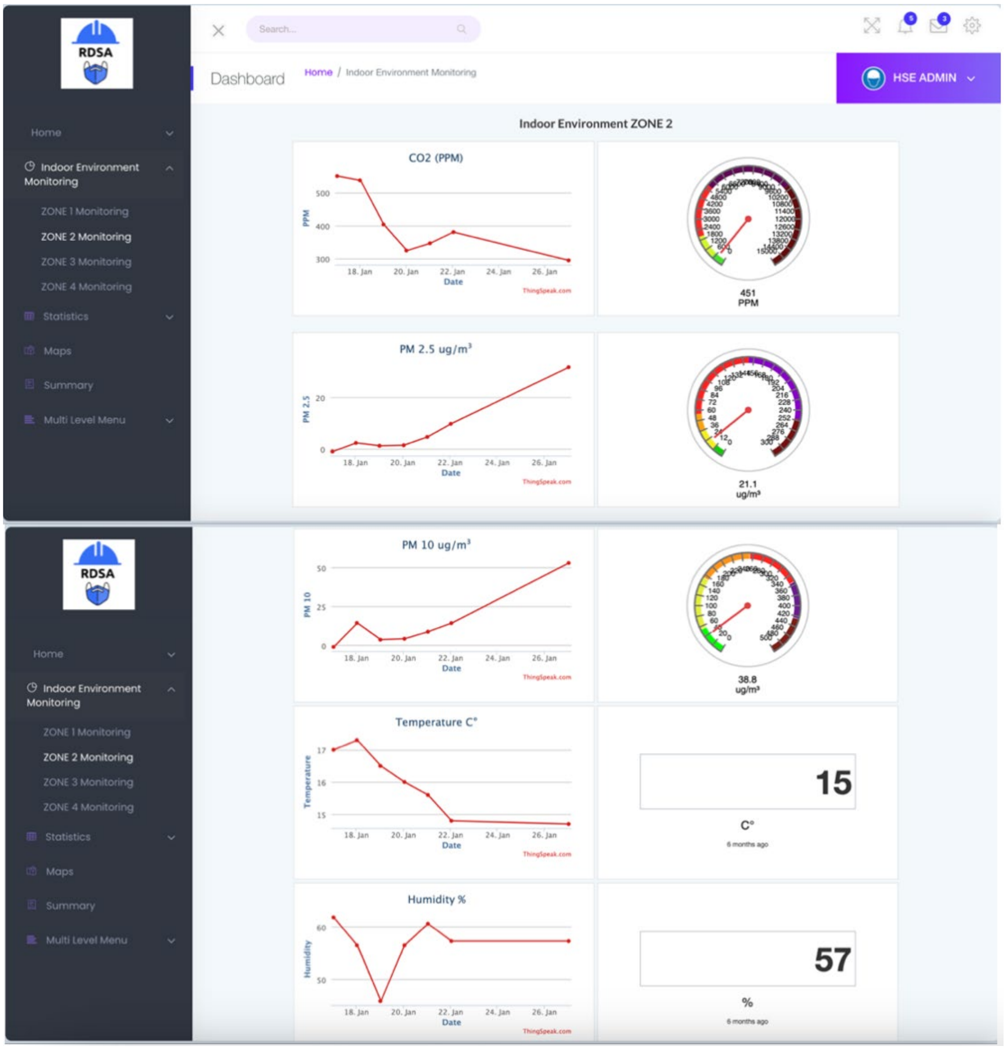


Figure 5. Real-time air quality dashboard.

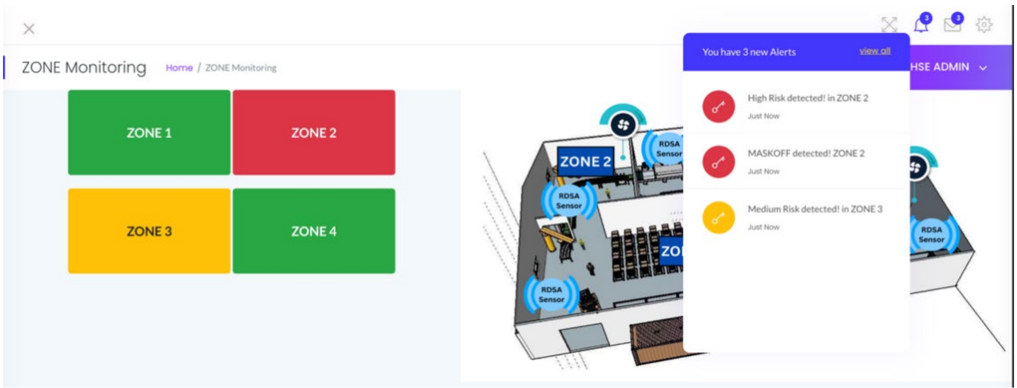
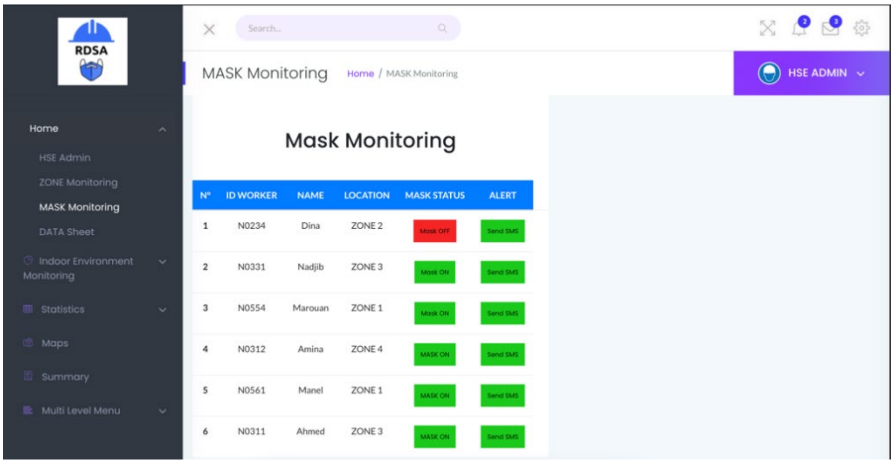
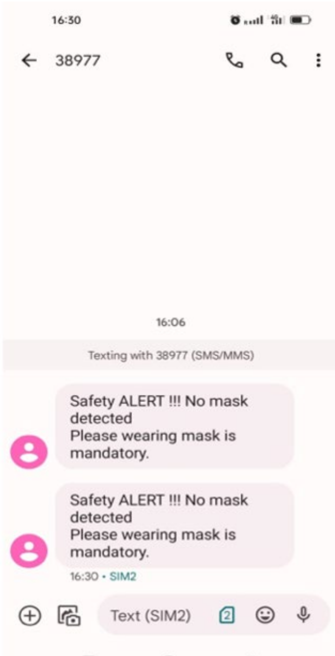


Figure 6. Notification Alerts about potential risks



(a)



(b)

Figure 7. (a) Mask Monitoring Notification; (b) SMS Alert to worker

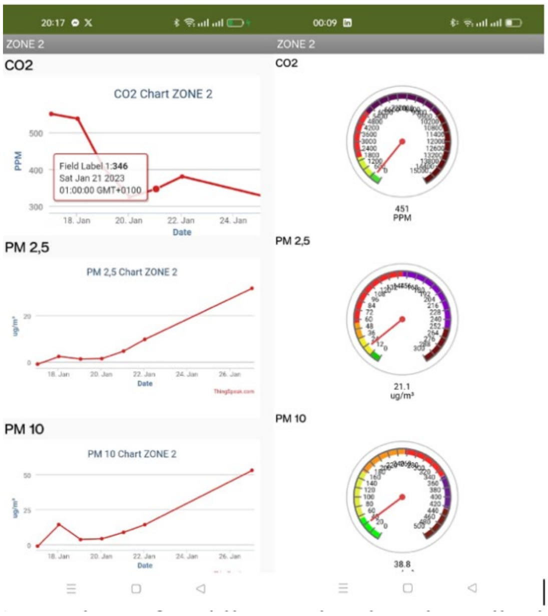


Figure 8. Mobile application showing air quality in real time

5.2. Facemask Detection using Artificial Intelligence

The cameras are used to capture images from different zones, the proposed web platform system processes these images to detect the workers without face masks. Mask detection is achieved using a deep learning algorithm that utilizes Convolutional Neural Network (CNN) Classification. For mask detection (classifying whether a worker is wearing a face mask or not), a Convolutional Neural Network (CNN) is commonly used due to its effectiveness in image-based tasks. CNN are a type of artificial neural network specialized in the interpretation of pixel-based input, as depicted in Figure 9 CNN are extensively utilized in the fields of image recognition and analysis [45].

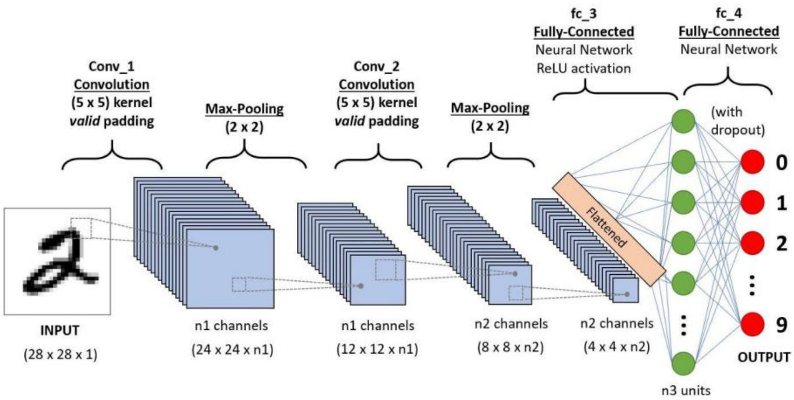


Figure 9. Convolutional Neural Network (CNN) for classification

The proposed model generally comprises convolutional layers, which serve the purpose of feature extraction, and dense layers that are employed for classification. The model is trained using Keras and TensorFlow software libraries, with the algorithm consisting of five main steps. Dataset Collection, Pre-processing, Splitting, Training, and Testing/Evaluation. The prediction model proceeds to identify the mask and subsequently transmits an alert to the system If the captured image lacks a face mask, it is automatically triggered to the RDSA platform and an SMS alert is immediately sent to both the workers concerned and the HSE manager to take the necessary actions. In order to initiate the development of a custom face mask detector, we split our project into two distinct phases, each with its respective sub-steps, as shown in Figure 10. The first phase, which we will refer to as the training phase, involves loading our face mask detection dataset from disk, training a model on this dataset using Keras/TensorFlow, and finally serializing the face mask detector to disk. The second phase, which we will call the deployment phase, will begin once the face mask detector has been trained. In this phase, we will load the mask detector, perform face detection, and then classify each face as either "with_mask" or "without_mask".

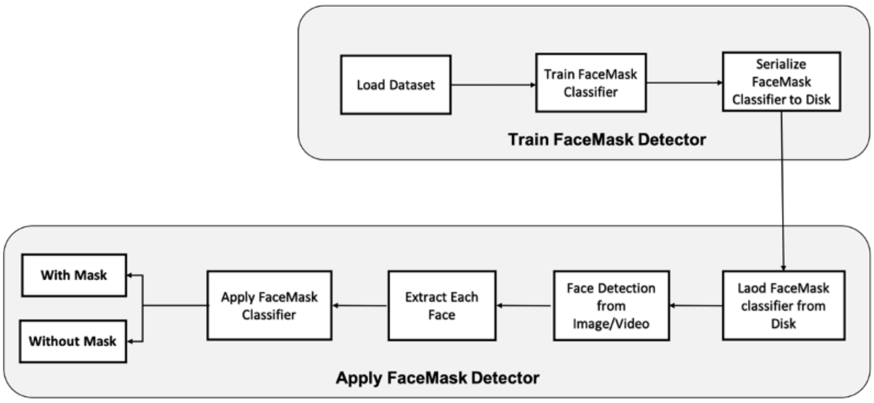


Figure 10. Overall Architecture Diagram of Facemask Detection

5.2.1. Data Collection

The images utilized for the training and testing of the model were procured from the internet, the dataset used in this project consists of 4095 images, divided into two distinct classes: 2165 images that include masks and an additional 1930 images that exclude masks, as shown in Figure 11. The sample images were collected from a variety of sources including the Bing search API, Kaggle datasets, and the Real-World Masked Face Dataset (RMFD) [46]. We used 80% of the data to train the model and 20% to validate its performance.

Figure 11. Facemask Dataset

5.2.2. Evaluation Metrics

In the present research, we employed a range of performance metrics to evaluate the effectiveness of the proposed framework, including accuracy, recall, precision, and the F1-measurement, which are concisely elaborated on in [47] and presented in Equations (1)-(4):

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}} \quad (1)$$

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \quad (2)$$

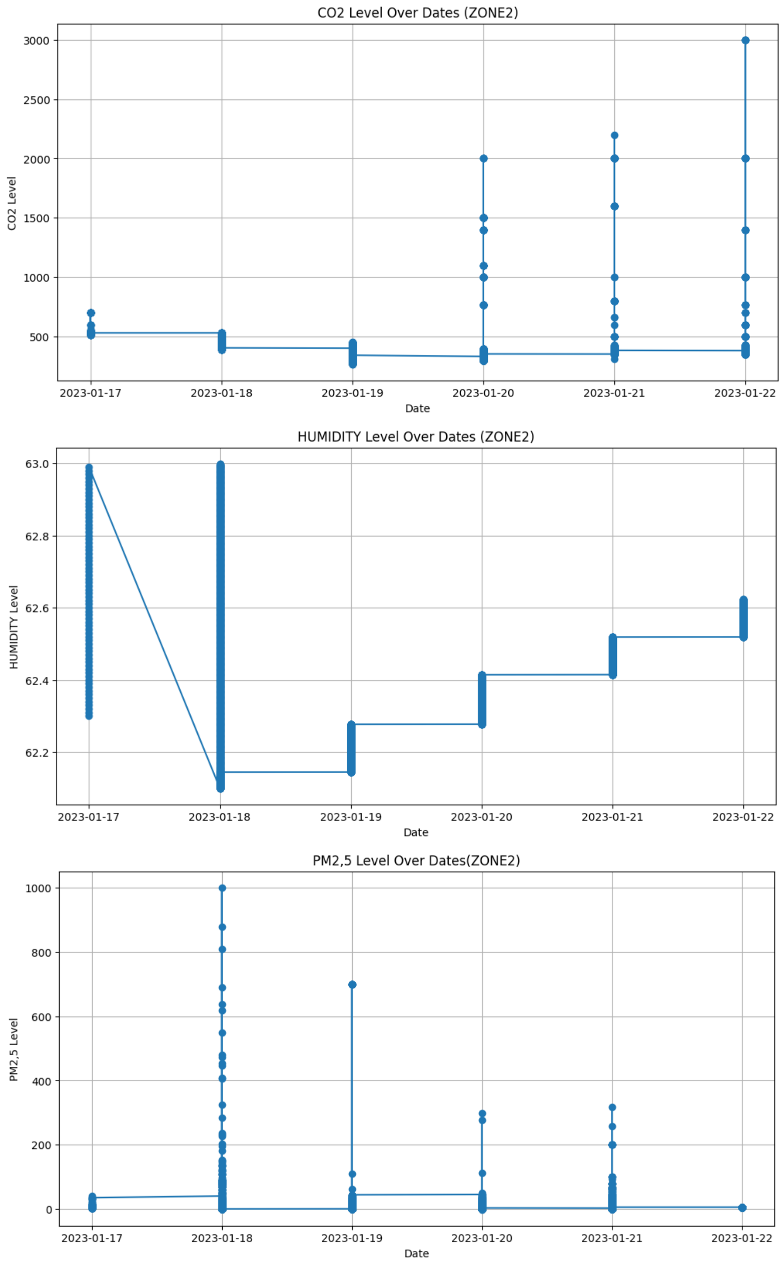
$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \quad (3)$$

$$\boldsymbol{F1 - Measure} = \boldsymbol{2} \times \frac{\boldsymbol{(Precision \times Recall)}}{\boldsymbol{(Precision+Recall)}} \quad (4)$$

where TP, TN, FP, and FN refer to the True Positive, True Negative, False Positive, and False Negative samples, respectively, as derived from a confusion matrix.

5.3. Indoor Air Quality Classification using Artificial Intelligence

In the proposed system, the indoor air quality data is obtained from an IoT-environmental node installed for testing inside the laboratory, defined as ZONE 2 in our results. The data from the various sensors are generated at a high temporal resolution. The system provides data every 30 seconds for six successive days (from January 17, 2023 to January 22, 2023), resulting in a rich dataset containing 6201 samples for each pollutant, which is available online [48]. The real-time graphical analysis is shown in Figure 12, where in Figure 13, the data regarding the range of each air pollutant, along with its level of taxonomy, are depicted below. For processing and analysis, various classification models are applied to the acquired data to predict indoor air quality and assess the risk to workers based on CO_2, $PM_{2.5}$, PM_{10}, Temperature, and relative Humidity. Moreover, Figure 14 illustrates the overall architecture of the general steps, and the detailed descriptions of each processing step provided in following subsections.



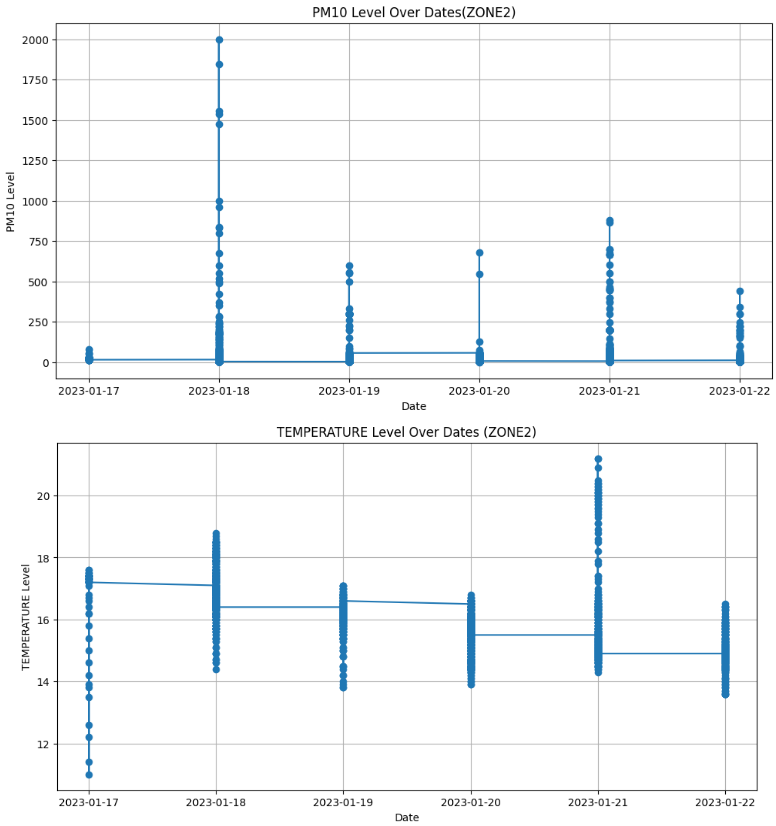
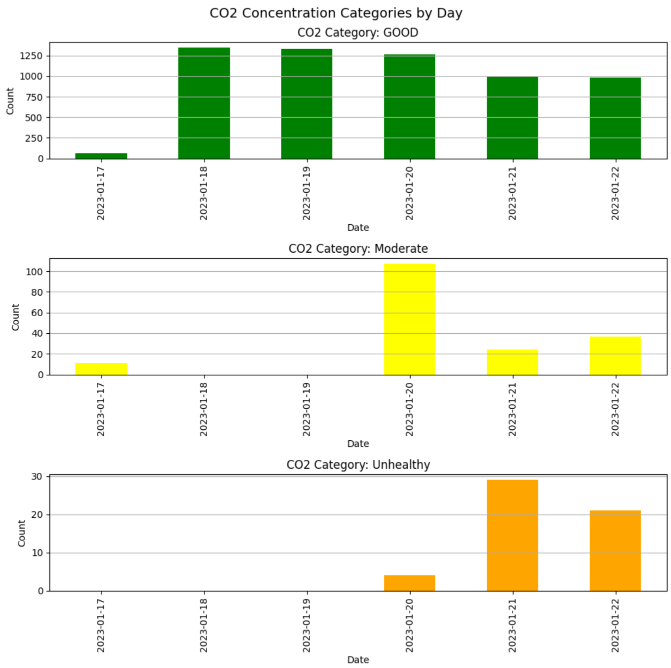


Figure 12. Variation in Concentration of CO_2, $PM_{2.5}$, PM_{10}, Temperature, and Humidity over 6 days.



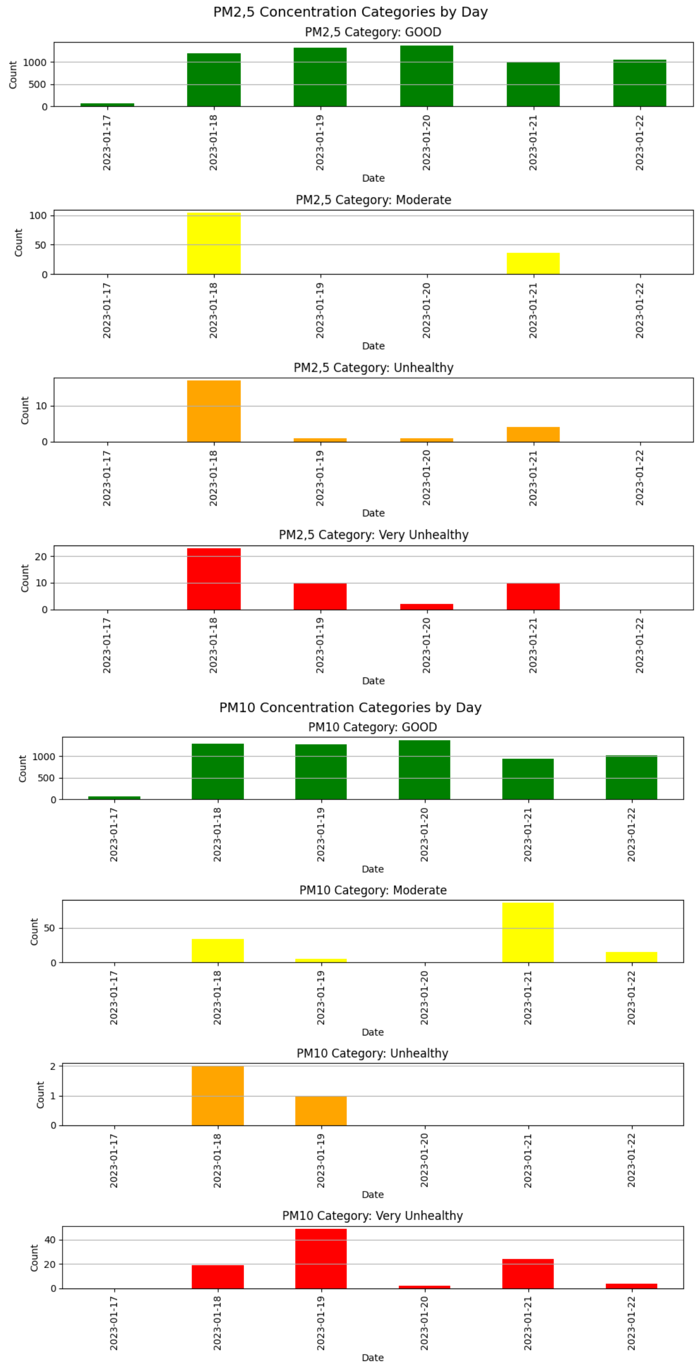


Figure 13. Concentration by range of CO_2, $PM_{2.5}$, and PM_{10} over 6 days.

5.3.1. Data Pre-processing

In our data pre-processing phase, we first collected a total of 6201 instances for each feature over six days. Following this, we conducted several steps to ensure the quality of the data and prepare it for modeling. This involved cleaning the data, handling missing values and outliers, and formatting it appropriately. Furthermore, as part of our pre-processing strategy, we categorized the data into four levels: Good, Moderate, Unhealthy, and Very Unhealthy, based on the pollutant levels. Our objective is to utilize these categorized pollutant levels as features for prediction. Specifically, our goal is to predict whether there is a risk to workers (1) or not (0) based on these features. To ensure that our features are on a similar scale and have similar magnitudes, we applied feature scaling. This involved using the MinMaxScaler given in the following equation (5):

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} (\max - min) + min \qquad (5)$$

where $\boldsymbol{X}$ represents the original value of each feature, $\boldsymbol{X}_{\text{min}}$ and $\boldsymbol{X}_{\text{max}}$ denote the minimum and maximum values of each feature in the dataset, min and max represent the minimum and maximum values of the desired scale range, typically set to 0 and 1, respectively. This pre-processing step ensures that our features are appropriately prepared and standardized for modeling, enabling us to effectively train our machine learning algorithms, including Logistic Regression, Decision Trees, Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN).

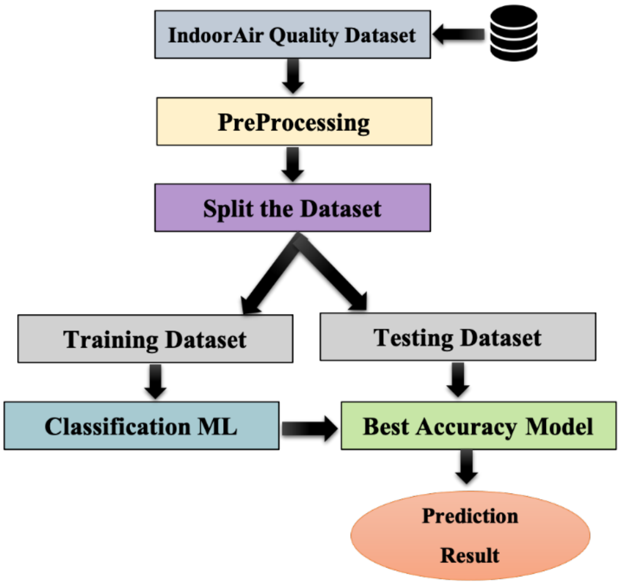


Figure 14. Overall architecture of IAQ Classification

5.3.2. Splitting the Dataset

In order to evaluate the performance of machine learning models, the dataset comprising 6,201 instances was divided into two parts: 80% for training and 20% for testing. This 80-20 split is widely accepted in supervised learning, offering a reliable balance between sufficient training data and the ability to generalize on unseen data. With 4,961 instances allocated to model training and 1,240 to testing, this split ensures a robust statistical evaluation while minimizing the risk of overfitting [49].

6. Results and Discussion

6.1. Model Selection Prediction and Evaluation Results of IAQ

Commonly used supervised machine learning is applied to the dataset such as Logistic regression, Decision tree, Random Forest, Support Vector Machines (SVM), and K-nearest neighbors (KNN). To assess the effectiveness of the classifier, we employed a range of evaluation metrics. These encompass precision, F1-score, recall, and accuracy, which were calculated using specific Equations (1)-(4) as mentioned before. Table 3. shows the precision, F1-score, accuracy, and recall metrics for each classification algorithm applied to the dataset. All the results of the performance evaluation of these classification models are listed in Table 2. All classifiers are observed to show strong performance with high accuracy rates. The SVM classifier exhibited comparatively lower performance relative to other classifiers, although still recommendable. Specifically, the SVM classifier excelled when confronted with large datasets characterized by substantial variability and numerous features.

Table 3. Model Performance Evaluation of the Classifiers

Model	Accuracy (%)	F1-Score (%)	Precision (%)	Recall (%)
KNN	99.7	1.00	1.00	1.00
RF	99.9	1.00	1.00	1.00
SVM	95.4	1.00	1.00	1.00
LR	99.9	1.00	1.00	1.00
D Tree	99.9	1.00	1.00	1.00

The result of the confusion matrix in Figure 15 shows that our model performed well in classifying safe instances (class 0) and risk instances (class 1). There were 1686 true positive instances that the model correctly classified as Safe (0). On the other side, there were 173 true negative instances, which indicate that the model correctly classified as Risk (1). The number of instances of false positives is just 1 that the model incorrectly classified as risky when they were safe conversely, there were no occurrences where the model misclassified risky air quality as safe. This absence of false negatives signifies an optimal outcome, indicating the model's ability to accurately discern all hazardous cases.

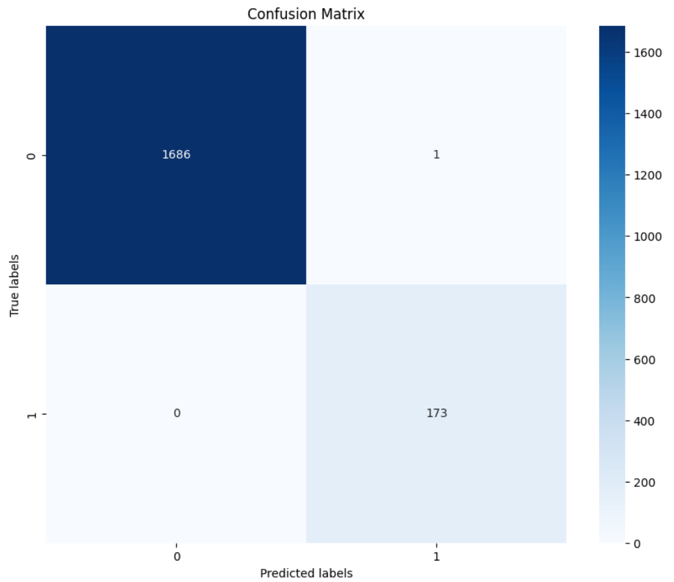


Figure 15. Confusion Matrix of the Performance Classification.

Figure 16 shows the report of the percentage of risky and safe indoor air quality detected in Zone 2 from the stored dataset over six days that can be analyzed by the HSE manager via the RDSA platform. Various previous machine learning algorithms are employed on the collected and stored dataset in the cloud to study the global status pattern to take the necessary actions to reduce the risks. From the tested dataset, 90.1% of the indoor air quality is found to be safe, and 9,9% is found to be risky. The safe and risky environments are detected by just taking a single instance of detecting good/poor air quality.

In addition, an IAQ time series analysis was performed to assess the robustness of the system during the continuous monitoring period. The results in Table 4, expressed in terms of RMSE, MAE, and MAPE, demonstrate the model's prediction accuracy for each pollutant: CO_2 (RMSE = 273.17, MAE = 67.54, MAPE = 7.49%), MA2.5 (RMSE = 16.03, 89%), MA2.5 (RMSE = 16.03, 89%), MA26 = 44,757.76%). These results indicate that CO2 concentrations actually reached high levels with low percentage errors, while $PM_{2.5}$ and especially PM_{10} showed large percentage errors due to their low mean values and high variability, a common problem in quantitative determination.

Table 4. Extended Time-Series Evaluation (RMSE, MAE, MAPE) of IAQ Prediction Models for CO_2, PM2.5, and PM10

Pollutant	**RMSE**	**MAE (%)**	**MAPE**
CO_2	273.170612	67.540818	7.493027
PM2.5	16.028346	6.806210	72.999945
PM10	44.257464	38.928630	757.759690

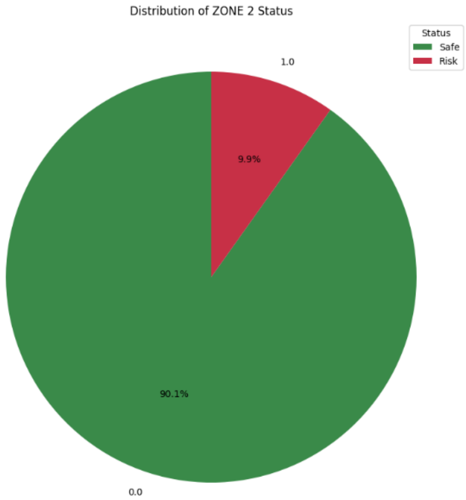


Figure 16. Safe vs Risk Air Quality in Zone 2.

6.2. Results of Facemask Model

In Figure 17, the line graph illustrates the training and validation performance of the proposed model over 20 epochs. It is evident that the model achieved high accuracy in both training and validation phases while minimizing loss throughout the epochs. The results in Figure 18 demonstrate the model's strong performance on a separate validation dataset.

The model achieved an overall accuracy of 0.99 (both weighted and macro averages), correctly classifying 99% of the images in the validation set. The evaluation metrics provide further insights into class-specific performance:

- Precision: For both the "with_mask" and "without_mask" classes, the precision is 0.99, indicating that when the model predicts a particular class, it is 99% likely to be correct.
- Recall: The recall also reaches 0.99 or higher, meaning the model successfully identifies 99% of images belonging to each class.
- F1-score: Close to 0.99 for both classes, reflecting an excellent balance between precision and recall.
- Support: The validation set includes 433 "without_mask" and 386 "with_mask" samples.

Figure 19 presents the confusion matrix, offering a visual representation of these results. It shows that the model correctly classified all 433 "with_mask" samples and 382 of the 386 "without_mask" samples, misclassifying only 4 instances. This confirms the model's robustness and reinforces the quantitative metrics discussed above.

Figure 17. Training Loss and Accuracy.

```
Epoch 20/20
102/102 [==============================] - 163s 2s/step - loss: 0.0355 -
 - val_loss: 0.0330 - val_accuracy: 0.9915
[INFO] evaluating network...
              precision    recall  f1-score   support

   with_mask       0.99      1.00      0.99       433
without_mask       0.99      0.99      0.99       386

    accuracy                           0.99       819
   macro avg       0.99      0.99      0.99       819
weighted avg       0.99      0.99      0.99       819

[INFO] saving mask detector model...
```

Figure 18. Classification Report.

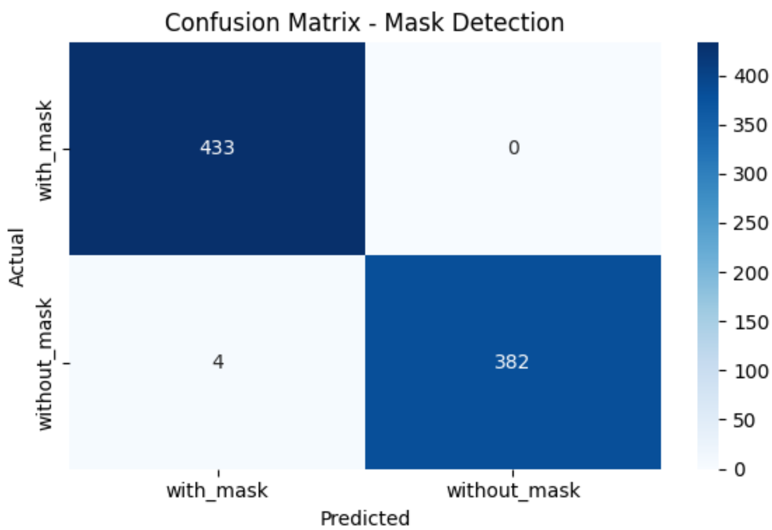


Figure 19. Classification Report.

Figure 20 depicts the test outcomes concerning the model's efficacy in identifying individuals wearing face masks, achieving a detection rate of 100%. When a mask is detected, the face is encased within a green rectangular box. Figure 21 shows the result of the model's performance in detecting individuals (workers) without face masks, achieving a detection rate of 100%. In instances where a mask is not detected, the alert message is displayed and the microcontroller sends an instant notification to the

RDSA platform. Overall, the results show that the model is extremely effective in distinguishing between images of workers with and without masks. It makes very few mistakes, and it's consistent in its performance regardless of whether the worker is wearing a mask or not.

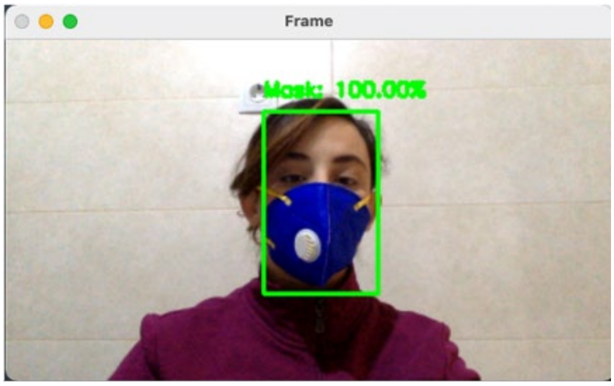


Figure 20. Result with Mask.

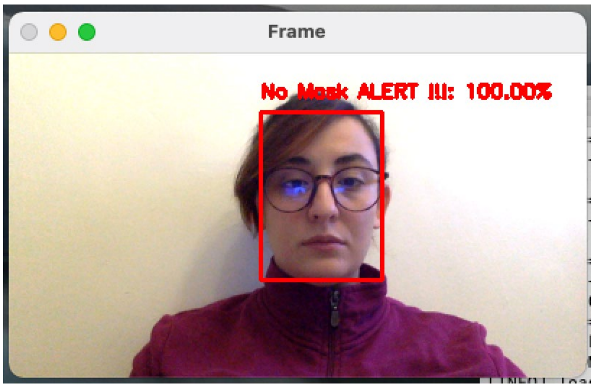


Figure 21. Result without Mask.

6.3 Latency Evaluation

The latency of the proposed system was evaluated across sensor data acquisition, cloud communication, processing, and alert mechanisms.

Sensor Response Time:

The SDS011 ($PM_{2.5}$/PM_{10} sensor) exhibits a fast response time (200 ms -1.5 s), making it suitable for real-time air quality monitoring. The MQ-135 (gas sensor) and DHT22 (temperature/humidity) require 1-2 s for stable readings due to their inherent response characteristics [50].

Cloud Communication (MQTT + ThingSpeak): Data transmission via MQTT to ThingSpeak achieves < 1s latency for single channel updates under stable network conditions [51]. Multi-channel updates or high server load may introduce additional delays.

Machine Learning Inference:

Models (Decision Tree, SVM, KNN, Logistic Regression, Random Forest) complete inference in 1-2s on moderately sized datasets when processed on edge/cloud platforms.

Notification Latency:

ThingSpeak dashboard updates reflect changes in < 1s.

SMS alerts experience 2-5 s latency due to telecom gateway delays (not sub-second).

Face Mask Detection Module:

Image capture (Raspberry Pi 4 + V1.3 camera) and CNN inference achieve a mean latency of 0.5-1.5 s in real-time video streams. The optimized CNN model sustains < 1s detection speed, ensuring prompt alerts for non-compliance.

In total the system integrated demonstrate a low-latency performance (sensors: 200 ms - 2 s, cloud: < 1 s, ML: 1-2 s, mask detection: 0.5-1.5 s) ensures real-time risk identification and compliance monitoring, enhancing its suitability for industrial safety application.

7. Conclusion Limitations and Future Work

The rapid integration of Industry 4.0 technologies, including the Internet of Things and artificial intelligence, offers considerable potential for improving occupational health and safety practices, particularly in indoor air quality monitoring in industrial environments. This study presented the Risk Detection and Safety Assistance (RDSA) system, a comprehensive solution leveraging IoT sensors and AI algorithms for continuous monitoring of airborne harmful substances and mask compliance.

Extensive experimental evaluation demonstrated consistently high classification performance across multiple models, with minimal false positives and no false negatives. Confusion matrix analysis confirmed the model's ability to accurately differentiate safe from unsafe conditions, enabling rapid interventions. Furthermore, the system achieved exceptional performance in real-time mask detection, thereby strengthening compliance with workplace safety regulations.

The results of the practical deployment indicate that the RDSA system is a valuable tool for OHS managers, enabling centralized and efficient monitoring while facilitating informed decision-making. This research highlights the transformative role of Industry 4.0 in creating safer industrial environments and underscores the importance of combining IoT and AI for proactive risk management.

7.1. Limitations

Although the proposed RDSA system exhibits robust real-time monitoring capabilities, some limitations remain:

Privacy concerns: The use of camera-based mask detection, even in limited deployment scenarios, may raise concerns about the privacy of worker data. Ensuring compliance with data protection regulations requires robust anonymization techniques, secure data processing, and transparent communication with employees.

Latency Sensitivity: Although designed for low-latency performance, delays in sensor data acquisition, cloud communication, and AI inference could impact the timeliness of alerts in high-risk environments. Even minimal latency could reduce the system's ability to prevent exposure to hazardous conditions or enforce mask use.

Industrial Data Constraints: Due to confidentiality agreements with industrial partners, validation in real-world industrial environments was limited, potentially limiting the range of operational scenarios tested.

7.2. Future Work

To advance the RDSA system, future research will focus on:

Extended Industrial Validation: Conducting long-term tests at multiple industrial sites to assess scalability, robustness, and adaptability under various operational conditions, once authorization from industrial partners has been obtained.

Automated alerting mechanisms: Implementation of a fully automated notification system that directly alerts workers via SMS or wearable devices, while providing the HSE manager with a real-time status dashboard.

Advanced predictive models: As part of this work, we have already performed extended time series evaluations (RMSE, MAE, MAPE) for indoor air quality forecasting. Future work will enhance this capability by integrating ensemble learning and transformer-based time series forecasting models to further improve forecast accuracy.

Privacy-preserving AI: Integration of privacy-enhancing technologies, such as edge AI inference and federated learning, to ensure data privacy while preserving system performance.

Author Contributions

Conceptualization, methodology, software, data curation, formal analysis, and writing original draft preparation: D.D. (Dina Djeghar);Validation and writing review and editing: K.A. (Karima Aksa), A.B. (Ahcène Bounceur), and M.A. (Mounir Aouadj); Supervision: K.A. (Karima Aksa) and A.B. (Ahcène Bounceur). All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Data Availability Statement

The dataset is available on the figshare dataset page: https://doi.org/10.6084/m9.figshare.27280983.v1, and https://github.com/X-zhangyang/ Real-World-Masked-Face-Dataset.

Ethical Declaration

This research does not involve human participants or animal subjects. The study exclusively used the author's own image for testing purposes. Therefore, no ethical approval was required. Informed consent was inherently given by the author for the use of their image.

References

1. H. Kagermann, Change through digitization value creation in the age of industry 4.0, in: H. Albach, H. Meffert, A. Pinkwart, R. Reich- wald (Eds.), Management of Permanent Change, Springer Gabler, Wies- baden, 2015. doi:10.1007/978-3-658-05014-6_2.
2. M. Ghobakhloo, Industry 4.0, digitization, and opportunities for sustainability, Journal of cleaner production 252 (2020) 119869. doi:https: //doi.org/10.1016/j.jclepro.2019.119869.
3. O. Demikhov, Y. Opanasiuk, N. Demikhova, E. Merisalu, A digital transformation into occupational health and safety systems: a review of the best practices in europe 21 (2023). doi:https://doi.org/10. 15159/ar.23.083.
4. N. Sias, E. Cellura, V. Mortara, et al., Occupational diseases: when union is not strength, Giornale Italiano di Medicina del Lavoro ed Er- gonomia 39 (1) (2017) 16–25.
5. F. Tanir, B. Mete, Impacts of the indoor air quality on the health of the employee and protection against these impacts, in: Air quality and health, IntechOpen, 2022. doi:10.5772/intechopen.102708.
6. J. Lemos, P. D. Gaspar, T. M. Lima, Environmental risk assess- ment and management in industry 4.0: a review of technologies and trends, Machines 10 (8) (2022) 702. doi:https://doi.org/10.3390/ machines10080702.
7. L. Parri, M. Tani, D. Baldo, S. Parrino, E. Landi, M. Mugnaini, A. Fort, A distributed iot air quality measurement system for high-risk workplace safety enhancement, Sensors 23 (11) (2023) 5060. doi:https://doi. org/10.3390/s23115060.
8. N. Uddin, S. G. Tarigan, K. A. Mannan, A low-cost iot system for monitoring air quality in indoor working places (2022) 781–786doi:10. 1109/ICITISEE57756.2022.10057879.
9. L. García, A.-J. Garcia-Sanchez, R. Asorey-Cacheda, J. Garcia-Haro, C.-L. Zúñiga-Cañón, Smart air quality monitoring iot-based infrastruc- ture for industrial environments, Sensors 22 (23) (2022) 9221. doi: https://doi.org/10.3390/s22239221.
10. J. B. da Costa, E. J. P. Souto, A iot device for monitoring particulate matter and gaseous pollutants in indoor industrial workstations (2022) 517–518doi:10.1109/ICCE-Taiwan55306.2022.9869034.
11. I. Campero-Jurado, S. Márquez-Sánchez, J. Quintanar-Gómez, S. Ro- dríguez, J. M. Corchado, Smart helmet 5.0 for industrial internet of things using artificial intelligence, Sensors 20 (21) (2020) 6241. doi: https://doi.org/10.3390/s20216241.
12. N. Singh, V. K. Gunjan, G. Chaudhary, R. Kaluri, N. Victor, K. Lak- shmanna, Iot enabled helmet to safeguard the health of mine workers, Computer Communications 193 (2022) 1–9. doi:https://doi.org/10. 1016/j.comcom.2022.06.032.
13. F. P. Panghurian, N. Surantha, A. Zahra, A low-power scenario for iot-based indoor air quality monitoring system at workplace, in: IOP Conference Series: Earth and Environmental Science, Vol. 195, IOP Publishing, 2018, p. 012048. doi:10.1088/1755-1315/195/1/012048.
14. P. Rotich, Development of indoor industrial environment monitoring system based on wireless sensor networks for a digital assembly plant (2021). doi:https://doi.org/10.58694/20.500.12479/1347.
15. R. K. Kodali, A. Valdas, Mqtt based environment monitoring in fac- tories for employee safety (2017) 152–155doi:10.1109/ICATCCT.2017. 8389123.
16. A. A. Jaber, F. K. I. Al-Mousawi, H. S. Jasem, Internet of things based industrial environment monitoring and control: a design approach, In- ternational Journal of Electrical and Computer Engineering (IJECE) 9 (6) (2019) 4657–4667. doi:10.11591/ijece.v9i6.pp4657-4667.
17. T.-Y. Chang, G.-Y. Chen, J.-J. Chen, L.-H. Young, L.-T. Chang, Ap- plication of artificial intelligence algorithms and low-cost sensors to estimate respirable dust in the workplace, Environment International 182 (2023) 108317. doi:https://doi.org/10.1016/j.envint.2023. 108317.
18. M. N. A. Ramadan, M. A. H. Ali, S. Y. Khoo, M. Alkhedher, and M. Alherbawi, "Real-time IoT-powered AI system for monitoring and forecasting of air pollution in industrial environment," *Ecotoxicology and Environmental Safety*, vol. 283, p. 116856, 2024. https://doi.org/10.1016/j.ecoenv.2024.116856
19. T. Veeramanikandasamy, G. S. Raj, A. Balamurugan, A. P. Ramesh, and Y. A. S. Khadar, *IoT-Based Real-Time Air Quality Monitoring and Control System to Improve the Health and Safety of Industrial Workers*. [Online]. Available: https://doi.org/10.35940/ijrte.d1604.018520
20. K. D. P. Mariano, F. L. N. Almada, and M. A. Dutra, *Smart air quality monitoring for automotive workshop environments*, arXiv preprint, 2024. https://doi.org/10.48550/arxiv.2410.03986
21. U. EPA, Particulate matter (pm) basics, USA: United States Environ- mental Protection Agency (2016).
22. G. W. Thomas, S. Sousan, M. Tatum, X. Liu, C. Zuidema, M. Fitz- patrick, K. A. Koehler, T. M. Peters, Low-cost, distributed environ- mental monitors for factory worker health, Sensors 18 (5) (2018) 1411. doi:https://doi.org/10.3390/s18051411.
23. T. Y. Wu, S. Horender, G. Tancev, K. Vasilatou, Evaluation of aerosol- spectrometer based pm2. 5 and pm10 mass concentration measure- ment using ambient-like model aerosols in the laboratory, Measurement 201 (2022) 111761. doi:https://doi.org/10.1016/j.measurement. 2022.111761.

24. H. Zhang, S. Zhang, W. Pan, Z. Long, Low-cost sensor system for monitoring the oil mist concentration in a workshop, Environmental Science and Pollution Research 28 (2021) 14943–14956. doi:https: //doi.org/10.1007/s11356-020-11709-9.
25. H. Zheng, V. Krishnan, S. Walker, M. Loomans, W. Zeiler, Labora- tory evaluation of low-cost air quality monitors and single sensors for monitoring typical indoor emission events in dutch daycare centers, Environment International 166 (2022) 107372. doi:https://doi.org/10. 1016/j.envint.2022.107372.
26. F. Lolli, A. M. Coruzzolo, S. Marinello, A. Traini, R. Gamberini, A bib- liographic analysis of indoor air quality (iaq) in industrial environments, Sustainability 14 (16) (2022) 10108. doi:https://doi.org/10.3390/ su141610108.
27. I. Brüske, E. Thiering, J. Heinrich, K. M. Huster, D. Nowak, Respirable quartz dust exposure and airway obstruction: a systematic review and meta-analysis, Occupational and environmental medicine 71 (8) (2014) 583–589. doi:https://doi.org/10.1136/oemed-2013-101796.
28. C.-T. Kuo, F.-F. Chiu, B.-Y. Bao, T.-Y. Chang, Determination and prediction of respirable dust and crystalline-free silica in the taiwanese foundry industry, International journal of environmental research and public health 15 (10) (2018) 2105. doi:https://doi.org/10.3390/ ijerph15102105.
29. A. Lenander-Ramirez, L. Bryngelsson, P. Vihlborg, H. Westberg, L. An- dersson, Respirable dust and silica: respiratory diseases among swedish iron foundry workers, Journal of Occupational and Environmental Medicine 64 (7) (2022) 593–598. doi:10.1097/JOM.0000000000002533.
30. A. M. Neophytou, S. Costello, S. Picciotto, D. M. Brown, M. D. Attfield, A. Blair, J. H. Lubin, P. A. Stewart, R. Vermeulen, D. T. Silverman, et al., Diesel exhaust, respirable dust, and ischemic heart disease: an application of the parametric g-formula, Epidemiology 30 (2) (2019) 177–185. doi:10.1097/EDE.0000000000000954.
31. H. P. Notø, K.-C. Nordby, W. Eduard, Relationships between personal measurements of 'total'dust, respirable, thoracic, and inhalable aerosol fractions in the cement production industry, Annals of Occupational Hy- giene 60 (4) (2016) 453–466. doi:https://doi.org/10.1093/annhyg/ mev093.
32. H. Zilaout, J. Vlaanderen, R. Houba, H. Kromhout, 15 years of mon- itoring occupational exposure to respirable dust and quartz within the european industrial minerals sector, International Journal of Hy- giene and Environmental Health 220 (5) (2017) 810–819. doi:https: //doi.org/10.1016/j.ijheh.2017.03.010.
33. G. Marques, C. R. Ferreira, R. Pitarma, Indoor air quality assessment using a co2 monitoring system based on internet of things, Journal of medical systems 43 (3) (2019) 67. doi:https://doi.org/10.1007/ s10916-019-1184-x.
34. T.-C. Yu, C.-C. Lin, C.-C. Chen, W.-L. Lee, R.-G. Lee, C.-H. Tseng, S.-P. Liu, Wireless sensor networks for indoor air quality monitoring, Medical engineering & physics 35 (2) (2013) 231–235. doi:https:// doi.org/10.1016/j.medengphy.2011.10.011.
35. A. Standard, Thermal environmental conditions for human occupancy, ANSI/ASHRAE, 55 5 (1992).
36. D. Clements-Croome, et al., Creating the productive workplace, Vol. 2, Taylor & Francis Books London, 2006.
37. American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE). (2022). ANSI/ASHRAE Standard 62.1-2022: Ventilation for acceptable indoor air quality. ASHRAE. https://www.ashrae.org/technical-resources/bookstore/standards-62-1-62-2.
38. O. Safety, H. Administration, et al., Osha technical manual: Section vi, chapter 2, Indoor Air Quality Investigation. Washington, DC: Author (1999).
39. E. J. Calabrese, E. Kenyon, Air toxics and risk assessment, CRC Press Books, 1991.
40. W. H. Organization, Air Quality Guidelines: Global Update 2005: Par- ticulate Matter, Ozone, Nitrogen Dioxide, and Sulfur Dioxide, World Health Organization, Geneva, 2006.
41. M. Tagle, F. Rojas, F. Reyes, Y. Vásquez, F. Hallgren, J. Lindén, D. Kolev, Å. K. Watne, P. Oyola, Field performance of a low-cost sensor in the monitoring of particulate matter in santiago, chile, Envi- ronmental monitoring and assessment 192 (3) (2020) 171. doi:https: //doi.org/10.1007/s10661-020-8118-4.
42. K. N. Genikomsakis, N.-F. Galatoulas, P. I. Dallas, L. M. Can- danedo Ibarra, D. Margaritis, C. S. Ioakimidis, Development and on- field testing of low-cost portable system for monitoring pm2.5 concen- trations, Sensors 18 (4) (2018) 1056. doi:https://doi.org/10.3390/ s18041056.
43. F. N. Abbas, I. M. Saadoon, Z. K. Abdalrdha, E. N. Abud, Capable of gas sensor mq-135 to monitor the air quality with arduino uno, Int. J. Eng. Res. Technol 13 (10) (2020) 2955–2959. doi:https://dx.doi. org/10.37624/IJERT/13.10.2020.2955-2959.
44. U.S. Environmental Protection Agency. (2014). Technical assistance document for the reporting of daily air quality – the Air Quality Index (AQI) (EPA-454/B-14-001). https://www.airnow.gov/sites/default/files/2020-05/aqi-technical-assistance-document-sept2018.pdf
45. Kaur, G., Sinha, R., Tiwari, P. K., Yadav, S. K., Pandey, P., Raj, R., ... & Rakhra, M. (2022). Face mask recognition system using CNN model. *Neuroscience Informatics*, *2*(3), 100035.
46. Z. Wang, B. Huang, G. Wang, P. Yi, K. Jiang, Masked face recognition dataset and application, IEEE Transactions on Biometrics, Behavior, and Identity ScienceAvailable at: https://github.com/ X-zhangyang/Real-World-Masked-Face-Dataset (2023). doi:10. 1109/TBIOM.2023.3242085.
47. D. M. Powers, Evaluation: from precision, recall and f-measure to roc, informedness, markedness and correlation, arXiv preprint arXiv:2010.16061 (2020). doi:https://doi.org/10.48550/arXiv. 2010.16061.
48. D. Djeghar, Indoor air quality dataset (pm2.5, pm10, co2, temperature, humidity) (2024).doi:10.6084/m9.figshare.27280983.v1. URL https://doi.org/10.6084/.

49. Kuhn, M., & Johnson, K. (2013). *Applied predictive modeling* (Vol. 26, p. 13). New York: Springer
50. Han, S., Kim, S., & Lee, J. (2018). Performance evaluation of low-cost gas sensors for real-time air quality monitoring. *Sensors and Actuators B: Chemical*, 255, 1129–1136. https://doi.org/10.1016/j.snb.2017.08.158
51. MathWorks. (2024). ThingSpeak Documentation – Latency and Update Rates. https://www.mathworks.com/help/thingspeak