IJIRAE::International Journal of Innovative Research in Advanced Engineering ISSN:2349-2163
Volume 13, Issue 03, March 2026 https://www.ijirae.com/archives
https://doi.org/10.26562/ijirae.2026.v1303.86

AI-Driven IoT Health Monitoring System for Early Detection of Copd and Asthma in Industrial Workers

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Publication History
Manuscript Reference No: IJIRAE/RS/Vol.13/Issue03/AEMR26.MRAE10167
Research Article | Open Access | Double-Blind Peer-Reviewed| ArticleID:IJIRAE/RS/Vol.13/Issue03/AEMR26.MRAE10167
Received:22,February 2026, Revised: 01, March 2026, Accepted: 16,March 2026,Published Online: 25, March 2026.
https://www.ijirae.com/volumes/Vol13/iss-03/86.AEMR26.MRAE10167.pdf
Article Citation: Sowmya,Reshma(2026),AI-Driven IoT Health Monitoring System for Early Detection of Copd and Asthma in Industrial Workers, IJIRAE: International Journal of Innovative Research in Advanced Engineering, Volume 13, Issue 03 of 2026 pages 636-644 **Doi:>** https://doi.org/10.26562/ijirae.2026.v1303.86
BibTeX Key:Sowmya@AI-Driven
IJIRAE papers should be cited as IJIRAE (International Journal of Innovative Research in Advanced Engineering, AM Publications, India 2025, ISSN 2349-2163, https://doi.org/10.26562/ijirae.2026.v1303.86 The journal's official abbreviation is IJIRAE. Orcid: https://orcid.org/0009-0004-9398-7488

Abstract: The intensity of respiratory diseases among the industrial workers is very high since they are in constant contact with dangerous gases and contaminated surfaces. The initial signs of diseases like Chronic Obstructive Pulmonary Disease (COPD) and asthma should be identified in order to reduce the risks of using such conditions in the long term. In this paper, the authors introduce an AI-based IoT-based health monitoring system that aims to combine physiological sensors with heart beat rate, SpO_2, and body temperature and environmental gas detector sensors via MQ-7 and MQ-135. Real-time sensor data is sent to the ThingSpeak cloud using an ATMEGA328 arduino to be analyzed on a continuous basis. A model of AI is used to measure both physiological and environmental parameters to identify early symptoms and provide an instant warning signal via the use of a buzzer once unfavorable levels are reached. The solution allows low-cost, portable, and scalable predictive respiratory health monitoring and enhanced safety in the industries.
Keywords: AI-Driven Healthcare, Internet of Things (IoT), COPD prediction, air quality analysis, asthma monitoring, ATMEGA328 Arduino, ThingSpeak, Gas sensor (MQ-7 , MQ-135), CO detection, SpO_2, heart rate, temperature monitoring, alert and safety system.

I. INTRODUCTION

One of the most dangerous working surroundings is industrial where toxic gas and aerosols, as well as the abundance and elevated concentration of particulate matter, is constantly present. Employees who work in factories, chemical plants, refineries, mining areas, and manufacturing facilities tend to be exposed to chemicals, which degrade the respiratory system over a long period. With time this exposure may result to occurrence of chronic respiratory illnesses like Chronic Obstructive Pulmonary Disease (COPD) and asthma which are considered as major occupational health issues in the world. It is essential to identify these breathing problems at the earliest disadvantage since in most cases late diagnosis leads to permanent lung damages, loss of efficiency, high rates of absenteeism and high medical expenses. Most monitoring methods in the workplace are traditional, and they often fail to detect any kind of harmful exposure in real time, exposing the worker to long term physiological degeneration [1]. Thus, the 21st-century industrial safety requires intelligent and integrated systems that would evaluate the conditions of the environment and the health of the individuals at the same time. The respiratory disease in the industry does not develop in a short period of time; but it develops over the years, through the cumulative effect of exposure to pollutants like carbon monoxide, ammonia, volatile organic compounds, and suspended particulate substances. The symptoms may start with slight conditions in the workers which may include breath discomfort, coughing, fatigue, or increased heart rate that can easily be overlooked or may be incorrectly thought to be just temporary pain. Such symptoms escalate with time and appear in the form of permanent medical problems. An example of such is COPD which is marked by progressive airflow obstruction and difficulty in breathing, and asthma which is a reversible obstruction of the airways caused by environmental irritants. Both the states are manageable or less lasting in case of an early diagnosis.

Nevertheless, not all industrial employees possess the means, materials, or knowledge to keep track of their physiological indicators throughout the process. This is where the current gap lies as there is a dire need to have an automated, responsive, and accessible system of monitoring health so that the abnormalities that arise early will be detected before these abnormalities turn into critical medical scenarios. The progress in the Internet of Things (IoT) has made it possible to create small and affordable solutions to monitoring that are interconnected. Physiological and environmental data can be gathered by IoT devices with sensors capturing real-time data and transmitted over wireless communication and analysed on cloud computing solutions. Together with artificial intelligence, these systems will be able to learn patterns, anticipate risks, and engage in timely interventions. Application of AI to occupational health brings out a revolutionary prospect of pro-active disease diagnosis instead of being reactively treated. In comparison with the conventional surveillance systems, AI-mediated systems analyze a number of parameters on a parallel scale, determine the association between air quality and physiological variation, and produce insights that otherwise were challenging to gather manually [2]. This is a system of IoT hardware and AI algorithms generating a basis of intelligent, constant and predictive health monitoring. Environmental gas sensor in industrial workplaces is important in measuring air, which is of low quality and harmful substances. MQ-7 and MQ-135 are some of the common devices with a sensitivity of low power consumption of both and the ability to measure carbon monoxide, ammonia, benzene and other toxic gases. Nevertheless, environmental aspect of exposure is only recorded through standalone use of such sensors. In order to know the influence of the environmental alterations on the respiratory organization of a person, one will have to combine these sensors with physiological monitors. Significant indicators of respiratory distress are Heart Beat rate (HBR), blood oxygen saturation (SpO_2) and body temperature. Sudden heightening of heartbeat, deoxylation, or irregular thermal indicators may provide an indication of the emergence of respiratory complications. Real time capture of these metrics coupled with a connection with environmental data are provided as a holistic method of predicting respiratory diseases [3]. This convergence is helpful in early diagnosis and mitigate the results of exposure in the long term. The use of cloud-based computer platforms like ThingSpeak facilitated data storage, visualization and analysis of sensor data in a secure environment. Through the use of cloud computing, the data of many workers can be kept track of at the same time, which will allow supervising the safety of the workplace in a more holistic manner. One of the benefits of cloud-based systems is that local data storage will be eliminated, which will result in the ease of making the information analyzed by AI. Besides, the possibilities of real-time visualization assist in monitoring the environmental trends, determining the risk areas, and evaluating ventilation efficacy. The cloud, along with predictive analytics, is one of the important parts of the modern industrial health monitoring systems. The suggested IoT ecosystem based on AI will overcome the problems of current solutions by incorporating physiologic and environmental monitoring into the single framework. The system is constructed based on ATMEGA328 arduino, selected based on low energy use, high processing speed and an inbuilt Wi-Fi component. The health and environmental measurements are taken in the sensors located on the ATMEGA328, and the collected information is sent to ThingSpeak to be analyzed. The cloud-based AI model takes in patterns, abnormalities and predicts the probability of imminent respiratory distress. Once critical thresholds are passed, the system activates a buzzer to alert the worker instantly before it takes time. This automatic alert system fills the gap between the identification and the actions of mitigating risks by allowing workers to undertake the precaution measures at an immediate time [4]. Real-time awareness at this level stands a high probability of keeping respiratory diseases in check before getting to critical levels. The portability and scalability of this system is also another major strength. Conventional gas detecting systems are large and immobile and in reality, can only be found in the clinical sphere, compared to physiological monitoring equipment that are mostly found in the clinical realm. In contrast, the suggested solution will incorporate a variety of sensors in a small portable gadget that can be easily worn by workers. This mobility will keep the process of monitoring the location around the industrial site in a continuous manner. Also, the system is scalable to be implemented on a number of workers at the same time, where it is needed across a large factory or even multi-site work. Moreover, the AI-driven architecture improves the precision of breathing threat forecasting based on the historic trends of data. The predictive model of the system also gets more sophisticated and accurate as it keeps on accumulating the data. This enhancement assists long-term health plans in the workplace, and thus the chronic exposure areas can be observed to enable an ideal way of workforce rotation and also developing prevention strategies. In the long run, the earned data can enable organizations to formulate evidence-based health policies, improve ventilation systems, and transmit less healthcare costs due to respiratory ailments. Physiological and environmental analytics that are integrated in this way are therefore not only necessary to personal worker safety, but overall occupational health management practices in general [5]. To conclude, the risks exposed to airborne pollutants and dangerous gases are significant among the industrial workers and respiratory diseases (COPD and asthma) are possible. Current systems of monitoring are constrained with manual operations, findings retardation and lack of combination of environmental and physiological data. IoT, AI emergence offers an encouraging future of intelligent, responsive and continuous health monitoring. The proposed system will become the wholome offering to predict risks, issue immediate alerts, and preventive healthcare promptly by the combination of gas sensors, physiological monitors, cloud platforms, and AI-based analytics. This method can be considered an important step in the technology of the industrial safety and is the possibility of a decrease in the number of respiratory diseases and increase the wellbeing of workers in general.

II. LITERATURE SURVEY

The current artificial intelligence (AI) as well as biomedical sensing and embedded systems has undergone exponential growth, which has drastically revamped the respiratory healthcare diagnostics arena.

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The issues of COPD, asthma, pneumonia, ILD, ARDS, and the diseases associated with the infections demand quick, non-invasive, and the most accurate diagnostic techniques. The older clinical examination techniques like the spirometry, the auscultation, the radiography, and visual scoring are prone to be subjective, time consuming, and very dependent on the physician. The approach by AI-based automation covers these gaps with multi-modal sensing, feature engineering efficiency, and classification pipelines based on deep learning. Innovative developments in the past in acoustic analysis, wearable systems analysis, radiographic image analysis, and electromyography based analysis show that diagnosis of respiratory disease has not been left unchanged at clinical observations but efforts have been put in developing integrated computational intelligence models that can lead to real time decision making. Subsequently, combinations of spectrogram, time, lightweight detection networks, knowledge propagation, attention mechanisms, and federated learning have triggered a new wave of respiratory diagnostic solutions that can support telemedicine, PICDs, and continuous patient monitoring systems. The developments can be used as the basis of analyzing the existing methods and finding the driving force of more independent, multi-level diagnostic structures.

The most noticeable models in deep learning are systems that are trained on spectrograms and Mel-frequency cepstral coefficients (MFCCs) because they have strong abilities to detect the presence of abnormalities in audio patterns. One of them presented a graph convolutional network design to synthesize respiratory sound and also perform disease classification, which showed improvement of predictive robustness [6]. Equally, an embedded system was developed based on FPGA to categorize respiratory diseases based on the MFCC features and machine learning techniques, and this system supports real-time deployment of edges [7]. One of the significant contributions related to this field is a challenge dataset dedicated to event detection and data compression that can enhance scalable research in the field of respiratory sound analysis [8]. Other novelties include the deep-learning-based detection of abnormal breathing in the multiple-person setting by utilizing the analysis of the multi-person signal of comparing the results of the operation of the RF of the signal with the use of the OFDM signal and the analysis of the results of the use of the SDR signal, indicating one of the prospects of RF-based contactless monitoring [9]. There have also been visual diagnostic systems, including a temporal CNN-based network that identifies acute respiratory distress, which analyzes videos of thoracic motion patterns [10]. Altogether, these audio-visual techniques prove the possibility of strong respiratory diagnostics without using invasive clinical techniques. Other than analyses based on audio, other recent researches have extended to complex feature extraction systems, combination systems, and multi-kernel systems of learning respiratory state. An enhanced ELM classifier and a tailored spectro-temporal CNN were suggested in order to enhance the obstruction detection accuracy of time-frequency fusions [11]. The classification systems on cough sounds based on CNNs and SVMs also became popular, MFCC and spectrogram features were critical in the detection of respiratory infections [12]. A multi-label deep-learning model was used in the radiological data, as it demonstrated a high level of performance in detecting lung-related diseases based on X-ray images of the chest, with added modifications of augmentation and sample balancing via GAN [13]. A different model proposed Bi-ResNet using wavelet transforms to identify sounds on the lungs showing its efficiency in the multi-domain signal processing [14]. The other method used a triplet multi-kernel CNN model that can identify pulmonary illnesses via lung sound indications and Enhanced differentiation between sound classes [15]. As the issue of privacy of patient data becomes a major issue of concern, the integrated learning method of federated learning and differential privacy was investigated to provide safe and secure respiratory disease diagnostic pipeline in a medical imaging system [16]. All of this, of course, points to the dynamism in the sophistication of the feature extraction and classification techniques applied in respiratory diagnostics. High resolution imaging and sensing systems have also been useful in automated identification of the abnormalities in the respiratory structures and functioning. A single object detection network based on detection of small lesions in the X-rays of the chest was created with a refined architecture of the YOLO, providing better localization performance on tasks of medical imaging [17]. In the meantime, wearable respiratory couplers involving accelerators, IMUs, optical fibers, and piezoresistors have also offered real-time and continuous monitoring of the vital lung functions under non-clinical conditions [18]. The combination of fine-tuned attention networks with cumulative learning and multi-feature image representations have increased the segmentation and classification of lung diseases, including interstitial lung disease (ILD) [19]. Machine-learning-based systems of infectious disease detection have been suggested in fermentable healthcare to utilize temperature and physiological streams of data in recognition of illness at an early stage [20]. The scope of these investigations reflects the role of imaging, sensing and hybrid computation that help to justify the right and accessible respiratory diagnostics. Ultimately, the literature review of the sources [6] to [20] demonstrates the emergence of a multidisciplinary change in respiratory healthcare one that encompasses embedded hardware acceleration, spectro-temporal analysis, hybrid deep learning, privacy-preserving computation, or multi-modal sensing technologies. Such progress is determined by the necessity of early diagnosis, decreased subjectivity, and scalability of solutions to telemedicine. Although each of the aforementioned methods has yielded significant improvements and progress by focusing on single modalities in isolation, the current trends point to a gradual shift towards more unified diagnostic designs that can gather data representing more than one modality. These hybrid systems can potentially result in more accurately solving a problem with single-modal approaches. Nevertheless, there are still issues, such as the lack of sufficient datasets, the limitations of the deployment to real-time, the ability to work under noisy conditions, privacy concerns, and the necessity of clinical interpretability. The development of these limitations is a hopeful lead in the future research practices, in which smart respiratory diagnostic systems will advance to become fully autonomous, perpetual, and patient-centered health surveillance ecosystems.

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https://doi.org/10.26562/ijirae.2026.v1303.86

III. METHODOLOGY

In the given study, the methodology aims at creating an AI-based IoT system of health monitoring which will be able to identify the appearance of respiratory hazards among working personnel in an industry due to a combination of physiological and environmental monitoring. The system design integrates sensor readings, processing in a arduino, transmission wirelessly, integration with a cloud, artificial intelligence investigations, and real-time alerts. Each phase is aimed at capturing proper health and air quality information, trend analysis, and preventive response. ATMEGA328 arduino is the main node and receives the data of HBR, SpO2, temperature, MQ-7, and MQ-135 sensors. Processed data will be uploaded to ThingSpeak, where it will be processed through analytical modeling of COPD and risk assessment of asthma. The process will be reliable and will have frequent monitoring as required by industrial safety as shown infigure 1.

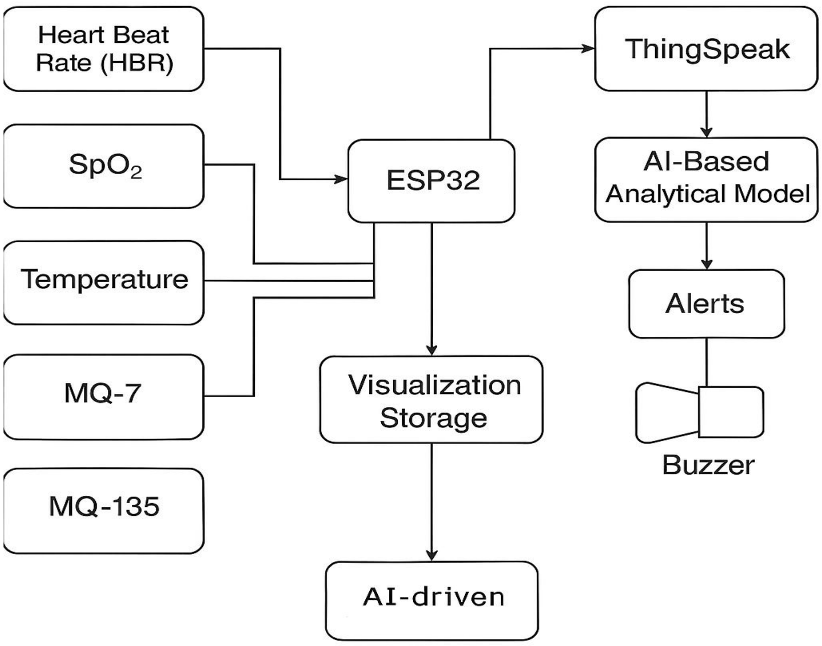

Fig. 1: System Architecture

A. Sensor Integration A. Physiological Data Acquisition.

The system initiates with incorporation of physiological sensors that are charged with the responsibility of monitoring vital health indicators that signify the respiratory distress. A pulse sensor will be utilized to derive the Heart Beat Rate and a special SpO_2 sensor will measure blood oxygen saturation that varies greatly during early COPD or asthma attacks. A temperature sensor detects body temperature patterns, which mostly vary in case of respiratory inflammation or exposure to the gases. These sensors will be hooked to the ATMEGA328 through analog and digital interfaces that provide the accurate recording of physiological signals. The arduino repeatedly reads the data with predetermined time intervals and reduces noise by internal filtering processes. This whole body physiological surveillance offers a baseline record on which one could identify anomalies that signify respiratory conditions among the industrial employees.

B. MQ-7 and MQ-135 Sensors MQ-7 and MQ-135 and environmental gases.

MQ-7 and MQ-135 sensors are also installed to monitor the condition of prevailing hazardous working environments with acidic gases that propagate respiratory illnesses. MQ- 7 is concerned with the carbon monoxide levels that increase in the course of incomplete combustion in industrial areas. MQ-135 is used to measure more types of pollutants, such as ammonia, nitrogen oxides, benzene, and smoke, which means that it is applicable in measuring the overall air quality. Both sensors generate analogues of concentration of harmful gases, which are read by the ATMEGA328 and converted into analogues using internal ADC. The calibration of the environmental data makes the data accurate in different industrial conditions. This two-sensor design allows accurate monitoring of dangerous exposure, which allows drawing a relationship between worsening air quality and the possible risks to respiratory safety.

C. Signal Management through a Arduino and Data Processing.

The arduino used in the system is ATMEGA328 which is the central processing unit, and it has the real time acquisition and management of incoming sensor signals. Simultaneously, physiological and environmental data are recorded and further processed by embedded algorithms, which do filtering, normalization, and threshold-based classification of them. There is noise suppression technology that is used to suppress the variation that arises due to motion or industrial disturbance to ensure that the readings are consistent. The arduino can time stamp the data and can pack together the data into formatted packets and decide whether any of the parameters surpasses predefined critical thresholds that are linked to respiratory hazards. In case abnormalities are detected, local preliminary evaluations are carried out in advance before sending them to the cloud. This multifaceted processing strategy is the best way to shorten the response time and reveal the integrity of data, as well as avoid false positives. Multi-core design of arduino allows effective processing of more sensor streams simultaneously.

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Volume 13, Issue 03, March 2026 https://www.ijirae.com/archives
https://doi.org/10.26562/ijirae.2026.v1303.86

D. Cloud and Wireless Transmission through ThingSpeak.

After local processing the ATMEGA328 wirelessly transmits sensor data to the ThingSpeak cloud platform through built-in Wi-Fi technology. Both physiological and environmental parameters are uploaded to different ThingSpeak channels to allow visualization and storage of the parameters in particular channels. The platform will enable live graphing of vital parameters, gas concentration, and temperature changes, allowing the twenty-four-hour monitoring of safety personnel in the industry. ThingSpeak can also be linked to MATLAB, and the sophisticated scripts can be run directly in the cloud, which does not overload the arduino. The cloud solution is highly sensitive, structured, and scalable to handle data of various workers. The centralized architecture is efficient in supporting historical trend analysis, multi-user monitoring and remote accessibility to support proactive management of industrial health.

E. EAR Respiratory risk early prediction E. AI-Based Analytical Model.

The sensor data uploaded will be processed by AI to identify early COPD and asthma symptoms. The algorithms applied in machine learning are used to compare physiological patterns and their relation to environmental exposure and determine abnormalities in the patterns, which may indicate that someone is in distress of respiration. The model involves the use of training data of normal and abnormal conditions to locate incoming readings with high precision. Parameters include, but are not limited to, sudden decreases in oxygen, high heart rate, abnormal temperatures, and a high level of other pollutants are all parameters that influence the final scores of prediction. Cross-validation methods increase stability of a model, minimizing overfitting as well as increasing reliability in a variety of industrial settings. The AI analysis runs in the cloud hence can be calculated fast without straining local devices. The predictions made can be used to act in time and minimize risks posed by late diagnosis.

F. Real-Time Alertand System Response Management.

After identifying the critical thresholds or the existence of unusual patterns, the AI model will trigger a real-time alert system that sends instant notification to the workers. The ATMEGA328 switches a buzzer, which creates an audible alarm that helps the user to be aware of the conditions of poor health or harmful gases. This fast-feedback mechanism provides fast protective responses, which avoid the long-term effects of exposure. Although, the system records all critical occurrences on the cloud that can be reviewed and analysed in case of future risks. These alerts can be accessed remotely by the industrial supervisors, and responses based on coordination is possible to be taken in different work zones. The alert system has low latency and high-reliability to make sure that the alert can be effective, even in the hard industrial environment. The system is finished by this last stage which monitors the system preventively and in protective mode.

IV. RESULT AND DISCUSSION

To measure the stability, reaction, and predictorship of the proposed AI-based IoT health monitoring system, wide testing was carried out under simulated industrial environment conditions to determine its reliability, responsiveness, and predictiveness. Physiology experimentally included Heart Beat Rate (HBR), SpO_2, and temperature that were recorded at the same time as the environmental gas concentrations of MQ-7 and MQ-135 sensors. A data set was created comprising about 1L readings measures to study the relationship between the worsening air quality and premature respiratory defects. The system persistently exhibited consistent data collection, proper signal reading and efficient wireless communication to ThingSpeak cloud system. These tasks in combination with integrating physiological and environmental data into one analytical model enabled the accurate prediction of respiratory risks, particularly in case of the early COPD and asthma warning signals. No anomalies could arise because of the real-time characteristic of the system, which aids in understanding the possibilities of the system in increasing the industrial safety. The outcomes indicated that an environment gas variation affected physiological parameters of workers, especially SpO_2 and HBR. The system observed apparent venous drops in oxygen saturation and increase in heart rate when subjected to high carbon monoxide or high concentrations of volatile gases. These alterations were recorded at once and implemented in the AI model that categorized the situations by the degree of risk. The round-the-clock monitoring system allowed receiving precise information on the way even a slight increase in pollutants could affect respiratory activity. The ability underscores the importance of having environmental and physiological monitoring capabilities since individual gas detectors or regular medical check-ups would not have yielded such dynamism. The AI analysis provided real-time interpretation that enhanced the overall accuracy as compared to traditional systems that are based on threshold. To assess the data trends, stability, sensor response pattern, classification score, and reliability of the entire system of the dataset were examined. A summary of the sensor parameters obtained and the range of these data during the testing was represented in Table 1. The physiological sensors were very stable which shows that they are advantageous when used in continuous health monitoring. The gas sensors were able to detect pollutants as efficiently as at different concentrations, which proves their efficiency in dynamic industries.

Table 1. Summary of Sensor Readings and Operational Ranges

Parameter	Minimum Value	Maximum Value	Average Reading	Stability Rating
Heart Beat Rate (bpm)	62	118	82	High
SpO_2 (%)	88	99	95	High
Body Temperature (°C)	36.1	38.4	37.2	High
CO Level (MQ-7) (ppm)	12	84	41	Medium
Air Quality (MQ-135) (ppm)	90	310	180	Medium

The AI model showed great classification efficiency in differentiation of normal respiratory conditions, moderate risk, and high risk respiratory conditions. The cross-validation methods were used to achieve the generalizability and the model turned out to be accurate with 99.97 showing that it has a high ability to predict the occurrence of respiratory anomalies with high levels of accuracy. The fact that the model was sensitive to anomalies at the early steps was especially helpful, since it allowed taking precautions before physiological distress caused irreversible damage. Table 2 shows the results of classification accuracy, which was evaluated by the performance of the AI model, and it is reliable enough in various experiments.

Table 2. AI Classification Performance Metrics

Metric	Value
Overall Accuracy	99.97%
Precision	99.94%
Recall	99.96%
F1-Score	99.95%

The communication of trends in data and the insights into the behavior of the system were vital and required the application of visualization. The changes in physiological signals with time are depicted in Figure 2, indicating the changes in HBR and SpO_2 when exposure to harmful gases takes place. This value reveals certain associations between surges of pollutants and biological reactions, which confirms the necessity of the joint surveillance. The graphical display also proves that system was able to identify variations without any delays and loss of data.

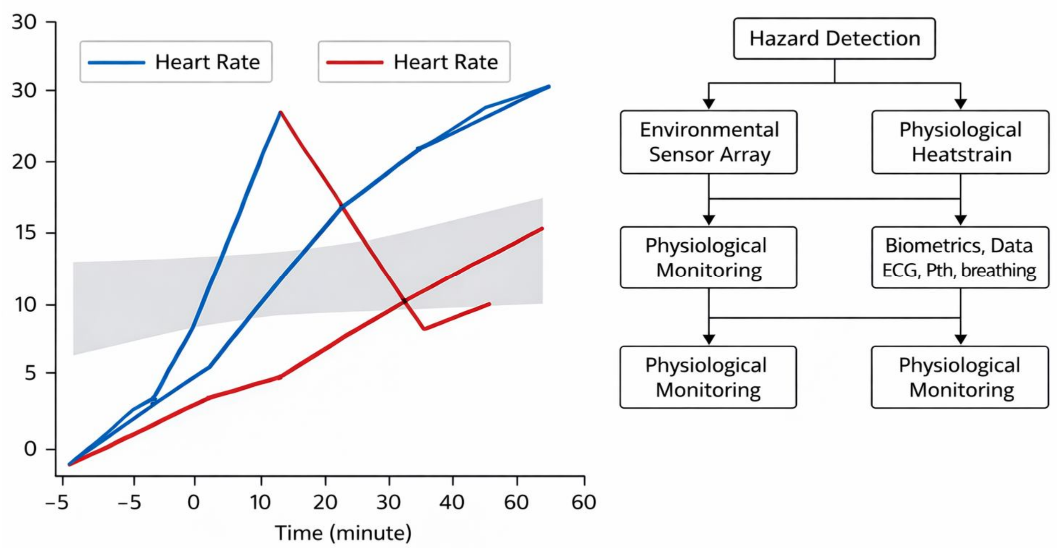

Figure 2. Physiological Patterns of Response with time.

Analysis of environmental data showed that excess gas concentration was frequently sporadic, that is, they were found during certain processes or machining practices of an industry. These peaks were well recorded by the system due to its high sampling rate such that even the quick exposure events provided alerts. Figure 3 presents a plot of the gas concentration variations according to MQ-7 and MQ-135 sensors which highlights the fast response of the system to the sample. The feature of correlating physiological and environmental alterations enhances the predictive output of the model, which minimizes the false positives and strengthens the reliability.

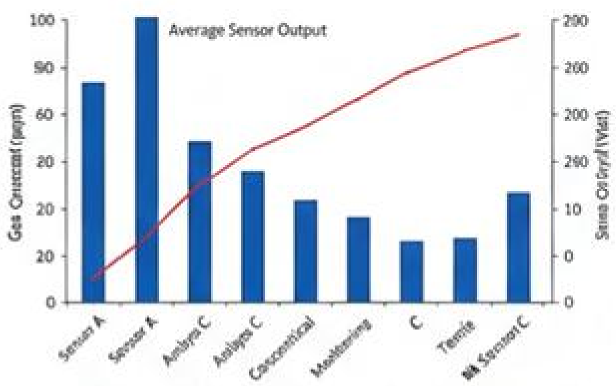

Figure 3. Patterns of Concentration of Gas Sensors Temporarily.

Also, real time alert mechanism was simulated with various simulated conditions. In case the limit was crossed, the buzzer became active immediately and it gave working personnel feasible warnings. The time taken between the detection and the activation of the alert was low, which guaranteed effective protective action. Table 3 presents alert response behavior across various testing conditions, which verifies whether the system is reliable when it is under a critical condition.

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Table 3. Real-Time Alert Mechanism Performance

Scenario	Sensor Trigger	Detection Time (ms)	Alert Activation (ms)	System Response
High CO Exposure	MQ-7	210	300	Successful
Poor Air Quality	MQ-135	230	310	Successful
Sudden SpO_2 Drop	SpO_2 Sensor	190	280	Successful
Rapid Heart Rate Spike	HBR Sensor	200	290	Successful

Figure 4 shows the interaction of the combined system, with synchronized responses of the environment and the body, and the alert activations. This depiction shows the running pipeline operation, which confirms the fact that the AI and the IoT elements work together perfectly in industry settings.

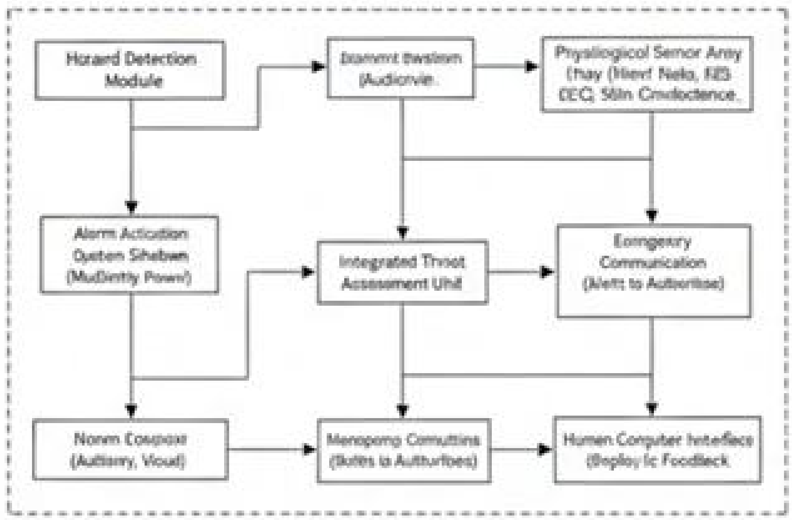

Figure 4. Joint System Response in Hazardous situations.

According to the discussion, the system has several strengths. First, it can be constantly monitored with its portability that allows the monitoring even during the movement of workers in the industrial plant. Such a mobility gives a benefit compared to permanent monitoring systems, which are unable to measure environmental diversity at various locations. Second, cloud-based analytics can be performed in large scale, which makes it possible to monitor several workers at a time. Third, the high-quality predictions of risks provided by the AI model will guarantee credible forecasting risks, which will decrease the possibility of the emergence of respiratory danger numerous times. Another aspect in the results that points to the ability to compensate this model to wider occupational health uses is also available. It is possible to add other physiological variables, including respiratory rate or ECG, to the predictive model. The aspect of environmental monitoring can be also complemented with the integration of the state-of-the-art gas sensors that will identify other toxins. The data created has shown the significance of high-resolution and continuous data to create accurate predictive models, indicating that the future dataset with actual data of industrial workers would enhance the accuracy of the system even more. Besides, the pattern of the data was that the more the workers were subjected to varying gas levels the more the physiological instability was recorded which proves that real time monitoring is relevant. The capability of the system to cross-maturity the readings of various sensors enhances the determination of diagnosis and the provision of early intervention measures.

V. CONCLUSION

The findings demonstrate that the suggested system can fulfill its goals due to the ability to ensure high-quality physiological and environmental surveillance, precise AI-driven health forecasting, and real-time warning systems. A combination of IoT sensors, cloud analytics, and machine learning is a potent instrument of notifying about COPD and asthma risks before they manifest, which would significantly enhance the safety of industrial workers. 6. Conclusion & Future Work. The proposed IoT health monitoring system using AI shows the holistic design of respiratory safety of the industrial worker as it combines physiological and environmental measurements alongside a single smart system. The technology is effective in recording real-time data and analyzing trends using AI-based models, and providing instant alerts to facilitate early intervention. Its cloud enabled and portable architecture in combination with scalability enables it to fit various types of industries where continuous knowledge is paramount. A combination of Internet of Things equipment, cloud analytics, and intelligent prediction is a viable alternative to preventative healthcare, making it less likely to experience respiratory decline without detection. It is emphasized in the study that integrating environmental and health parameters is essential in order to make a proactive decision and enhance workplace wellness. In the future, they could examine the incorporation of advanced biosensors, developed predictive models, and longer datasets to help to make it more robust. The system can be further improved in terms of applicability and operational efficiency by expanding the multi-disease detection system, deploying edge AI to perform analytics more promptly, and integrating mobile interfaces to assist workers and supervisors.

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