Journal of Iraqi Al-Khwarizmi (JIKh) Volume:10 Issue:1 Year: 2026 pages: 136-159

Internet of Things and Artificial Intelligence-Based Sensing Systems for Environmental Monitoring and Risk Assessment: A Systematic Review

Authors Names

Humam Adnan Sameer[a]
Rusul Mohammed Alkhafaji[b]
Mizher Abdul Hassan Najim[c]
Othman M. Anssari[d]
Shaymaa awad kadhim[e]

Publication date: 6/ 6 /2026

Keywords: AI models, sensor, IoT, pollution, environmental.

ABSTRACT

Environmental risks have become a primary threat to the ecosystem and human health, and identifying the most influential factors is a crucial issue. Technological advancements have made it possible to identify and detect these factors, most notably artificial intelligence (AI), which has played an effective role in analysis, detection, and inference. IoT, sensors, and AI technology are highly effective in environmental monitoring, such as detecting water, air, and soil pollutants. Therefore, this review aims to present and explore the most important recent developments in the use of sensors, AI technologies, and the Internet of Things in monitoring and controlling environmental pollution, while considering the complexities of the prediction process and the dynamic nature of the environment, taking into account the variables of pollution type. However, they also present challenges. Key considerations include understanding and selecting the most appropriate AI models, the ability to adjust and balance model performance, data processing, and the problems associated with their sharing, and finally, the interpretability of results. This study aims to monitor environmental pollution by leveraging artificial intelligence and its technologies, sensors, IoT, the latest trends, and the findings of recent studies.

1.Introduction

Hazardous materials that threaten the environment are considered a high-risk factor for human health, the animal and plant environment, and environmental life in general. These substances are numerous and include pesticides, organic pollutants, heavy metals, and herbicides, which are used excessively through various means in different environmental settings[1]. There are also sources containing hazardous materials, such as industrial activities, agricultural practices, and hazardous waste, along with their improper and unplanned disposal. Furthermore, the level of toxic and harmful fumes in the air has risen significantly due to the increased number and concentration of vehicles in cities and factories near cities, coupled with high population density in most cities worldwide. All of this has a negative impact on human health and on plants, given that air, soil, and water are crucial elements in direct interaction with humans, the animal environment, and its products[2]. The types of sources of hazardous materials, their pollutants, and the forms of their effects vary according to the concentration of the material and its duration on the environment. The degree of impact on health varies from mild to acute and chronic, such as skin irritation, nausea, poisoning, respiratory infections, and vomiting, and in more serious cases, such as reproductive disorders, cancer, and growth malformations[3]. Many factors influence air quality and its levels, including organic and inorganic pollutants, volatile organic compounds, particulate matter, and gases (carbon monoxide, carbon dioxide, radium, sulfur dioxide, and ozone), as well as biological particles such as fungi, pollen, and bacteria[4]. Air quality levels are also affected by humidity and temperature, which are significant factors in many air quality complaints.

Effective management strategies are required to monitor and address hazardous materials in the environment. These strategies include conducting regular soil, water, and air tests to identify any sources or hazards from harmful substances. This process allows for early detection, enabling subsequent treatment or removal. Another strategy is prevention, which focuses on limiting or controlling the sources, emissions, and disposal of hazardous materials by establishing best practices for the long term. This is essential to ensuring the sustainability of soil, water, and air quality, as well as the overall health of the ecosystem[5]. Ensuring the health of humans, livestock, food crops, and the environment in general is also of paramount importance, as is preventing exposure to many harmful substances. This can be achieved through the use of AI-enhanced devices, sensors, and detectors for monitoring and identifying hazards and harmful substances in soil, plants, water, and air, and determining their quantities with high accuracy and efficiency[6]. Using AI-powered sensors and devices to monitor the environment for hazardous materials in real time offers several advantages. First, these technologies and systems provide greater flexibility in detecting hazardous materials and emissions with higher accuracy and reliability

---

Kufa of University, Faculty of Science College-Najaf, Iraq, E-Mail: humama.jarullah@uokufa.edu.iq

compared to traditional laboratory methods. Second, they enable the rapid and immediate acquisition of data, which in turn facilitates a response to any potential pollution incident. Finally, they simplify data analysis, reduce manual workload, and enhance the efficiency of monitoring and detection processes[7]. It is also crucial to utilize diverse AI-based methods for detection and prediction, including deep learning and machine learning techniques, as well as models that combine these approaches to create a hybrid model. Furthermore, maximizing the use of diverse data closely related to the source of the event, such as toxicological data, chemical composition, environmental and physiological factors, their dates, times, and impact, all contribute to improving the accuracy of the model and the reliability of its predictions[8].

Recent developments indicate the use of artificial intelligence (AI) technologies, integrated with the Internet of Things (IoT), in detecting and monitoring hazardous materials and toxic emissions. This is achieved using low-cost sensors that can be easily deployed across diverse environmental locations. These devices collect data on levels of toxic or harmful emissions and transmit it to a central point for analysis. AI algorithms then process the data into a database, providing real-time results on the content and levels of hazardous materials, as well as predictions of their future potential[9]. This integrated, internet-enabled approach also provides scientists with tools for exchanging complex and extensive scientific data, including atmospheric, climate, biodiversity, hydrology, soil, and environmental data[10]. This data is used for analysis, testing, and interpretation of theories, experimental data, and predictive models, leading to a better understanding of the ecosystem and its related issues.

This comprehensive review presents the applications of artificial intelligence (AI) models in monitoring and detecting hazardous material sources and their emissions in various environments, including air, soil, and water. It will showcase the latest scientific discoveries and advancements in this field, based on AI algorithms combined with sensors and sensor technologies enhanced by the Internet of Things (IoT) for communication and transportation. This modern approach to monitoring and tracking environmental hazards in soil, water, and air has made significant scientific strides, offering greater accuracy and efficiency, coupled with timely detection and analysis of potential hazards.

To access relevant literature, a search was conducted in Google Scholar groups using keywords or search terms in the topics, including: (“machine learning” or “DL” or “artificial intelligence” or “AI” or “deep learning” or “DL” or “computer vision” or “natural language processing” or “NLP” or “Internet of Things” or “IoT” or “sensors” or “electronic nose” or “e-nose” or “real-time” or “robotic” or “Arduino”). The search also included topics such as (“hazardous material” or “hazardous chemical” or “pollutant” or “poison” or “pollution” or “pesticides” or “heavy metals” or “persistent organic pollutants” or “herbicides” or “microplastics”). Additionally, the search included topics such as (“environment” or “land” or “soil” or “leak” or “river” or “air” or “air quality” or “water” or “atmosphere”). A total of 7,647 search results were retrieved. To display the final results, the Visualization of Similarities (VOS) program, version 1.6.20, was used. The results of the systematic search are shown in Fig.1 in the literature, which included the common keywords among them, which contained the number of publications in one map on the topic of the review (Using the IoT in AI technologies and sensors to monitor and address environmental pollution).

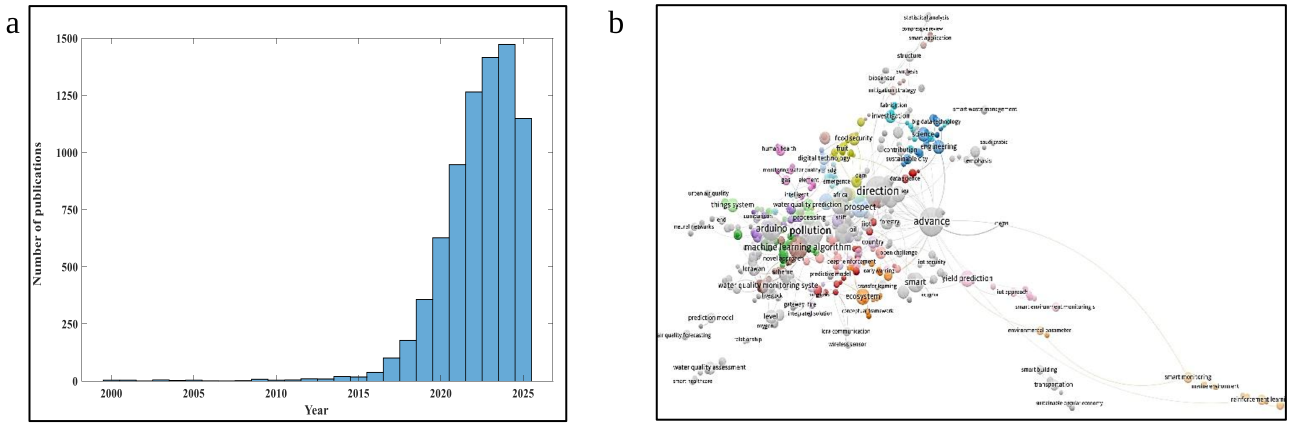

Fig. 1 -Results of the systematic search for literature on the topic "Using the IoT in AI technologies and sensors to monitor and address environmental pollution." (**a**) Number of publications, after sorting, per year that correspond to the topic "Using the IoT in AI technologies and sensors to monitor and address environmental pollution." (**b**) A network map based on relevant keywords in the literature, indicating clusters related to research topics. This map was created using VOSviewer.

1.1. AI methods for monitoring emissions and hazardous materials in various environments

In recent years, interest in artificial intelligence (AI) has grown with the increasing levels of environmental pollution and the need to find ways to predict and mitigate it. AI solutions can be divided into three main stages: the primary input (the data used), the AI models and algorithms that address the problem, and finally, the outputs of AI processes for decision support or monitoring. Fig.2 illustrates the main mechanism of this process.

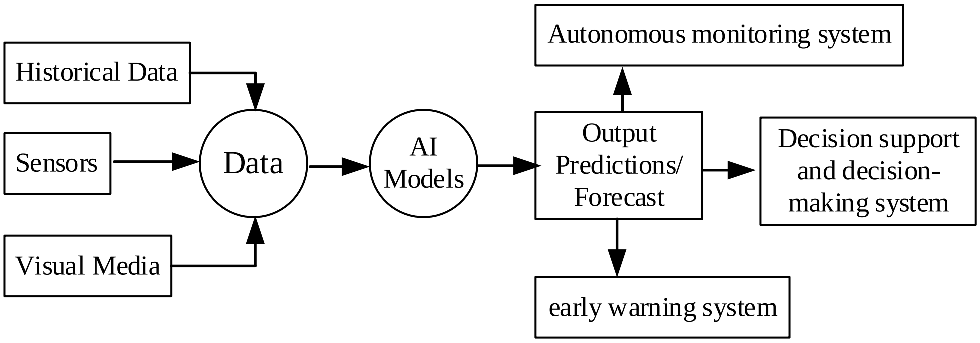

Fig. 2 -The mechanisms used to monitor hazardous materials and their emissions, and AI-powered methods for containing them.

2. Artificial intelligence and environmental monitoring of various hazardous materials

Model efficiency increases when large amounts of data are available from diverse sources, particularly data derived from continuous monitoring or time-bound observations of environmental conditions. This contributes to providing solutions for anticipated or potential actions. Data sources now take many different forms, including various types of sensors such as non-photographic and imaging sensors, remote sensing devices, digital or frequency sensors, contact sensors, and others that provide data in large quantities. Additionally, there is recorded, historical, or archival data[11].

Artificial intelligence algorithms are capable of analyzing data from multiple sources and in large quantities. They can also analyze various readings, such as detecting types and levels of pollution resulting from hazardous materials and pollution from chemical, industrial, and environmental accidents. These algorithms can identify trends, patterns, and anomalies in the data and extract them using deep learning and machine learning techniques. For example, hazardous materials and their emissions, or unhealthy pollutants, can be detected by analyzing satellite imagery or using images captured by drones. Computer vision algorithms can recognize the shapes and patterns of chemical substances, pollution sources, and the extent of changes in vegetation cover[12].

Historical data on environmental pollution, hazardous materials, and harmful emissions can be used to train AI models. These models offer solutions for environmental monitoring, independent pollution monitoring systems, and early warning systems for hazardous material emissions, with the potential to support decision support systems. They also contribute to helping organizations and government agencies prepare for, respond to, and manage emergencies. These models have proven highly efficient in handling diverse environmental conditions, including air, water, and soil. AI algorithm designers and developers must provide a comprehensive explanation of how the model supports itself, how its parameters are controlled, and how it is evaluated during its development[13].

Artificial neural networks (ANN) have been used in many short- and long-term prediction applications to provide an environmental model for detecting toxins and air pollution and synchronizing them with Internet of Things (IoT) technology[14]. A hybrid model (LSTM-CNN-WOA-AM) was developed based on Convolutional Neural Network (CNN) technology, the improved Whale Algorithm (WOA), and Long Short-Term Memory (LSTM), in addition to the Attention Mechanism (AM). CNN analyzes historical air quality data, represented by PM2.5 concentration, humidity, temperature, and wind speed, from specific time periods to detect patterns and predict their future. WOA improves the performance of the CNN and automatically adjusts its parameters to achieve optimal accuracy. It uses the LSTM algorithm to analyze and retain correlations in daily time-series data. As for the AM mechanism, it determines the influential weights and directs the model to the most important variables that influence the prediction process[15]. A hybrid intelligent model combining LSTM and a MOV-inspired optimization algorithm was used to predict NO2 and SO2 air pollution from a power plant. Data included air temperature, velocity, and NO2 and SO2 values over a five-month period. The LSTM-MOV model demonstrated superior performance compared to traditional methods for analyzing plant emissions and yielding valuable results for air pollution prediction[16]. The potential of machine learning models Random Forest Regression (RFR), Support Vector Regression (SVR), and Ranger is demonstrated in analyzing land cover characteristics derived from digital soil maps to predict nitrogen content without extensive sampling, in addition to remote sensing for spectral indices. This model contributes to sustainable agricultural planning and management by producing economical soil maps[17]. Yingyue Han et al.[18] developed a method for detecting and estimating cadmium (Cd) concentrations in soil using unmanned aerial vehicles (UAVs) as an alternative to traditional laboratory sampling. They integrated spatial data with images to identify contamination hotspots by creating a spatial map, thus rapidly pinpointing hazardous areas. Their data sources included multi-band spectral images, a digital elevation model, and high-resolution aerial photographs. They also employed several machine learning models, most notably the Gradient Boosting Decision Tree (GBDT), which demonstrated the highest detection accuracy.

Wenjie Ai et al. [19] used the CNN model to distinguish between soil-contaminating polymer types. Samples were collected from several agricultural fields to classify industrial plastic particles such as PVC, PE, and PP. Additionally, ATR-FTIR reference techniques were used on the samples to determine the polymer type. A hyperspectral camera was also used on the soil samples to read and distinguish the spectra per pixel. The spectra were then pre-processed to smooth and remove noise using a Savitzky-Golay smoothing filter. The results were then compared with other models, such as Decision Tree (DT) and Support Vector Machine (SVM), and the CNN model demonstrated its superiority. H. Chojer et al. [20] developed a real-time air monitoring system based on multiple artificial intelligence models and IoT sensors to measure and predict various air pollutants within an industrial area. Low-cost sensors were used in a network design to measure several pollutants, including CO, CH4, SO2, NH3, NO2, CO2, O3, and fine particulate matter PM2.5 and PM10. The measured data is transmitted in real time within the IoT network, and a neural network algorithm is used for analysis and prediction of future pollutant levels, such as Linear Regression, LSTM, and Random Forest models.

3. Monitoring pollution through AI models

3.1. Spectroscopy

The field of remote sensing is of great importance, as it deals with spectral analysis and its functions in measuring the energy of matter, which has influenced its use in identifying materials in the field of astronomy and also in the field of chemistry extensively. With the advancement of the capabilities of the devices used, the need for its use in the study of remote sensing has increased. The near-infrared visible and infrared reflectance spectroscopy technique used is environmentally friendly and low-cost, in addition to its capabilities in estimating the concentrations of various heavy metals present in the soil. It is also an ideal method for assessing the levels and distribution of types of heavy metals over large areas and over long periods of time[21]. Zhao et al.[22] used the extreme gradient (XGBoost) enhancement algorithm and combined it with visible and near-infrared spectroscopy as an integrated and effective machine learning approach to build a model for measuring and estimating heavy metal pollution and its levels in soils containing mangrove plants. P. He et al.[23] used a Transfer Learning-based method to estimate lead concentration in soil and improve prediction accuracy, relying on spectral data from near-visible infrared readings. A one-dimensional framework and ResNet network were constructed to identify spectral features, and wavelengths were evaluated using the SHAP interpretation tool and ranked according to their importance for prediction.

Researchers employed a technique combining 3D SERS imaging with dynamic imaging, along with advanced substrates of perovskite/silver nanoparticles (CaTiO3/Ag@BONPs). They also utilized several artificial intelligence techniques, such as Euclidean distance analysis (ED), Vertex Component Analysis (VCA), and spatial machine learning (SML) + clustering (e.g., K-means), to classify, identify, and map pesticide distribution within the tissues and MCR-ALS (multivariate curve resolution – alternating least squares). The aim was to detect pesticides present on the surfaces of fruits and vegetables, as well as to determine their penetration into the pulp or their persistence on the peel[24].

3.2. Ground-based sensor monitoring

I. Shahid et al.[25] presented a comprehensive study based on the use of the Internet of Things with the integration of sensors represented by carbon nanomaterials, with the use of artificial intelligence tools to monitor air quality. It also plays a role in the proposed model for analyzing data and the possibility of identifying pollution sources, providing future predictions, and creating strategies to reduce pollution and its effects. A. Zafra-Pérez et al.[26] designed an air quality monitoring system consisting of wireless sensors connected to a network distributed across a geographic area containing mining sites. The system transmits data via a cloud network, which is then analyzed, processed, stored, and visually displayed. The system detects fine particulate matter and improves detection methods for it, in addition to serving as an early warning system for potential air pollution. M.B. Arboleda and A. Shamim[27] used an integrated, standalone design of wireless sensor nodes in multiple industrial and urban environments to monitor air quality and monitor polluting gases with high accuracy and low cost, without relying on atmospheric stations, where they measure readings of air pollutants such as CO, PM2.5, and NO2, and send them to the central system in real time for analysis and pollutant mapping.

O. Alsamrai et al.[28] designed an intelligent system consisting of several sensors with added IoT technology to monitor and predict air quality in urban areas. This system uses machine learning algorithms to analyze air quality data. The system utilizes an ESP32 controller with network connectivity and sensors to measure humidity, PM2.5, temperature, and harmful gases. The readings are then transmitted to a cloud-based storage and analysis platform. HRC Arante et al.[29] used a predictive system to simulate flood hazard levels in the Philippines. They relied on data streaming using a network of sensors (rain gauge, soil-moisture probes, and water-level sensors) connected to IoT units, ensuring secure data transfer to a cloud server as a first step. A combined model was built using several algorithms (fuzzy logic, genetic algorithm, and LSTM neural network) for continuous, real-time training on field data to generate short-term hazard level predictions and trigger alerts to protect the community and minimize losses. Z. Wang et al.[30] developed a multi-channel acoustic signaling system supported by a deep analysis model to identify flammable materials and differentiate between types of initial ignition, flames, and fuels within buildings. The system consists of a fire detection module and a transformer module that classifies materials and identifies the type of fire, with the Circuits-LSTM-Conformer (CLCFormer) serving as an enhanced classification unit for the detection process.

3.3. Drones and aerial photographs

The use of aerial photography for monitoring and tracking hazardous waste emerged in the early 1990s. More recently, high-resolution aerial imagery has proven more effective in detecting various types of hazardous waste, their locations, and landfills, thus preventing their illegal disposal, with the assistance of AI[31]. Historical aerial photographs are used as a means of assessing and documenting changes that may occur in hazardous locations over time, serving as a reliable tool in the monitoring process.

J. Sedano-Cibrián et al.[32] used a low-cost, effective drone methodology to monitor heat emissions at a municipal solid waste (MSW) site in Mireillo, Spain. The drones were equipped with visual and thermal sensors to search for and detect landfill gas emissions, harmful decomposition of organic materials, or internal weeding, which are called hot spots. The aim was to create a three-dimensional model using captured images, while the fourth dimension, temperature, was used to create a four-dimensional image.

S. M. Popescu et al.[6] employed satellite, aerial, and drone/UAV imagery combined with artificial intelligence and real-time spectral indicators to identify the sources and traces of pollution found in leaking liners, drums, waste dumping spills, open dumps, chemical spills, and oil leaks. The images were then compared with historical data to assess the expansion or contraction of landfill sites, determine the extent of damage caused by pollutants by monitoring vegetation patterns, and track the movement of surface and groundwater and its contamination through sewage networks.

Hyperspectral images have played an active role with predictive models for identifying soil and its heavy metal content. Tan et al.[33] proposed a working approach in adaptive competitive sampling reweighted (CARS), and then compared the accuracy of several different models with the enhanced clustering method (CARS), which gave stability in the prediction process and higher accuracy. Environmental monitoring methods have evolved in aerial surveillance and surveying. D Xu et al.[34] utilized drones equipped with advanced sensing systems to detect methane gas using a cutting-edge technique called TDLAS (Tunable Diode Laser Absorption Spectroscopy). This technology can determine the amount of diffused gases and their emissions from multiple oil and gas well sites, even at low concentrations, allowing for wide spatial coverage and high detection rates. Furthermore, they employed an advanced (TERRA) algorithm, which relies on the divergence theorem and is supported by a mass balance model, to convert measured concentrations into emission rates.

Iwaszenko et al.[35] tracked natural gas pipelines to detect potential leaks using drones equipped with laser methane detectors. Data was collected from an actual leak site and analyzed using machine learning models to identify areas with high gas concentrations. A study by Krishnakumar et al.[36] demonstrates the development of a system comprising multiple drones equipped with GPS sensors and high-resolution cameras. This system is used to detect and automatically track smoke plumes and their sources. The process is centrally controlled by a single drone, which directs the other drones to define the area, fly around it, and synchronize to capture images from multiple angles. Neural radiation field (NeRF) technology is used to process and reconstruct the images in detail, creating a three-dimensional model that shows the evolution of the smoke plumes, including changes in size, temporal behavior, and direction. Additionally, an artificial intelligence model is employed to enhance decision-making and predict dispersion.

Sobti et al.[37] developed a cost-effective aerial gas leak detection system using a real-time, amateur-grade drone equipped with optical gas imaging (OGI) sensors. They employed inferential models to detect gas plumes and accurately analyze leaks based on an AI inference algorithm, as well as pinpoint their location using a platform that transmits and relays thermal images to the model. By utilizing intelligent processing and integrating it with low-cost drone sensors in an independent mechanism for leak detection, this approach provides highly efficient and advanced support for gas plume tracking, contributing to improved environmental awareness and risk reduction.

In short, drones have become a reliable approach in assessing and managing risks and incidents with dangerous dimensions. Their flexible and wide ability to collect data, rapid access, and speed of deployment in monitoring and surveillance of vital areas and access to hard-to-reach places have greatly and effectively helped response and treatment teams to understand and reason in decision-making, identify risks and their effects, and protect lives, property, and the ecosystem in general.

3.4. Remote sensing

One of the leading and most advanced scientific technologies is remote sensing, which is distinguished by its ability to identify and assess the diverse features and characteristics of terrestrial targets from great distances. It is considered an approach to repeatedly monitoring numerous features of the Earth's surface, including water, vegetation, climate, land, living organisms, pollution, and the atmosphere. Remote sensing has contributed effectively to measuring, detecting, monitoring, and mapping pollution levels and their effects[38]. Remote sensing is used in many applications, including waste management, monitoring, and hazardous sites. Multispectral sensors (MS-S) are mounted on remote sensing platforms. These sensors digitally collect the reflected energy of various levels of the electromagnetic spectrum within specific ranges. These systems offer superior statistical data analysis and wide-area observation capabilities compared to aerial photography. Multispectral imaging via satellites, along with other systems mounted on aircraft, is used to monitor land use, pollution profiles, assess regional risks, and locate hazardous waste sites and their resulting spectral characteristics. Studies using remote sensing have shown that soil contamination with heavy metals is highly efficient, relying on hyperspectral data based on its fundamental spectral properties. For example, high-resolution spectral data from the near-infrared (VNIR) and visible-infrared (SWIR) bands were used and combined with soil and chemical measurements to map the concentrations of lead, zinc, and cadmium, providing a reliable indication of the presence of heavy metals based on spectral reflectance characteristics[39].

Many researchers have also used multispectral imaging to detect previously unknown sites of hazardous and illegal waste. V. K. Mishra et al.[40] proposed a mechanism for integrating multispectral satellite imagery with synthetic aperture radar (SAR) data, followed by GIS-based processing, to detect and monitor environmental hazards. The study demonstrates the benefits of combining sensory data to identify and assess phenomena such as water quality, surface anomalies, and other indicators of ecological stress, relying on optical remote sensing, radar data, and their complementary strengths. Furthermore, maps containing the locations of various heavy metals can be drawn and accurately identified based on hyperspectral images.

L. Zhong et al.[41] demonstrated the ability to map soil heavy metals within a regional range using airborne spectroscopic imaging data. Spectral/vegetation spectra can provide direct predictions based on the abundance of signals reflected from bare soil, which occurs in early spring and winter or when vegetation cover is reduced due to crop rotation. Crop spectra, such as those of wheat leaves, can also be used as an indirect method for effective monitoring. N. Yang et al.[42] A recently conducted study was conducted to map and estimate soil concentrations of lead, cadmium, copper, and mercury using hyperspectral remote sensing. They utilized GF-5 hyperspectral images, which were modified and calibrated to align with machine learning models for prediction. Several models were employed to predict heavy metal distributions: Partial Least Squares Regression (PLSR), Back-Propagation Neural Network (BPNN), and Support Vector Machine (SVM). These models demonstrated high accuracy in assessing environmental pollution after fine-tuning.

3.5. Ground robotic systems

The emergence of ground robotic systems as advanced technologies, especially in recent years, particularly when equipped with gas sensors to assess the situation and estimate the risk in enclosed spaces with poor ventilation, in addition to monitoring the distribution of harmful gases, thus becoming "like a sense of smell". H. Fan et al. [43] presented an advanced gas identification system using an electronic nose (e-Nose), represented by an array of metal oxide (MOS) sensors. These sensors detect and respond chemically to pollutants and gases within the ambient air. Based on the sensor signals, the system utilizes statistical and temporal readings, employing a combination of machine learning algorithms, including Random Forest (RF) and SVM. Additionally, ensemble techniques are used to combine the outputs from multiple models into a single model, thereby narrowing down the decision and increasing reliability. This significantly improved discrimination and enhanced the system's ability to handle spectrally similar gases.

I. Kulbaka et al.[44] proposed a framework called GDM-Net for Gas Source Localization (GSL) in dynamic environments, along with the construction of accurate gas concentration maps using a mobile ground robot, resulting in improved monitoring speed. Their work relied on the Deep Reinforcement Learning (DRL) model as a core component for the robot to learn from its environment and take measurements within the expected information gains. Additionally, they employed a Gaussian Process Regression model to estimate and model gas levels, supporting accurate and informed decisions regarding future exploration sites.

A. Gongora et al.[45] presented an advanced study on gas distribution mapping (GDM) using a swarm of mobile robots. These robots efficiently and accurately monitored gases in unfamiliar and hazardous environments. A spatiotemporal statistical prototype, the Gaussian Markov Random Field Weighted (GW-GMRF), was used to represent the spatial distribution of gas concentrations, while also addressing noise and uncertainty in sensory measurements. This model was integrated with an intelligent, information-based planning algorithm to optimize the number of measurements and reduce the distance traveled. This enabled the robot swarm to improve gas monitoring, accelerate field surveys, and enhance reliability and interoperability. A. Haldorai et al.[46] developed a self-contained robotic model for cleaning water surfaces of floating pollutants. This robot incorporates two Arduino microcontrollers and features object recognition capabilities using the Single Shot Detection (SSD) algorithm. The algorithm is used to locate and detect plastic waste using several deep learning models, including VGG-16, Inception-v3, and ResNet-50. The model is further supported by ultrasonic sensors and a GPS navigation system to avoid obstacles and optimize waste collection. The ResNet-50 algorithm demonstrated superior performance and speed in detection.

The degree of improvement in environmental monitoring has increased significantly with the use of advanced technologies, particularly in identifying and controlling hazardous and illegal waste sites. The widespread use of spectroscopy in remote sensing, not just in astronomy and chemistry, provides cost-effective and environmentally friendly tools for estimating heavy metal concentrations and their distribution in soil. Spectroscopic analysis of near-infrared and visible light is a cost-effective and environmentally friendly technique for estimating heavy metal concentrations and their distribution in soil. AI techniques, such as neural networks, contribute to increased prediction accuracy and enhanced gradients when combined with spectral data related to soil pollution and the concentration of various heavy metals. Furthermore, ground-based sensors, including automated and manual networks, have become increasingly important in air quality monitoring after being integrated with machine learning models.

Aerial imaging techniques, including hyperspectral and historical imagery, are widely used in environmental monitoring, pollution assessment, and hazardous waste monitoring, including the locations where these wastes are found. Furthermore, drones, equipped with various sensors, are used for real-time tracking of smoke plumes and hazardous gases, enhancing their response speed, arrival time, and ability to handle challenging situations, thus making them highly valuable and effective.

Ground robots play a vital and valuable role, particularly in enclosed spaces. Equipped with advanced gas sensors and multispectral and visible sensors, they utilize remote sensing techniques, making them effective tools for systematically tracking and monitoring the Earth's surface. This includes identifying and mapping areas contaminated with heavy metals. These systems and tools employ diverse strategies to address environmental issues, playing a crucial role in maintaining ecological balance and systems by leveraging advanced technologies to serve the environmental needs of the environment.

4. The role of AI in monitoring and increasing safety in hazardous environments

Currently, it has become necessary to consider the safety of workers in various industrial work environments, whether in the manufacturing process or production processes that involve hazardous materials or toxic emissions, and to give it the highest priority. This requires serious monitoring of the concentrations of pollutants and their emissions or leakage, and resorting to effective and safe methods and techniques to reduce their risks to humans and the environment, in addition to reducing the accidents caused by hazardous materials[47]. Implementing and managing safety plans in industrial sectors in cases of risk of leakage or emissions of pollutants requires rapid, accurate, early, and intelligent intervention to prevent and control dangerous leakage of materials. Since the challenges and threats exceed human ability to identify them in a timely manner, due to the nature of most gases not showing their effect because of the lack of color, smell, and taste[48]. Therefore, the use of AI-powered devices in the process of detecting and monitoring the environment and its pollutants is increasing day by day, as AI and its capabilities and use in unmanned machines provide an immediate and effective solution when used in hazardous locations in various environments. It can also intervene to isolate detected threats and prevent or reduce the cause of significant damage without the need for human intervention, even if limited[49, 50].

J.H. Lee et al.[51] have designed an intelligent robotic system that integrates ultrasonic waves and a camera, enhanced with a deep learning network (CNN), to detect leaking gases in an industrial environment and classify their hazards. It works independently in the process of identifying and detecting the gas, as well as processing the data without human intervention. R. Bitriá et al.[52] designed a portable indoor robotic system with an integrated electronic nose (eNose) for the early detection of leaking gases during operation. Equipped with several non-specialized metal oxide semiconductor (MOX) sensors capable of detecting various types of gases after training, it is used for indoor environmental monitoring. D. Ma et al.[53] used a drone (UAV) to monitor leaking gases in the environment, as it was equipped with special gas sensors. An integrated sensing system was designed with improved performance for the gas reading process with high efficiency.

The Wireless Microcontroller Unit (MUC) provides real-time data collection capabilities, compared to a Global Positioning System/Global System for Mobile Communication (GPS/GSM) modem, giving an accurate description of the route and location, with the ability to measure gas concentration. A. Bouras et al.[54] designed a mobile gas monitoring system based on a small, quadcopter aircraft equipped with gas sensors, which was tested in a laboratory environment. The system maps gas distribution after identifying and determining its source based on measurements obtained during flight. W. A. S. Norzam et al.[55] designed a system that detects hazardous gases using a mobile robot equipped with a MOX gas sensor, in addition to using a Simultaneous Localization and Mapping (SLAM) model to build a map of the place while moving. It works to detect in an unknown environment and has the ability to avoid obstacles and barriers, and the ability to accurately map gas concentrations and determine their location. A. Husnain et al.[56] turned to using unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) equipped with an array of MOX gas sensors. These sensors identify the source of gas emission, map the gas concentration, and automatically generate a path to the leak point. Machine learning and reinforcement learning algorithms were also used to analyze the data received from the sensors, enabling the tracking of gas plumes and their concentrations, even when fluctuating, in complex environments. To protect buried gas pipelines from damage or external threats such as human activities or nearby mechanical drilling, L. Qiao et al.[57] proposed a monitoring system based on accelerometers linked to an AI algorithm (Q-SVM) for initial detection as the first stage. The second stage uses a CNN algorithm to identify and classify the type of threat resulting from external vibrations with an efficiency of 96.1%.

The principle adopted by U.I. Abdullahi et al.[58] is to protect individuals and ensure their safety by monitoring hazardous environments while they work in them. They developed a real-time sensor system distributed throughout the building to monitor internal environmental conditions such as temperature, CO2, and smoke. They used a framework that integrates IoT sensors and a Building Information Model (BIM) to monitor the environment and its associated hazards, and to improve evacuation and response decision-making. M. A. I. Anik et al.[59] designed a real-time, smart IoT-based system for monitoring and identifying gas leaks inside homes, detecting fire hazards, and automatically implementing safety measures to protect property and people. The system consists of several gas sensors, such as the MQ-2 and MQ-9, to detect methane, carbon monoxide, natural gas, and liquefied petroleum gas (LPG), and an ESP32-CAM camera. These sensors are connected to a central ESP32 control unit to receive and transmit data to a cloud server. The system then triggers an alert via a mobile application, activates an audible alarm in case of danger, and shuts off the gas supply using a solenoid valve. Additionally, it cuts off the power supply to prevent ignition problems.

M.S. Murty et al.[60] presented an intelligent, real-time gas leak detection system based on IoT and gas sensors connected to an Arduino microcontroller and communication modules. Gas levels and concentrations are monitored and displayed in real time via an LCD screen, enabling the activation of audible and visual alarms and the automatic transmission of the alert's GPS location to the relevant personnel via SMS. V. González et al.[61] proposed a smartwatch-like device worn by workers that continuously measures air quality at their work site to protect them from exposure to harmful gases and pollutants within specified levels. The watch contains several MOX sensors to measure methane (CH4), CO2, and volatile organic compounds such as ethylbenzene, xylene, and toluene. M. El Barkani et al.[62] worked on an intelligent system based on a Tiny Machine Learning algorithm, using small, low-power devices with the ability to process sensor data in real-time, without the use of external servers, to accurately and early detect gas leaks in different environments and improve the accuracy of prediction.

G.M. Dimitri et al.[63] designed a wearable air quality monitoring sensor system called WeAIR, which is equipped with sensors to measure CO, CO2, and NO concentrations, as well as humidity, temperature, air pressure, and particulate matter (MP10). The data is collected in real time and processed temporally and spatially by an artificial neural network for the predictive process and to improve its accuracy. S.K. Reddy et al.[64] developed a real-time monitoring system for toxic gases in underground mining areas to warn workers and ensure their safety. The system consists of several IoT sensor nodes distributed throughout the mines, operating with LoRa Module technology. These nodes contain sensors for CH4, CO2, and CO, as well as sensors for humidity and temperature. The sensor nodes transmit the data they collect using LoRa technology to a central gateway, taking advantage of their low power consumption and long transmission range.

P. Beldar et al.[65] developed an intelligent integrated system for predicting air quality using an Arduino-ESP-32 controller integrated with sensors (noise, PM2.5, CO2, PM10, and humidity) with a filter layer and fan design, based on AI to purify the air from pollutants and fine particles with high efficiency and low energy consumption through precise control of the filter performance in a dynamic way. The problem of waste and its management has taken on significant dimensions as it is a source of pollution. Therefore, S. Seker.[66] proposed an efficient and intelligent system for real-time waste collection that is also cost-effective. This system utilizes multiple technologies to perform tasks, such as Radio Frequency Identification (RFID), Ground Penetrating Radar (GPRS), and Geographic Information Systems (GIS), in addition to the use of the Internet of Things (IoT). Waste collection in residential or densely populated areas using such systems is effective because it reduces the risk of environmental pollution. R.S.A. Qurashi et al.[67] also presented an effective and intelligent real-time waste management design in the city of Makkah during the Hajj season. They used a container with ultrasonic sensors that measure the level of waste and its fullness in real time, as well as detecting harmful gases generated inside the container using a gas sensor. This intelligent design brings economic benefits in terms of reducing unnecessary fuel consumption in waste collection, rationalizing the resources used and managing them, as well as mitigating health and environmental risks and a proactive approach to preventing waste accumulation. The transport and storage of hazardous materials pose a threat to both the environment and human life due to their toxicity, potential for corrosion, explosiveness, and associated radioactive properties. Y. Zhang et al.[68] proposed an intelligent system to monitor safety during the journey of a vehicle transporting hazardous materials via a wireless sensor network (WSN). This system collects real-time information on the vehicle's direction, speed, deviation, and tilt via GPS, as well as its temperature, tire pressure, operating conditions, and performance, to improve safety and monitor stability during transport.

Z. Wang et al.[69] proposed an analytical approach to transporting hazardous materials and determining the best routes for them in avoiding densely populated areas and reducing environmental risks, relying on an enhanced intelligent multi-objective genetic algorithm (NSGA-II) in addition to real-time collected data and instant prediction of any change in environmental and ground conditions moment by moment to select the optimal alternative route, to achieve maximum safety and increase the level of security in addition to balancing the time required to reach and the cost of transport. Integrating advanced machine learning algorithms with IoT technology in monitoring and analysis for water quality prediction is an effective approach to developing an intelligent, scalable system presented by S. Kushwaha et al.[70] It relies on collecting data on organic matter levels, turbidity, electrical conductivity, and pH in real time via WSN, and analyzing it via a machine learning network such as LSMT or Random Forest to detect abnormal pollution patterns and predict quality parameters and their future deterioration, to take the necessary measures and immediate and preventive decisions.

A hybrid system designed by N. K. Balaraman et al.[71] integrates IoT technology with Raspberry Pi and Arduino Uno to monitor water quality, achieving a balance between reliability and efficiency. Sensors are used to read pH, turbidity, temperature, and flow rates, and a local server is used to collect and transmit the data to the controller for display in a graphical interface. Y. Durgun[72]. designed a water monitoring and quality system based on machine learning networks such as XGBoost and Random Forest, in real-time synchronization to form an integrated approach in an urban environment, supported by spectroscopic sensors with IoT technology. His work aims to accurately identify the types of pollutants, whether organic, biological, or chemical. In the same vein, R.K. Nishan et al.[73] presented a system for monitoring wastewater and its quality at multiple levels in real time, based on AI and IoT. This system consists of an Arduino Uno R3 controller for processing collected data, and a WSN (Wastewater Sensing System) for measuring turbidity, total suspended solids (TSS), electrical conductivity (EC), pH, dissolved oxygen (DO), and their critical parameters. Additionally, a GSM/LTE communication module is used to send alerts when thresholds are exceeded or anomalies are detected. The system also employs a machine learning model, such as Logistic Regression or Isolation Forest, pre-trained on historical data, to distinguish abnormal changes or illegal contamination.

In an approach to address the problems facing water bodies in remote areas, which are difficult to reach, C Pham-Quoc & N. C. Tri et al.[74] presented an IoT-based design for a USV (Unmanned Vehicle) for monitoring the water quality of the Mekong River, where sensors were used to measure water quality from several different locations, combined with open-source software (Ardupilot), and the measurements were sent via IoT to the central station, enhancing the design with a positioning system, as it operates within a radius of a circle of 573 meters from the main control station. J.H. Ryu.[75] also developed a design for monitoring water quality at various water body locations using real-time USV (Uninterruptible Water Vessel) technology. This system incorporates multiple sensors to read data such as temperature (WT), pH, electrical conductivity (EC), and dissolved oxygen (DO), transmitting the data to cloud services via a network communication protocol (LET). GPS was also used for navigation, control, and data collection for documentation, analysis, and display. Also, I.A. Adeleke et al.[76] used a sophisticated and accurate water quality monitoring system that incorporates a machine learning-based sensor array to predict hazardous water pollution. This system collects real-time water quality data remotely and automatically, and is equipped with a feature to measure pollutant levels and initiate treatment when they exceed permissible limits, thus preventing the spread of waterborne diseases. A. A. Abu Bakar et al.[77] presented a design for an intelligent water quality monitoring system consisting of several sensors to measure turbidity, temperature, and pH. These sensors are connected to an Arduino microcontroller board for data reception and transmission via Wi-Fi, integrating with IoT technology. The system transmits data in real time to a cloud platform for analysis and display, enabling early detection of pollution and facilitating the implementation of necessary measures to ensure water safety.

Table 1 - shows some of the research studies that have been used to monitor and detect hazardous gases and materials with the help of AI.

Table 1- Research studies on hazardous environments and the role of AI in them.

RER/Year	Detected parameter	Devices/ Technology used	Algorithm used	Advantages	Disadvantages
[47]/2022	PM, CO, SO2, NO2	Smart Sensors & IoT-based infrastructure	Cloud Computing Data Processing	Full integration with industrial systems; Real-time monitoring	Efficiency depends on the internet connection stability
[55]/2022	Ethanol Gas (Source Localization)	Mobile Robot with Graphene-based MOX Sensor	SLAM-GDM	56% lower power consumption; Fast response	High sensitivity may lead to false alarms
[66]/2022	Weight and waste level sensors	Smart bin & IoT sensors	fuzzy logic	supports systematic evaluation and sustainable decision-making	requires high-quality data and computational complexity
[75]/2022	pH, temperature, and turbidity sensors	UVS	traditional control	suitable for remote areas, open source, low cost	Limited communication and accuracy
[48]/2023	Methane CH4	Multivariate Analysis & Intelligent Mining System	Optimized Random Forest	100% prediction accuracy; Reduced error compared to SVM	Requires large and diverse datasets for training

[64]/2023	Humanity, Temperature, gas sensors	LoRa Communication	Real-time processing	Low power consumption and Wide coverage	Possible latency and low data rate
[54]/2023	Volatile Organic Compounds (VOCs)	MUC, GPS/GSM, & Nano Quadcopters	Gas Distribution Mapping (GDM)	Ultra-small size; Access to confined spaces	Very limited payload for sensors
[57]/2023	Vibrational Disturbances (Pipeline Threats)	Fiber-optic Vibration Sensing (DFOVS)	APEM Algorithm, Q-SVM, & CNN	96.1% efficiency; Real-time localization	High sensitivity to non-hazardous ambient vibrations
[74]/2023	Water quality sensor	USV & IoT	Control algorithm	Suitable for remote areas	Navigation and maintenance are required
[76]/2023	Dissolved oxygen, temperature, pH, and turbidity sensors	Embedded ML with IoT integrated	Hybrid ML algorithm	Improved accuracy of prediction	Requires computation resources and training data
[56]/2024	Gas Plumes & Source Localization	Unmanned Aerial Systems (UAS) & MOX	Reinforcement Learning (Q-learning)	Autonomous path generation to the source	High computational complexity for training
[60]/2024	Gas sensor	Gas leak detection powered by IoT	Detection based on the threshold limit	Low cost and simple design	Susceptibility to false alarms
[61]/2024	CO2, humidity, gas, and temperature sensors	A wearable platform like a smartwatch	Analyze the data statistically	Continuous monitoring by the person	Battery life limited
[62]/2024	Gas sensor	Embedded system & Tiny model	Lightweight ML	Edge intelligence and low power consumption	Accuracy decreases with large-scale ML algorithms
[68]/2024	Safety, gas, and motion sensors	WSN	Event detection model	Enhancing safety during transport	Network unreliability
[72]/2024	UV and water quality sensors	Smart water system based on AI	ML (XGBoost and Random)	Effective for detecting pollutants	The system is expensive
[73]/2024	Industrial multi-level	IoT multi-layered architecture	Real-time data	Effective in monitoring	Complex system

	water sensors		processing	industrial wastewater	
[50]/2025	Chemicals (Nanoparticle Synthesis)	Autonomous Chemical Robotic Platform	A* Algorithm & GPT Decision Module	High synthesis efficiency; Precise repeatability	Complexity of initial platform programming
[51]/2025	Gas Leaks & Arc Discharge Hazards	Vision-Ultrasound Robotic System	Deep Learning & Inception-inspired CNN	99% accuracy; Fusion of visual and acoustic data	High cost of advanced acoustic cameras
[52]/2025	Gas Leaks (e.g., Ethanol)	Compact eNose in Mobile Delivery Robot & MOX	LDA (Linear Discriminant Analysis)	Early detection during delivery; Low power consumption	MOX sensors are affected by humidity and temperature
[53]/2025	Atmospheric Gas Leakage (Hydrogen)	UAV with Optimized Sampling Structure	Computational Fluid Dynamics (CFD)	Reduced rotor airflow interference on samples	Limited flight time due to battery capacity
[58]/2025	Gas, temperature, and smoke sensors	Fire monitoring powered by IoT	Risk analysis and assessment	Models for early fire detection and safety improvement	The system's setup is complex.
[59]/2025	Camera modules, gas sensors	Image processing with IoT	Computer vision model	Dual detection and identification of fire and gas	Equipment cost is high
[63]/2025	Multi-gas sensors	Wearable Swarm Sensors with IoT	Collaboration between analysis and sensing	Improving environmental awareness	Challenges of managing consumed energy
[65]/2025	(AQI, gas) sensors, nitrogen dioxide, carbon monoxide, and dioxide	Intelligent air purifier with IoT	ML (prediction and forecast) models	Improvement and treatment of indoor air quality	Implementation costs are high
[67]/2025	Location and waste level sensors	Waste system and IoT	ML algorithm	Effective for the waste collection process	Adaptability to expanding challenges
[69]/2025	Risk, traffic, and location sensors	IoT with an intelligent transportation system	Dynamic optimization model	Avoid transportation risks	Real-time data availability is relied upon

[70]/2025	turbidity, electrical conductivity, and pH	IoT and WSN	LSMT and Random Forest	Support for the forecasting process and assistance in decision-making.	requires a large amount of data
[71]/2025	pH, turbidity, flow rates, and temperature sensors	DL with IoT	CNN algorithm	High accuracy in prediction	High complexity computational
[77]/2025	turbidity, temperature, and pH sensors	Wi-Fi with IoT and Arduino microcontroller	Calibration modules	Improvements in accuracy and reliability	Requires regular maintenance

5. Recent Developments and Challenges

5.1. BeeTox model and other AIs

In a study published by J. Adamczyk et al.[78] an AI-based approach was proposed to predict acute toxicity by testing chemical compounds on honeybees (Apis mellifera). To assess acute toxicity, the study relied on a large, up-to-date dataset that included measurements of a wide range of chemicals via ingestion and contact. Several advanced machine learning algorithms, traditional classification algorithms, and graphical neural networks were trained on this dataset. The mechanism aimed to classify compounds with high accuracy as toxic or non-toxic. Explainable AI algorithms were also employed to analyze various molecular structures to predict toxicity, providing a broad and in-depth understanding of the impact of chemical agents on toxic effects.

Groundwater pollution has become a serious problem due to rising nitrate levels, a consequence of the excessive use of nitrogen fertilizers in agriculture. This poses a significant threat to public health and the environment. To address this, J.K. Mogaraju.[79] developed a mechanism for analyzing and accurately predicting groundwater nitrate levels using interpretable learning algorithms combined with machine learning. This mechanism also identifies pollution hotspots and guides effective environmental interventions, supporting informed decision-making to mitigate risks.

Several studies have shown the possibility of using artificial intelligence to predict and treat pollution affecting the ecosystem. J. Chen et al.[80] used an advanced machine learning model (Random Forest) combined with the XGBoost model to measure the concentration of heavy metals in the soil and evaluate its performance in predicting pollutants to improve soil quality monitoring and select optimal reclamation methods. The study conducted by Y. Zha. and Y. Yang.[81] focused on providing a Graph Neural Network-based system to find the spatial relationship between soil data, and to show the levels of heavy metals by predicting and estimating their concentrations. R. Hassan and M.R. Kazemi.[82] also built a predictive model using AI models to estimate the adsorption capacity of organic materials on coal and resin. They used several input data for descriptive solubility parameters: total pore volume (Vt), equilibrium concentration (logCe), Abraham type, and specific surface area (BET). They employed clustering algorithms such as CatBoost, XGBoost, and LightGBM, combined with several machine learning techniques, including linear regression, Lasso regression, support vector regression (SVR), decision trees, gradient enhancement machines, CNNs, ridge regression, elastic networks, the nearest neighbor algorithm (KNN), random forests, artificial neural networks (ANNs), and Gaussian processes, to provide realistic insights into the key variables and their adsorption mechanisms.

In the same vein, F. Talebkeikhah et al.[83] presented eleven machine learning models aimed at estimating and predicting the adsorption of lead ions (Pb(II)) on biochar. These models employed crowdsourced data processing using decision trees, radio frequency (RF) analysis, multilayer perception (MLP), SVM, and adaptive European fuzzy inference systems (ANFIS). Furthermore, they improved the predictive modeling by using the Bat algorithm and the Goosebump Optimization Algorithm (GOA), and combined ANFIS and MLP. M. Al Duhayyim et al.[84] also developed a drinking water quality monitoring model using an intelligent predictive system based on atomic search optimization technology and integrated with a deep fuzzy convolutional network (WQP-ASOFDCN), further enhanced by an IoT environment. Data is processed and optimized for prediction using the F-DCN model, and its performance is further improved by adjusting hyperparameters using the ASO algorithm.

AI has played a significant role in the medical field, bringing about remarkable and noteworthy transformations across various medical specialties, particularly in clinical, surgical, rehabilitative, diagnostic, therapeutic, and predictive practices. Its impact extends far beyond theoretical research. AI methodologies at all levels have demonstrated the ability to analyze and process vast amounts of medical data from diverse sources, enabling disease detection and differentiation, providing crucial support for healthcare decision-making, developing multiple scenarios for managing health and epidemiological situations, reducing errors, improving patient outcomes, and optimizing resource utilization[85].

5.2. medical waste and refuse

Due to recent advancements across all sectors, particularly in healthcare, there has been a corresponding increase in medical waste generated by laboratories, hospitals, and surgical clinics. Wastewater from hospitals contains hazardous pollutants, including pharmaceuticals, hormones, personal care products, endocrine disruptors, and blood waste. These pollutants include antibiotics, disinfectants, contrast agents used in radiology, and other medications. These chemical compounds are resistant to conventional water and wastewater treatment systems, and their leakage into water systems threatens both human health and aquatic environments[86]. Medical waste and refuse are a source of serious risks to public health and the environment around the world, because they cause diseases or may have toxic or infectious effects on humans, animals, and the environment[87]. Medical waste and refuse pose a danger to the environment and a major health threat. Improper or unprofessional treatment of these wastes leads to air pollution from incinerators and the emission of gases, as well as soil pollution from burying waste in it, and sewage water contaminated with chemicals and bacteria[88].

H. Zhou et al.[89] conducted a study by introducing an AI-based image recognition system called Deep MW, which aims to sort and process medical waste. The system consists of a basic CNN model that improves the accuracy and efficiency of sorting and recycling medical waste, as well as protecting workers and reducing health risks in medical waste facilities. M.H. Moktar et al.[90] also developed an automated system integrated with IoT and AI technologies for the purpose of classifying and sorting medical waste such as gloves, sharps, needles, and masks, sorting them automatically without human intervention. The system consists of IoT sensors and cameras in the automated sorting line, with the ability to continuously improve the system and is practical in smart waste management in medical complexes.

AI has played a vital role in the COVID-19 pandemic and other dangerous epidemics. A. Kumar et al.[91] reviewed a range of AI-powered wearable devices for managing critical clinical and health conditions, such as vital signs analyzers and ultrasound sensors for cancer patients, as well as real-time glucose sensors and insulin pumps for diabetic patients.

5.3. Additional applications

The use of AI has advanced significantly with the improvement of prediction, monitoring and surveillance capabilities in healthcare by putting health and public data under deep and intelligent analysis, with its many modern and diverse tools for analyzing diverse data, such as electronic health records, social media posts, mobile device data and travel, in order to detect diseases early, respond quickly or predict their spread accurately and with high efficiency[92]. D. Wagner et al.[93] demonstrated that current preventive measures in operating rooms, such as the use of multi-filter respirators and professional smoke extraction or evacuation systems, are insufficient. Based on data analysis, staff who regularly use these systems are less likely to be affected than those who do not. While surgical smoke poses risks during operations, improving ventilation systems and increasing training in operating rooms effectively mitigate the health risks associated with smoke exposure.

Given the risks to medical staff from surgical smoke, which results in repeated smoke emissions over the years, AI models have proven to be highly efficient and accurate in identifying smoke characteristics and pollution levels[94]. The use of AI in manufacturing, operations, real-time quality control, predictive maintenance, and improved production planning in companies and factories has led to improved performance in terms of increased operational flexibility and production line performance. Computer vision models have also contributed to reducing effort and waste in products, and detecting defects in manufactured materials and their products [95]، As shown in Fig. 3.

AI and the Fourth Industrial Revolution have significantly contributed to increasing the productivity and efficiency of the manufacturing sector. The convergence of industry and technology across various fields has fueled the Fourth Industrial Revolution, largely driven by AI. The achievements of the Fourth Industrial Revolution have made a significant difference, with cyber-physical systems, data analytics, and the IoT playing a crucial role in enhancing, monitoring, and overseeing industrial activities around the clock [96]. The use of AI in its various forms represents a qualitative leap in smart factories and modern industrial sectors, as it effectively contributes to the decision-making process based on historical and current data, in order to prevent human errors and reduce the effort and need for human intervention.

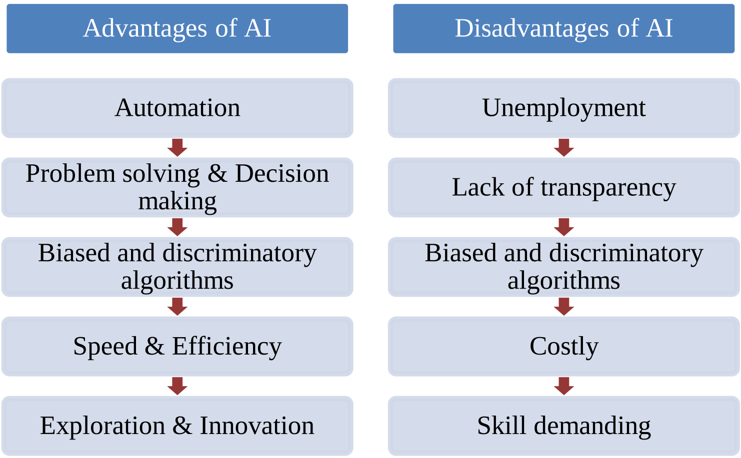

Fig. 3 - shows the advantages of AI versus its disadvantages[6].

A. T. Sufian et al.[97] used operational data from manufacturing companies and analyzed it to find the relationship between performance indicators such as production quality, efficiency, and cost reduction with big data analytics techniques, in order to contribute to reducing breakdowns and improving production plans. In the context of employing an intelligent system within a factory, I. Kazmi et al.[98] proposed analyzing data using ML algorithms for the information structure within the factory, received from sensors via IoT operated by intelligent control systems, for the purpose of increasing production efficiency, reducing malfunctions, and improving decision-making.

On the other hand, C. Picard et al.[99] used multimedia AI algorithms (Vision-Language Models) in engineering design and their application in manufacturing, by recognizing patterns from the analysis of engineering drawings and images, and using them in manufacturing or generating diagrams or recommendations that can be used in later stages. The impact of AI, automation, and ML has become very prominent and has led to a leap forward in detection and risk reduction. The expansion of e-commerce and the increase in the complexity of global supply chains have led to a greater demand for self-driving trucks to improve and support logistics by employing AI with crash systems in operational prediction and guidance [100]. In the face of mineral exploration and its difficulties, AI has provided modern methods for analyzing multi-dimensional geological data and for exploring sites with high accuracy and economic value, relying on ground imaging techniques [101].

In the context of working with construction sites, which are considered a multi-risk industrial environment due to their association with heavy equipment, accidents, and unsafe handling of workers, AI was used in a virtual reality training environment that adopted risk data and construction information models in generating and designing customized training scenarios, in addition to analyzing performance during operation, through which workers are trained on the types of potential risks [102]. The advancements in AI have significantly focused efforts on mitigating pollution. Advanced technologies are being employed to enhance air quality modeling using diverse environmental data sources, such as climate data, satellite imagery, and pollutant monitoring reports, leading to more accurate predictions. The integration of satellite technology with AI effectively contributes to the precise and comprehensive monitoring of environmental changes. Furthermore, the introduction of edge computing for real-time data processing and source analysis has greatly facilitated rapid response times to pollution incidents. Hybrid models, combined with ML-based simulations and physics, have also enhanced the accuracy of pollution hotspot identification[103].

AI technologies provide insights into pollution levels through data analysis, enabling the prediction of future environmental degradation, its stages, and how to implement measures to prevent or mitigate it. AI also makes a significant contribution to the energy sector by intelligently optimizing power distribution and grids to reduce environmental impact. The use of autonomous robotic systems operating with advanced artificial intelligence models for field surveying in polluted environments enabled them to identify and accurately assess various pollutants and deal with them directly and automatically through advanced processing via multiple and diverse sensors linked to IoT technology [104].

The deployment of IoT-enabled sensors to measure the concentrations and levels of air pollutants in urban areas in real time, and also to monitor pollution using AI algorithms by analyzing spatiotemporal pollution patterns and data processing operations, enabling citizens and decision-makers to view them within dedicated applications and digital interfaces[105]. Many capabilities of artificial intelligence are provided to provide a modern structure and keep pace with climate changes and environmental threats in real time, relying on different and multiple sources in predicting and assessing environmental risks, which enhances the overall situation in developing proactive strategies or reducing health risks and their effects[106].

Recent studies indicate a clear gap between the application of IoT and AI in applied research in developing and developed countries. Research in developed countries focuses on developing advanced DL models that rely directly on massive amounts of diverse data, temporal and spatial analysis, diverse and intelligent sensor networks, and a broad and integrated digital infrastructure. This, in turn, contributes to increasing the scope and improving the accuracy of monitoring systems. Furthermore, recent studies rely heavily on the vast size of environmental databases and the high-performance computing platforms, which enhance understanding of environmental risks and enable high-precision early warnings for environmental risk management[107].

Developing countries in the Middle East, such as Kuwait, Saudi Arabia, and Iraq, face technological challenges related to infrastructure, its high costs, the lack of diverse environmental data, and the low level and lack of integration of their smart systems. This limits the effective and widespread application of AI and IoT technologies. These countries also tend to focus on low-cost solutions based on simple machine learning models and limited sensor networks, with little emphasis on advanced environmental data analysis compared to developed countries[108].

Current research indicates that AI and IoT applications face limitations in developing countries, including local environmental contexts, data scarcity, and limited data diversity. These factors negatively impact the accuracy, generalizability, and reliability of forecasting. A comparison between developed and developing countries in the Middle East, as shown in Table 2, highlights the critical need for scalable research and application strategies tailored to the specific environmental, economic, and technological characteristics of these countries. This includes the development of comprehensive, local environmental databases that effectively integrate with AI and IoT models to achieve the highest standards of environmental safety and more sustainable management.

Table 1 - A comparison of the gap between developed countries and Third World countries in terms of the requirements for developing their environmental management systems.

REF/ Foundations	developed countries	Third World (developing) countries
[109]/Digital infrastructure	Integrated infrastructure and wide-ranging sensor networks	Incomplete and limited architecture
[110]/Level of AI algorithms used	Utilization of advanced analytics and DL algorithms	Use of simple and limited algorithms
[111]/Overall cost of technologies	Industrial, corporate, and governmental funding	Funding constraints and high costs
[107]/Available and diverse data sources	Indexed, organized, comprehensive, and large-scale data with analyzability	Scarce, irregular, and limited data
[112]/Digital skills	Owned by highly qualified specialists and personnel	Lack of digital skills
[113]/Impact on decision-making	Strong integration between environmental policies and smart systems	Very weak link between policy and technology
[114]/Sustainability and scalability	Continuous system development and scalability	Resource constraints and limitations limit expansion
[115] /Research development and innovation	Significant contribution to scientific output in journals	Low contribution to scientific output

6. Challenges

The use of AI has accelerated significantly recently across a wide range of sectors, including medicine, industry, services, agriculture, and other facilities. It has not only functioned as a tool for data analysis but has also served as an integrated system for decision-making and performance improvement in various complex social and economic environments[116, 117]. Despite the numerous benefits and solutions offered by AI, it still faces limitations and challenges that require effective solutions and methods to address them. These challenges include the efficiency of task execution, risk management and mitigation, and the accurate assessment of material hazards. The high computing power and increased energy consumption that have accompanied AI development raise serious concerns about its environmental impact, particularly regarding carbon emissions[118].

Furthermore, training and operating these models requires a huge amount of electrical energy, in addition to water consumption for the process of cooling the data centers, especially in dry areas, which puts pressure on the environmental impact in the long term[119]. The costs of obtaining, collecting, and processing data are still high, due to the need for an integrated digital database, the use of advanced sensors, the unification of multiple data sources into groups, and their monitoring and linking within a digital cloud with the help of IoT technology. This poses an obstacle for farmers with limited resources in adopting AI technologies due to their high costs, which negatively affects increasing and improving production[120]. The issue of databases and historical records is an important one in maintaining them, ensuring their security from tampering, achieving integrity, and promoting transparency through cybersecurity means. To achieve data security and integrity, blockchain is utilized to provide protection, thereby reducing reliance on a single intermediary entity to control data ownership and minimizing centralized cyberattacks[121].

While AI technologies have taken on a very important role in the manufacturing sector, with development trends in various components such as improving performance, monitoring quality, and automating processes across different stages of production, there is a lack of coverage for its applications in the diverse processes of sub-components such as machine operation, product design, production control, and assembly lines[122]. The complex social and ethical considerations associated with the use of AI technologies have far-reaching dimensions, risks, and implications that extend beyond their benefits to the economy, jobs, society, and privacy[123]. They also extend beyond the realm of responsible and ethical decision-making. Furthermore, AI systems face a significant challenge in making reliable and moral decisions, as they may be capable of making harmful or unfair choices that violate ethical principles[124].

The increased reliance on AI technologies is also having negative effects on the employment sector, particularly in replacing workers with automated technologies in some tasks, leading to a rejection of technology due to fears of increased inequality and disruption in employment[125]. It is worth noting that AI technologies face challenges in understanding individual strategies and individual or group cognitive processing patterns, which negatively affect the decision-making process or the design of support systems for dealing with incentives or guidance[126]. Therefore, AI, with its various technologies, presents both great opportunities and challenges to various sectors, which require conducting in-depth and extensive research to develop its infrastructure, and taking into account the ethical aspects.

7. Conclusion

The development of sensors and detectors, increasingly reliant on AI, is crucial for monitoring and tracking hazardous materials and pollutants in various environments. This has the potential to revolutionize environmental risk management, monitoring, and response. These devices possess the capability to process massive amounts of data in real time, identifying anomalies, patterns, and variables that indicate the presence or presence of hazardous materials. Furthermore, these devices significantly contribute to enhancing our ability to protect the environment and improve overall public health.

Several challenges remain, such as ensuring the accuracy and reliability of sensors and finding optimal ways to integrate them into monitoring systems for the best results. Despite these limitations, the benefits offered by sensors, especially those supported by AI, are significant, making them a promising approach and a promising avenue for research and development in the near future across all fields. Applications of AI in environmental monitoring include the creation of sophisticated models capable of handling emerging variables, advanced automation, and the integration of modern IoT technologies.

AI technologies can provide a more efficient and reliable approach in the near future in the areas of decision-making, optimization, and prediction. This, in turn, plays a role in automating traditional work, keeping pace with rapid development, and taking a step towards digital transformation to increase safety under hazardous conditions. This makes risk factors specific while providing a wide range for choosing the best ways. It can also prioritize in light of the environmental reality and evaluate its ability to monitor, analyze, identify, and predict potential risks in terms of efficiency, quality, safety, and cost in various work locations with multiple teams, taking into account the existence of a high probability of uncertainty. AI has become crucial after its integration with monitoring systems to detect hazardous materials, fires, harmful gases, and other substances directly and instantly, pinpointing their location with minimal risk to public health. It has been applied in various sectors, including healthcare, manufacturing, agriculture, mining, transportation, and other industries.

AI technologies are characterized by their ability to adapt to diverse environments and revolutionize the prediction, monitoring, and detection of hazards, based on real-time, simultaneous event analysis. Furthermore, AI-powered sensors, deep and machine learning algorithms, and data processing systems can significantly enhance the accuracy of hazard identification, along with the speed of data flow analysis and outcome prediction, particularly in industrial environments, chemical processing sites, or areas with gas leaks or hazardous emissions. Furthermore, AI can contribute to risk assessment, degree, and predictive modeling by considering various environmental factors and analyzing historical data.

AI algorithms can also assess incidents, their severity, and predict their likelihood, particularly in hazardous locations, thus facilitating the implementation of safety procedures and preventative measures. Integrating data from multiple sources, such as satellite imagery, sensors, and historical records, with AI algorithms provides a comprehensive understanding of hazards, their impact, movement, and scope. AI can also provide tools that significantly support decision-making for operators and supervisors in hazardous areas through natural language processing and user-friendly interfaces. AI technologies can also assist in anomaly identification, data interpretation, decision-making, and timely fault detection, enabling operators and supervisors to better manage and respond to hazardous situations.

References

[1] V. M. Pathak, V. K. Verma, B. S. Rawat, B. Kaur, N. Babu, A. Sharma, *et al.*, "Current status of pesticide effects on environment, human health and it’s eco-friendly management as bioremediation: A comprehensive review," *Frontiers in microbiology,* vol. 13, p. 962619, 2022.

[2] M. Sairam, S. Maitra, S. Praharaj, S. Nath, T. Shankar, U. Sahoo, *et al.*, "An insight into the consequences of emerging contaminants in soil and water and plant responses," in *Emerging contaminants and plants: Interactions, adaptations and remediation technologies*, ed: Springer, 2023, pp. 1-27.

[3] M. H. Lafta, A. Afra, I. Patra, A. T. Jalil, M. J. Mohammadi, A. M. Baqir Al-Dhalimy, *et al.*, "Toxic effects due to exposure heavy metals and increased health risk assessment (leukemia)," *Reviews on Environmental Health,* vol. 39, pp. 351-362, 2024.

[4] T. Horvat, G. Pehnec, and I. Jakovljević, "Volatile Organic Compounds in Indoor Air: Sampling, Determination, Sources, Health Risk, and Regulatory Insights," *Toxics,* vol. 13, p. 344, 2025.

[5] A. Bărbulescu, L. Barbeş, and C. Ș. Dumitriu, "Advances in Water, Air and Soil Pollution Monitoring, Modeling and Restoration," vol. 12, ed: MDPI, 2024, p. 244.

[6] S. M. Popescu, S. Mansoor, O. A. Wani, S. S. Kumar, V. Sharma, A. Sharma, *et al.*, "Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management," *Frontiers in Environmental Science,* vol. 12, p. 1336088, 2024.

[7] F. D. Mobo, A. L. R. Garcia, and K. Miłek, "Leveraging AI for Real-Time Environmental Monitoring: Innovations and Impacts," in *Harnessing AI in Geospatial Technology for Environmental Monitoring and Management*, ed: IGI Global Scientific Publishing, 2025, pp. 201-212.

[8] R. Zhang, H. Wen, Z. Lin, B. Li, and X. Zhou, "Artificial Intelligence-Driven Drug Toxicity Prediction: Advances, Challenges, and Future Directions," *Toxics,* vol. 13, p. 525, 2025.

[9] A. M. H. Saad and A. Myat, "AI-powered IoT frameworks for real-time environmental monitoring and sustainable urban development in smart cities," *AIP Conference Proceedings,* vol. 3327, 2025.

[10] D. Montero, G. Kraemer, A. Anghelea, C. Aybar, G. Brandt, G. Camps-Valls, *et al.*, "Earth system data cubes: Avenues for advancing earth system research," *Environmental Data Science,* vol. 3, p. e27, 2024.

[11] I. A. Aderemi, T. O. Kehinde, D. O. Ugochukwu, K. H. Ahmad, K. Y. Adjei, and C. E. Chijioke, "Beyond the Black Box: a systematic review of explainable AI for transparent and trustworthy water quality monitoring," *IEEE Sensors Reviews,* 2025.

[12] V. J. León-Muñoz, F. Santonja-Medina, F. Lajara-Marco, A. J. Lisón-Almagro, J. Jiménez-Olivares, C. Marín-Martínez, *et al.*, "The accuracy and absolute reliability of a knee surgery assistance system based on ArUco-type sensors," *Sensors,* vol. 23, p. 8091, 2023.

[13] T. Hua, W. Zhao, F. Cherubini, X. Hu, and P. Pereira, "Upgrading protected areas can improve or reverse the decline in conservation effectiveness: Evidence from the Tibetan Plateau, China," *Science of the Total Environment,* vol. 873, p. 162345, 2023.

[14] P. Asha, L. Natrayan, B. Geetha, J. R. Beulah, R. Sumathy, G. Varalakshmi, *et al.*, "IoT enabled environmental toxicology for air pollution monitoring using AI techniques," *Environmental research,* vol. 205, p. 112574, 2022.

[15] Q. Wei, H. Zhang, J. Yang, B. Niu, and Z. Xu, "PM2. 5 concentration prediction using a whale optimization algorithm based hybrid deep learning model in Beijing, China," *Environmental Pollution,* vol. 371, p. 125953, 2025.

[16] A. Heydari, M. Majidi Nezhad, D. Astiaso Garcia, F. Keynia, and L. De Santoli, "Air pollution forecasting application based on deep learning model and optimization algorithm," *Clean Technologies and Environmental Policy,* vol. 24, pp. 607-621, 2022.

[17] A. Auzzas, G. F. Capra, A. D. Jani, and A. Ganga, "An improved digital soil mapping approach to predict total N by combining machine learning algorithms and open environmental data," *Modeling Earth Systems and Environment,* vol. 10, pp. 6519-6538, 2024.

[18] Y. Han, S. Zhang, C. Dai, J. Peng, Y. Chen, and H. Ke, "Estimating soil cadmium concentration using multi-source UAV imagery and machine learning techniques," *Environmental Monitoring and Assessment,* vol. 197, pp. 1-19, 2025.

[19] W. Ai, G. Chen, X. Yue, and J. Wang, "Application of hyperspectral and deep learning in farmland soil microplastic detection," *Journal of Hazardous Materials,* vol. 445, p. 130568, 2023.

[20] H. Chojer, P. Branco, F. Martins, and S. Sousa, "A novel low-cost sensors system for real-time multipollutant indoor air quality monitoring–Development and performance," *Building and Environment,* vol. 266, p. 112055, 2024.

[21] J. M. Meyer, R. F. Kokaly, and E. Holley, "Hyperspectral remote sensing of white mica: A review of imaging and point-based spectrometer studies for mineral resources, with spectrometer design considerations," *Remote Sensing of Environment,* vol. 275, p. 113000, 2022.

[22] D. Zhao, J. Wang, X. Jiang, J. Zhen, J. Miao, J. Wang, *et al.*, "Reflectance spectroscopy for assessing heavy metal pollution indices in mangrove sediments using XGBoost method and physicochemical properties," *Catena,* vol. 211, p. 105967, 2022.

[23] P. He, X. Cheng, X. Wen, Y. Yi, Z. Chen, and Y. Chen, "Transfer Learning-Based Interpretable Soil Lead Prediction in the Gejiu Mining Area, Yunnan," *Sensors,* 2025.

[24] X. Wang, X. Sun, Z. Liu, Y. Zhao, G. Wu, Y. Wang, *et al.*, "Surface-Enhanced Raman Scattering Imaging Assisted by Machine Learning Analysis: Unveiling Pesticide Molecule Permeation in Crop Tissues," *Advanced Science,* vol. 11, p. 2405416, 2024.

[25] I. Shahid, M. I. Shahzad, E. Tutsak, M. M. Mahfouz, M. S. Al Adba, S. A. Abbasi, *et al.*, "Carbon based sensors for air quality monitoring networks; middle east perspective," *Frontiers in Chemistry,* vol. 12, p. 1391409, 2024.

[26] A. Zafra-Pérez, J. Medina-García, C. Boente, J. A. Gómez-Galán, A. S. de la Campa, and J. De La Rosa, "Designing a low-cost wireless sensor network for particulate matter monitoring: Implementation, calibration, and field-test," *Atmospheric Pollution Research,* vol. 15, p. 102208, 2024.

[27] M. B. Arboleda and A. Shamim, "Self-powered and cost-effective wireless sensor node for air quality monitoring with an optically transparent smart antenna system," *IEEE Sensors Journal,* 2024.

[28] O. Alsamrai, M. D. Redel-Macias, and M. Dorado, "Real-time intelligent monitoring of outdoor air quality in an urban environment using IoT and machine learning algorithms," *Applied Sciences,* vol. 15, p. 9088, 2025.

[29] H. R. C. Arante, E. Sybingco, M. A. Roque, L. Ambata, A. Chua, and A. N. Gutierrez, "Development of a Secured IoT-Based Flood Monitoring and Forecasting System Using Genetic-Algorithm-Based Neuro-Fuzzy Network," *Sensors,* vol. 25, p. 3885, 2025.

[30] Z. Wang, Z. Zhang, Z. Wang, J. Lu, and W. An, "A novel intelligent indoor fire and combustibles detection method based on multi-channel transfer learning strategy with acoustic signals," *Process Safety and Environmental Protection,* vol. 189, pp. 1217-1225, 2024.

[31] O. A. Wani, F. Akhter, S. S. Kumar, S. Babu, R. H. Kanth, S. A. Mir, *et al.*, "Mitigating soil erosion through biomass-derived biochar: exploring the influence of feedstock types and pyrolysis temperature," *Land,* vol. 12, p. 2111, 2023.

[32] J. Sedano-Cibrián, J. M. de Luis-Ruiz, R. Pérez-Álvarez, R. Pereda-García, and J. D. Tapia-Espinoza, "4D models generated with UAV photogrammetry for landfill monitoring thermal control of Municipal Solid Waste (MSW) landfills," *Applied Sciences,* vol. 13, p. 13164, 2023.

[33] K. Tan, W. Ma, L. Chen, H. Wang, Q. Du, P. Du, *et al.*, "Estimating the distribution trend of soil heavy metals in mining area from HyMap airborne hyperspectral imagery based on ensemble learning," *Journal of Hazardous Materials,* vol. 401, p. 123288, 2021.

[34] D. Xu, C. Wang, T. Gu, Z. Long, H. Luan, Z. Tang, *et al.*, "An Unmanned Aerial Vehicle (UAV)-Based Methane Quantification Method for Oil and Gas Sites," *Drones,* vol. 9, p. 785, 2025.

[35] S. Iwaszenko, P. Kalisz, M. Słota, and A. Rudzki, "Detection of Natural Gas Leakages Using a Laser-Based Methane Sensor and UAV," *Remote Sensing,* vol. 13, p. 510, 2021.

[36] N. Krishnakumar, S. Sharma, S. K. Pal, and J. Hong, "3D characterization of smoke plume dispersion using multi-view drone swarm," *Science of The Total Environment,* vol. 980, p. 179466, 2025.

[37] R. SOBTI, S. HORMOZIAN, and E. VU, "Remote Gas Leak Detection on a low-cost UAV platform," 2025.

[38] S. P. Mertikas, P. Partsinevelos, C. Mavrocordatos, and N. A. Maximenko, "Environmental applications of remote sensing," in *Pollution assessment for sustainable practices in applied sciences and engineering,* ed: Elsevier, 2021, pp. 107-163.

[39] A. Mangafić, K. Oštir, M. Kolar, and M. Zupan, "Hyperspectral Soil Heavy Metal Prediction via Privileged-Informed Residual Correction," *Remote Sensing,* vol. 17, p. 1987, 2025.

[40] V. K. Mishra, H. Maurya, F. Nicolls, and A. K. Mishra, "Application of Multispectral Imagery and Synthetic Aperture Radar Sensors for Monitoring Algal Blooms: A Review," *Phycology,* vol. 5, p. 71, 2025.

[41] L. Zhong, X. Chu, J. Qian, J. Li, and Z. Sun, "Multi-scale stereoscopic hyperspectral remote sensing estimation of heavy metal contamination in wheat soil over a large area of farmland," *Agronomy,* vol. 13, p. 2396, 2023.

[42] N. Yang, L. Li, L. Han, K. Gao, S. Qu, and J. Li, "Retrieving heavy metal concentrations in urban soil using satellite hyperspectral imagery," *International Journal of Applied Earth Observation and Geoinformation,* vol. 132, p. 104079, 2024.

[43] H. Fan, E. Schaffernicht, and A. J. Lilienthal, "Ensemble learning-based approach for gas detection using an electronic nose in robotic applications," *Frontiers in chemistry,* vol. 10, p. 863838, 2022.

[44] I. Kulbaka, A. Dutta, O. P. Kreidl, L. Bölöni, and S. Roy, "GDM-Net: Gas Distribution Mapping with a Mobile Robot Using Deep Reinforcement Learning and Gaussian Process Regression," in *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS),* 2024, pp. 4511-4518.

[45] A. Gongora, J. Monroy, F. Rahbar, C. Ercolani, J. Gonzalez-Jimenez, and A. Martinoli, "Information-driven gas distribution mapping for autonomous mobile robots," *Sensors,* vol. 23, p. 5387, 2023.

[46] A. Haldorai, M. Suriya, and M. Balakrishnan, "An improved single short detection method for smart vision-based water garbage cleaning robot," *Cognitive Robotics,* vol. 4, pp. 19-29, 2024.

[47] L. García, A.-J. Garcia-Sanchez, R. Asorey-Cacheda, J. Garcia-Haro, and C.-L. Zúñiga-Cañón, "Smart air quality monitoring IoT-based infrastructure for industrial environments," *Sensors,* vol. 22, p. 9221, 2022.

[48] H. Li, Y. Zhang, and W. Yang, "Gas explosion early warning method in coal mines by intelligent mining system and multivariate data analysis," *PLoS one,* vol. 18, p. e0293814, 2023.

[49] E. Alotaibi and N. Nassif, "Artificial intelligence in environmental monitoring: in-depth analysis," *Discover Artificial Intelligence,* vol. 4, p. 84, 2024.

[50] F. Gao, H. Li, Z. Chen, Y. Yi, S. Nie, Z. Cheng*, et al.*, "A chemical autonomous robotic platform for end-to-end synthesis of nanoparticles," *Nature Communications,* vol. 16, p. 7558, 2025.

[51] J.-H. Lee, D. Nam, R. I. Kee, Y. Kim, and S.-J. Buu, "Vision-Ultrasound Robotic System based on Deep Learning for Gas and Arc Hazard Detection in Manufacturing," *arXiv preprint arXiv:2502.05500,* 2025.

[52] R. Bitriá, J. Palacín, E. Rubies, and E. Clotet, "Experience Embedding a Compact eNose in an Indoor Mobile Delivery Robot for the Early Detection of Gas Leaks," *Applied Sciences,* vol. 15, p. 3430, 2025.

[53] D. Ma, S. Guo, and Y. Zhou, "Optimization of sampling structure on unmanned aerial vehicle for gas leakage monitoring in the atmosphere," *Robotica,* vol. 43, pp. 499-513, 2025.

[54] A. Bouras, A. Gutierrez-Galvez, J. Burgués, Y. Bouzid, A. Pardo, M. Guiatni*, et al.*, "Concentration map reconstruction for gas source location using nano quadcopters: Metal oxide semiconductor sensor implementation and indoor experiments validation," *Measurement,* vol. 213, p. 112638, 2023.

[55] W. A. S. Norzam, H. F. Hawari, K. Kamarudin, Z. H. M. Juffry, N. A. A. Hussein, M. Gupta*, et al.*, "Mobile robot gas source localization using SLAM-GDM with a graphene-based gas sensor," *Electronics,* vol. 12, p. 171, 2022.

[56] A. u. Husnain, N. Mokhtar, N. B. Mohamed Shah, M. B. Dahari, A. A. Azmi, and M. Iwahashi, "Gas concentration mapping and source localization for environmental monitoring through unmanned aerial systems using model-free reinforcement learning agents," *Plos one,* vol. 19, p. e0296969, 2024.

[57] L. Qiao, H.-E. Chen, K. Deng, Z. Wang, Y. Zhao, S. Xie*, et al.*, "An inversion scheme for sizing crack from signals of the motion-induced eddy current testing method based on a new formula of signal gradient of ferromagnetic materials," *Mechanical Systems and Signal Processing,* vol. 198, p. 110453, 2023.

[58] U. I. Abdullahi, W. Zhang, Y. Cao, and G. Irankunda, "Integrating IoT Technology for Fire Risk Monitoring and Assessment in Residential Building Design," *Buildings,* vol. 15, p. 1346, 2025.

[59] M. A. I. Anik, M. T. Rahman, A. S. Zishan, M. N. C. Onkon, N. T. Rakhi, and A. Shufian, "IoT-Based Gas Leak Detection and Fire Hazard Recognition System Using Image Processing for Household Safety Enhancement," in *International Conference on Robotics, Electrical and Signal Processing Techniques*, 2025, pp. 239-243.

[60] M. S. Murty, "Smart Gas Leakage Detector Using IoT Sensors," *International Journal of Intelligent Systems and Applications in Engineering,* vol. 12, pp. 2613 – 2620, 08/14 2024.

[61] V. González, J. Godoy, P. Arroyo, F. Meléndez, F. Díaz, Á. López*, et al.*, "Development of a Smartwatch with Gas and Environmental Sensors for Air Quality Monitoring," *Sensors,* vol. 24, p. 3808, 2024.

[62] M. El Barkani, N. Benamar, H. Talei, and M. Bagaa, "Gas Leakage Detection Using Tiny Machine Learning," *Electronics,* vol. 13, p. 4768, 2024.

[63] G. M. Dimitri, L. Parri, E. Vitanza, A. Pozzebon, A. Fort, and C. Mocenni, "WeAIR: Wearable Swarm Sensors for Air Quality Monitoring to Foster Citizens' Awareness of Climate Change," *Computer Standards & Interfaces,* vol. 94, p. 104004, 2025/08/01/ 2025.

[64] S. K. Reddy, A. S. Naik, and G. R. Mandela, "Development of a Novel Real-Time Environmental Parameters Monitoring System Based on the Internet of Things with LoRa Modules in Underground Mines," *Wireless Personal Communications,* vol. 133, pp. 1517 - 1546, 2023.

[65] P. Beldar, P. Kushare, A. Patil, and G. Kumar, "AI-powered AQI forecasting in an intelligent air purifier featuring intense field dielectric and Zeolite filters," *Journal of Engineering and Applied Science,* vol. 72, p. 150, 2025/09/10 2025.

[66] S. Seker, "IoT based sustainable smart waste management system evaluation using MCDM model under interval-valued q-rung orthopair fuzzy environment," *Technology in Society,* vol. 71, p. 102100, 2022/11/01/ 2022.

[67] R. S. A. Qurashi, M. M. Almnjomi, T. L. Alghamdi, A. H. Almalki, S. S. Alharthi, A. S. Alharthi, *et al.*, "Smart Waste Management System for Makkah City using Artificial Intelligence and Internet of Things," *arXiv preprint arXiv:2505.19040*, 2025.

[68] Y. Zhang, J. Long, and B. Xu, "Research on Safety Monitoring System for Dangerous Goods Transport Vehicles Based on Wireless Sensor Networks," *Journal of Intelligence and Knowledge Engineering (ISSN: 2959-0620),* vol. 2, p. 7, 2024.

[69] Z. Wang, T. Li, M. Yang, and Z. Wu, "Dynamic optimization of hazardous materials vehicle transportation routes based on real-time risk," *Journal of Loss Prevention in the Process Industries,* p. 105864, 2025.

[70] S. Kushwaha and R. Pandey, "Intelligent IoT-Based Water Quality Monitoring and Predictive Analysis Using Machine Learning," *AI Systems Engineering,* vol. 1, pp. 8-16, 2025.

[71] N. K. Balaraman, H. Pandey, M. K. Chandol, K. Sutaria, S. M. U. Iqbal, and R. Maranan, "Smart Water Quality Monitoring and Prediction using IoT with Improved Local Binary Pattern Shallow Deep Convolutional Neural Networks and Starling Murmuration Optimization," in *2025 6th International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2025, pp. 1643-1650.

[72] Y. Durgun, "Real-time water quality monitoring using AI-enabled sensors: Detection of contaminants and UV disinfection analysis in smart urban water systems," *Journal of King Saud University-Science,* vol. 36, p. 103409, 2024.

[73] R. K. Nishan, S. Akter, R. I. Sony, M. M. Hoque, M. J. Anee, and A. Hossain, "Development of an IoT-based multi-level system for real-time water quality monitoring in industrial wastewater," *Discover Water,* vol. 4, p. 43, 2024.

[74] C. Pham-Quoc and N. C. Tri, "Towards an IoT-Based Unmanned Surface Vehicle Design for Environment Monitoring in Mekong Delta," in *International Conference on Context-Aware Systems and Applications*, 2023, pp. 139-148.

[75] J. H. Ryu, "Prototyping a low-cost open-source autonomous unmanned surface vehicle for real-time water quality monitoring and visualization," *HardwareX,* vol. 12, p. e00369, 2022.

[76] I. A. Adeleke, N. I. Nwulu, and O. A. Ogbolumani, "A hybrid machine learning and embedded IoT-based water quality monitoring system," *Internet of things,* vol. 22, p. 100774, 2023.

[77] A. A. Abu Bakar, Z. A. Bakar, Z. M. Yusoff, M. J. Mohamed Ibrahim, N. A. Mokhtar, and S. N. a. Zaiton, "IoT-Based Real-Time Water Quality Monitoring and Sensor Calibration for Enhanced Accuracy and Reliability," *International Journal of Interactive Mobile Technologies,* vol. 19, 2025.

[78] J. Adamczyk, J. Poziemski, and P. Siedlecki, "Evaluating machine learning models for predicting pesticides toxicity to honey bees," *arXiv preprint arXiv:2503.24305*, 2025.

[79] J. K. Mogaraju, "Explainable Artificial Intelligence integrated with Machine learning operations to predict the nitrate concentrations in Groundwater," 2025.

[80] J. Chen, W. Zhang, Y. Peng, J. Wang, and M. Wu, "Machine learning prediction of the heavy metal concentration in soil," *Journal of Soils and Sediments,* pp. 1-12, 2025.

[81] Y. Zha and Y. Yang, "Innovative graph neural network approach for predicting soil heavy metal pollution in the Pearl River Basin, China," *Scientific Reports,* vol. 14, p. 16505, 2024.

[82] R. Hassan and M. R. Kazemi, "Machine learning frameworks to accurately estimate the adsorption of organic materials onto resin and biochar," *Scientific Reports,* vol. 15, p. 15157, 2025.

[83] F. Talebkeikhah, S. Rasam, M. Talebkeikhah, M. Torkashvand, A. Salimi, and M. K. Moraveji, "Investigation of effective processes parameters on lead (II) adsorption from wastewater by biochar in mild air oxidation pyrolysis process," *International Journal of Environmental Analytical Chemistry,* vol. 102, pp. 3975-3995, 2022.

[84] M. Al Duhayyim, H. A. Mengash, M. Aljebreen, M. K Nour, N. M. Salem, A. S. Zamani, *et al.*, "Smart water quality prediction using atom search optimization with fuzzy deep convolutional network," *Sustainability,* vol. 14, p. 16465, 2022.

[85] Y. A. Fahim, I. W. Hasani, S. Kabba, and W. M. Ragab, "Artificial intelligence in healthcare and medicine: clinical applications, therapeutic advances, and future perspectives," *European Journal of Medical Research,* vol. 30, pp. 1-21, 2025.
[86] C. Sharma, S. Gupta, V. Kumar, and V. Kumar, "Hospital-associated effluents: the masked environmental threat that needs urgent attention and action," *Discover Applied Sciences,* vol. 7, p. 40, 2024.
[87] E. Çetin, A. Hussein, and S. Güneş-Durak, "Advancing Sustainable Medical Waste Management: A Case Study on Waste Generation and Classification in a University Hospital Microbiology Laboratory," *Sustainability,* vol. 17, p. 4325, 2025.
[88] R. S. Gautam, S. K. Singh, K. Arpita, V. Chandra, S. Kumar, K. Singh*, et al.*, "Measuring environmental sustainability concerns for medical waste management through scale development and validation," *Discover Environment,* vol. 3, p. 223, 2025.
[89] H. Zhou, X. Yu, A. Alhaskawi, Y. Dong, Z. Wang, Q. Jin*, et al.*, "A deep learning approach for medical waste classification," *Scientific reports,* vol. 12, p. 2159, 2022.
[90] M. H. Moktar, H. Mohamed, S. S. H. Hajjaj, and M. Z. Baharuddin, "Medical waste sorting machine development with IoT and YOLO model utilization," *Journal of Engineering and Applied Science,* vol. 72, p. 86, 2025.
[91] A. Kumar, S. Goel, A. Chaudhary, S. Dutt, V. K. Mishra, and R. Kumar, "Artificial Intelligence-Based Wearable Sensing Technologies for the Management of Cancer, Diabetes, and COVID-19," *Biosensors,* vol. 15, p. 756, 2025.
[92] J.-H. Li, Y.-J. Tseng, S.-H. Chen, and K.-F. Chen, "Artificial Intelligence in Infection Surveillance: Data Integration, Applications and Future Directions," *Biomedical Journal,* p. 100929, 2025.
[93] D. Wagner, S. Pearcey, C. J. Hudgins, and B. C. Ulmer, "Surgical smoke knowledge and practices before and after onset of COVID-19: A national survey of OR personnel," *Perioperative Care and Operating Room Management,* vol. 35, p. 100411, 2024/06/01/ 2024.
[94] A. R. Raju, U. U. M. Mohammed, M. Prabha, K. Preethi, M. Muthulekshmi, and B. Murukesh, "Autonomous Robots for Air Quality Control and Sterility Maintenance in Surgical Rooms Using AI and IoT," in *2025 International Conference on Smart & Sustainable Technology (INCSST)*, 2025, pp. 1-6.
[95] D. A. Barua, S. A. Sami, and L. Barua, "Leveraging artificial intelligence for smart production management in industry 4.0," *Scientific Reports,* vol. 15, p. 41559, 2025.
[96] M. S. Ahmmed, S. P. Isanaka, and F. Liou, "Promoting Synergies to Improve Manufacturing Efficiency in Industrial Material Processing: A Systematic Review of Industry 4.0 and AI," *Machines,* vol. 12, p. 681, 2024.
[97] A. T. Sufian, B. M. Abdullah, and O. J. Miller, "Smart Manufacturing Application in Precision Manufacturing," *Applied Sciences,* vol. 15, p. 915, 2025.
[98] I. Kazmi, "Big Data Analytics in Smart Manufacturing: Transforming Decision-Making Processes," *Integrated Journal of Science and Technology,* vol. 1, 2024.
[99] C. Picard, K. M. Edwards, A. C. Doris, B. Man, G. Giannone, M. F. Alam*, et al.*, "From concept to manufacturing: Evaluating vision-language models for engineering design," *Artificial Intelligence Review,* vol. 58, p. 288, 2025.
[100] E. C. Onukwulu, M. O. Agho, N. L. Eyo-Udo, A. K. Sule, and C. Azubuike, "Advances in automation and AI for enhancing supply chain productivity in oil and gas," *International Journal of Research and Innovation in Applied Science,* vol. 9, pp. 654-687, 2024.
[101] J. Muir, G. Olivier, and A. Reid, "End-to-End Mineral Exploration with Artificial Intelligence and Ambient Noise Tomography," *arXiv preprint arXiv:2403.15095,* 2024.
[102] K. Speiser, G. Maciocci, and J. Teizer, "Risk Assessment for Construction Safety with Retrieval-Augmented Generation and Agentic Artificial Intelligence," in *International Conference on Construction Applications of Virtual Reality*, 2024, pp. 397-411.
[103] D. Anthony, H. Siriwardana, S. Ashvini, S. Pallewatta, S. M. Samarasekara, S. Edirisinghe*, et al.*, "Trends in marine pollution mitigation technologies: Scientometric analysis of published literature (1990-2022)," *Regional Studies in Marine Science,* vol. 66, p. 103156, 2023.
[104] R. Kundavaram, A. R. Onteddu, K. Devarapu, and M. Nizamuddin, "Advances in autonomous robotics for environmental cleanup and hazardous waste management," *Asia Pacific Journal of Energy and Environment,* vol. 12, pp. 1-16, 2025.
[105] E. Bainomugisha, P. Adrine Warigo, F. Busigu Daka, A. Nshimye, M. Birungi, and D. Okure, "AI-driven environmental sensor networks and digital platforms for urban air pollution monitoring and modelling," *Societal Impacts,* vol. 3, p. 100044, 2024/06/01/ 2024.
[106] M. Rajesh, R. G. Babu, U. Moorthy, and S. V. Easwaramoorthy, "Machine learning-driven framework for realtime air quality assessment and predictive environmental health risk mapping," *Scientific Reports,* vol. 15, p. 28801, 2025.
[107] I. Gryech, C. Asaad, M. Ghogho, and A. Kobbane, "Applications of machine learning & Internet of Things for outdoor air pollution monitoring and prediction: A systematic literature review," *Engineering Applications of Artificial Intelligence,* vol. 137, p. 109182, 2024/11/01/ 2024.

[108] M. A. Albreem, A. M. Sheikh, M. J. Bashir, and A. A. El-Saleh, "Towards green Internet of Things (IoT) for a sustainable future in Gulf Cooperation Council countries: Current practices, challenges and future prospective," *Wireless Networks*, vol. 29, pp. 539-567, 2023.

[109] R. M. P. N. S. Bandara, A. B. Jayasignhe, and G. Retscher, "The Integration of IoT (Internet of Things) Sensors and Location-Based Services for Water Quality Monitoring: A Systematic Literature Review," *Sensors,* vol. 25, p. 1918, 2025.

[110] I. Essamlali, H. Nhaila, and M. El Khaili, "Advances in machine learning and IoT for water quality monitoring: A comprehensive review," *Heliyon,* vol. 10, 2024.

[111] A. Garcia, Y. Saez, I. Harris, X. Huang, and E. Collado, "Advancements in air quality monitoring: a systematic review of IoT-based air quality monitoring and AI technologies," *Artificial Intelligence Review,* vol. 58, p. 275, 2025.

[112] P. Mhaske, B. Bhattacharjee, N. Haldar, P. Upadhyay, and A. Mandal, "Bridging digital skill gaps in the global workforce: A synthesis and conceptual framework building," *Research in Globalization,* vol. 11, p. 100311, 2025/12/01/ 2025.

[113] D. B. Olawade, O. Z. Wada, A. O. Ige, B. I. Egbewole, A. Olojo, and B. I. Oladapo, "Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions," *Hygiene and Environmental Health Advances,* vol. 12, p. 100114, 2024.

[114] N. Ahmed and N. Shakoor, "Advancing agriculture through IoT, Big Data, and AI: a review of smart technologies enabling sustainability," *Smart Agricultural Technology,* p. 100848, 2025.

[115] V. Bhardwaj, A. Anooja, L. S. Vermani, Sunita, and B. K. Dhaliwal, "Smart cities and the IoT: An in-depth analysis of global research trends and future directions," *Discover Internet of Things,* vol. 4, p. 19, 2024.

[116] Chatrabhuj, K. Meshram, U. Mishra, and U. Rathnayake, "Application of artificial intelligence in agri-tech, environmental and biodiversity conservation," *Array,* vol. 26, p. 100412, 2025/07/01/ 2025.

[117] U. Nawaz, M. Z. Zaheer, F. S. Khan, H. Cholakkal, S. Khan, and R. M. Anwer, "AI in agriculture: A survey of deep learning techniques for crops, fisheries and livestock," *arXiv preprint arXiv:2507.22101,* 2025.

[118] A. Lal and F. You, "Advances and challenges in energy and climate alignment of AI infrastructure expansion," *Advances in Applied Energy,* vol. 20, p. 100243, 2025/12/01/ 2025.

[119] J. Xu, "Research on AI Computational Energy Consumption Optimization and Green AI," in *SHS Web of Conferences*, 2025, p. 02027.

[120] A. J. Atapattu, L. K. Perera, T. D. Nuwarapaksha, S. S. Udumann, and N. S. Dissanayaka, "Challenges in achieving artificial intelligence in agriculture," in *Artificial intelligence techniques in smart agriculture*, ed: Springer, 2024, pp. 7-34.

[121] A. M. Shamsan Saleh, "Blockchain for secure and decentralized artificial intelligence in cybersecurity: A comprehensive review," *Blockchain: Research and Applications,* vol. 5, p. 100193, 2024/09/01/ 2024.

[122] Z. Akhtar, "Artificial intelligence (AI) within manufacturing: An investigative exploration for opportunities, challenges, future directions. Metaverse, 5 (2), 2731," ed, 2024.

[123] T. Hagendorff, "Mapping the ethics of generative AI: A comprehensive scoping review," *Minds and Machines,* vol. 34, p. 39, 2024.

[124] P. R. Brandao, "The impact of artificial intelligence on modern society," *AI,* vol. 6, p. 190, 2025.

[125] M. Nigar, J. F. Juli, U. Golder, M. J. Alam, and M. K. Hossain, "Artificial intelligence and technological unemployment: Understanding trends, technology's adverse roles, and current mitigation guidelines," *Journal of Open Innovation: Technology, Market, and Complexity,* vol. 11, p. 100607, 2025/09/01/ 2025.

[126] Z. Li, Z. Lu, and M. Yin, "Decoding ai’s nudge: A unified framework to predict human behavior in ai-assisted decision making," in *Proceedings of the AAAI Conference on Artificial Intelligence*, 2024, pp. 10083-10091.