frontiers | Frontiers in Environmental Science

TYPE Review
PUBLISHED 20 February 2024
DOI 10.3389/fenvs.2024.1336088

OPEN ACCESS

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RECEIVED 10 November 2023
ACCEPTED 06 February 2024
PUBLISHED 20 February 2024

CITATION
Popescu SM, Mansoor S, Wani OA, Kumar SS, Sharma V, Sharma A, Arya VM, Kirkham MB, Hou D, Bolan N and Chung YS (2024), Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management.
Front. Environ. Sci. 12:1336088.
doi: 10.3389/fenvs.2024.1336088

Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management

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Detecting hazardous substances in the environment is crucial for protecting human wellbeing and ecosystems. As technology continues to advance, artificial intelligence (AI) has emerged as a promising tool for creating sensors that can effectively detect and analyze these hazardous substances. The increasing advancements in information technology have led to a growing interest in utilizing this technology for environmental pollution detection. AI-driven sensor systems, AI and Internet of Things (IoT) can be efficiently used for environmental monitoring, such as those for detecting air pollutants, water contaminants, and soil toxins. With the increasing concerns about the detrimental impact of legacy and emerging hazardous substances on ecosystems and human health, it is necessary to develop advanced monitoring systems that can efficiently detect, analyze, and respond to potential risks. Therefore, this review aims to explore recent advancements in using AI, sensors and IOTs for environmental pollution monitoring, taking into account the complexities of predicting and tracking pollution changes due to the dynamic nature of the environment. Integrating machine learning (ML) methods has the potential to revolutionize environmental science, but it also poses challenges. Important considerations include balancing model performance and interpretability, understanding ML model requirements, selecting appropriate models, and addressing concerns related to data sharing. Through examining these issues, this study seeks to highlight the latest trends in leveraging AI and IOT for environmental pollution monitoring.

KEYWORDS

environmental pollution, monitoring, safety, advance technologies, machine learning, IoT

1 Introduction

Hazardous substances in the environment are those that pose a threat to human health, plant, and animal life, or the environment. These substances include heavy metals, pesticides, herbicides, and persistent organic pollutants (POPs) that have been introduced into the environment through various means (Young et al., 2004). Sources of hazardous substances in soil include industrial activities, improper disposal of hazardous waste, agricultural practices, and natural processes such as erosion and weathering. These substances can persist in the environment for long periods and can have a negative impact on soil quality, plant growth, and human health (Bachmann, 2006; Baran et al., 2011; Bolan et al., 2021; Rani et al., 2021). The effects of hazardous substances in the environment can vary depending on the type and concentration of the substance, as well as the duration of exposure. Some hazardous substances can cause acute health effects, such as respiratory problems, skin irritation, poisoning, nausea, and vomiting, while others can lead to chronic health problems, including cancer, reproductive disorders, and developmental abnormalities (Baran et al., 2011; Li et al., 2022; Yang et al., 2022).

Effective management of hazardous substances in the environment requires monitoring, remediation, and prevention strategies. Monitoring involves regular testing of soil for the presence of hazardous substances, which allows for early detection and appropriate management strategies to be implemented. Remediation involves the removal or treatment of contaminated sites. Prevention strategies include reducing the use of hazardous materials (i.e., source control) and implementing best practices for waste disposal and land use. Effective management is essential for ensuring the long-term health and sustainability of soil and its ecosystems (Mansoor et al., 2022; Sharma et al., 2022; Sonne et al., 2023).

Real-time monitoring of hazardous materials in soil and plants is an important task that can help to ensure the safety of food crops, protect the environment, and prevent human exposure to harmful substances. The use of artificial intelligence (AI) powered sensors and devices can greatly enhance the accuracy and efficiency of this monitoring process. AI-powered sensors and devices can be used to detect and quantify the presence of various hazardous materials in soil and plants (Wilson, 2012; Yang et al., 2021). These sensors and devices can be designed to measure parameters such as pH, temperature, moisture, conductivity, and various chemical properties of the soil and plant tissue. Machine learning algorithms can be used to analyze the data collected by these sensors and devices, enabling the identification of specific hazardous materials in real-time (Wilson, 2012; Yang et al., 2021). These algorithms can also be used to predict the potential impact of these materials on human health and the environment. For example, E-nose (olfactory) algorithms are used to analyze data generated by sensors and identify the presence of hazardous chemicals based on their unique chemical signature (Jeong and Choi, 2022). These algorithms can use a variety of techniques, such as pattern recognition, artificial neural networks, and fuzzy logic. One of the key advantages of E-nose technologies is their ability to detect hazardous chemicals in real-time, allowing for immediate response to potential threats. E-nose technologies can be used for a variety of applications, such as monitoring air quality in urban areas, detecting leaks from industrial processes, and detecting explosives and other hazardous materials (Jeong and Choi, 2022).

The use of AI-powered sensors and devices for real-time monitoring of hazardous materials in soil and plants has several benefits (Singh and Kaur, 2022). Firstly, it allows for more accurate and reliable detection of these materials compared to traditional laboratory-based methods. Secondly, it provides real-time data, allowing for quick responses to any potential contamination events. Finally, it reduces the need for manual data collection and analysis, reducing the workload and increasing the efficiency of the monitoring process (Jeong and Choi, 2022). The use of AI-powered sensors and devices for real-time monitoring of hazardous materials in soil and plants is a promising approach that can help to ensure the safety of food crops, protect the environment, and prevent human exposure to harmful substances. Various approaches can be used for AI-based toxicity prediction, including machine learning methods, deep learning methods, and hybrid approaches that combine both methods. Integrating various sources of data, such as chemical structures, toxicological and physiological data, and environmental factors, to improve the accuracy and reliability of toxicity predictions, is important (Jeong and Choi, 2022; Chen et al., 2023).

One of the recent advances is the combination of AI and Internet of Things (IoT) technologies, for particulate matter (PM) monitoring, which uses low-cost sensors that can be easily deployed in various environments (Bhagat et al., 2020). These sensors can collect data on PM levels and send it to a centralized platform for analysis. AI algorithms can then process these data to provide real-time information on PM levels and predict future trends. Heavy metals can also be monitored using AI. Numerous studies have been conducted over the last 10 years to forecast the effectiveness of heavy metal removal from soil using machine learning (Zafar et al., 2017; Zhu et al., 2019). AI models for the optimization and prediction of heavy metal removal include black box, fuzzy logic, kernel, evolutionary, and hybrid models.

With the rapid changes that the environment is experiencing, data sharing and reuse with the help on AI algorithms and instruments (Shen, 2018), plays an important role in supporting researchers to safeguard the continuous threatened environment and ensure the implementation of sustainable environmental management practices (Aggestam and Mangalagiu, 2020). Scientists can make use of online data sharing tools and platforms that comprise vast and intricate Earth and environmental science data like climatic and atmospheric data, pedology, hidrology, ecology, and biodiversity data (Crystal-Ornelas et al., 2022; Basel et al., 2023) for testing, analyzing, interpretation of theories, prediction models and experimental data (Kostal et al., 2022) that lead to better undestanding environmental issues.

In this comprehensive review, we will examine the application of artificial intelligence (AI) in monitoring hazardous materials across different environments, namely, soil, air, and water. We will explore the latest breakthroughs and progress made in this field, which integrates machine learning algorithms with sensor technologies. We will also consider the benefits and drawbacks associated with AI-powered monitoring systems. This new field has revolutionized soil, air, and water monitoring, enhancing accuracy, efficiency, and timeliness in detecting and analyzing hazardous substances.

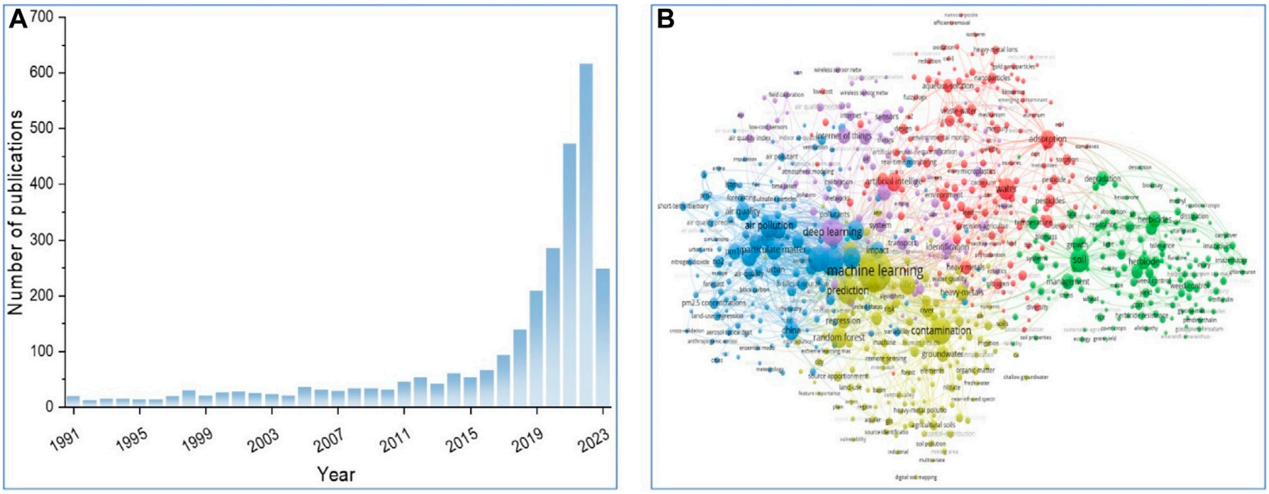

FIGURE 1
Systematic literature search results on AI-Driven Technologies for Hazardous Substance Monitoring topic. **(A)** The number of publications related to AI-Driven Technologies for Hazardous Substance Monitoring topic in each year following literature screening. **(B)** A network visualization map delineating keywords within the associated literature is depicted, revealing clusters indicative of distinct research themes. Nodes sharing analogous colors denote cohesive clusters comprising interrelated terms. This map was generated through the utilization of VOSviewer.

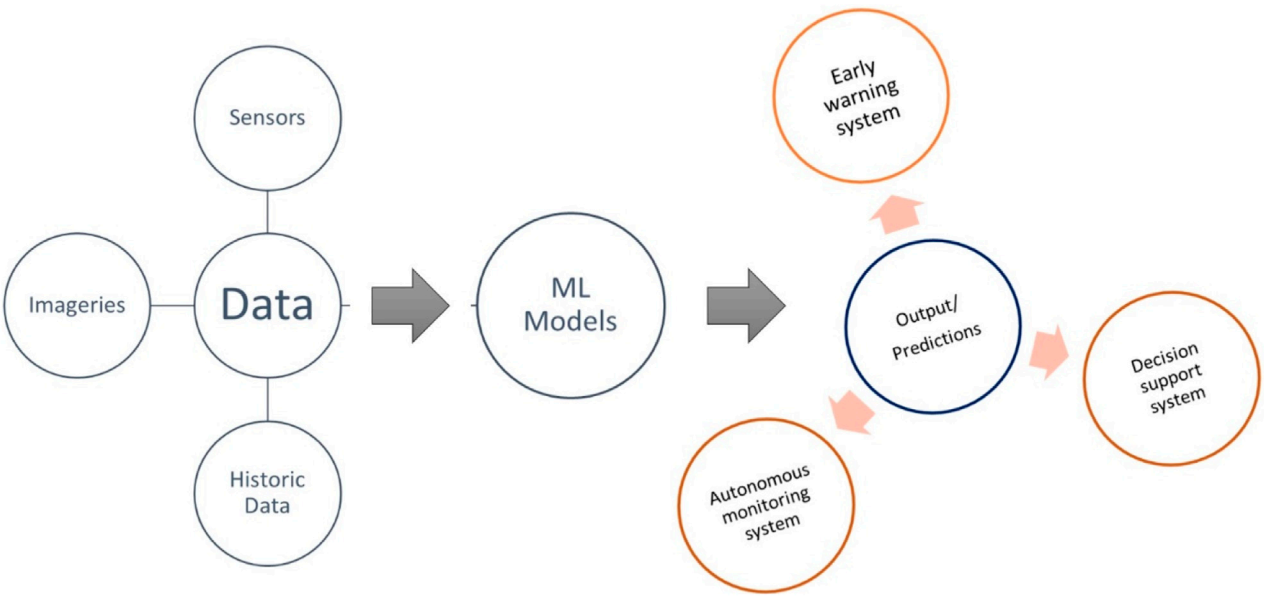

FIGURE 2
AI solutions: making use of Data and AI algorithms for hazardous substance monitoring and containment.

A literature search was conducted in Web of Science Core Collections with the following search terms (TS stands for Topic Searches): TS=("artificial intelligence" or "AI" or "machine learning" or "deep learning" or "Internet of Things" or "IoT" or "computer vision" or "robotics" or "natural language process" or "real-time monitoring" or "e-nose") AND TS=("hazardous substance" or "hazardous chemical" or "hazardous material" or "pollutant" or "contamination" or "toxin" or "heavy metal" or "pesticide" or "herbicide" or "persistent organic pollutants" or "POPs" or "microplastic") AND TS=("environment" or "soil" or "terrestrial" or "aquatic" or "aqueous" or "freshwater" or "lake" or "river" or "sediment" or "marine" or "ocean" or "air" or "atmosphere"). A total of 2828 results were retrieved. The results were visualized using the VOS (visualization of similarities) viewer software (version 1.6.19). Figure 1 presents the systematic literature search results covering the number of publications and the keyword co-occurrence map on the topic of the review (AI-Driven Technologies for Hazardous Substance Monitoring).

2 AI solutions for hazardous substance monitoring in different environments

In recent years, there has been an increase in interest for using AI to anticipate and predict environmental pollution. We can split AI solutions into three steps or phases that include inputs (data), models (AI algorithms), and outputs (monitoring or decision support) (Figure 2). Data forms the basis of any AI solution. These models work best when they have a high number of data points, especially the ones that are coming from environments that are continually being monitored and expending solutions for probable actions. Data sources today can be a variety of sensors, ranging from imaging to non-imaging types or remote to in-contact sensors that provide large volumes of data. Then there are the historic or legacy data. AI algorithms can analyse massive amounts of sensor readings, historical data, and other important information from monitoring systems. AI can detect hazardous material levels and contamination events by identifying patterns, trends, and anomalies in data using machine learning and data mining. Image analysis can detect hazardous material spills via satellite photos or drone images. Computer vision algorithms can recognise chemicals, vegetation changes, and pollution sources.

AI algorithms can be trained on past data to predict hazardous material releases and environmental pollution. AI solutions for environmental monitoring, thus, would include early warning systems for hazardous material release, autonomous pollution monitoring systems as well as decision support systems. These models can help authorities and organisations prepare for and respond to emergencies. These models have proved useful for multiple environmental conditions, be it soil, air, or water. AI modellers, however, should offer sufficient details to explain and support the selection of model parameters, as well as their creation and assessment.

Many short- and long-term forecasting applications use ANNs (artificial neural networks). One has created an IoT-enabled environmental toxicology model to detect air pollution (Asha et al., 2022). The model uses artificial intelligence to report the status of the quality of air in real-time utilising a cloud server and broadcasts alarms when hazardous pollutants are present. The AAA (artificial algae algorithm)-based ENN (Elman neural network) model classifies and predicts air quality in future timestamps (a timestamp is the current time of an event that a computer records). WiFi gateways send the data collected by sensors to a cloud server. AAA optimises the ENN model parameters during data processing. For monitoring and enforcement, mobile electronic-nose (E-nose) devices and algorithms have been developed to quickly detect pollution from point sources. Due to their sensitivity, E-nose devices can detect carbon, GHG emissions, and particle pollutants emitted into air or water (Wilson, 2012).

Traditional soil mapping entails physically collecting soil samples and transferring them to a laboratory for additional analysis (Signes-Pastor et al., 2016; Sharma et al., 2017). The advent of technologies permitting high-resolution, quick, and inexpensive mapping of soil pollutants has favourable aspects over traditional techniques. Jia et al. (2021) created an unique modelling method that forecasts soil arsenic levels using high resolution aerial imagery (HRAI) photos. The method makes use of cameras that are installed on aircraft to take high-resolution (0.1–0.5 m) pictures of broad areas. The first layer of a model for displaying soil arsenic levels shows a thorough report on soil contamination and HRAI. The image is broken down into pixels in the second layer, and sample points are represented by pixel features. In order to forecast the risk levels of arsenic, four alternative machine learning algorithms were constructed. The Extreme Random Forest (ERF) algorithm had the best prediction and accuracy (Jia et al., 2021). Remote sensing and aerial imageries provide continuous spatial data which, coupled with machine learning models, are providing highly accurate maps of hazardous substances in the environment that were not possible with standard geostatistical techniques.

Microplastics in the environment have become a cause for concern, but their evaluation in soils is a laborious process. Hyperspectral imaging (HSI) and convolutional neural network (CNN) technology-based methods have been developed for identifying microplastic polymers (Ai et al., 2023). The technique developed by Ai et al. (2023) provides a non-destructive, rapid approach to detection of microplastics in soils. Microfluidic devices using machine learning and AI promise to be next-generation monitoring systems (Pouyanfar et al., 2022). Sensitive microfluidic devices produce high-quality pollutant data and reveal important environmental information. Artificial intelligence can categorize, characterize, and predict data from microfluidic systems. The two can be easily set up. Ahmadi et al. (2021) used ANN to predict the concentrations of organophosphorus pesticides in water. Their model worked best for prediction of Malathion ($R^2 = 0.887$), followed by parathion ($R^2 = 0.711$), and Diazinon ($R^2 = 0.714$). However, the R-squared value was acceptable for all pesticide types (Sarkar and Pandey, 2015). Used flow discharge data from the Yamuna River in northern India, as well as biochemical oxygen demand, temperature, pH, and dissolved oxygen collected on a monthly basis in the vicinity of Mathura, India, and employed a feed forward, error back propagation algorithm to develop ANN models. The predictions from the ANN models were accurate, with correlation values being as high as 0.9, indicating that ANNs can be efficiently utilized to predict water quality.

3 AI-powered technologies for pollution monitoring

3.1 Spectroscopy

Spectroscopy, which involves measuring the functions of energy with matter, is of preeminent importance in remote sensing. It has been widely utilized in field of chemistry and astronomy to identify materials, and advancements in instrumentation have led to its increasing use in remote sensing studies (Slonecker et al., 2010). Visible and near-infrared reflectance spectroscopy is an environmentally friendly and cost-efficient technique that shows promise for estimating concentrations of various heavy metals in soil. Additionally, it offers a viable alternative for assessing heavy metal levels across large areas and for an extended period (Shi et al., 2022).

For example, Zhao et al. (2022) used visible and near-infrared spectroscopy with extreme gradient boosting (XGBoost) - as an effective machine learning technique to create an estimation model for heavy metal pollution in mangrove sediment sites. Vis-NIR spectroscopy coupled with partial least squares (PLS) and radial basis function neural network (RBFNN) prediction models, were engaged by Sanaeifar et al. (2022) in their study to investigate the effects of airborne Pb on tea plants. Elevated concentrations of Pb had deleterious effects on the plant and the results revealed PLS–RBFNN models to be more accurate and superior to conventional methods in terms of prediction, giving Vis-NIR spectral data traits like high speed and simplicity in monitoring heavy metal pollution.

Lately, there has been significant interest in the development and application of flexible, surface-enhanced Raman scattering (SERS) substrates for the detection of hazardous substances. Bharati and Soma (2021) conducted a comprehensive 4-year investigation into various flexible SERS substrates, such as paper or cellulose, polymer nanofibers, 3D sponges, and fabrics. They explored the potential of these substrates for on-site detection of explosives, pesticides, chemical warfare agents, and drugs, and the research was related to fields such as homeland security, food safety, and medicine. The results of their study highlight the considerable opportunities for SERS substrates in the detection and monitoring of hazardous waste.

3.2 Ground-based monitoring sensors

As reported by Pant et al. (Pant et al., 2019), air quality monitoring mainly employs two types of sensor networks: manual and automatic monitoring sensors (like wireless or community sensor networks). According to Kim et al. (Kim et al., 2008; Kumar et al., 2022), after combining air quality monitoring sensors with geo-sensor network technologies, the collection and interpretation of geospatial and pollution data were transformed. Levy et al. (2010) observed that the monitoring of pollutants, like particulate matter, nitrite, and sulphur dioxide, can be achieved using various sensor networks, including instruments like Met One Instrument BAM-1020 Beta Attenuation Monitor (Met one instruments ltd. 1,600 Washington Blvd. Grants Pass, Oregon), Alphasense OPC-N2 Particle Monitor (Halo labs 1828 Burlingame, CA, 94,010 USA) and Aeroqual Series 500 with NO_2 Sensor Head (Aeroqual Limited, London). Ground-based aerosol optical measurements not only help characterize ambient aerosols, but also assist in validating satellite retrievals and numerical modeling algorithms (Levy et al., 2010; Mansoor et al., 2021). Amado and Cruz (Amado et al., 2018; Naz et al., 2023) used machine learning to calibrate a predictive model for monitoring and characterizing air quality. Their methodology involved creating a prototype with integrated sensors, including DHT 11 temperature and relative humidity sensors, as well as MQ2, MQ5, and MQ135 gas sensors (Zhengzhou Winsen Electronics Technology Co., Ltd.). The study developed five predictive models: k-nearest neighbors (KNN), support vector machine (SVM), naïve-Bayesian classifier, random forest, and neural network. The models demonstrated 99% accuracy.

Artificial intelligence has found its way into agricultural systems, incorporating various sensors for improved performance. Soil moisture sensors are used to ensure adequate irrigation, while temperature sensors monitor the ambient conditions of grain storage. Manickavasagan et al. (2006) utilized temperature and humidity monitoring technology to enhance quality control of stored products by indirectly measuring key parameters. This approach also enabled the prediction of quantitative and qualitative losses in stored grains, providing valuable insights for decision-making in agricultural businesses.

Under field conditions, Liu et al. (2019) explored the application of acoustic sensors, specifically piezoelectric sensors, for detecting insect infestation. Piezoelectric crystals, which transform mechanical stress into electrical charge, are the fundamental component of an acoustic sensor. By measuring sound waves or vibrations and transforming them into electronic signals, piezoelectric sensors can effectively indicate the presence of insects. To aid decision-making and improve management practices, Cruz et al. (2018) conducted a study on predicting flood levels in advance. They put in place a real-time monitoring system with numerous sensors that can gauge variables including rainfall volume and intensity, soil moisture, water level, and rate of water level rise. Using a multi-layered artificial neural network developed with MATLAB, they created a prediction model based on the gathered sensor data. The results showed a high level of accuracy, with goodness-of-fit values of 0.99889 for the training dataset, 0.99362 for the test dataset, and 0.99764 for the validation dataset.

3.3 Aerial imaging and unmanned aerial vehicles (UAVs)

Since the early 1990s, aerial imagery has been employed to monitor hazardous waste. Aerial photographs have proven useful in various applications for detecting and analyzing the presence of hazardous waste, waste-disposal sites, and landfills (Pope et al., 1996; Wani et al., 2023). Historical aerial photographs provide valuable documentation for compiling a record of changes occurring at hazardous sites and are considered reliable for monitoring changes over time. The U.S. Environmental Protection Agency (USEPA) has made use of an aerial imagery library that dates back to the 1930s to retrace the history of waste management and disposal at hazardous waste sites. Environmental clean-up programmes have generated more than 4,000 historical aerial photographic reports on hazardous waste activity and employed them in clean-up (Benger et al., 2004).

Aerial photography allows for the interpretation of various objects at hazardous waste sites, including evidence of discarded materials, barrels and drums, open dumps, spills, and disturbance. These features enable monitoring and analysis of potential impacts related to hazardous waste. Aerial imagery facilitates the identification of vegetation patterns, investigation of local groundwater movement to assess potential pollutant migration, determination of drainage routes, examination of hydrological conditions, and evaluation of subsequent land use on closed landfills (Slonecker et al., 2002; Garofalo, 2003).

Hyperspectral imagery-based models have proven effective in predicting heavy-metal distribution in soils. In a study conducted by Tan et al. (Tan et al., 2021), a competitive adaptive reweighted sampling (CARS) method was proposed for this purpose. The researchers compared the accuracy of various models and discovered that CARS in combination with a stacking method exhibited the highest accuracy and stability. This method utilized the spectrum in the range of 2–2.3 μm, which is a common characteristic band for heavy metals. Additionally, it effectively addressed challenges, such as overfitting due to imbalanced data and limited training sample sets. Importantly, even in the presence of spatial heterogeneity, the distribution of heavy-metal concentrations derived from the CARS-stacking method showed consistency in the verification analysis.

Increased population and industrialization have led to a rise in hazardous waste spillage or leakage incidents. Detecting and monitoring toxic, flammable, and inert gas leaks are a global priority and have been the subject of extensive research. The emergence of Unmanned Aerial Vehicles (UAVs) or drones has significantly enhanced the collection of aerial imagery. This technological advancement has provided a boost in obtaining high-resolution and up-to-date aerial data for various applications, including the monitoring and analysis of heavy-metal distribution in soils. Forward reconnaissance drones, equipped with sensors, are valuable tools for enhancing situational awareness in environments that are challenging for humans. Remote gas detection systems, utilizing mobile robotic platforms such as drones, have emerged as a promising approach in this field, especially in environments too hazardous for human exploration (Gerhardt et al., 2014).

By augmenting drones with sensors, hazardous materials or spills can be identified, and waste can be monitored to enable effective planning and management, thereby minimizing the exposure of first-response teams (Seiber et al., 2018). Also, integrating sensor-based particulate detection with autonomous drone flight control enables dynamic identification and real-time tracking of aerial plume boundaries. The findings of Seiber et al. (2018) demonstrate that UAVs can precisely recognize and track contaminant plumes over time, thus providing visual indicators and aid data collection that can be used to validate and advance the plume movement models. In synopsis, the utilization of sensor-equipped drones for forward reconnaissance purposes can significantly contribute to identifying and monitoring hazardous materials, spills, and gas leaks in environments where human access is unsafe. The integration of sensors and autonomous flight control enhances the capabilities of drones in real-time plume tracking and provides valuable data for improved modelling and management of hazardous incidents.

In incidents that involve hazardous materials, drone flights play a crucial role in promptly and accurately identifying the direction of spillage or gaseous material dispersion (Restas, 2015). Numerous studies have highlighted the ability of UAVs to be rapidly deployed to disaster sites and gather essential data about the extent and impact of spills. This information is vital for effective planning, management, and response efforts. Integrating UAVs into the toolkits of industry and government spill response teams can greatly enhance response capabilities, mitigation strategies, and overall accountability (Messinger and Silman, 2016). In summary, UAVs are indispensable in assessing and managing incidents involving hazardous materials. Their ability to be quickly deployed, gather data, and monitor critical areas provides valuable insights for response teams, enabling them to make informed decisions, mitigate risks, and safeguard both human lives and the environment.

3.4 Ground robotics

In recent years, ground robotics have emerged as a technology with gas-sensitive sensors that can be employed to assess situations in enclosed and unventilated spaces by detecting gas distributions, essentially acting as a "sense of smell." A study conducted by Wandel et al. (Wandel et al., 2003) aimed to develop a unified algorithm for localizing the source of odors using ground robotics. They conducted experiments with ethanol as a test substance and successfully determined its concentration. However, a few irregularities occurred due to external factors that influenced the data. For instance, summertime natural convection caused heat transfer from the glass window in the enclosed space, increasing the concentration of ethanol. The researchers demonstrated the advantage of this tool in its ability to monitor suspected areas and detect the presence of hazardous substances.

Vincent et al. (2019) conducted an experiment in a laboratory wind tunnel and a real-world environment to study the formation of gas plumes. Typically, sensors used for gas detection are characterized using data from controlled gas rigs, where precise step changes in gas mixtures are produced. However, in real-world scenarios, such as mobile robot exploration, gas sources do not emit steady concentrations. Instead, they generate plumes, resulting in areas of high and low gas concentrations in the surrounding environment.

An algorithm method to control mobile robots - iRobot Create was designed by Ahmed et al. (2016). The robotized mobile nodes are integrated in a WSN structure, have built-in sensors, equipped with a microprocessor Gumstix Verdex Pro™ XL6P. The real-time experiments demonstrated the suitability of this wireless sensor network robotized nodes that enables two robots to receive information from each other for detecting a pollutea area, based on pollution searching, reorientation and surveillance parameters.

Haldorai et al. (2024) developed a robot for polluted water surface cleaning. The autonomus robot is equiped with two Arduino microcontrollers, powered by a 6 V lead-acid battery, implemented with SSD real-time object detection deep learning model for the precise detection of wastes from water surface. The robot reaches maximum potential, can avoid obstacles and colect by itself the wastes from the water surface when it gets to 45 and 75 cm from the floating debris making it an effective tool for waste removal from water bodies.

As highlighted by Tsitsimpelis et al. (2019), robotic systems offer an ideal solution for identifying and monitoring extreme radiation exposure levels, as well as toxic and combustible atmospheres. These systems address several challenges by eliminating the need for humans to physically access hazardous locations. Furthermore, they can provide valuable data on the conditions of these places that would otherwise remain inaccessible. Ground robotics equipped with gas-sensitive sensors offer a valuable means of monitoring and detecting hazardous materials. Despite certain challenges and external influences on data accuracy, this technology holds promise in identifying and localizing odour sources in enclosed spaces, contributing to the overall effort of managing and minimizing the presence of dangerous substances.

3.5 Satellite remote sensing

Remote sensing is a scientific and technological approach that enables the identification and assessment of various characteristics and properties of Earth's targets from a distance. On both a global and local level, it has offered systematic and repeated observations of numerous features of the Earth's surface, including the atmosphere, water, land, living things, vegetation, pollution, and climate. The utilization of remote sensing has played a crucial role in detecting and quantifying pollution rates, mapping, monitoring, and mitigating pollution (Mertikas et al., 2021).

One of many applications of remote sensing is monitoring and managing hazardous waste and sites. Multispectral sensors (MSS) mounted on remote sensing platforms are capable of digitally collecting energy levels of reflectance in specific bands of the electromagnetic spectrum. These systems offer advantages such as statistical analysis of data and the ability to extend observations beyond the capabilities of aerial photography. Land use, regional risk assessment, and hazardous waste site spectral characteristics and pollution profiles have been monitored using multispectral imaging systems mounted on satellites and various aircraft-based systems. For instance, Bølviken et al. (Bølviken et al., 1977) demonstrated that MSS data could be employed to identify heavy metal contamination based on fundamental spectral characteristics.

Furthermore, multispectral imagery has been used by several researchers to identify and locate previously unknown as well as illegal hazardous waste sites. Errico et al. (Errico et al., 2014) proposed a methodology that combines synthetic aperture radar (SAR), multispectral data, and GIS-based processing for detecting environmental hazards. This system yielded satisfactory results and contributed to countering and controlling environmental crimes. Additionally, hyperspectral imagery can be employed to identify and map the spatial distribution of various heavy metals. For instance, Kemper and Sommer (Kemper et al., 2004) used a HyMap sensor and utilized airborne hyperspectral images to map lead and arsenic contamination in the Guadiamar flood plain, Andalusia. Similarly, Wu et al. (2011) reported satisfactory outcomes in heavy metal mapping in Nanjing City of China, using simulated HyMap data. They reported that direct predictions based on hyperspectral images often require signals from bare soils, which can be achieved during winter or early spring or when there is low vegetation coverage due to crop rotation in agricultural areas. Therefore, remote sensing has been instrumental in monitoring and managing hazardous waste and sites. Multispectral sensors and airborne hyperspectral images have provided valuable data for assessing pollution, identifying contamination, and mapping the distribution of heavy metals. These technologies offer a non-intrusive and comprehensive approach to understanding and addressing environmental concerns related to hazardous waste.

The incorporation of diverse advanced technologies has significantly improved the field of environmental monitoring, especially in the identification and control of hazardous waste. Spectroscopy, rooted in chemistry and astronomy, has been widely applied in remote sensing. Visible and near-infrared reflectance spectroscopy is presented as an environmentally friendly and cost-effective technique for approximating concentrations of heavy metals in soil. Machine learning methods, such as extreme gradient boosting and neural networks, enhance the accuracy of predictions regarding heavy metal pollution when combined with spectroscopic data. Ground-based monitoring sensors, encompassing both manual and automatic networks and utilizing machine learning models, play a role in robust air quality monitoring. Aerial imaging, covering historical images and hyperspectral imagery, provides a comprehensive perspective on hazardous waste sites, aiding in the evaluation of pollution. Unmanned Aerial Vehicles (UAVs) equipped with sensors are essential for real-time identification and tracking of contaminant plumes, thereby improving response capabilities. Ground robotics, equipped with gas-sensitive sensors, are valuable in enclosed spaces for the detection of hazardous substances. Ultimately, remote sensing, facilitated by multispectral and hyperspectral sensors, serves as a potent tool for systematic Earth observation, particularly in the identification of heavy metal contamination and mapping the distribution of pollutants. This holistic approach underscores the varied strategies employed to tackle environmental issues and emphasizes the pivotal role of advanced technologies in preserving ecosystems.

4 Maximizing safety in hazardous environments with AI-Driven monitoring

Nowadays awareness of the safety of employees working in the production and manufacturing operations in different industrial environments that involve hazardous substances and materials has become of utmost interest (Farrokhi-Asl et al., 2020). Thus, monitoring the concentration and leakage of pollutants (Fung et al., 2019) and development of safe and efficient methods (Fung et al., 2019) to reduce the exposure of humans and the detrimental risks for the environment, with fewer accidents provoked by hazardous substances (Wong et al., 2018; Wang et al., 2020), are becoming a priority in the implementation of safety plan management in many sectors of the economy (Binajjaj et al., 2018). In pollutant discharge events, immediate, precise, and intelligent intervention is needed to alarm, prevent, and control hazardous leakage (Mendil et al., 2022; Wang B. et al., 2023). Due to the fact that humans cannot identify in time possible threats, because the majority of gases are odorless, colorless, and tasteless (Visvanathan et al., 2018), implementation in environmental monitoring and detection of artificial intelligence based devices is getting more popular (Daam et al., 2019; Emaminejad and Akhavian, 2022). The popularity of AI and unmanned machines arises from the effective, real-time, automated solutions that these technologies provide when placed in hazardous environments. They can detect and isolate possible threats before they cause harm, with less or no human involvement (Palacín et al., 2019; Das et al., 2020; Jiang et al., 2022). Recent advances have been developed for the combination of autonomous robots with sensors that are flexible and easily and remotely deployed in unsafe and toxic environments (Ristic et al., 2017). They can improve the safety of workers and neighborhood areas without the risk of involving human life (Fan et al., 2019). These devices are embedded with systems capable of exploring, monitoring, detecting, and alarming, in case hazardous events occur (Maedche et al., 2019). For example, Joshna et al. (Joshna et al., 2019) developed an independent robot using Arduino UNO (R3), equipped with sensors that can detect and identify toxic gases. It can also perform degasification making use of oxidizing agents that are sprayed on the gases, reducing their deleterious effects. Fan et al. (Fan et al., 2019) developed a mobile robotic system equipped with an E-nose that is highly accurate in detecting and identifying different toxic gases like CO and NO_2 present in the environment. It can be used in fire and emergency response departments. Gallego et al. (2015) developed an unmanned aerial vehicle (UAV) equipped with metal oxide semiconductor (MOX) gas sensors, capable of detection of toxic gas leaks, to monitor gas pipes in outdoor areas. Novelty traits of the system include improved velocity and reduced energy consumption and investment costs.

A wireless microcontroller (MCU) offers acquisitions of real-time data, and a GPS/GSM (Global Positioning System/Global System for Mobile Communication) modem offers accurate registration and communication of the location and route in addition to measuring the gas concentration. With the intention of maximizing safety for staff workers in factories, Shi et al. (2016) Burgués et al. (2019) proposed a Crazyflie 2.0 nano-drone assembled with a MOX gas sensor. This nano-air vehicle (NAV) can accurately localize the gas source with instantaneous gas distribution mapping, which requires less time for concentration measurements than other previous devices. Similarly, Das et al. (Das et al., 2020) proposed a robot that can be deployed in an unknown and uneven environment that can recognize hazardous gases (carbon dioxide, vaporized alcohol, and liquefied petroleum gas) with an average accuracy of 98%. The robot can be operated to avoid collision obstacles and detect the presence of humans, while mapping in real-time the locations of the gases detected through a GPS module. A mobile robot combined with MOX gas sensors to detect early gas leaks in hazardous events was also developed by Palacín et al. (2019). The innovative system has 16 E-nose gas sensors that are low-cost. They can detect two chemicals at low concentrations that are located at broad distances from the source. In case two gas sources are present simultaneously, the mobile robot will detect the chemical that has the highest concentration. To detect and identify possible threats before damage takes place, Chen et al. (2023) proposed an AI-based monitoring system using processing parts that were designed to be simple. It had a 96.1% efficiency of detecting and localizing in real time external vibrational disturbance of a buried pipeline. Table 1 summarizes some important research studies that have used AI applications for monitoring and detection of hazardous substances.

Monitoring of hazardous environments to increase safety and to protect humans while they are operating in them was the goal of the work of Cheung et al. (2018). These authors developed a wireless sensor network (WSN) monitoring system with sensor nodes that can gather information regarding hazardous gases, temperature and humidity. They are embedded into a building information model (BIM) that displays the safety status in real-time with colors and shows the precise location of a possible dangerous event in advance. When high concentrations of gases are detected, the system is activated automatically using a flashing alarm that can warn the staff and workers. A ventilator and other safety devices are enabled to reduce toxic and flammable gas flow, which will prevent hazardous accidents. In a similar way, Jualayba et al. (2018) designed a monitoring and warning system that can display the safety status with colors when different levels of gases are detected. An exhaust fan is triggered when a medium level is displayed. At dangerous levels, an alarm buzzer is activated to inform people of a gas leakage and the need to decrease the concentration of the detected gas. The system has sensors for hydrogen, liquefied petroleum gas, and methane.

Wilson (2012) suggested a multifunctional gas detection system utilizing an Arduino Uno R3 and an Internet of Things module equipped with an MQ-6 gas sensor, capable of identifying methane, propane, and butane. The primary objective is to avert potential dangers in industrial settings. Upon surpassing predetermined gas threshold levels, the system activates a combination of a light-emitting diode (LED), buzzer, and notification message. There have been additional AI-powered devices devised for identifying hazardous gases in factories and industrial environments, all geared towards enhancing employee safety. They can collect data in real-time and identify the source of the gas leak and map the location (Manes et al., 2016). They are built with climatic sensors in addition to the gas sensors. They offer accurate, continuous monitoring of gas concentrations and are cost-effective (Thomas et al., 2018). Wearable smart sensing devices attached to workers cloths can be used for continuous gas monitoring in different industrial and other toxic areas. They provide accurate and real-time data acquisition that allows users to take rapid safety measures (Antolín et al., 2017). For instance, Binajjaj et al. (2018) proposed a wearable gas sensor network provided with an MQ-7 sensor that can detect both CO and CH_4, accurately and rapidly, using an accelerometer and an on-demand on/off switch that reduces energy consumption. It has a GPS and communication module that can transmit messages to other employees.

Wu et al. (2011) developed "WE-Safe", a wearable IoT sensor node capable of promptly warning workers in hazardous environments. This device is based on LoRa wireless technology. It has one microcontroller unit (MCU) and sensors for detection of CO, CO_2, as well as other sensors for environmental conditions (temperature, humidity, and UV light). It gives real time data and has a low energy exhaustion. Other researchers have designed devices with accurate and real time detection using MQ2, MQ5 gas sensors, which are capable of detecting hazardous gases in people's houses. The devices alarm the users through a buzzer and a short message service (SMS) notification is sent to tell them that the gas leakage needs to be controlled (Karthika et al., 2019; Panganiban, 2019).

Another application based on AI technology, as a strategy to control indoor ventilation by rapidly getting rid of PM, was developed by Kim et al. (2021). The ventilation system has a high removal rate of the hazardous airborne particles, which is done in a short time with low power consumption. Mendil et al. (2022) proposed a machine learning (ML)-based surrogate model for transport and dispersion of air pollutants that can predict, fast and accurately, the concentration and dose of pollutants in urban areas. Asha et al. (2022) designed an IoT and ML based model (ETAPM-AIT) for air quality monitoring that uses a sensor array for eight pollutants, such as NH_3, CO, NO_2, CH_4, CO_2, and $PM_{2.5}$. It also measures temperature and humidity. In this model an AAA-

TABLE 1 Research studies for AI applications in hazardous environments.

Detected parameter	Technology/Device used	Advantages	References
CO, CH_4	Wearable gas sensor network, Wireless sensor network, MQ-7 sensor, Arduino module with Xbee module	Accurate measurement of toxic gases, in time warning messages, low cost, low maintenance, reduced power consumption	Binajjaj et al. (2018)
Ethanol, acetone	Assistant Personal Robot (APR-02), 16 MOX gas sensors (e-nose), PLS-DA classifier	Autonomus, low cost, real-time, early detection, low gas concentration detection, two chemicals detection	Palacín et al. (2019)
CO_2, liquefied petroleum gas (LPG), vaporized alcohol (ethanol) gas, ambient gas	Six wheeled rocker-bogie robot, MQ gas sensors, HC-SR501 passive infrared (PIR) motion detector, HCSR04 ultrasonic sensors, Zigbee	98% accuracy for hazardous gases recognition, real-time gas detection, remote handling, obstacles avoidance, GPS location, human detection	Das et al. (2020)
CO, NO_2	SmokeBot platform, Mobile Robotic Olfaction (MRO) system, MOX gas sensors (UWAR nose)	Gas distribution mapping and navigation in environments with low visibility, accuracy of gas discrimination, search and rescue first responders' protection, less computational power	Fan et al. (2019)
Chlorofluorocarbon, CO, CH_4	Robotic vehicle, MQ sensors, Arduino UNO (R3)	Autonomous, obstacle avoidance, gas detection and degasification	Joshna et al. (2019)
C_2H_5OH, CO, H_2	Quad-rotor Unmanned Aerial Vehicle UAV, STM32F1 control chip, MQ-2 gas sensor, communication module NRF24L01 and SPI protocol	Autonomous navigation in dangerous environments, real-time detection of hazardous gases, wireless transmission	Shi et al. (2016)
Hydrogen, methane, Liquefied Petroleum Gas (LPG)	Hazardous gases detection and notification system, MQ gas sensors, Arduino, GSM module, indicator lamps	Gas leak SMS notifications, LCD display of detected gas level, buzzer alarm, exhaust fan to lower the gas concentration	JUALAYBA et al. (2018)
VOC, H_2S	Gas monitoring platform, gas and weather-climatic sensors, wireless sensor network (WSN), LAN/Ethernet (IEEE 802.1) with TCP/IP protocols, ARM Cortex-M3 32-bit micro-controller	Cost-effective, real-time emission identification, redeployable monitoring stations, continuous gas monitoring, rapid warning of hazardous events	Manes et al. (2016)
Particulate matter, CO, O_3 NO_2, noise, temperature, humidity	Monitor sensor network, Dragino WiFi IoT module HE, microprocessor (ATmega32u4)	Continuous monitoring of multiple hazards, low cost, accurate measurements	Thomas et al. (2018)
CO_2, CO, ultraviolet (UV), temperature, humidity	WE-Safe Platform, IoT sensor node, LoRa wireless technology, Arduino Uno, ATmega328p as MCU	Real-time data acquisition, remote cloud server, early warnings for workers in dangerous environments, low power consumption	Wu et al. (2011)
LPG, CO	Smart gas leakage, IoT with Arduino mega 2560, MQ-2 gas sensor, "BLYNK" mobile app, Wi-Fi module, Node-MCU ESP-8266	Gas leakage notification, gas level monitoring, automatic safety system, cost-effective	Zinnuraain et al. (2019)
H_2, LPG, CH_4, CO, alcohol	Gas detection system, Arduino UNO, MQ-5 Sensor	High sensitivity, fast response time, continuous update, alarm buzzer, LCD display, low cost	Bazrafshan and Kord Mostafapoor (2011)
NH_3, CO, NO_2, CH_4, CO_2, $PM_{2.5}$, temperature, humidity	ETAPM-AIT model based on IoT, ML techniques, WiFi, Artificial Algae Algorithm (AAA), Elman Neural Network (ENN) model	Real-time monitoring, alarm when hazardous substances are above limit, sensor array that can detect 8 parameters, cost-effective	Asha et al. (2022)
Temperature, ph, turbidity, conductivity, dissolved oxygen	IoT, Raspberry PI B+ core controller, WiFi, cloud computing, water monitoring sensors	Real-time monitoring, efficient processing, low cost	Vijayakumar and Ramya (2015)
pH, turbidity, temperature, humidity	Water quality monitoring system, IoT, ESP8266 Wi-Fi module, ThingSpeak mobile application, Arduino Mega	Efficient, real-time water quality monitoring, low cost	Pasika and Gandla (2020)
pH, temperature, conductivity	Water quality measurement machine, IoT, ESP8266 Wi-Fi module, ThingSpeak, Arduino Mega 2560 microcontroller	Real-time monitoring, highly accurate, track the level of water contamination, immediate warnings, low cost	Sarkar and Pandey (2015)
pH, dissolved oxygen, temperature, turbidity, conductivity	unmanned surface vehicle (USV) for water status monitoring, IoT, Wireless Sensor Network (WSN), ZigBee, IEEE 802.15.4 transceiver	Real-time data acquisition, remote handling in unreachable areas, high accuracy, efficient, reduced power consumption, cost-effective	Vasudevan and Baskaran (2021)

(Continued on following page)

TABLE 1 (*Continued*) Research studies for AI applications in hazardous environments.

Detected parameter	Technology/Device used	Advantages	References
Temperature, pH, turbidity, conductivity, DO, TDS, ORP	Water Quality Monitoring System, IoT, Arduino Nano, ESP8266 Wi-Fi module, ANN and SVM machine learning algorithms, ThingSpeak database	Remote monitoring, real-time data gathering, accurate water monitoring, automated water treatment corrective measure	Agrawal et al. (2017)
pH, temperature, turbidity, dissolved oxygen, conductivity	Smart Water Monitoring System (SWMS), four sensors, Arduino UNO, Raspberry Pi (RPi)	Real-time remote monitoring, SMS notification and alert signal, prevention of health hazards	Jha et al. (2018)

based ENN is used to classify air pollutants, and the model provides real-time detection of the pollutants. It has an alarm option that can alert people when hazardous pollutants are detected in the air. For safety purposes, Seo and Lee (2022) used an algorithm based on a CNN to accurately classify hazardous compounds to avoid hazardous chemicals being improperly used in laboratory environments. An intelligent system equipped with different sensors for CO, CO_2, NO_2, CH_4, and H_2S measurements using an Arduino Uno card and IoTs module monitors landfill biogas to prevent potential hazardous emissions (Mabrouki et al., 2021). Oduah and Ogunye (2023) developed a low-cost, smart, remote-sensing septic tank that can be used onsite to prevent sewage overflow. It uses an ultrasonic sensor for detection and monitoring the wastewater level in the septic tank and a GSM module to send SMS alerts to the users, avoiding spills of contaminants that can cause health problems.

Seker (2022) developed a real-time smart, cost-effective waste collection system that employs IoT with technologies like radio frequency identification (RFID), GIS, and ground penetrating radar systems (GPRS). It is effective for municipal waste collection and transportation and has the goal of reducing environmental pollution. Transportation and storage of hazardous materials can cause considerable risk to human life and the environment, due to their toxicity, corrosiveness, explosiveness, and radioactive characteristics (Mabrouk et al., 2017; Paredes-Belmar et al., 2017). In this respect, to design of a remote monitoring system based on a wireless sensor network that can offer real-time information on the vehicle that is transporting the hazardous materials. It can report the status of the vehicle (its attitude and tire pressure) and its location. In addition, the temperature of the transported hazardous chemicals is reported. This remote monitoring of hazardous materials during transportation provides safety measures for the workers and for citizens, minimizing the occurrence of accidents.

Hosseini and Verma (2021) proposed an analytical method that can determine the best route for transportation of hazardous materials, to assure the safety of inhabitants. It can exclude route zones that have high population density. Over the years, pollution of water resources has increased, making uncontaminated water bodies even more scarce all over the globe. The pollution has destroyed aquatic ecosystems and resulted in health and safety issues for humanity (Zhai et al., 2021; Yusuf et al., 2023). Protecting water resources and preventing the release of different pollutants represent the first steps in ensuring safety for the environment and people (Berman et al., 2020). Various approaches for monitoring the physico-chemical parameters of water resources have led to the implementation of novel smart technologies (Geetha and Gouthami, 2016; Huang et al., 2018). Water-quality smart monitoring systems using the Internet of Things (IoT) has gained popularity by engaging WSNs that offer continuous, remote and real-time monitoring and measurement of different water parameters. They can identify pollution sources and give the opportunity of early warnings, when possible threats or hazards are detected, and they can provide proper safety measures (Pule et al., 2017; Lakshmikantha et al., 2021).

A low cost system making use of the IoT for detection of water parameters in real time, like temperature, turbidity, conductivity, pH, and dissolved oxygen, which uses raspberry PI B+ as a core controller, has been designed (Vijayakumar and Ramya, 2015). Subsequently, Pasika and Gandla (Pasika and Gandla, 2020) proposed a low cost, efficient system based on the IoT using ThinkSpeak and various sensors to monitor drinking water quality in real time. In a similar way, Kumer et al. (Kumer et al., 2021) used ThinkSpeak and an Arduino Mega 2560 microcontroller in a device to analyze in real-time water parameters to detect levels of contamination when it happens and to warn inhabitants of hazardous health risks. It is very accurate and inexpensive.

Khan et al. (2020) developed a system that can monitor water quality for an industrial effluent treatment plant. It is composed of wireless sensor networks, a GSM module for notifications in case of emergency, an Arduino Uno R3 microcontroller, and an IoT-based cloud server. This system proved to be efficient and cost-effective. It gives continuous, real-time water quality monitoring, which allows the local authorities the benefit of supervising and checking to see if the released water from a specific industry is polluted or not. To tackle the problem of unreachable water bodies that are in secluded areas, Vasudevan and Baskaran (2021) proposed an innovative unmanned surface vehicle (USV) based on the IoT and sensors that provided control of these waters and diminished water pollution. They confirmed its efficiency, low investment, reduced energy consumption, and real-time data acquisition for surface water quality monitoring. Similarly, Ryu (2022) proposed an unmanned aircraft system (UAS) for water sampling and monitoring, which can be used in potentially hazardous environments, minimizing the involvement of humans. Its UASWQP platform can take water samples from various points and is effective in presenting real-time data regarding measurements of water parameters.

Adeleke et al. (2023) developed a highly accurate water quality monitoring system interfaced with sensors and machine learning algorithms to predict the level of water pollution. The remote system gathers water quality data in real-time and is built with an automated control system that can apply water treatment when the level of pollutants are above the standard limits, which reduces the expansion of diseases from contaminated water (Adeleke et al.,

TABLE 2 AI models for monitoring the environment for hazardous substances.

Environment	Approach/Models	Utility	Authors
Air	Hybrid Hidden Markov Model (HMM) - ANN	Harmful gas monitoring and error detection in sensor datasets	Praveenchandar et al. (2022)
Air	Artificial Algae Algorithm (AAA) based Elman Neural Network (ENN)	IoT enabled environmental toxicology for air pollution monitoring; classification of air pollutants	Asha et al. (2022)
Air	Random Forest (RF), Bagged Classification and Regression Trees (Bagged CART), and Mixture Discriminate Analysis (MDA)	Hazard prediction of particulate matter (PM_{10})	Choubin et al. (2020)
Air	Spatiotemporal deep learning (STDL)-based method using Stacked autoencoder (SAE) model	Air quality predictions	Li et al. (2016)
Soil	ANN, adaptive neuro-fuzzy inference system (ANFIS) models, multiple linear regression (MLR)	Lead and cadmium estimation from clay, organic carbon, pH, phosphorus, and total nitrogen	Bazoobandi et al. (2022)
Soil	ANN	Determine essential heavy metals based on Ca, K, and Mg concentrations	Sari et al. (2022)
Soil	Hybrid model integrating least absolute shrinkage and selection operator (LASSO), genetic algorithm (GA) and error back propagation neural network (BPNN) with remote sensing imageries	Spatial distribution of heavy metals in soil	Shi et al. (2022)
Soil	ANN and Support Vector Regression (SVR)	Rapid estimation of soil trace/heavy metals and related decision-making	Tawabini et al. (2022)
Soil	SVM with mid-infrared (MIR) laser spectroscopy	*In Situ* detection of petroleum in soils	Galán-Freyle et al. (2020)
Water	Artificial neural networks (ANN)	Lead removal from aqueous solution	Yetilmezsoy and Demirel (2008)
Water	ANN	Describe adsorption of benzene, toluene, ethyl benzene, and xylene on iron nano particles for their effective removal from aqueous systems	Mahmoud et al. (2018)
Water	ANN, Support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), genetic algorithms (GA)	Modelling and optimization of electrochemical processes for water and wastewater treatment	Shirkoohi et al. (2022)
Water	Logistic regression (LR), random forest classifier, and K-nearest neighbours (KNN)	Monitoring system for onsite septic systems failure	Ravi and Johnson (2021)

2023). A smart water monitoring system that collects real-time data for water quality and quantity was designed by Jha et al. (2018). The system uses sensors connected to an Arduino UNOTM and a Raspberry PiTM(RPi) microprocessor. It can avoid hazardous events caused by contaminated water seepage into drinking water sources by sending SMS and e-mail notifications when the monitored water is contaminated, which gives the opportunity for authorities and consumers to take rapid safety measures.

5 Advancements and challenges

5.1 BeeTox AI and other models

In a recent study (Moreira-Filho et al., 2021), a novel web application called BeeToxAI was introduced. It utilizes AI to assess the acute toxicity of chemicals to *Apis mellifera*, commonly known as the honey bee. BeeToxAI offers users a comprehensive set of features, including the classification as toxic or non-toxic of acute contact toxicity and acute oral toxicity endpoints. In addition, confidence scores for the prediction are given along with a visual representation of the results through maps. These color-coded maps illustrate the relative contribution of chemical fragments to toxicity. Since pesticides contain toxic substances that are injurious to health (Demirel and Kumral, 2021), AI algorithms are needed for controlling and tracking them, to reduce their toxicity. Because nitrogen based chemical fertilizers increase the amount of nitrate in groundwater, AI might be used to control excessive nitrate in soil.

The analysis of water quality as a source of irrigation can be done using AI-ANN models (Ostad-Ali-Askari et al., 2017). Over the past decade, a multitude of studies have been conducted to forecast the efficacy of machine learning in removing heavy metals from soil (Table 2). These investigations have focused on predicting the effectiveness of various techniques for soil remediation and heavy metal removal utilizing machine learning methodologies (Zafar et al., 2017; Zhu et al., 2019; Bhagat et al., 2020). Models used for optimizing and predicting heavy metal removal have encompassed black box, fuzzy logic, kernel, evolutionary, and hybrid models, and each offers distinct advantages.

In a study conducted by Talebkeikhah et al. (2022), which focussed on the adsorption of Pb (II) on biochar, eleven models were employed, which included group-data handling methods such as support vector machines (SVM), radiofrequency (RF), adaptive neuro-fuzzy interference systems (ANFIS), multilayer perception (MLP), and Decision Tree. Additionally, to evaluate the significance of coupling in creating predictive models for estimating adsorption efficiency, the researchers developed four coupled predictive models using the grasshopper optimization algorithm (GOA) and the bat algorithm, and they combined ANFIS and MLP.

Chen et al. (2020) developed a CNN architecture specifically designed for deep calibration using near-infrared (NIR) spectroscopy data. Their study focused on assessing the level of water pollution originating from domestic and industrial sources, with the aim of enabling suitable agricultural irrigation practices. The researchers successfully established intelligent spectroscopic models using the CNN architecture, which could be instrumental in addressing water recycling and conservation issues in agricultural cultivation.

The field of medicine is experiencing gradual transformations due to the development of AI. Various medical disciplines, including clinical, diagnostic, rehabilitative, surgical, and predictive practices, are being influenced by AI applications (Secinaro et al., 2021). AI technologies have the capacity to process and analyze large volumes of data from diverse modalities to aid disease detection and guide clinical decision-making (Cho et al., 2020).

5.2 Medical waste

Recently, global healthcare advancements have led to an increase in the generation of medical waste, thereby contributing to a rising trend in waste production (Bazrafshan and Kord Mostafapoor, 2011). Various types of hazardous waste, such as hospital waste, dental waste from medical laboratories, blood wastage, and clinical waste, pose potential risks to both human health and the environment (Bazrafshan and Kord Mostafapoor, 2011). Medical waste (MW) encompasses infectious waste, sharp waste, toxic waste, chemical waste, and pharmaceutical waste. Inadequate management of medical waste can lead to the transmission of infectious diseases, including AIDS, hepatitis, typhoid, and many others (Askarian et al., 2010; Aghapour et al., 2013). These wastes have the potential to pollute the environment and spread acute and latent viral infections. They contain significant amounts of bacteria and viruses. If they are not properly controlled, they have the potential to contaminate the environment, which includes air, water, plants, animals, and land (Rajan et al., 2019). This can lead to the spread of disease. The quality of life, physical and emotional health, and overall health of medical personnel and patients are all seriously threatened by MW (Nwachukwu et al., 2013).

In a recent study (Zhou et al., 2022), a novel image recognition system was introduced called Deep MW for the purpose of sorting medical waste. Deep MW utilizes a CNN as its underlying architecture. The system aims to enhance the ease, accuracy, and efficiency of medical waste sorting and recycling processes, while also reducing the risk of occupational exposure for workers in medical waste facilities. Other similar systems exist, like iWaste (Chen et al., 2020), Deep MW excels in recognizing and sorting diverse categories of medical waste, showcasing remarkable accuracy and practicality in classification. Its proficiency makes it adaptable for expanding its use to other object classifications. Amidst the ongoing COVID-19 pandemic and other outbreaks, artificial intelligence has proven pivotal in creating surveillance tools aimed at identifying individuals not adhering to quarantine regulations. Monitoring bracelets exemplify one such tool. Furthermore, AI-enhanced technologies, such as smartphones and thermal cameras, are utilized for detecting fever and signs of illness. (Whitelaw et al., 2020).

5.3 Other applications

These advancements in AI have significantly contributed to improving surveillance and monitoring capabilities in public health and safety. A country like Taiwan treats coronavirus patients based on their travel history and symptoms by integrating data from the immigration and customs database with the national medical insurance database (Wang J. et al., 2023). Based on research conducted by Taiwan's Occupational Safety and Health Administration (OSHA), a significant number of surgical staff, approximately 50,000 individuals, face exposure to smoke hazards during procedures involving the use of lasers and electrocautery (Wang et al., 2020). This exposure poses potential risks to the health and safety of surgical personnel. AI can be used for assessing the characterization of the smoke emitted and also for carrying out an AI-powered air quality assessment (Kaginalkar et al., 2021).

Industry 4.0 is revolutionizing the way companies manufacture, improve, and distribute their products, and AI is widely recognized as a crucial technology for it (Mao et al., 2019). Its incorporation in these domains has significantly transformed and enhanced various aspects of industrial processes, enabling advanced automation, data-driven decision-making, predictive maintenance, and optimization of manufacturing operations (Figure 3). AI's capabilities have played a pivotal role in driving efficiency, productivity, and innovation in the manufacturing sector, making it a key enabler of the Industry 4.0 paradigm. Industry 4.0 has brought about a number of cutting-edge technologies, and this new phase of AI development is known as AI 2.0 (Pan, 2016). The utilization of AI in smart factories and its application in modern industrial sectors have been acknowledged as transformative (Mao et al., 2019). It enables efficient decision-making processes based on real-time and historical data, minimizing the need for human intervention.

Liu et al. (2019) proposed the integration of intelligent manufacturing in-shop service modules with Big Data analytics, to enhance productivity in various industries. For the facial mask industry, Zhang (2019) suggested a remote design system utilizing AI for image processing and pattern recognition, coupled with a client wireless communication. Yan et al. (2018) highlighted the significance of AI algorithms in forecasting the lifespan of industrial equipment, particularly in the context of Industry 4.0.

AI, machine learning, and autonomous technologies have significantly impacted the mining industry by detecting hazards and reducing risks [136, 137]. The introduction of autonomous trucks and the utilization of AI and machine learning have brought cost savings, increased productivity, improved worker safety, and continuous production (Hyder et al., 2018). AI systems analyzing geological, topographical, mineralogical, and mapping data can identify anomalies, locate potential areas of interest, and facilitate autonomous drilling operations (Hyder et al., 2018).

In the architecture, engineering, and construction (AEC) sector, AI has been increasingly employed to enhance existing procedures and address challenges. Applications and algorithms of AI in the AEC industry have been studied. Virtual reality and augmented reality have been used for hazard identification and risk assessment

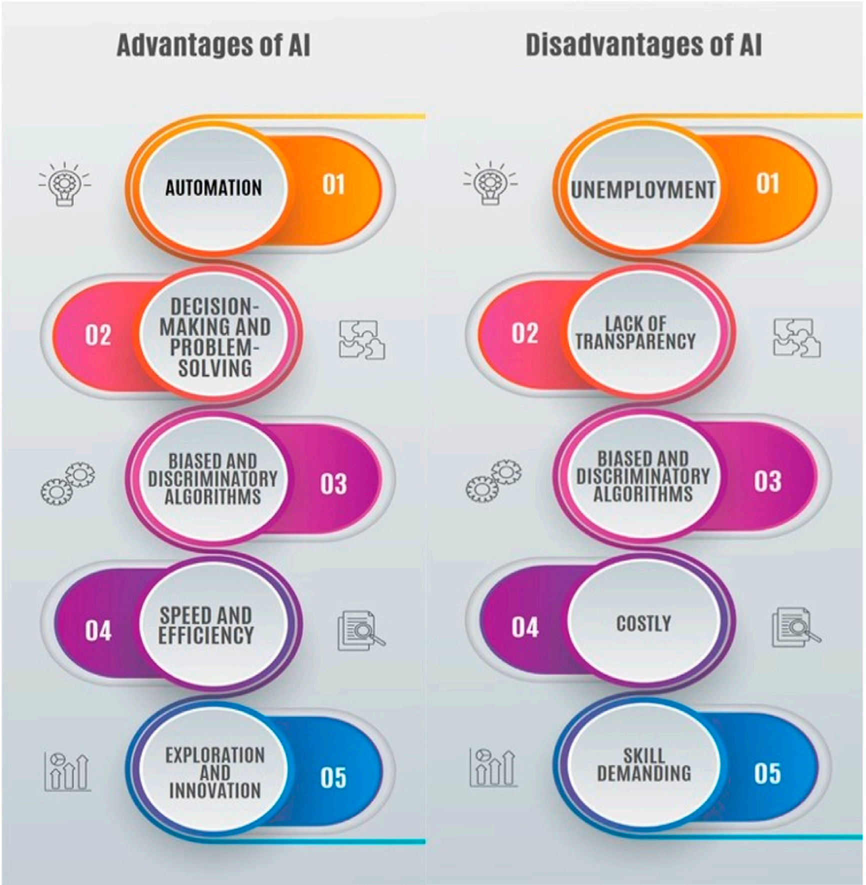

FIGURE 3
The figure illustrates the advantages and disadvantages associated with AI.

in construction environments (Von Meding et al., 2009; Perlman et al., 2014; Abioye et al., 2021).

Advancements in artificial intelligence (AI) and machine learning (ML) have significantly improved efforts in mitigating pollution (Chen et al., 2023). State-of-the-art technologies are being utilized to improve air quality modeling, integrating a variety of data sources such as satellite imagery and meteorological data for more accurate predictions. The amalgamation of AI with satellite technology allows for comprehensive monitoring of environmental shifts, assisting in the identification of pollution sources. The introduction of edge computing enables real-time analysis of environmental data at its origin, facilitating swift responses to pollution incidents. Hybrid models, which merge physics-based simulations with ML, enhance the precision of identifying pollution sources (Anthony et al., 2023). ML-driven predictive analytics forecast pollution levels, enabling proactive measures to prevent environmental deterioration. In the energy sector, AI is optimizing smart grids and energy distribution, reducing the environmental impact (Gautam et al., 2023). AI-guided robotics are deployed for pollution clean-up, autonomously recognizing and addressing contaminants. The combination of AI and block chain technology ensures transparency and traceability in environmental data (Zhao et al., 2023). ML-powered adaptive monitoring networks intelligently allocate resources for effective pollution monitoring. Mobile applications, leveraging AI, empower citizens to contribute to environmental monitoring, promoting a decentralized approach to data collection (Sahil et al., 2023). These recent strides underscore the transformative potential of AI and ML in reshaping pollution mitigation strategies, steering towards a more sustainable and resilient future (Zahed et al., 2022).

6 Limitations

In recent years, there has been a notable surge in the utilization of AI as an emerging technology across various sectors, such as agriculture, medicine and healthcare, mining and manufacturing, environmental conservation, and numerous other domains (Trasande et al., 2011; Perez Santin et al., 2021). While AI brings forth numerous benefits, it is not extempted from challenges and limitations that require efficient and notable solutions. These issues encompass the effective execution of tasks and management and mitigation of risks, as well as the assessment of hazardous materials. The requirement for significant processing power raises concerns about environmental impact and energy consumption (Singh and Kaur, 2022). Developing countries may face infrastructure limitations that hinder the efficient deployment of AI (Singh and Kaur, 2022). Data acquisition costs in data-driven agriculture remain high, limiting the widespread impact of AI on agricultural productivity (Linaza et al., 2021). Furthermore, issues of data ownership, privacy, and cybersecurity arise, necessitating standardized protocols and integration with technologies like block chain to ensure data integrity and security (Abedjan et al., 2019; Misra et al., 2020). Block chain is a system in which a record of transactions is maintained across computers that are linked.

In the manufacturing field, there is a need for further research on the application of AI in various sub-components, such as design, machinery used, assembly, and production (Zeba et al., 2021). Ethical considerations also arise, including concerns about genetic engineering, moral decision-making by AI systems, and the impact on jobs, economy, and society (Zeba et al., 2021), including privacy under surveillance. The AEC industry faces challenges related to funding, data, ethics, privacy, trust, scalability, and expertise (Motawa, 2017; Hagendorff, 2020). Resistance to technology adoption stems from concerns about job displacement, uncertainty, wealth distribution, and the complex relationship between humans and technology (Kappal, 2017). Additionally, there are challenges in understanding how AI can effectively support individual and group decision-making (Maedche et al., 2019). Overall, the application of AI in various industries brings about significant opportunities and challenges, necessitating further research, infrastructure development, and ethical considerations.

7 Conclusion and future perspectives

The development of artificial intelligence-driven sensors for environmental monitoring of hazardous substances has the potential to revolutionize how we detect and respond to environmental threats. With their ability to process large amounts of data in real-time and identify patterns and anomalies that may indicate the presence of hazardous substances, these sensors can greatly improve our ability to protect public health and the environment.

However, there are still many challenges that must be addressed, such as ensuring the accuracy and reliability of these sensors and determining the best ways to integrate them into existing monitoring systems. Despite these challenges, the potential benefits of AI-driven sensors make them a promising avenue for future research and development in the field of environmental monitoring. In the near future, AI-powered hazardous substance monitoring has the potential for enhanced automation, the creation of more sophisticated models, and the fusion of AI with novel technologies like the IoT.

AI could deliver promises about prediction, optimization, and decision-making in the near future to help the traditional construction industry keep up with the rapid speed of automation and digitalization in a variety of risky and dangerous circumstances (Pan, 2016). It can offer a wide range of risk identification factors as well as assess and deliver for prioritization, because it can monitor, recognize, analyze, and anticipate possible risk in terms of safety, quality, efficiency, and cost across teams and work areas even in the presence of significant uncertainty (Afzal et al., 2021). AI-powered monitoring systems can provide real-time, on-ground detection of potentially dangerous substances and the location of the incident sites. They may prevent any serious accidents from happening that would be harmful to human health. These systems are applicable in the fields of agriculture, health, mining, manufacturing, and other industries (Ghayvat et al., 2021; Kim et al., 2021).

AI has the potential to remodel the monitoring and detection of hazardous substances in various environments by offering real-time analysis. This can be achieved through the integration of sensors, data processing capabilities, and machine learning algorithms. By leveraging these technologies, AI systems can swiftly and accurately analyse data streams to identify potential hazards. This application is particularly valuable in industrial settings or areas susceptible to chemical spills or leaks (Leppert et al., 2012). Furthermore, AI can contribute to predictive modelling and risk assessment of hazardous substances. By examining historical data and considering various environmental factors, AI algorithms can forecast the probability and severity of incidents involving hazardous substances. This allows for proactive mitigation measures to be implemented. AI can also integrate data from multiple sources, such as sensors, satellite imagery, and public health records. By combining diverse datasets, AI algorithms provide a holistic understanding of the distribution, movement, and impacts of hazardous substances (Wu et al., 2011; Hurlbert et al., 2019; Shafique et al., 2022; Shi et al., 2022). In addition, AI can offer decision support tools for human operators engaged in hazardous substance monitoring. Through user-friendly interfaces and natural language processing, AI systems can aid in data interpretation, anomaly detection, and timely decision-making. These features assist operators in effectively managing hazardous substance situations.

Author contributions

SP: Investigation, Visualization, Writing–original draft. SM: Conceptualization, Visualization, Writing–original draft, Writing–review and editing. OW: Writing–original draft, Writing–review and editing. SK: Writing–original draft. VS: Investigation, Visualization, Writing–original draft. AS: Writing–original draft. VA: Writing–original draft. MK: Data curation, Formal Analysis, Investigation, Writing–original draft, Writing–review and editing. DH: Formal Analysis, Validation, Visualization, Writing–original draft, Writing–review and editing. NB: Formal Analysis, Investigation, Supervision, Visualization, Writing–original draft, Writing–review and editing. YC: Formal Analysis, Funding acquisition, Investigation, Resources, Supervision, Writing–original draft, Writing–review and editing.

Funding

The author(s) declare financial support was received for the research, authorship, and/or publication of this article. The Basic Science Research Program supported this research through the National Research Foundation of Korea (NRF), funded by the Ministry of Education (2019R1A6A1A11052070).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Glossary

AAA	artificial algae algorithm
AEC	Architecture, Engineering, and Construction
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
CARS	Competitive Adaptive Reweighted Sampling
CNN	Convolutional Neural Network
ENN	Elman Neural Network
ERF	Extreme Random Forest
GHG	Green House Gas
GIS	Geographic Information System
GOA	Grasshopper Optimization Algorithm
GPS/GSM	Global Positioning System/Global System for Mobile Communication
HIS	Hyperspectral imaging
HRAI	High Resolution Aerial Imagery
IoT	Internet of Things
LED	Light-Emitting Diode
MCU	Wireless Microcontroller Unit
ML	Machine Learning
MLP	Multilayer Perception
MOX	Metal Oxide Semiconductor
MRO	Mobile Robotic Olfaction
MSS	Multispectral Sensors
MW	Medical Waste
NAV	Nano-Air Vehicle
NIR	Near-Infrared
PM	Particulate Matter
RF	Random Forest
RFID	Radio Frequency Identification
RNN	Recurrent Neural Network
SAR	Synthetic Aperture Radar
SERS	surface-enhanced Raman scattering
SMS	Short Message Service
SVM	Support Vector Machine
UAS	Unmanned Aerial Systems
UASWQP	Unmanned Aerial Systems Water Quality Platform
UAV	Unmanned Aerial Vehicles
WSN	Wireless Sensor Network