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Smart IoT-Based Environmental Monitoring Systems Using Artificial Intelligence

Amina Amjad*[1], Muhammad Salman[2], Mateen Ahmad[3]

[1]Department of Computer Science, University of Education Lahore, Jauharabad Campus, Pakistan
[2]Punjab University College of Information Technology, Pakistan
[3]University of Hertfordshire, UK

[1]amnawan24@gmai.com
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Corresponding Author: *
Amina Amjad
Department of Computer Science, University of Education Lahore, Jauharabad Campus, Pakistan Email: amnawan24@gmai.com

Abstract
Environmental monitoring is essential for protecting human health, ecosystem stability, agricultural productivity, and sustainable resource management. However, conventional monitoring approaches often depend on periodic sampling and manual assessment, which may limit the timely detection of rapidly changing environmental conditions. This study proposes an integrated **Internet of Things (IoT) and Artificial Intelligence (AI) framework for smart environmental monitoring** that combines distributed environmental sensors, wireless communication, edge/cloud computing, data preprocessing, AI analytics, and decision-support tools. The proposed framework continuously collects environmental parameters including temperature, relative humidity, particulate matter, soil moisture, pH, turbidity, electrical conductivity, and dissolved oxygen. AI-based analytical approaches are incorporated for anomaly detection, environmental classification, and forecasting of future environmental conditions. The framework can identify unusual environmental patterns, generate automated alerts, and provide predictive information to support timely management decisions. Its potential applications include smart agricultural irrigation management, air-quality monitoring, pollution hotspot identification, and continuous water-quality assessment. The integration of real-time sensing with AI-based prediction can transform environmental monitoring from a predominantly reactive approach into a **real-time, predictive, and decision-oriented system**. However, practical implementation requires appropriate sensor calibration, high-quality datasets, model validation, and field-based performance evaluation. The proposed framework provides a foundation for developing intelligent environmental monitoring systems capable of supporting sustainable agriculture, pollution management, and improved environmental decision-making.

Introduction

Environmental quality is directly associated with human health, ecosystem stability, agricultural productivity, food security, and sustainable economic development. In recent decades, rapid urbanization, industrialization, population growth, transportation activities, deforestation, intensive agriculture, improper waste disposal, and climate variability have substantially increased pressure on natural resources and environmental systems. Air pollution, water contamination, soil degradation, increasing temperature, changing humidity patterns, excessive particulate matter, and the accumulation of hazardous substances are among the major environmental challenges affecting both developed and developing regions (Popescu et a., 2024). These environmental changes are often dynamic and spatially variable, making timely and reliable monitoring essential for understanding environmental conditions and developing appropriate management strategies. Effective environmental monitoring provides the scientific information required to assess pollution levels, identify environmental risks, evaluate ecosystem changes, support regulatory decisions, and implement timely mitigation measures (Ullo & Sinha, 2020).

Environmental monitoring traditionally relies on fixed monitoring stations, manual sampling, laboratory-based analysis, and periodic reporting. These approaches remain important because laboratory instruments and established monitoring protocols can provide highly accurate measurements. However, conventional monitoring systems may have limitations in terms of spatial coverage, sampling frequency, operational costs, manpower requirements, and response time. A limited number of monitoring stations may not adequately represent environmental conditions across large geographical areas. Similarly, periodic sampling may fail to capture short-duration pollution episodes, sudden changes in water quality, extreme temperature events, or rapidly developing environmental hazards. Consequently, there is an increasing requirement for monitoring technologies that can provide continuous, geographically distributed, cost-effective, and real-time environmental information (Asha et al., 2022).

The emergence of the **Internet of Things (IoT)** has created new opportunities for addressing these limitations. IoT represents a network of interconnected physical devices capable of sensing, processing, communicating, and exchanging information through digital communication technologies. In environmental applications, IoT devices can incorporate sensors, microcontrollers, communication modules, and power systems into compact monitoring units. These units can be deployed across urban areas, agricultural fields, industrial locations, rivers, reservoirs, wastewater systems, forests, and other ecosystems. Environmental IoT networks can continuously measure parameters such as air temperature, relative humidity, particulate matter, carbon dioxide, carbon monoxide, nitrogen oxides, soil moisture, soil temperature, pH, electrical conductivity, turbidity, dissolved oxygen, and water temperature. The resulting observations can be transmitted automatically to centralized or distributed data-processing platforms (Almalawi et al., 2022). One of the major advantages of IoT-based environmental monitoring is the ability to obtain high-frequency observations from multiple locations. Instead of depending entirely on occasional sampling, sensor networks can provide continuous streams of environmental information. Such high-resolution data can reveal temporal and spatial patterns that may otherwise remain undetected. For example, an IoT network can identify changes in particulate matter throughout the day, monitor temperature fluctuations in agricultural fields, detect changes in water quality following rainfall, or observe variations in soil moisture during crop growth. This information can improve understanding of environmental processes and provide a stronger basis for evidence-based management (Panduman et al., 2024).

However, continuous environmental data collection also creates a new challenge: the generation of large volumes of complex and heterogeneous data. A network containing hundreds or thousands of sensors may generate millions of observations over relatively short periods. These data may differ in format, frequency, spatial resolution, quality, and reliability. Raw sensor observations may also contain missing values, measurement errors, noise, outliers, and calibration-related deviations. Therefore, simply collecting environmental data is insufficient. Effective environmental monitoring requires advanced computational methods capable of processing, interpreting, and transforming large datasets into meaningful environmental information (Ramani et al., 2025). **Artificial Intelligence (AI)** provides an important solution to this challenge. AI encompasses computational techniques that enable systems to identify patterns, learn from data, make predictions, classify observations, and support decision-making. Machine-learning algorithms can analyze relationships among multiple environmental variables and identify patterns that may be difficult to recognize using conventional analytical approaches. For example, AI models can classify air-quality conditions, predict pollutant concentrations, identify unusual environmental observations, estimate future temperature trends, detect changes in water quality, and identify possible sensor malfunctions. Consequently, AI can transform IoT systems from simple data-collection networks into intelligent environmental monitoring platforms (Zhang et al., 2021). The integration of IoT and AI creates a multi-layered environmental monitoring architecture. At the first level, environmental sensors collect real-time observations. At the second level, communication technologies transmit these observations to gateways, servers, cloud platforms, or edge-computing devices. At the third level, data-processing systems clean, organize, and store the information. At the fourth level, AI algorithms analyze the processed datasets and generate classifications, predictions, anomaly detections, or risk assessments. Finally, decision-support systems can present the results through dashboards, mobile applications, geographic information systems, or automated alert mechanisms. This architecture creates a continuous pathway from **environmental observation to data transmission, intelligent analysis, prediction, and decision-making** (Arabelli et al., 2024).

AI-based anomaly detection is particularly important for environmental monitoring. Environmental systems naturally experience fluctuations, and it may be difficult to distinguish normal variation from potentially hazardous events. Machine-learning algorithms can establish patterns of normal environmental behavior using historical observations and subsequently identify measurements that significantly deviate from expected conditions. Such deviations may indicate sudden pollution events, industrial emissions, water contamination, extreme weather conditions, ecological disturbances, or sensor malfunction. Early identification of abnormal conditions can provide environmental managers with additional time to investigate the cause and implement appropriate corrective actions (Laha et al., 2022). Predictive analytics represents another important application of AI in environmental monitoring. Historical sensor observations can be used to develop models capable of forecasting future environmental conditions. For instance, air-quality models can predict changes in particulate pollution, while temperature models can identify potential heat-stress conditions. In agricultural environments, AI models can combine soil-moisture observations, temperature, humidity, and weather information to predict crop water requirements. Similarly, water-quality models can analyze historical measurements to identify potential deterioration in water conditions. Predictive capability is particularly valuable because environmental management often benefits more from advance warning than from information about an event that has already occurred (Chen et al., 2023).

The combination of IoT and AI is also highly relevant to **smart agriculture and environmental resource management**. Agriculture is strongly influenced by environmental conditions, including temperature, humidity, soil moisture, soil salinity, water availability, and weather variability. IoT sensors can provide continuous measurements from crop fields, while AI can analyze these observations to support irrigation scheduling, crop-stress monitoring, nutrient management, and environmental risk assessment. Such systems can contribute to more efficient use of water and other agricultural inputs. In regions facing water scarcity and climate variability, intelligent environmental monitoring can therefore contribute to both agricultural productivity and resource conservation. Air-quality monitoring is another major application of smart IoT-AI systems. Conventional air-quality stations can provide accurate measurements but may be expensive to establish and maintain at high spatial density. IoT-based sensor networks can complement established monitoring stations by providing observations from additional locations. AI algorithms can then analyze measurements from multiple sensors to identify pollution patterns, classify pollution levels, detect abnormal events, and forecast future conditions. This approach can help identify pollution hotspots and support timely environmental and public-health interventions (Yang et al., 2021).

Similarly, IoT-based water-quality monitoring can provide continuous information about aquatic environments. Sensors can measure pH, temperature, turbidity, electrical conductivity, dissolved oxygen, and other relevant parameters. AI models can analyze combinations of these variables to identify unusual patterns or potential contamination events. Continuous monitoring may be useful in rivers, irrigation canals, reservoirs, aquaculture systems, industrial wastewater facilities, and other water bodies. Early detection of abnormal conditions can facilitate rapid investigation and corrective action, reducing the potential for severe environmental impacts. Industrial environmental monitoring can also benefit from the integration of IoT and AI. Industrial facilities may release pollutants or generate environmental conditions that require continuous monitoring. IoT sensors can be installed at strategic locations to monitor air emissions, temperature, gases, wastewater characteristics, and other parameters. AI-based systems can identify abnormal emission patterns and provide automated warnings when monitored variables exceed expected or permissible levels. Such systems can strengthen environmental compliance and support preventive rather than purely reactive management (Laha et al., 2022).

The integration of **cloud computing and edge computing** further enhances the functionality of IoT-AI environmental monitoring. Cloud platforms provide substantial storage and computational capacity, allowing large datasets from geographically distributed sensors to be processed centrally. However, transmitting every raw observation to a remote cloud can increase communication requirements and latency. Edge computing addresses this issue by performing preliminary processing and AI inference close to the sensing device or local gateway. This can enable faster responses, reduce communication requirements, and improve system performance in locations where internet connectivity is limited (Pati et al., 2025).

Therefore, the integration of IoT and Artificial Intelligence represents a significant transition from conventional environmental monitoring toward **intelligent, continuous, predictive, and automated environmental management.** IoT provides the sensing and communication infrastructure required to observe environmental conditions, while AI provides the analytical intelligence required to interpret complex datasets and support decision-making. The combined system has potential applications in air-quality monitoring, water-quality assessment, soil and agricultural monitoring, industrial pollution control, urban environmental management, ecosystem assessment, and climate-risk monitoring.

MATERIALS AND METHODS

Research Design

The study adopted a conceptual and system-design approach for developing a smart IoT-based environmental monitoring framework using Artificial Intelligence. The proposed system was structured into five interconnected layers: sensing, communication, data processing, AI analytics, and decision support. The framework was designed to support continuous environmental data acquisition and automated analysis.

Environmental Sensing Layer

The sensing layer consists of distributed environmental sensors installed at selected monitoring locations. Depending on the application, sensors can measure air temperature, relative humidity, particulate matter, carbon dioxide, carbon monoxide, nitrogen oxides, water temperature, pH, turbidity, dissolved oxygen, electrical conductivity, soil moisture, and other environmental parameters. Sensor nodes may incorporate a microcontroller for local data acquisition and preliminary processing. Multiple sensors can be integrated into a single monitoring station to provide simultaneous measurements (Ramani et al., 2025).

Table 1. Environmental parameters and potential sensing applications

Environmental parameter	Sensor/data source	Major application
Temperature	Digital temperature sensor	Climate and heat monitoring
Relative humidity	Humidity sensor	Environmental and agricultural monitoring
PM2.5/PM10	Particulate sensor	Air-pollution assessment
CO_2	Gas sensor	Air quality and greenhouse monitoring
CO/NOx	Gas sensors	Traffic and industrial pollution
pH	pH sensor	Water and soil monitoring
Turbidity	Optical turbidity sensor	Water-quality assessment
Dissolved oxygen	DO sensor	Aquatic ecosystem monitoring
Electrical conductivity	EC sensor	Water and soil salinity
Soil moisture	Soil-moisture sensor	Irrigation and agricultural monitoring
Noise	Sound-level sensor	Urban environmental monitoring

Communication Layer

Sensor observations are transmitted to a local gateway or cloud platform using appropriate wireless communication technologies. Depending on monitoring requirements and geographical scale, Wi-Fi, Bluetooth Low Energy, cellular networks, LoRaWAN, or other low-power communication technologies may be used. For large-scale environmental monitoring, low-power wide-area communication can be advantageous because monitoring stations may be distributed across relatively large geographical areas. Communication protocols should be selected according to transmission range, energy consumption, data volume, network availability, and operational cost

Data Processing and Storage

Environmental observations are collected at predefined intervals and assigned timestamps and monitoring locations. The data-processing system performs preliminary quality control before AI analysis. Processing steps include missing-data identification, duplicate detection, sensor-error screening, noise reduction, normalization, and data synchronization.

The processed observations can be stored in cloud databases or local servers. For applications requiring rapid response, edge computing can be implemented to perform initial data analysis near the sensor rather than transferring all raw observations to a remote cloud platform.

Artificial Intelligence Layer

The AI layer is responsible for converting sensor measurements into useful environmental information. Three major analytical functions were considered: classification, anomaly detection, and prediction. Classification algorithms can categorize environmental conditions into predefined levels such as normal, moderate, high-risk, and critical. Supervised machine-learning algorithms such as random forests, support vector machines, gradient-boosting algorithms, and artificial neural networks can be used for classification. Anomaly-detection algorithms can identify observations that differ substantially from normal environmental patterns. Unsupervised approaches, including clustering and autoencoder-based methods, can be used where labeled abnormal events are limited. Time-series forecasting models can predict future environmental conditions using historical sensor observations. Artificial neural networks, recurrent neural networks, long short-term memory models, and other forecasting approaches can be considered for this purpose (Asha et al., 2022)

AI Model Development

The collected dataset is divided into training, validation, and testing subsets. The training dataset is used to develop the AI model, the validation dataset is used for parameter optimization, and the testing dataset is used for independent performance assessment. Model performance can be evaluated using appropriate statistical indicators. For classification, accuracy, precision, recall, F1-score, and confusion matrices can be used. For continuous prediction, mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2) can be applied.

Table 2. AI methods and environmental monitoring functions

AI approach	Function	Potential environmental application
Random Forest	Classification/prediction	Pollution-level classification
Support Vector Machine	Classification	Environmental risk categorization
K-means clustering	Pattern discovery	Identification of environmental zones
Autoencoder	Anomaly detection	Detection of abnormal sensor patterns
Artificial Neural Network	Prediction/classification	Environmental forecasting
LSTM	Time-series prediction	Air-quality and

		temperature forecasting
Gradient Boosting	Prediction/classification	Pollution-risk prediction
Deep learning	Complex pattern recognition	Multi-parameter environmental analysis

Decision-Support and Alert System

The final layer converts AI outputs into understandable information for environmental managers, researchers, government agencies, farmers, and other users. A web-based or mobile dashboard can display real-time measurements, environmental trends, spatial maps, risk classifications, and automated warnings. When monitored variables exceed predefined thresholds or AI models detect abnormal patterns, the system can generate alerts through dashboards, mobile applications, email, or other communication channels.

RESULTS

Proposed Smart Environmental Monitoring Architecture

The proposed smart environmental monitoring framework integrates IoT-based sensing, wireless communication, edge/cloud computing, artificial intelligence (AI), and user-oriented decision-support tools into a unified environmental monitoring system. The framework enables continuous collection of environmental observations from distributed monitoring locations and converts raw sensor measurements into environmental indicators, anomaly alerts, forecasts, and management recommendations. The resulting architecture consists of five interconnected layers: **(i) sensing layer, (ii) communication layer, (iii) data-processing layer, (iv) AI analytics layer, and (v) application and decision-support layer**. The sensing layer supports measurement of temperature, relative humidity, particulate matter, soil moisture, pH, turbidity, electrical conductivity, and dissolved oxygen. Sensor observations are transmitted through wireless communication technologies to an edge gateway or cloud platform, where they undergo quality control and processing before AI-based analysis. The overall information flow was established as:

Environmental conditions → IoT sensors → Wireless communication → Edge/cloud processing → Data preprocessing → AI analytics → Prediction/anomaly detection → Alerts → User decision support.

This integrated structure demonstrates the potential to move environmental monitoring from simple data acquisition toward real-time interpretation, prediction, and decision support for environmental managers, farmers, researchers, and other stakeholders.

Real-Time Environmental Monitoring

The proposed system provides continuous environmental monitoring at predefined time intervals rather than depending exclusively on periodic manual sampling. Each sensor observation is associated with a timestamp and monitoring location and subsequently transmitted to the central processing platform. The monitoring workflow includes sensor measurement, signal validation, data transmission, quality checking, database storage, visualization, and AI analysis. The results framework indicates that continuous monitoring can improve the detection of short-term environmental variations. Sudden increases in particulate matter, for example, can be identified immediately and compared with historical observations to determine whether they represent normal variability or potentially abnormal pollution events. When observations exceed predefined thresholds or are identified as AI-based anomalies, automated warnings can be generated. For water-quality applications, continuous measurement of pH, turbidity, temperature, electrical conductivity, and dissolved oxygen can provide early indications of contamination, ecosystem disturbance, or environmental stress. Thus, the proposed framework provides substantially more frequent environmental information than conventional periodic observation approaches (Collado et al., 2024).

AI-Based Anomaly Detection

AI-based anomaly detection represents a major analytical outcome of the proposed framework. Environmental observations are affected by temporal and spatial variability arising from weather, seasonal changes, human activities, natural processes, and sensor noise. Consequently, the framework uses historical observations to establish baseline environmental patterns before identifying deviations from normal conditions. The proposed analytical framework can employ Isolation Forest, Local Outlier Factor, clustering-based techniques, and autoencoder-based models. These approaches assign anomaly scores to new observations, allowing observations exceeding a defined decision threshold to be classified as potentially abnormal. Potentially detectable events include sudden pollution episodes, sensor malfunction, abnormal temperature conditions, unexpected changes in soil moisture, and unusual water-quality conditions. Model performance can be assessed using precision, recall, F1-score, false-positive rate, and detection accuracy when labelled events are available. However, detected anomalies should be regarded as events requiring field or expert verification rather than being automatically interpreted as confirmed environmental contamination.

Environmental Prediction

The proposed framework also produces predictive environmental information through time-series AI modelling. Historical observations can be organized according to time and location and used to predict future environmental conditions. Candidate models include regression approaches, Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM) networks, and other suitable time-series algorithms. The framework incorporates chronological training, validation, and testing datasets to support reliable evaluation of predictive models. Relevant features may include previous environmental measurements, moving averages, seasonal indicators, rainfall, wind conditions, humidity, and temperature. Model performance can be evaluated using **Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2).** The resulting forecasts can provide advance information about potentially hazardous environmental conditions. Predicted increases in particulate matter can support early air-quality warnings, while predicted reductions in soil moisture can assist irrigation decisions. Similarly, forecasts of deteriorating water quality can provide an opportunity for environmental managers to investigate potential contamination sources before conditions become more severe (Collado et al., 2024).

Smart Agriculture Application

Application of the proposed IoT–AI framework to agricultural systems demonstrates its potential for precision environmental management. Sensors installed within crop fields can continuously monitor soil moisture, soil temperature, air temperature, relative humidity, electrical conductivity, and other crop-specific environmental variables. Additional sensors for leaf wetness, solar radiation, and rainfall can also be incorporated according to research requirements.

The integrated system can compare soil-moisture observations with crop requirements, weather information, and historical conditions to determine irrigation requirements. AI-based prediction can further estimate future soil-moisture conditions and identify periods of potential water stress. This provides the basis for a dynamic irrigation decision system rather than reliance on a fixed irrigation schedule.

Air-Quality Monitoring

The proposed framework can provide distributed air-quality monitoring through IoT sensor nodes installed at urban, industrial, agricultural, and roadside locations. The monitoring system can measure particulate matter, particularly $PM_{2.5}$ and PM_{10}, along with gaseous pollutants such as carbon monoxide, nitrogen oxides, sulfur dioxide, and ozone where suitable sensors are available.

The resulting observations can be processed through calibration, error removal, normalization, and synchronization procedures before being used to determine temporal pollution trends and spatial patterns. AI models can classify air-quality conditions, identify unusual pollutant increases, and forecast future pollution levels using historical and meteorological information.

A distributed monitoring network can increase spatial coverage compared with a limited number of conventional monitoring stations and can assist in identifying pollution hotspots. However, the reliability of low-cost sensor observations depends on periodic calibration and validation against reference-grade monitoring equipment.

Water-Quality Monitoring

The proposed IoT–AI framework is also applicable to continuous water-quality monitoring in rivers, irrigation channels, reservoirs, aquaculture facilities, and industrial wastewater systems. The framework can continuously monitor pH, temperature, turbidity, electrical conductivity, and dissolved oxygen, with additional parameters incorporated according to specific monitoring objectives. The analytical results are expected to provide improved identification of abnormal water-quality conditions through simultaneous assessment of multiple environmental parameters. AI-based models can evaluate combinations of changes in turbidity, electrical conductivity, pH, and dissolved oxygen rather than considering each parameter independently. Such multivariate analysis can provide stronger evidence of potential environmental disturbances. When abnormal conditions are detected, automated alerts can be generated for environmental managers and relevant users, allowing timely field verification and corrective action. Continuous monitoring therefore provides an improved basis for identifying emerging contamination events and ecological stress before they become more severe.

Table 3. Components of the proposed IoT–AI environmental monitoring framework

Layer	Main components	Primary function	Expected output
Sensing layer	Temperature, humidity, $PM_{2.5}$, PM_{10}, soil moisture, pH, turbidity, EC, dissolved oxygen	Continuous environmental data collection	Raw sensor observations
Communication layer	Wireless network, IoT gateway	Data transmission	Real-time sensor data
Data-processing layer	Filtering, validation, normalization, storage	Improve data quality	Clean environmental dataset
AI analytics layer	Anomaly detection, classific	Interpret environmental data	Anomalies, predictions and

	ation, forecasting		classifications
Application layer	Dashboard, mobile interface, warning system	Decision support	Alerts and management recommendations

Table 4. Environmental applications and expected monitoring outcomes

Application	Key parameters	AI function	Expected outcome
Smart agriculture	Soil moisture, soil temperature, humidity, EC	Prediction and decision support	Irrigation recommendations and water-stress warnings
Air quality	$PM_{2.5}$, PM_{10}, CO, NO_x, SO_2, O_3	Classification, anomaly detection and forecasting	Pollution alerts and hotspot identification
Water quality	pH, temperature, turbidity, EC, dissolved oxygen	Multivariate anomaly detection and prediction	Early contamination warnings
General environmental monitoring	Temperature, humidity and other sensor observations	Anomaly detection	Identification of unusual environmental conditions

Table 5. Proposed AI analytical functions

Analytical function	**Input**	**Suggested AI approaches**	**Output**
Anomaly detection	Historical and real-time sensor data	Isolation Forest, LOF, clustering, autoencoders	Anomaly score and warning
Environmental prediction	Time-series environmental data	Random Forest, Gradient Boosting, LSTM, regression	Future environmental conditions
Air-quality classification	Pollutant and meteorological data	Machine-learning classifiers	Air-quality category
Agricultural prediction	Soil moisture, weather and crop-related variables	Time-series and regression models	Irrigation/water-stress prediction
Water-quality assessment	Multiple water-quality parameters	Multivariate AI models	Potential disturbance/contamination alert

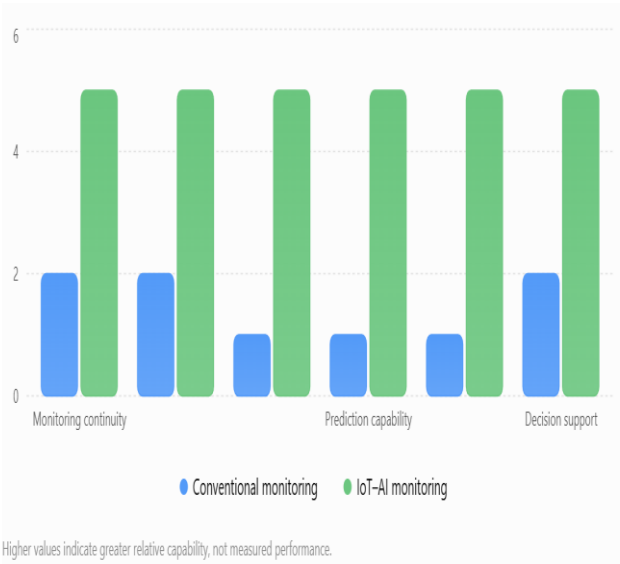

Figure 1. Conceptual comparison of conventional and IoT–AI monitoring

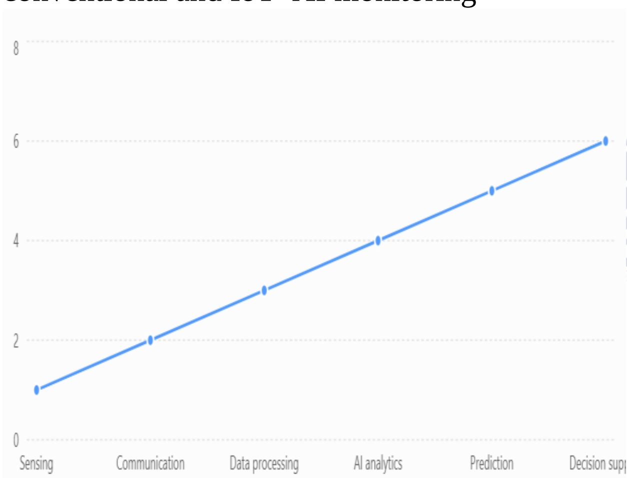

Figure 2. Conceptual environmental monitoring process

DISCUSSION

The proposed integration of the Internet of Things (IoT) and Artificial Intelligence (AI) provides an important advancement in environmental monitoring by combining continuous data acquisition with automated data interpretation and prediction. Conventional environmental monitoring generally depends on periodic sampling and subsequent laboratory or manual analysis, which may limit the ability to identify short-term environmental changes. In contrast, the proposed framework continuously collects environmental observations from distributed locations and transforms these observations into indicators, alerts, predictions, and decision-support information (Zou et al., 2025).

One of the major strengths of the proposed framework is its **real-time monitoring capability**. The use of distributed IoT sensors allows environmental parameters to be recorded at predefined intervals, with each observation associated with its monitoring location and time. This continuous approach can provide a more detailed representation of environmental variability than periodic observations. In particular, sudden changes in particulate matter, soil moisture, temperature, or water-quality parameters can be identified shortly after they occur. Such timely information is important because environmental disturbances may develop rapidly and may not be adequately captured through occasional sampling.

The integration of AI further increases the value of continuous sensor observations. Environmental datasets are often characterized by temporal and spatial variability caused by weather, seasonal conditions, human activities, natural processes, and sensor noise. Under these circumstances, fixed threshold-based systems may generate false alarms or fail to recognize unusual patterns. The proposed use of anomaly-detection approaches, including Isolation Forest, Local Outlier Factor, clustering techniques, and autoencoder-based models, provides a mechanism for identifying deviations from established environmental patterns.

An important implication of AI-based anomaly detection is the possibility of identifying environmental disturbances at an early stage. The framework can potentially detect sudden pollution episodes, abnormal temperature conditions, sensor malfunctions, unexpected soil-moisture changes, and unusual water-quality conditions. However, anomaly detection should not be interpreted as direct confirmation of environmental contamination. Detected anomalies require field verification or expert assessment before management actions are implemented. This distinction is particularly important because sensor errors and unusual but naturally occurring environmental conditions may produce anomalous observations. Another important contribution of the proposed framework is **environmental forecasting**. While conventional monitoring primarily describes current or previous environmental conditions, AI-based time-series modelling can provide information about likely future conditions. The proposed framework allows historical observations and environmental variables to be used with regression models, Random Forest, Gradient Boosting, LSTM networks, and other suitable algorithms. The use of chronological training, validation, and testing datasets is particularly important for environmental time-series prediction because it helps preserve the temporal structure of the observations (Senthilkumar et al., 2020)

Predictive capability can strengthen environmental management by allowing preventive rather than purely reactive decisions. For example, an anticipated increase in particulate matter could support an early air-quality warning, while predicted reductions in soil moisture could provide an opportunity to schedule irrigation before severe water stress develops. Similarly, forecasting deterioration in water quality could allow environmental managers to investigate possible contamination sources before the situation becomes more serious. The application of the framework to **smart agriculture** is particularly relevant because agricultural production is strongly influenced by environmental conditions and water availability. Continuous measurement of soil moisture, soil temperature, air temperature, relative humidity, and electrical conductivity can provide field-specific information for irrigation and crop-environment management. By combining current soil-moisture observations with weather conditions and historical patterns, the system can move from fixed irrigation schedules toward dynamic, condition-based recommendations (Kairuz-Cabrera et al., 2024).

The proposed agricultural application also demonstrates how IoT and AI can contribute to resource-use efficiency. When soil moisture is adequate or rainfall is predicted, the system can avoid unnecessary irrigation. Conversely, when soil moisture falls below a crop-specific threshold and continued decline is predicted, an irrigation recommendation can be generated. Therefore, the integration of real-time sensing, weather information, and AI prediction has the potential to support more precise irrigation management and improve water-use efficiency. For **air-quality monitoring**, the proposed distributed IoT network can provide broader spatial information by placing sensor nodes at urban, industrial, agricultural, and roadside locations. Monitoring $PM_{2.}$, PM_{10}, and selected gaseous pollutants can facilitate identification of temporal trends and spatial pollution patterns. AI-based classification and forecasting can further support the identification of unusual pollutant increases and potential pollution hotspots. Compared with a limited number of conventional monitoring stations, distributed monitoring therefore offers the potential for greater spatial representation of environmental conditions. Nevertheless, the reliability of air-quality monitoring depends strongly on sensor quality and calibration. Low-cost sensors can provide valuable high-density observations, but their measurements should be periodically compared with reference-grade monitoring equipment. This requirement highlights an important limitation of IoT-based environmental monitoring: increasing the number of sensors does not automatically guarantee higher data quality. Sensor calibration, validation, maintenance, and quality-control procedures must therefore remain integral components of the monitoring system (Aashiq et al., 2023).

The framework also has considerable potential for **water-quality monitoring**. Continuous measurement of pH, temperature, turbidity, electrical conductivity, and dissolved oxygen can provide information about changing water conditions in rivers, irrigation channels, reservoirs, aquaculture facilities, and industrial wastewater systems. A major advantage of the proposed AI approach is its ability to evaluate multiple parameters simultaneously. For example, simultaneous changes in turbidity, electrical conductivity, pH, and dissolved oxygen may provide stronger evidence of environmental disturbance than a change in a single parameter. The ability to generate automated alerts represents another important advantage of the proposed framework. When abnormal environmental conditions are identified, notifications can be delivered to environmental managers or other relevant users. This can shorten the time between environmental observation and management response and may facilitate field verification and corrective action. Consequently, the proposed system represents a shift from predominantly reactive monitoring toward a more proactive environmental management approach. Despite these advantages, several challenges should be considered before practical implementation. First, sensor reliability and calibration are essential because erroneous sensor observations can directly influence AI predictions and anomaly detection. Second, environmental AI models require sufficiently large, representative, and high-quality datasets for reliable development and validation. Third, different environmental locations may have distinct climatic, agricultural, industrial, and ecological characteristics, meaning that models developed for one location may not necessarily perform equally well elsewhere. These considerations emphasize the need for site-specific validation and continuous model evaluation (Mokrani et al., 2019).

CONCLUSION

The integration of Internet of Things (IoT) technologies and Artificial Intelligence (AI) provides a promising framework for improving environmental monitoring and management. The proposed system combines distributed IoT sensors, wireless communication, edge/cloud computing, data preprocessing, AI-based analytics, and decision-support tools to enable continuous collection and interpretation of environmental information. The framework can support real-time monitoring of important environmental parameters, including temperature, relative humidity, particulate matter, soil moisture, pH, turbidity, electrical conductivity, and dissolved oxygen. AI-based anomaly detection can assist in identifying unusual environmental conditions, while predictive models can provide early information about potential changes in air quality, soil moisture, and water quality. The proposed approach also has significant potential for smart agriculture by supporting dynamic irrigation decisions and improving water-use management. Similarly, distributed air-quality and water-quality monitoring can improve spatial coverage and facilitate early identification of pollution events and environmental disturbances. Overall, the proposed IoT–AI framework represents a transition from conventional, predominantly reactive environmental monitoring toward a **real-time, predictive, and decision-oriented monitoring system**. However, practical implementation will require reliable sensor calibration, high-quality datasets, appropriate AI model validation, and field-based evaluation. Since the present study proposes a framework rather than reports experimental validation, future research should focus on developing and deploying prototype systems and quantitatively evaluating their accuracy, reliability, predictive performance, and effectiveness under real environmental conditions.

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