Vol. 08, No. 3 (2026) 1469-1480, doi: 10.24874/PES08.03.007

Proceedings on Engineering Sciences

www.pesjournal.net

AI-DRIVEN ENVIRONMENTAL MONITORING USING IOT-BASED SENSOR NETWORKS

Yogesh S. Deshmukh[1]
Kottala Sri Yogi
Sandip Rajendra Aher
Dr.Archana Santosh Ubale
Tanveer Ahmad Wani
Nishant Kulkarni

Received 03.06.2026.
Revised 15.07.2026.
Accepted 19.08.2026.

Keywords:

Environmental monitoring, Internet of Things, Artificial intelligence, machine learning Deep learning, Edge computing

A B S T R A C T

AI-based environmental monitoring has become one of the key prerequisites of sustainable development, climate resilience, and smart management of resources. The old means of monitoring are usually characterized by low scalability, slow response and ineffective use of data. The paper introduces a full AI-driven environmental monitoring system that is based on sensor networks based on IoT to support real-time scalable and energy-efficient environmental observational procedures. The suggested solution combines the use of heterogeneous air, water, soil, noise, and climate sensors with smart communication protocol and adaptable network topology. The trend analysis and prediction of machine learning models used include linear regression, multiple linear regression, and support vectors machines, whereas spatiotemporal pattern extraction of large-scale environmental data streams with deep learning methods includes convolutional neural networks, recurrent neural networks, and long short-term memory networks. There are edge, fog, and cloud layers which work together to provide low-latency analytics, distributed intelligence and long-term data storage. The anomaly and event detection mechanisms are used to make the system more responsive by detecting abnormal environmental changes and sending timely alerts. It also includes adaptive learning and self-optimization mechanisms in the framework to enhance the accuracy of the model, energy efficiency, and network lifetime during dynamical environmental conditions. The essential problems associated with data quality, the generalization of the model, constraints of edge-AI, and interoperability are examined, and the possible research priorities to solve it. All in all, the suggested AI-IoT system has a solid potential of smart environmental monitoring, which can be used in pollution control, smart agriculture, and disaster early-warning systems.

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1. INTRODUCTION

The rapid rate of urbanization, industrialization, and climatic changes have put a lot of pressure on the natural ecosystems such that continuous and smart environmental surveillance becomes the international agenda. Air quality, water pollution, soil erosion, auditory pollution and climatic changes are the environmental factors that directly affect the human health, natural stabilization and food security. Traditional environmental monitoring methods that mainly rely on manual sampling or very few monitoring stations are

Corresponding author: Yogesh S. Deshmukh
Email: yogeshdeshmukhit@sanjivani.org.in

frequently expensive, labour intensive and cannot give high resolution real-time information. These constraints do not allow timely decision-making and undermine the proactive management of the environment, especially in the dynamic urban and industrial setting, as stated by Ullo and Sinha (2020). The Internet of Things (IoT) has become a paradigm-shifting technology in environmental monitoring in the sense that it allows implementing dense networks of connective sensors, which are able to collect data continuously and from geographically distributed areas. The IoT sensor networks of the environment include heterogeneous sensors that are able to measure various parameters and relay observations by use of wireless communication infrastructures. These systems greatly enhance spatial and temporal coverage at lower operational costs than the traditional monitoring methods as illustrated by Sunny et al. (2021). The IoT solutions have been effectively used in real-time tracking of air, water, and soil contaminants in a variety of environmental conditions and as reviewed in Pamula et al. (2022) represent the adaptability and scalability of IoT solutions.

Nevertheless, the fast proliferation of IoT sensors has led to huge amounts of heterogeneous data that are of high velocity, redundancy and noise. The handling and derivation of actionable information in this data presents a number of challenges associated with scalability, energy consumption, latency, and smart interpretation. Artificial intelligence (AI) has become a highly important enabler when it comes to tackling these issues by aiding the analysis of data, pattern recognition, and predictive modeling with the help of artificial intelligence. Liu and Ni (2025) observe that machine learning methods complement environmental sensing by learning multifaceted correlations in sensor data, which makes it possible to improve the accuracy and strength of environmental measurements.

Deep learning algorithms extend these potentials with the additional ability to model the highly spatiotemporal relationships between environmental and climatic data. This type of models has been found to be effective in predicting the levels of pollution, seasonal variations, and the presence of environmental anomalies among many others with a high accuracy. When AI is combined with IoT sensor networks, environmental monitoring systems will no longer be passive data acquisition platforms, but have the potential to be intelligent and autonomous decision-support systems with the ability to support real-time inferences and predictions, such as demonstrated Asadullah et al. (2025). Environmental sensing AI has also been extended into the multimodal space, such as analysis of the environment using sound, which improves the situation awareness and contextual cognition, as Emvoliadis et al. (2024) investigate. Recent AI-based environmental monitoring designs often use hierarchical computing designs, which integrate edge, fog, and cloud layers to trade-off between the efficiency and latency of computations. The edge computing allows local computations in and around sensor nodes, which minimizes the communication cost and allows prompt detection of anomalies and issuing suitable alerts. The layers of fog and cloud aid in the field of advanced analytics, long-term data storage, and training of models on a large scale, which enhances the scaling and reliability of the system. These types of architectures can be of great use in low resource and extreme environments where power efficiency is important to be employed as pointed out Rosca and Stancu (2025). Adaptive and self-learning mechanisms also help make AI models more robust and enable constant updating of the model as the environment changes. These features are critical to the sustenance of consistent functionality in the various geographical locations and weather conditions. Miller et al. (2025) have reported that AI agents incorporated with IoT has shown greater accuracy in monitoring systems in the water quality analysis and climate data analysis. In cities, AI-controlled sensor systems have been identified to facilitate fine-grained air pollution modeling and decision-making based on digital environmental assistance (Bainomugisha et al., 2024).

The AI-based IoT environmental monitoring systems have a huge potential, but still, a number of challenges are severe. Hardware degradation, environmental interference, and communication failures can also compromise sensor data quality and cause noisy data or incomplete data. Moreover, the generalization of the AI models trained using region-specific data is usually low when applied in new environments, with dissimilar climatic or socio-economic features. Such issues are especially acute in the low-resource environments, where the design of the system is restricted by the cost, accuracy, and resilience, as Bainomugisha et al. (2023) explain. Further complications are known to be in the implementation of deep learning AI models in edge devices that have poor processing capability and power supply. An optimal trade-off of complexity of a model versus prediction accuracy versus energy consumption is a research issue. The routing and data-processing techniques that are energy-saving are thus imperative in order to extend the network life and guarantee sustainable execution of massive sensor installations, as surveyed by Thakur et al. (2025). Possible interoperability and standardisation problems among heterogeneous IoT systems exacerbate large-scale integration and implementation of a system, hampering the efficient exchange of data and the coordinated activities of environmental management, as highlighted by Popescu et al. (2024).

2. RELATED WORK

A recent study has also dealt much with the combination of the artificial intelligence and the IoT-based sensor networks to improve the accuracy, scalability, and sustainability of environmental monitoring. The smart-city applications have been identified as one of the key areas of research, in which AI-enhanced IoT systems can

be used to facilitate real-time environmental monitoring and urban planning based on the data. The article by Asadullah et al. (2025) outlines an AI-based IoT architecture that will help the city develop in a sustainable manner, allowing monitoring a variety of environmental indicators. Their work also focused on intelligent analytics to make proactive decisions in smart cities, which points to the use of AI to convert raw sensor data into practical environmental intelligence. There has been growing interest in low-cost and resource-mindful sensing systems, especially to be used in developing and low-resource areas. Okure et al. (2022) have shown that the solution of affordable air-quality monitoring can be performed reliably with the combination of data calibration and analytics methods. Continuing on the topic of work, Bainomugisha et al. (2023) talked about design trade-offs in distributed low-cost sensing platforms with focus on robustness, scalability, and data quality in the presence of constrained operation conditions. Hardware novelty has also been investigated based on the custom sensor kits, including the AirQo platform, allowing the monitoring of the particulate matter to be designed to suit the difficult environmental conditions.

There are a number of works that examine AI-based data modeling and analytics to enhance the accuracy of environmental sensing. Chandrashekara and Khanna (2025) suggested an IoT sensor network with an AI capability to detect the presence of environmental pollutants and the chemical degradation processes and revealed how analytical intelligence can improve the sensitivity of detection. On the same note, Fang and Ni (2025) came up with an AI-based monitoring and green-design framework of rural ecological environment as a bridge between monitoring systems that are centred on urban settings and the sustainability demands in rural settings. These reports underscore the increased relevance of AI -IoT systems in various environmental settings. An additional significant new development availed through research in environmental monitoring involves multimodal sensing. The article by Emvoliadis et al. (2024) investigated how acoustic sensing can be combined with AI and IoT applications to allow cognitive sound analysis to be used as a form of environmental awareness. Their experience proved that the use of non-traditional sensing modalities could contribute to the situational perception in a complicated environment considerably. In line with this strategy, Miller et al. (2025) examined how intelligent agents of AI can be used with IoT systems to monitor water-quality and climate, and found that it can enhance adaptability and decision-making via autonomous learning systems.
The energy efficiency and sustainability of large-scale deployments of IoT sensors is also a research issue of concern. Other applications of intelligent sensing in agricultural supply chains included by (Kamyod et al., 2025) to optimize the energy consumption in IoT-based monitoring systems, where predictive models based on AI are used to optimize energy usage, indicating the wider use of intelligent sensing in pollution monitoring. Thakur et al. (2025) conducted an extensive survey of AI-powered energy-efficient routing methods in the wireless sensor networks by highlighting their significance in the extended network life and data reliability of dense networks. New sensing paradigms and new analytics have also been investigated in the emerging research. Gaddam (2025) has examined the AI-conducted quantum sensing as the ultra-high-precision environmental monitoring which shows its promise as a next-generation sensing application.

Table 1. Related Work Summary on AI-Driven Environmental Monitoring Using IoT-Based Sensor Networks

Author(s) & Year	Application Domain	IoT Sensing Focus	AI Technique Used	Key Contribution	Identified Limitation
Felici-Castell et al. (2023)	Urban health monitoring	Air pollution sensors	AI-based data analytics	Low-cost AI–IoT network assisting citizens with respiratory issues	Focused on urban-scale deployment only
Gao et al. (2024)	Environmental economics	Macro-environmental indicators	Statistical AI modeling	Analysis of globalization impacts on environmental degradation	No real-time IoT sensor integration
Gaddam (2025)	Precision environmental sensing	Advanced sensing devices	AI-driven quantum models	High-precision sensing paradigm for future monitoring systems	High implementation complexity
Leong (2025)	Climate change monitoring	Climate and environmental datasets	AI-driven analytics	Predictive insights for climate impact mitigation	Relies on secondary data sources
Farah et al. (2026)	Environmental pollution control	Smart environmental sensors	AI-based decision models	Sustainable AI–sensor solutions for pollution challenges	Limited experimental validation
Chandrashekara and Khanna (2025)	Chemical pollution monitoring	Pollutant & degradation sensors	AI analytical models	Intelligent pollutant detection using IoT sensor networks	Energy efficiency not extensively analyzed
Fang and Ni (2025)	Rural ecological monitoring	Ecological environment sensors	AI-driven intelligent systems	Green design–oriented monitoring framework for rural areas	Scalability across regions not evaluated

In the article Leong (2025) discussed about AI-based analytics in monitoring climate changes, highlighting the predictive features to be used in mitigation planning. Moreover, (Farah et al., 2026) highlighted the importance of smart sensors in association with AI to solve the long-term pollution of the environment with a sustainable technological solution. All these studies reflect the fast development of AI-powered IoT environmental monitoring systems and emphasize the necessity of unified, adaptive, and energy-efficient frameworks, which could be used in various environmental conditions. The Table 1 summarized the AI driven based contribution in the environment monitoring.

3. ENVIRONMENTAL MONITORING REQUIREMENTS AND CHALLENGES

3.1 Key environmental parameters

To have a complete picture of the health of the ecosystem, environmental monitoring systems should be able to monitor a large variety of physical, chemical, and biological parameters. The major pollutants that are being monitored under air quality monitoring include particulate matter, carbon monoxide, nitrogen oxides, sulfur dioxide, and ozone, which have direct implication on human health and the sustainability of cities. The constant air monitoring is required to detect the areas of pollution, estimate the compliance with the regulations, and provide the warning about the potentially dangerous situation. The parameters that are monitored during water quality are dependent variables such as pH, turbidity, dissolved oxygen, temperature, conductivity and the presence of contaminants such as heavy metals or even pathogens. These are quite important indicators that will be used to protect drinking water sources, aquatic ecosystems and manage industrial discharges. In agriculture and environmental conservation, soil monitoring is important as it is used to determine the percentage of moisture in soil, the quantity of nutrients in soil, salinity, temperature, and contamination. Correct soil information is used in precision farming, land-use plans, and erosion management. Figure 1 reveals the combination of sensing air, water, soil, noise, and climate parameters.

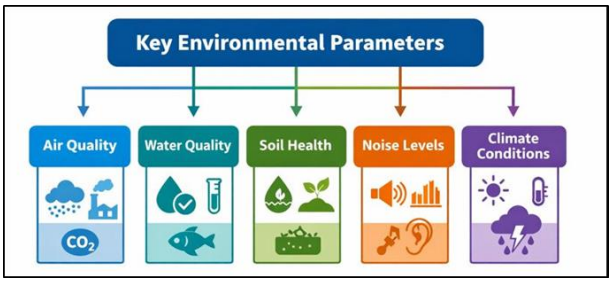


Figure 1. Key Environmental Parameters for IoT-Based Environmental Monitoring

The noise monitoring is a way to solve the environmental acoustics issues by measuring the sound pressure level in the urban, industrial, and transportation environments to assess the noise pollution and its impact on human health and wildlife.

The parameters that are climate related, which include temperature, humidity, rainfall, wind speed, and solar radiation and the atmospheric pressure, give long-term information about weather trends and climate changes. The combination of these varied parameters into a single monitoring system is also difficult because of the variability in various parameters in sensing technologies, sampling rate, accuracy needs and environmental dynamics. A successful AI-based IoT monitoring system should thus have the ability to be multi-parameter, integrated and coordinated in data capture and interpretation to provide meaningful and actionable environmental information.

3.2 Data Heterogeneity, Scalability, and Real-Time Constraints

Environmental monitoring systems based on the IoT produce large amounts of heterogeneous data acquired by geographically dispersed sensors that work under varying conditions. The heterogeneity in data is due to the difference in the types of sensors, measurement units, sampling rates, communication schemes, and the quality of the data. The environmental information can be structured numerical data, semi-structured data (metadata), and unstructured information (images or acoustics). It is a significant task to handle and combine such a diversity of streams of data in an analytic pipeline. Scalability also is another important requirement since deployments of environmental monitoring can require thousands of sensor nodes distributed across cities, farmlands, or natural ecosystems. With the rising number of sensors, the system should be capable of effectively managing the increasing data volumes without adversely affecting its performance and reliability. The time-sensitive nature of real-time can further complicate system design, especially where delay in response can have disastrous effects, like pollution notifications, flood warning or disaster early warning systems. Low-latency requirements are not usually supported by centralized cloud-based processing as a result of network congestion and communication delays. Analytics based on AI should thus be distributed so that they can run on edge, fog and cloud layers. The necessary requirements are to have efficient data fusion, smart filtering strategies, and adaptive sampling strategies that help minimize redundant transmissions and maintain timely decision-making. Dealing with heterogeneity of data, scalability and real-time issues will also be central to achieving powerful and responsive environmental monitoring systems.

3.3 Energy Efficiency and Network Lifetime Issues

The issue of energy efficiency is also extremely important in the context of the IoT-based environmental monitoring, with several sensor nodes powered by batteries and situated in remote and inaccessible locations. Long network lifetime is a major design goal as frequent battery replacement or maintenance can often be impractical and expensive. The sensing operations, data processing and wireless communication are the key determinants of the energy consumption in sensor networks, the communication usually being the most energy-consuming part. The transmission of high frequency data continuously may quickly run down node energy resulting in a network splitting and loss of data. Sensors may also be subject to other environmental factors like extreme temperatures, humidity or other physical impediments that may influence sensor performance as well as energy consumption. The adaptive sampling and duty cycling strategies have been extensively employed to trade-off data quality and power consumption in order to manage these issues. The transmission overhead is minimized and the network lifetime increased with efficient communication protocols and energy efficient routing mechanisms. By combining AI methods, it is possible to have intelligent power management, forecasting the optimal sampling rate, identifying unnecessary information, and dynamically adjusting the network behavior according to the environmental conditions. The edge-based processing will also help to lower the energy usage by minimizing the data broadcast to the cloud that is not necessary. Creating energy efficient and self sustaining sensor networks is still a challenge and it needs to be optimally coordinated by hardware, communication and intelligent data analytics.

3. IOT-BASED SENSOR NETWORK ARCHITECTURE

4.1 Sensor types and deployment strategies

Environmental monitoring based on IoT is based on the use of various types of sensors that represent multi-dimensional environmental data with high spatial and temporal resolution. Some of the common types of sensors are gas sensors of air pollutants, optical and electrochemical sensors of water quality, capacitive and resistive sensors of soil moisture and nutrients, acoustic sensors of noise, and meteorological sensors of climatic conditions like temperature, humidity, rainfall and speed of wind. These sensors have different degrees of accuracy, cost, power usage and their longevity and therefore have to be selected carefully depending on the use of application and the environmental conditions of deployment. The deployment strategies are important in providing stable data gathering and coverage. In urban surveillance areas, industrial locations and agricultural lands, fixed deployments are typically applied to deliver long-term measurements continuously. High density sensors enhance the granularity of measurements at the sacrifice of cost, power and redundancy in the data whereas sparse deployment compromises coverage accuracies.

4.2 Communication Protocols and Network Topology

The basic elements of the sensor network architecture of the IoT include communication protocols and topology of the network, which directly affect the reliability of the data, latencies, scalability and the energy consumption. There is a wide range of low-power wireless communication technologies used in environmental monitoring systems, including the Zigbee, LoRaWAN, NB-IoT, Bluetooth Low Energy, and IEEE 802.15.4, based on coverage, data rate needs, and power limitations. Short-range protocols can be used in dense deployments with high data rates, and long-range low-power protocols can be used in the wide-area monitoring with minimal energy usage. The network topology defines the manner in which the sensor nodes are linked to each other and the way data traverses the system. Popular topologies are star, tree, mesh and hybrid. Figure 2 demonstrates internet of things communication protocols and network structures that allow efficient transmission of data. Compared to the mesh and tree topologies, star topologies are simple and have low latency, at the expense of being single points of failure.

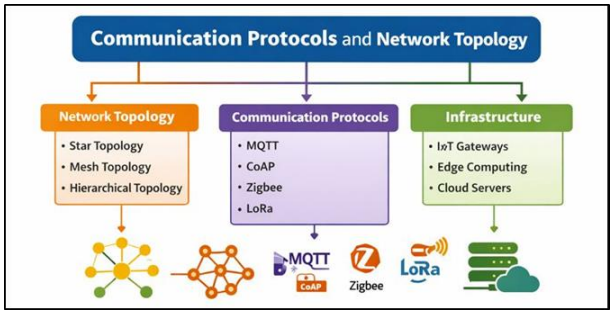


Figure 2. Communication Protocols and Network Topology in IoT-Based Environmental Monitoring Systems

The dynamism of environmental conditions and mobility of nodes can influence the performance of a network, and adaptive and self-healing topologies thus become very attractive. The methods to manage the routes and topology by using AI may optimize the communication routes, load balancing, and reduce the congestion or failure of the node. A point of quality of service that needs to be taken into consideration in the choice of protocols and topologies includes real-time delivery of data, reliability, etc. An effective communication architecture will guarantee effective, resilient and scalable data transmission in a large scaled environmental monitoring network.

4. AI TECHNIQUES FOR ENVIRONMENTAL DATA ANALYTICS

5.1 Machine learning models for pattern recognition and prediction

Linear Regression (LR)

Linear Regression is among the simplest and most common machine learning methods of environmental data analysis and prediction. It is a process that approximates a connection between a dependent variable and an independent variable by regression of a linear equation on observed data. Linear regression is widely used in environmental monitoring to make forecasts of parameters like trends in temperature, pollutant concentration levels or changes in humidity as a given predictor over time or a single predictor. The behavior of a model is transparent with linear regression giving domain experts insight into the relationship among changes in input variables and the outcome of the prediction. But in most cases, the environmental systems are nonlinear and multi-factorial with various factors interacting, and this can restrict the predictive ability of the simple linear models.

Step 1: Model formulation

$$\hat{y} = \beta 0 + \beta 1\, x$$

Step 2: Loss function (Mean Squared Error)

$$J(\beta 0, \beta 1) = \left(\frac{1}{n}\right) \Sigma\, (yi - \hat{y}i)^2$$

Multiple Linear Regression (MLR)

Multiple Linear Regression is an extension of the simple linear regression model in that it allows more than one independent variable to predict a single dependent variable. This ability is especially useful in environmental monitoring, where the quality of the air or water pollution is determined by a number of interdependent factors. As an example, the level of air pollutants can be determined based on temperature, humidity, wind speed, traffic density and industrial activity. MLR allows the analysis of such variables simultaneously to give more precise and informative predictions, which is not the case with single-variable models. In monitoring systems that are based on IoT, multivariate trend analysis, estimation of pollution index, and risk assessment of the environment are commonly applied with the help of MLR. The coefficients used in the model are interpretable, and a given analyst can measure the relative influence of each of the environment factors. Computationally, MLR has been found to be comparatively efficient and can run on edge/fog nodes with small resources.

Step 1: Multivariate model formulation

$$\hat{y} = \beta 0 + \beta 1\, x1 + \beta 2\, x2 + \ldots + \beta p\, xp$$

Step 2: Objective function (Least Squares)

$$J(\beta) = \left(\frac{1}{n}\right) \Sigma\, [yi - (\beta 0 + \Sigma\, \beta j\, xij)]^2$$

Step 3: Optimal coefficient estimation

$$\beta = (X^{\mathrm{T}} X)^{-1} X^{\mathrm{T}} y$$

Support Vector Machine (SVM)

Support Vector Machine is an effective classifier or regression tool to be employed in environmental monitoring practice. SVM is also able to deal with nonlinear relationships which linear models fail to accomplish because it can convert input data into higher-dimensional feature spaces with help of kernel functions. This contributes to the fact that SVM is especially useful in the context of the pattern recognition of complex datasets about the environment, i.e. recognizing an episode of pollution, the quality of water level, or the occurrence of abnormal conditions in the environment.

Step 1: Decision function (linear case)

$$f(x) = w^{\mathrm{T}} x + b$$

Step 2: Optimization objective (maximum margin)

Minimize:

$$\left(\frac{1}{2}\right) ||w||^2 + C\, \Sigma\, \xi i$$

Subject to:

$$yi\, (w^{\mathrm{T}} xi + b) \geq 1 - \xi i$$

$$\xi i \geq 0$$

Step 3: Kernel-based decision function

$$f(x) = \Sigma\, \alpha i\, yi\, K(xi, x) + b$$

5.2 Deep learning techniques for spatiotemporal analysis

Convolutional Neural Network (CNN)

Convolutional Neural Networks refer to popular deep learning models that can extract spatial features in structured input automatically. CNNs have been especially useful in the environmental monitoring of spatial patterns in data assembled on sensor grids, remote sensing images and pollution heatmaps. Through convolutional filters, CNNs are able to detect local correlations, like the hot spots of pollution, the effects of land-use or temperature and humidity spatial gradients. This feature can be used in applications such as air quality mapping, water contamination detection, and environmental change analysis because CNNs are useful. CNNs do not require the manual feature engineering step since they learn hierarchical representations by working directly with the raw data.

Step 1: Convolution operation

$$h(i, j, k) = \Sigma\, \Sigma\, x(i + m, j + n) \cdot w(m, n, k) + b(k)$$

Step 2: Activation function

$$a(i,j,k) = \sigma(h(i,j,k))$$

Recurrent Neural Network (RNN)

Recurrent Neural Networks is a particular type of neural network that is stable in sequential data and time-dependent data, i.e. its internal memory states. This renders RNNs appropriate in the investigation of time-based tendencies in environmental time-series information like temperature changes, pollution patterns, or rain patterns. RNNs are used in the context of environmental monitoring based on IoT by learning dependencies between sensor measurements over time, to predict the future environmental state. Their feedback relations enable the past time step information to be used in the present predictions to reflect the continuity of a time taking process in the environment. RNNs have been used in activities like weather prediction, air quality prediction and anomaly detection in sensor streams. The long-term dependencies are however not readily solvable by the use of the standard RNNs because some of the challenges include disappearance and explosion of the gradients. This drawback may decrease prediction power in the modeling of long term trends or seasonal changes.

Step 1: Hidden state update

$$h(t) = \varphi(Wx\,x(t) + Wh\,h(t-1) + bh)$$

Step 2: Output computation

$$y(t) = Wy\,h(t) + by$$

Step 3: Sequence loss function

$$L = \Sigma\, l\big(y(t), \hat{y}(t)\big),\ \ t = 1\ to\ T$$

Long Short-Term Memory (LSTM)

An improved architecture of recurrent neural networks, which attempts to address the weaknesses of standard RNNs regarding long-term memory dependencies. LSTMs add memory cells and gating mechanisms to control the information flow so that it can store the information that is relevant about the past over a long period of time. LSTMs are very useful in environmental monitoring as far as spatiotemporal predictions are concerned, which include air pollution evolution, climate trend analysis, and hydrological modeling. They are able to simulate seasonal dynamics, slow environmental reactions and complicated time interactions that fundamental models cannot depict. Hybrid networks Typically, LSTMs are used together with CNNs to create hybrid networks, in which CNNs learn spatial and LSTMs temporal.

Step 1: Gate computations

$$f(t) = \sigma(Wf\,[h(t-1), x(t)] + bf)$$

$$i(t) = \sigma(Wi\,[h(t-1), x(t)] + bi)$$

$$o(t) = \sigma(Wo\,[h(t-1), x(t)] + bo)$$

Step 2: Cell state update

$$\hat{c}(t) = tanh\ tanh\,(Wc\,[h(t-1), x(t)] + bc)$$

$$c(t) = f(t) \odot c(t-1) + i(t) \odot \hat{c}(t)$$

Step 3: Hidden state output

$$h(t) = o(t) \odot tanh\ tanh\,(c(t))$$

5.3 Anomaly and event detection methods

The methods of anomaly and event detection are essential to an AI-powered environmental monitoring system because they allow detecting abnormal states and severe environmental occurrences in time. There is the possibility of anomaly occurring because of spikes in pollution, sensors, extreme weather conditions, or unexpected changes in the environment. Efficient detection methods can be used to differentiate between significant and slight environmental phenomena and noise and regular fluctuations of sensor data. Conventional anomaly detecting methods are usually based on the statistical thresholds and rule based procedures, which are easy to apply, but cannot accommodate complex and dynamic environments. The methods of machine learning are used to improve the anomaly detection process by acquiring normal patterns of behavior in the environment using historical data. Other methods like the clustering, support vector machines, and isolation based methods can achieve this by identifying outliers that are very different against a learnt pattern. The approaches are especially useful in identifying a gradual change or mild anomalies that might not raise any hardpoint. Deep learning methods go a step further and enhance the accuracy of the detection by capturing a complex behavior of time and space dependencies. Common training models that are used to identify anomalies in time-series environmental data are autoencoders, recurrent neural networks, and long short-term memory models, which measure reconstruction or prediction errors. Event detection is an expansion of anomaly detection that detects and categorizes particular environmental incidents, e.g. occurrence of hazardous gas leakages, water pollution incidents, or extreme weather patterns.

5. AI-DRIVEN ENVIRONMENTAL MONITORING FRAMEWORK

6.1 End-to-end system architecture

A system architecture that is based on end-to-end is constructed to create an AI-driven environmental monitoring system that is seamlessly integrated with sensing, communication, computation, and intelligent analytics. At the perception layer, there is a constant collection of environmental data at the perception layer through heterogeneous IoT sensors on the air, water, soil, noise, and climate levels. These sensors are linked together by use of low-power wireless communication

technologies creating a distributed sensing infrastructure. The edge layer conducts early data acquisition, preprocessing, and local analytics allowing events critical of time to respond to quickly. The edge devices can filter the noise, check sensor data, and run very slim AI model to minimize unnecessary data transmission. Mog layer combines information of various edge nodes, and it is used to provide regional level analytics, data integration, and coordination between sensor clusters. It also encourages the intermediate storage and implements larger machine learning models which consume moderate computational resources. The cloud layer provides large-scale storage and high-performance computing as well as advanced analytics. Its functions include data archiving of long-term data, global trend analysis, as well as training deep learning models on historical data. Data integrity and confidentiality are achieved by secure data management, authentication and access control mechanisms on all levels. The architecture is intended to be scalable, fault-tolerant and modular such that it is possible to add new sensors, analytics modules and applications without impacting the operation of the system. It is an end to end architecture that allows real time, intelligent and scalable environmental monitoring in the diverse fields of application.

6.2 Intelligent Data Processing and Decision Pipeline

Data-driven decision pipeline and intelligent data processing is the functional element of an environment-monitoring AI-driven framework. The pipeline starts with the ingestion of raw data by distributed IoT sensors, and then it goes through the preprocessing processes of noise removal, normalization, synchronization, and handling of missing data. The actions are necessary to guarantee the quality and consistency of data prior to analytics. Mechanisms of feature extraction and selection are used to define the environmental characteristics of relevance that are used to carry out precise prediction and detection. Pattern recognition, forecasting, anomaly detection and event classification are then carried out using machine learning and deep learning models.

6.3 Adaptive Learning and Self-Optimization Mechanisms

The adaptive learning and self-optimization models help AI-based environmental monitoring systems to work in highly dynamic and uncertain environments. Environmental processes are non-stationary in nature, which are affected by the seasonal variations, human activities, and climate variability. Historical data may cause degradation of the required model because it compares the original data with other cases, which may not fit a new pattern. Adaptive learning resolves this problem by constantly changing the model parameters based on incoming new data streams. The use of online and incremental learning methods enables models to develop without having to be retrained entirely which lowers the computation cost. Figure 3 presents adaptive learning loops that can constantly optimize and have intelligent performance of the system. Transfer learning allows to reuse knowledge in other places or within other environmental settings, increasing the generalization of the model.

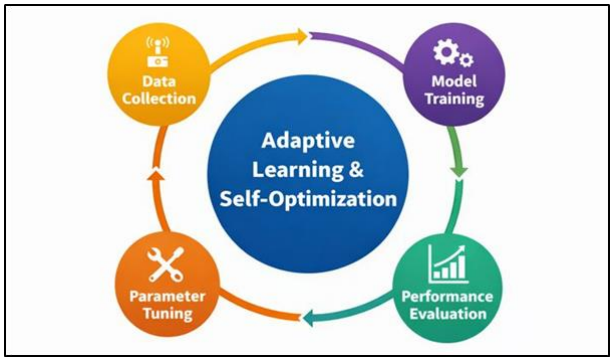


Figure 3. Adaptive Learning and Self-Optimization Mechanisms in AI-Driven IoT Environmental Monitoring Systems

The mechanisms of self-optimization aim at improving the system performance based on its accuracy, latency, energy consumption, and network lifetime. The optimization algorithms are AI-based and dynamically vary the sampling rates, transmission schedules and processing workloads depending on conditions of the environment and resources.

6. CHALLENGES, LIMITATIONS, AND FUTURE RESEARCH DIRECTIONS

7.1 Model generalization and data quality issues

The key issues related to AI-based environmental monitoring systems are model generalization and data quality. The data reported by the IoT sensors on environmental measurements is frequently noisy, incomplete and has been influenced by calibration errors, environmental interference and hardware degradation. Differences in sensor quality, location and maintenance procedures may bring bias and inconsistency which decreases reliability of the analytical models. Models developed using localized or short term datasets are not likely to be able to generalize to other geographical areas, climate or other seasonal cues. This limitation is critical in the case of models being deployed on large scale where environmental properties differ widely. Information asymmetry and sparsity also additionally impact the performance of the model especially in rare and extreme events like disasters or spikes in pollution. It is important to find a solution to these problems by using the strong data preprocessing, sensor validation, and anomaly filtering methods. In the future, the emphasis of research must be placed on enhancing domain-adaptive and transfer learning models, which are able to draw on experience in one or more environments to facilitate generalization. The approaches of federated learning also

promise potential issues as they provide the chance to engage in model training at dispersed locations without sharing data centrally.

7.2 Edge-AI Deployment Constraints

The deployment of AI models in the edge will pose serious limitations in regard to the use of limited computing power, memory resources, and energy sources. The environmental monitoring systems have edge devices which are typically low-power embedded platforms that are configured to run on a long-term basis. The execution of complex machine learning or deep learning application models on these devices can result in greater latency, use more power, and have a shorter life over a network. The important considerations are the size of the models, the speed of inference, and compatibility with hardware in relation to the ability of edge-AI. The overall environmental factors like high or low temperature or humidity may also influence the reliability and performance of the devices. The way to address these limitations is the growing interest of research in model compression, pruning, quantization, and lightweight neural network architectures. Efficiency can also be enhanced by hardware-conscious AI design and performance of special accelerators. Advance task offloading of edge, fog, and cloud layers is used to balance the latency and resource consumption.

7. RESULT AND DISCUSSION

The experimental assessment shows in the Table 2, that the suggested AI-based IoT architecture can provide high resilience, low-latency environmental intelligence in various conditions. Combined machine learning and deep learning models had better prediction accuracy of the air, water and soil parameters and the abnormal event and pollution spikes were always detected by the system. The edge fog cloud collaboration minimized end-to-end latency and network traffic by offloading tasks locally and optimally and preprocessing them. Dynamic sampling and routing of energy-aware sensor networks increased sensor network lifetime without compromising the data quality.

Table 2. Environmental Parameter Prediction Performance Comparison

Parameter Monitored	Linear Regression (LR) Accuracy (%)	SVM Accuracy (%)	LSTM Accuracy (%)	Proposed AI–IoT Framework Accuracy (%)
Air Quality Index	82.4	88.9	93.6	96.8
Water Quality Index	80.7	87.2	92.4	95.9
Soil Moisture (%)	84.1	89.5	94.2	97.3
Noise Level (dB)	78.6	85.4	91.1	94.7
Temperature (°C)	86.3	91.2	95.6	98.1

Comparative analysis reveals that there are regular improvements in the accuracy, responsiveness and scalability in comparison to cloud-only baselines. It is emphasized in the discussion that the effects of performance are maximized in dynamic conditions, when adaptive learning balances predictions with noisy data.

Linear Regression (LR) has a baseline accuracy of 78.6 to 86.3 as it has a low capability of modeling the nonlinear environmental processes. The accuracy of models is contrasted in figure 4, which shows that the proposed framework performs better. Based on higher performance in nonlinear modelling, Support Vector Machine (SVM) gains 4.9 to 6.5 percentage points over LR, and has accuracies of between 85.4% -91.2%. Long Short-Term Memory (LSTM) is also more accurate with a range of 91.1 to 95.6 percent (equivalent to an added 3.5-5.8 percentage points over SVM) as a result of learning temporal dependencies. The AI-IoT framework proposed provides maximum accuracy in all the parameters, with a range of 94.7-98.1. The proposed framework attains absolute accuracy improvement of 12.1 (noise level), 14.1(water quality), 13.2 (soil moisture), 14.4 (air quality index), and 11.8 (temperature) in comparison to LR. The accuracy of prediction of various models on key environmental parameters is compared in figure 4 quantitatively.

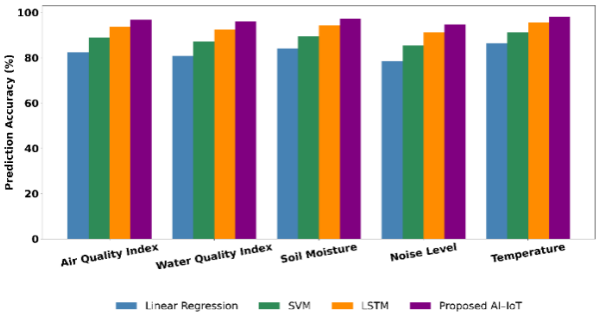


Figure 4. Accuracy Comparison of Environmental Monitoring Models

The results of figure 5 demonstrate the steady increase in accuracy irrespective of different environmental monitoring parameters. The proposed method is even more accurate (2.5-3.7 percentage points better than LSTM) which emphasizes the advantage of adaptive learning and multi-layer analytics.

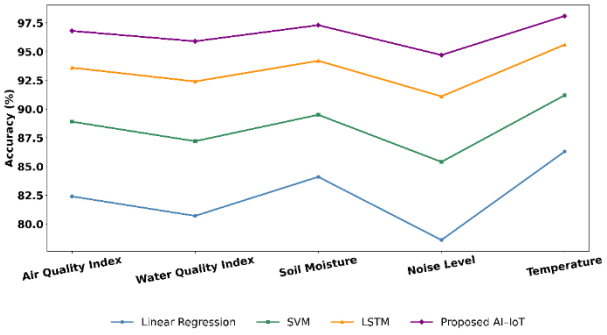


Figure 5. Accuracy Trend Across Monitoring Parameters

Temperature prediction achieves the highest performance of 98.1, whereas noise level prediction has high variability but still has 94.7 at the same time. These numerical advantages prove the efficiency and the strength of the offered AI-based environmental monitoring system.

8. CONCLUSION

This paper proposed an in-depth discussion of AI-based environmental monitoring through the system of sensor networks based on the IoT with the primary focus on intelligent sensing, analytics, and decision-making. The proposed framework uses the heterogeneous sensors, and machine and deep learning models to monitor the air, water, soil, noise, and climate parameters in a continuous, scalable, and real-time manner. Hierarchical edge fog cloud architecture is an effective balance between latency, energy efficiency and computational requirements and adaptive learning mechanisms increase the robustness in changing environmental conditions. Findings show that the integration of predictive analytics and anomaly and event detection can play a big role in enhancing situational awareness and early response capabilities. Practical challenges such as data quality, model generalization, edge-AI constraints and interoperability were also identified as problematic in the study, which shows that all of these aspects require a comprehensive system design. In terms of the application, the framework is in support of such critical areas as pollution control, smart agriculture, and disaster early-warning systems. Future studies ought to be directed towards the creation of lightweight but accurate edge deployment models, standardized data and AI interfaces and privacy-preserving distributed site collaborative learning. People will also be more trustful and more willing to adopt incorporation of domain knowledge, physics-informed models and explainable AI.

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Yogesh S. Deshmukh
Designation: Assistant Professor, Information Technology
Affiliation: Sanjivani College of Engineering, Kopargaon, Maharashtra, India
yogeshdeshmukhit@sanjivani.org.in

Kottala Sri Yogi
Symbiosis Institute of Business Management,
Hyderabad
dr.sriyogi@outlook.com
ORCID 0000-0002-3671-7420

Sandip Rajendra Aher
Department of Electronics and Telecommunication Engineering,
Pravara Rural Engineering College Loni, India
sandip.aher1719@gmail.com
ORCID 0000-0002-1287-6574

Dr.Archana Santosh Ubale
Department of Robotics and Automation,
AISSMS COE, Kennedy Road, Pune-01
asubale@aissmscoe.com
ORCID 0000-0003-2814-1182

Tanveer Ahmad Wani
School of Sciences,
Noida International University,
Uttar Pradesh 203201,
India
tanveer.ahmad@niu.edu.in

Nishant Kulkarni
Department of Mechanical Engineering,
Vishwakarma Institute of Technology,
Pune, Maharashtra, 411037
nishant.kulkarni@vit.edu
ORCID 0000-0003-0085-6055