IoT-Driven Environmental Intelligence for Sustainable Tomorrow Through Advanced Machine Learning: A Systematic Literature Review

R.M.N. Rathnayaka and A. M. A. Sujah

Abstract— In the context of increasing environmental challenges, the integration of Internet of Things (IoT) with machine learning has emerged as a pivotal approach to enhancing environmental monitoring and prediction. This systematic literature review investigates the current state of research on IoT-driven environmental intelligence systems, with a focus on the application of machine learning techniques for real-time data analysis and prediction. To identify the current status of research and existing gaps in this domain, we examined key aspects such as IoT sensor technologies, data transmission protocols, machine learning algorithms, and their implementation in environmental monitoring systems. A search across six electronic databases was conducted for studies published up to 2023. From an initial pool of 200 articles, 48 were chosen for thorough analysis. Our findings revealed that while significant advancements have been made in integrating IoT with machine learning for environmental intelligence, challenges also remain. The findings of this review contribute to a deeper understanding of the technological advancements in this domain and highlight the potential for further research to address existing limitations, thereby enhancing the effectiveness of environmental monitoring systems in promoting sustainability.

Index Terms – **Environmental monitoring, IoT, Machine learning, Predictive analytics, Systematic literature review**

I. Introduction

IN the rapidly evolving technological environment of by today, the implementation of Internet of Things (IoT) and machine learning has emerged as a pivotal approach to developing sophisticated environmental monitoring systems. This need is driven by the growing demand for improved living standards and the necessity of enhancing the quality of life through better environmental management [1].

Intelligent environmental monitoring systems are increasingly recognized for their role in promoting physical and mental well-being, reducing disease prevalence, and positively influencing daily life. However, existing IoT- based systems face significant challenges, particularly in achieving real-time monitoring and accurate predictions. To overcome these obstacles, there is a focus on integrating cloud computing, smart sensors, and advanced machine learning techniques, which together can enable real-time monitoring andpredictive analytics for various environmental parameters [2]. These advancements have enabled the creation of systems capable of continuously collecting and analyzing environmental data in real-time, offering insights that were previously unattainable. The significance of these systems is particularly evident in fields such as climate change monitoring, pollution control, agriculture, and disaster management, where timely and accurate data is crucial for decision-making.

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A critical component of these advanced environmental monitoring systems is the selection and application of machine learning techniques. Among the various approaches explored, Artificial Neural Networks (ANNs) and Random Forest Regression stands out for its effectiveness, offering low error rates and high accuracy in predictions. ANNs are particularly well- suited for detecting patterns and making predictions based on large and noisy datasets, which are common in environmental monitoring. For example, ANNs can be used to model updates or correlations between environmental sensors, enabling more accurate detection of outliers and anomalies [3]. This capability is especially important in applications such as air quality monitoring, where small changes in sensor data can indicate significant environmental shifts. Furthermore, the integration of more sophisticated algorithms is anticipated to enhance the reliability and accuracy of these systems, paving the way for more precise and actionable insights.

The practical applications of IoT, mobile applications, and machine learning in environmental monitoring are already evident in various case studies. For example, the development of an IoT-based temperature monitoring system for underground cable tunnels demonstrates how these technologies can be used to ensure safety and reliability in industrial settings [4]. Similarly, in agriculture, IoT-based systems have been developed to provide real-time, precise measurements of environmental conditions in greenhouses, enabling farmers to make informed decisions that enhance crop yields. In agriculture, IoT devices combined with machine learning algorithms play a critical role in tracking essential factors like soil moisture, temperature, and humidity, which are crucial for optimizing crop yields. These mobile applications enable farmers to receive real- time data, enhancing their ability to make timely decisions that improve farming outcomes. The integration of mobile apps with IoT-based systems enhances their usability by providing

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interactive interfaces for monitoring and controlling environmental factors from virtually anywhere. Such systems can be customized to address specific needs, exemplified by the development of smart agriculture systems that leverage predictive modeling and data fusion techniques to improve farming practices [5].

The application of IoT and machine learning extends across diverse domains, including smart homes, agriculture, industrial environments, and urban air quality monitoring. In smart home settings, these technologies are employed to continuously monitor indoor environmental conditions, directly contributing to the comfort and health of residents. Mobile applications play a crucial role in enhancing the usability and accessibility of these smart monitoring systems. By leveraging mobile technology, users can interact with IoT devices and receive real-time data and alerts, making it easier to monitor environmental conditions on the go. For instance, mobile apps in smart homes allow residents to track indoor environmental conditions continuously, ensuring both comfort and health [6].

Looking ahead, there are numerous opportunities to further improve environmental monitoring systems through technological advancements. For instance, the incorporation of additional sensor technologies, such as soil pH sensors and air quality sensors, could significantly enhance the system's capabilities [7]. Moreover, the potential for integrating real-time image analysis into these systems presents an exciting avenue for improving anomaly detection, particularly in agricultural environments. This could empower farmers with the ability to monitor crop health remotely and receive timely alerts when abnormal conditions are detected, thereby minimizing potential harm [8], [9].

However, the potential of these systems, is not fully realized due to several challenges and limitations that have been identified in the literature. A key issue is the variability in the effectiveness of IoT-driven environmental monitoring systems, which is often attributed to differences in the implementation of technologies across various studies [10]. These differences may include the type of sensors used, the data transmission protocols employed, the specific machine learning models integrated, and the environmental contexts in which the systems are deployed [11]. For instance, while some studies have demonstrated the effectiveness of IoT systems in specific applications such as air quality monitoring or precision agriculture, others have reported inconsistent results. These inconsistencies are often linked to factors such as the quality of the data collected, the appropriateness of the machine learning models applied, and the ability of the system to scale across different environmental conditions. Moreover, the integration of diverse environmental parameters into a cohesive system remains a significant challenge, with many systems still focusing on isolated data points rather than providing a holistic view of the environment [12].

Given these challenges, there is a critical need to conduct a systematic literature review (SLR) that thoroughly examines the current state of research on IoT-driven environmental monitoring systems. Such a review is essential for identifying the existing gaps in the literature, understanding the limitations of current systems, and proposing directions for future research. By focusing on key aspects such as sensor technologies, data transmission methods, machine learning algorithms, and their practical applications, this review aims to provide a comprehensive and up-to-date analysis of the field.

II. Methodology

A. Systematic Literature Review

The mapping study in this research was organized into three key phases: Planning, Conducting, and Reporting. During the Planning phase, electronic databases such as IEEE Xplore, Springer, and the ACM Digital Library were utilized. Also, the research questions were defined, specific search strings were developed for retrieving relevant studies, and the mapping procedure was established.

During the Conducting phase, the defined search terms were applied to the selected databases to identify and select relevant studies. The selected studies were thoroughly reviewed to finalize the mapping study. Additionally, a snowballing technique was employed to discover further related studies through the references of the initially selected papers.

In the Reporting phase, all necessary results were documented, with a focus on prioritizing the retrieved studies and addressing the research questions established during the planning phase. The selected research papers were compiled and presented in a table format, including information such as the title, abstract, keywords, research objectives, research questions, methodology, key findings, potential limitations, and, future perspectives. These findings were compiled into three documents: A systematic literature review (SLR) was conducted, providing a comprehensive overview of research along with an in-depth literature analysis. The SLR document comprised all relevant research articles gathered from multiple databases, while the research overview presented details of the filtered papers. The literature review document provided a comprehensive view of the mapping study.

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B. Research Questions

The foundation of each mapping study is its research questions. Table I presents the specific research questions this study aimed to address. Through the analysis of these questions, a mapping study helps identify gaps in the existing research landscape.

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C. Study Selection

Terms and Search Strings

In this study, the primary search was conducted using search strings across scientific databases, as well as manual keyword browsing. The search strings were structured based on four elements: population, intervention, comparison, and outcome (PICO). The research topics guided this structure, with each element contributing relevant keywords to refine the search strings effectively.

TABLE I
RESEARCH QUESTIONS

No	Research Questions
RQ1	What are the fragmented methods currently used in different environmental monitoring systems be combined to develop a better system than existing systems?
RQ2	What specific functionalities or features should the predictive framework accomplish to improve existing environment monitoring systems?
RQ3	What are the problems or issues that are in the traditional systems to be overcome to implement the introduced system?

TABLE II
SEARCH TERMS OF THE MAPPING STUDY ON
IOT BASED ENVIRONMENTAL INTELLIGENCE THROUGH
ADVANCED MACHINE LEARNING

Area	Search Terms
IoT Environmental Monitoring	"IoT environmental monitoring", "IoT in environmental data collection"
Machine Learning in IoT	"Machine learning for IoT", "IoT machine learning applications", "ML algorithms in IoT systems"
IoT Sensor Technologies	"Sensor technologies in IoT", "Environmental sensors IoT"
Predictive Analytics in IoT	"IoT prediction models", "Real-time analytics in IoT systems"
Search String	"IoT environmental monitoring" OR "IoT in environmental data collection") AND ("Sensor technologies in IoT" OR "Environmental sensors IoT") ("Machine learning for IoT" OR "IoT machine learning applications" OR "ML algorithms in IoT systems") AND ("IoT prediction models" OR "Real-time analytics in IoT systems")

Sources

This Systematic Literature Review was conducted using the following electronic databases, focusing on the most relevant studies.

1) IEEE Xplore
2) Springer Link
3) Science Direct
4) JSTOR
5) ACM Digital Library
6) Academia

Inclusion and Exclusion Criteria

The selection process for this study followed two inclusion criteria and five exclusion criteria. The inclusion criteria are shown in Table III, while Table IV details the exclusion criteria used to filter the results.

Data Extraction and Synthesis

For this study, publications from 2017 to 2023 were evaluated. In the initial retrieval process, a total of 200 publications were gathered, including 50 from IEEE Xplore, 30 from Springer, 20 from JSTOR, 40 from ScienceDirect, 35 from Academia, and 25 from the ACM Digital Library. Next, the selection criteria were applied to the retrieved publications to identify and extract the most relevant studies for further analysis.

The method of selecting process involved five stages, as illustrated in Fig. 1. In the initial stage, the study title, keywords, and abstract were used as the primary selection criteria. The goal of this phase was to identify the most relevant studies and exclude those not aligned with the research topic. As a result, 140 out of 200 publications were eliminated, leaving 60 retained, accounting for approximately 70% of the total publications being excluded.

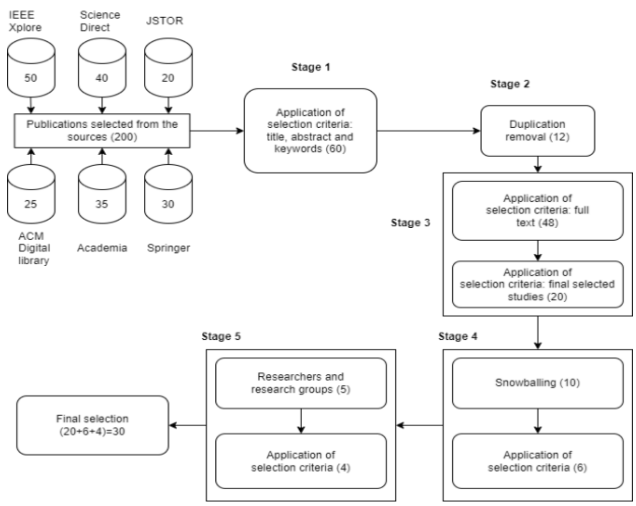

Fig. 1 Selection Process Flow

In the second stage, duplications of studies existing in more than one database were identified, and 12 duplicate publications were removed from the initial set of 60 selected studies. This accounted for approximately 20%.

In the third stage of the selection process, 48 publications were considered for further evaluation. This stage involved a thorough examination of the full texts of these studies to ensure their relevance and completeness. Specific inclusion and exclusion criteria were applied to refine the selection. As a result, 28 studies were excluded from the review. Of these, 11 were eliminated for being published only as abstracts (EC2),

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9 were removed because they were not primary studies but rather editorials or summaries of keynotes and tutorials (EC5), and 8 studies were excluded for not meeting the requirements outlined in Inclusion Criteria 1 (IC1) and Inclusion Criteria 2 (IC2). This rigorous process ensured that only the most relevant and complete studies were retained, leaving a total of 20 publications for the next stage.

In the fourth stage of the selection process, attention shifted to sources outside the initially chosen databases to address the limitations of relying solely on specific databases. The references of the 20 selected publications were reviewed, leading to the discovery of 10 additional studies through the snowballing technique. After applying the selection criteria to these 10 studies, 6 were identified as the most relevant for the research.

In the fifth stage of the selection process, the focus shifted to identifying key researchers and research groups that have made significant contributions to the field. This stage involved a deeper analysis of the works of selected researchers to ensure the inclusion of the most impactful studies. Out of the 5 researchers and research groups initially identified, 4 publications were found to be highly relevant after applying the final set of selection criteria. These publications were added to the pool, making a total of 30 publications that were selected for the final synthesis.

TABLE III
INCLUSION CRITERIA OF THE SELECTION PROCESS

No	Inclusion criteria (IC)
IC1	Studies that focus on the integration of IoT and sensor technology for environmental monitoring, emphasizing efficient data collection and transmission methods
IC2	Research that applies machine learning techniques for developing prediction models and real-time analytics in IoT-driven environmental monitoring systems

TABLE IV
EXCLUSION CRITERIA OF THE SELECTION PROCESS

No	Exclusion criteria (EC)
EC1	The paper lacks an abstract.
EC2	The paper is published only as an abstract.
EC3	The paper is not written in English.
EC4	The paper is an earlier version of an already selected study.
EC5	The paper is not a primary study, but an editorial or a summary of keynotes/tutorials.

III. RESULTS AND DISCUSSION

This section provides a comprehensive analysis of IoT driven smart environmental monitoring systems, focusing on their integration with advanced machine learning techniques. The reviewed literature highlights the various applications of these technologies across multiple domains, including smart homes, agriculture, urban air quality, and industrial environments [1], [13], [14]. This review highlights not only how these technologies have been applied to improve the accuracy and reliability of environmental predictions, but also the key findings and discuss their implications, challenges, and potential future directions for research and implementation.

The integration of the Internet of Things (IoT) with smart sensory techniques has been identified as a significant advancement in environmental monitoring, offering enhanced capabilities across various applications. In agriculture, IoT-based systems have led to significant improvements in crop yield predictions by providing real- time monitoring of environmental conditions [15], [16]. In urban environments, these technologies are used to monitor air quality, offering valuable data for public health and urban planning. In disaster management, IoT and machine learning have enabled the development of early warning systems that predict natural disasters such as floods and landslides, allowing for timely interventions that can save lives. Moreover, the literature reveals that IoT-based systems are being increasingly utilized in agriculture to monitor and optimize crop conditions [17]. By integrating smart sensors and IoT devices in agricultural settings, farmers can continuously gather and analyze data, leading to more informed decision-making. This method has demonstrated improvements in crop productivity and has contributed to reducing the use of resources, especially water and fertilizers. The use of edge computing and cloud- based data analytics further facilitates global access to critical agricultural data, promoting sustainable farming practices. The literature also highlights the use of IoT in monitoring noise pollution, coastal erosion, and energy consumption, demonstrating the versatility and scalability of these technologies across different environmental domains [18].

In smart agriculture, IoT devices paired with machine learning algorithms, such as Random Forest Regression and Artificial Neural Networks (ANNs), have demonstrated a marked improvement in predicting crop yields by monitoring essential environmental factors like soil moisture, temperature, and humidity. These systems enable real-time data collection and predictive analysis, empowering farmers to optimize their practices for better outcomes [19], [20]. The ability of these technologies to provide actionable insights based on real-time data represents a notable advancement in agricultural practices. In the context of urban environments, the integration of IoT with data fusion and machine learning techniques has advanced the capabilities of air quality monitoring systems. These systems can now provide real-data These systems can now provide real- time data on air pollution levels, predict future air quality trends, and offer actionable insights for mitigating pollution. Also, air quality monitoring has similarly benefited from the integration of IoT and machine learning [21]. The use of IoT sensors combined with machine learning models has allowed for more precise detection of pollution levels, offering critical data that informs urban planning and public health strategies. The capability to predict future air quality based on current data is particularly valuable, as it al- lows for proactive measures to mitigate pollution-related risks. Moreover, the application of sophisticated machine learning algorithms has proven

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effective in managing the large, noisy datasets typical of environmental monitoring [22], [23].

TABLE V
FEATURE EXTRACTION AND SYSTEM RESULTS ACROSS STUDIES

Paper ID	Title	System Type	Key Features	Results	Limitations
1	"An indoor environment monitoring system using low-cost sensor network"	Indoor Environment Monitoring	Low-cost sensors, Arduino based Indoor monitoring	Improved HVAC control with temp accuracy within 0.5°C	Initial temp errors, Sensor placement issues
2	"An IoT-based greenhouse monitoring system with Micaz motes"	IoT-based Greenhouse Monitoring	WSN with MicaZ nodes, IoT for greenhouse	Real-time monitoring and IoT data access	One-way communication, No automated control
3	"Monitoring Manufacturing Environment using WSN and IoT"	Manufacturing Environment Monitoring	WSN & IoT Energy/resource efficiency in manufacturing	Effective temp monitoring in scalable framework	Limited to small office and Data security concerns
4	"Comparative analysis of ML techniques for predicting air quality"	Air Quality Prediction in Smart Cities	ML comparison; Apache Spark; IoT in smart cities	Random Forest best accuracy. Decision Tree fastest	Limited to 5 cities and poor peak detection by Gradient Boosting
5	"Smart Agriculture using IoT and MQTT Protocol"	Smart Agriculture	IoT with MQTT based automated irrigation, IBM Watson cloud	Successful automation, Global data access	Prototype limitations, Needs scalability
6	"An IoT-based Temperature Monitoring System for Underground Cable Tunnels"	Underground Cable Temperature Monitoring	IoT for underground cables	Stable real-time monitoring in tunnels	High power consumption, Physical constraints
7	"IoT Mobile - Air Pollution Monitoring System (IoT-Mobair)"	Air Pollution Monitoring	Mobile IoT for air pollution, ML for AQI prediction	Effective real-time monitoring and pollution prediction	Big data processing complexity, Fog computing potential
8	"Development of ML-based Predictive Models for Air Quality Monitoring"	Air Quality Monitoring and Characterization	Machine learning models integrated gas sensors-based monitoring	Artificial Neural network 99.56% accuracy, Effective air quality characterization	Slower in large scale, Limited testing conditions
9	"Smart Agriculture System Based on Deep Learning"	Smart Agriculture	IoT & CNNs, AlexNet for farming	Accurate crop/pest monitoring	Challenges with field data, Dependent on good training data
10	"Big Data Analytics, ML&AI for Precision Agriculture"	Precision Agriculture and Smart Farming	Big data, ML, AI for smart farming,	Enhanced decision-making in agriculture	Data security issues and High investment needed
11	"A Mobile Greenhouse Environment Monitoring System"	IoT-based Mobile Greenhouse Monitoring	Raspberry Pi & Arduino, Mobile greenhouse monitoring	Effective multi-point monitoring	Scalability and maintenance potential challenges
12	"Air Quality System Using IoT for Indoor Environmental Monitoring"	IoT-based Indoor Air Quality Monitoring	IoT for indoor air quality, Predictive model	Accurate monitoring, Early warnings provided	Sensor accuracy and data processing issues
13	"A Novel Framework for Smart Crop Monitoring Using IoT"	Smart Crop Monitoring	IoT framework, Solar-powered sensors and cloud integration	Improved crop yield with real-time monitoring	Sensor integration complexity, High initial cost
14	"Intelligent Environment Monitoring System for Industrial Safety"	Environmental Monitoring	PSoC with ZigBee/GPRS, Industrial monitoring	Real-time data transmission and early warning alerts	High error rate in humidity, Wireless transmission latency
15	"IoT based Smart Agricultural System"	IoT-based Smart Agricultural System	Solar-powered Agrobot, Raspberry Pi & Arduino	89.55% cutting efficiency and Real-time monitoring	Scalability challenges in larger environments
16	"Using Machine Learning for Outlier Detection in Environmental Monitoring"	ML-based Environmental Monitoring	ANN for outlier detection, Aquatic monitoring	Improved outlier detection accuracy	Model training complexity, Need for labeled data
17	"Intelligent Monitoring System of Residential Environment"	Cloud Computing and IoT-based Residential Monitoring	Cloud & IoT for residential monitoring, Fuzzy algorithm	Effective monitoring and enhanced comfort/safety	Cloud-IoT integration complexity and internet dependency

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18	"Design and Implementation of Anomaly Condition Detection in Agriculture"	IoT-based Agricultural Anomaly Detection	LoRaWAN & MQTT, Anomaly detection in farming	Real-time anomaly detection, Better farm management	Precise thresholds needed, ML & image analysis improvements
19	"Prospects of Distributed Wireless Sensor Networks for Urban Environmental Monitoring"	Wireless Sensor Network based Environment Monitoring	Miniaturized sensors, energy harvesting, data fusion, fixed and mobile sensor nodes.	Adoption of UAVs for environmental monitoring, static and mobile sensors integrated successfully.	High operational costs and challenges in data fusion from heterogeneous sources.
20	"ZigBee-Based Remote Environmental Monitoring for Smart Industrial Mining"	Wireless Sensor Network (ZigBee-based)	ZigBee-based WSN system for temperature and fire monitoring in underground mines.	Real-time monitoring of temperature and fire detection in mines.	Challenges with network performance in complex environments,
21	"Novel Soil Environment Monitoring System Based on RFID Sensor and LoRa"	RFID and LoRa-based Soil Monitoring	RFID and LoRa sensors for soil temperature, humidity, sensing.	Successfully monitored soil temperature and moisture with relative error of 1.5%	Communication range limited to 1.3 meters. System is sensitive to soil moisture levels, requiring adjustments
22	"Intelligent Environment Monitoring System Based on Innovative Integration Technology via PSoC"	ZigBee-based Intelligent Monitoring System	PSoC platform integrated with ZigBee, TCP/IP, GPRS/SMS for smart grid and bridge monitoring.	High accuracy in temperature monitoring and fast warning for bridge inclination.	High error rate for humidity monitoring, short-range ZigBee communication may limit scalability for larger environments.
23	"IoT-Equipped and AI-Enabled Next Generation Smart Agriculture: A Critical Review"	IoT and AI-based Smart Agriculture	IoT and AI integration for soil, temperature, humidity monitoring, UAVs for imaging, and smart irrigation.	IoT and AI significantly increased crop yield, reduced water usage, and minimized pesticide use.	High implementation and maintenance costs. AI model training complexity and interoperability challenges between IoT platforms.
24	"Using Machine Learning for Dependable Outlier Detection in Environmental Monitoring Systems"	Machine Learning and Sensor Networks based Environmental Monitoring and Detection System	ANN for outlier detection in aquatic monitoring, improving data quality and sensor behavior modeling.	Improved outlier detection accuracy using ANN, Performed better than PCA and SVM techniques.	Performance depends on historical data availability for model training.
25	"Analysis of Three IoT-Based Wireless Sensors for Environmental Monitoring"	IoT-based Wireless Sensor Monitoring	Three IoT sensors using UDP, HTTP, and Bluetooth for environmental monitoring.	UDP sensor was most power-efficient but had higher packet loss.	Higher packet loss in UDP-based sensors (3.29%). HTTP-based sensors had high power consumption
26	"A Real-time Underground Environment Monitoring System for Sustainable Tourism of Caves"	Real-time Environmental Monitoring System for Caves	Real-time environmental monitoring system for cave ecosystems	Real-time monitoring of cave visitor impact on the microclimate.	Accurate sensor placement is difficult in cave environments,
27	"Internet of Things in Marine Environment Monitoring: A Review"	IoT-based Marine Environment Monitoring	IoT-based sensors and WSNs for monitoring marine environments	IoT enhanced real-time marine environment monitoring with improved data collection and control.	Energy inefficiency and high maintenance costs for remote deployments.
28	"Advances in Smart Environment Monitoring Systems Using IoT and Sensors"	IoT and Sensor-based SEM System	Machine learning, smart sensors, and the Internet of Things are used to monitor radiation, water, and air pollution.	SEM systems improved real-time data collection and analysis of air, water, and radiation pollution.	High computational complexity for big data processing, Interoperability issues
29	"Towards a Smart City: Development and Application of an Improved Integrated Environmental Monitoring System"	Integrated Environmental Monitoring System	Portable integrated environmental monitoring system for urban environments, measuring nine environmental parameters.	Detected significant environmental changes after a typhoon. Used nine parameters to monitor urban environmental impacts.	Calibration issues in the field, limited battery life (6–8 hours), and scaling costs. SO2 detection was limited during tests.
30	"Investigation on Environment Monitoring System for a Combination of Hydroponics and Aquaculture in Greenhouse"	IoT-based Hydroponics and Aquaculture Monitoring System	IoT-based hydroponics and aquaculture monitoring system using multiple sensors, LoRa, and 4G for data transmission.	High stability and accurate data transmission in a greenhouse. Showed correlation between indoor and outdoor temperatures.	Limited range and signal strength of LoRa in dense environments.

ML = Machine Learning, IoT = Internet of Things, WSN = Wireless Sensor Network, AI = Artificial Intelligence, ANN = Artificial Neural Network, CNN = Convolutional Neural Network, PSoC = Programmable System on Chip, GPRS = General Packet Radio Service, LoRaWAN = Long Range Wide Area Network, HVAC = Heating, Ventilation, and Air Conditioning, UAV = Unmanned Aerial Vehicle, LoRa = Long Range, TCP/IP = Transmission Control Protocol/Internet Protocol, PCA = Principal Component Analysis, SVM = Support Vector Machine, UDP = User Datagram Protocol, HTTP = Hypertext Transfer Protocol, CO2 = Carbon Dioxide, SO2 = Sulfur Dioxide.

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When comparing different machine learning models, Random Forest Regression and Artificial Neural Network stands out for its superior performance in terms of accuracy and less error rates. These models have shown a strong ability to identify data peaks and forecast outcomes accurately and show great performance, particularly in applications that require the analysis of large datasets. In contrast, Decision Tree Regression, while faster, has demonstrated higher error rates, especially in complex scenarios [24], [25].

Moreover, despite advancements in IoT-driven smart environmental monitoring systems, several challenges continue to hinder their widespread adoption. A primary issue is the computational complexity of processing large volumes of sensor data in real-time, where further optimization of fog computing and big data analytics is needed [26], [27]. Also, current systems often focus on isolated environmental parameters, limiting comprehensive assessments. While cloud computing and data fusion have improved real-time data collection and analysis, gaps remain in creating integrated monitoring frameworks that combine multiple parameters. Efficient data processing techniques are essential for supporting large-scale deployments without compromising accuracy. Addressing these challenges is crucial for the successful and scalable deployment of IoT- driven environmental monitoring systems [28], [29], [30].

V. Conclusion

This paper enhances the field of IoT-driven environmental intelligence by integrating advanced machine learning techniques, offering valuable insights into current research. The combination of IoT and machine learning has demonstrated significant benefits across various applications, including agriculture, urban air quality monitoring, environmental surveillance, and disaster management etc. These technologies improve real-time data collection, predictive analytics, and decision-making, ultimately promoting more sustainable environmental practices. However, the review highlights critical challenges, such as the computational complexity involved in processing large datasets in real-time and the need for more integrated systems that combine multiple environmental parameters. Despite technological advancements, the potential of IoT- driven systems remains underutilized due to issues like data interoperability and scalability. Future research should focus on addressing these gaps by developing more comprehensive and scalable systems that enhance the ability to monitor and predict environmental conditions effectively. Overall, while substantial progress has been made in IoT-driven environmental intelligence, significant opportunities for improvement still exist, particularly in fostering systems that can seamlessly integrate and analyze diverse environmental data for better decision-making and sustainability outcomes.

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