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AI and RF-Based Water Quality Monitoring Systems for Rural and Urban Nigeria

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ABSTRACT

This paper investigates the use of Artificial Intelligence (AI) and Radio Frequency (RF)-based sensor systems to monitor water quality in rural and urban Nigeria. Nigeria suffers serious water quality issues as a result of insufficient facilities, pollution, and limited real-time monitoring capacity. Conventional water monitoring methods are frequently manual, time-consuming, and ineffective. Recent advances in RF sensor networks and AI-driven analytics present intriguing options for continuous, real-time water quality monitoring and prediction. This paper examines the existing technologies, communication protocols, sensor types, and AI models used in water monitoring systems. It assesses their performance, applicability, and limitations in the Nigerian setting. The combination of RF sensing technology with machine learning models improves anomaly identification, pollutant tracking, and decision-making processes. Obstacles such as infrastructural gaps, expensive deployment costs, and a lack of technical competence impede large-scale implementation. The paper highlights research gaps and makes recommendations for the scalable and sustainable implementation of smart water surveillance systems in Nigeria.

INTRODUCTION

Access to safe and clean water is a major issue in Nigeria, affecting both urban and rural populations. Despite the country's abundant water resources, pollution, poor infrastructure, and insufficient monitoring systems have severely hampered water quality and accessibility. Rapid urbanization, industrial discharge, agricultural runoff, and poor waste management all contribute to water contamination, which poses major health hazards such as cholera and typhoid (UNICEF, 2023; Khan *et al.,* 2025). The problem is considerably more serious in rural areas, where there are no centralized water treatment facilities and limited access to contemporary monitoring equipment. As a result, providing constant and consistent water quality monitoring has become a top concern for sustainable development. Conventional water quality monitoring methods in Nigeria rely mainly on manual sampling and laboratory analysis. While these procedures produce reliable findings, they are frequently time-consuming, labor-intensive, and incapable of providing the real-time information required for quick decision-making (Adewumi *et al.,* 2022). The absence of continuous monitoring results in delayed discovery of contamination incidents, increasing the danger of major public health problems. Furthermore, the high cost of laboratory testing and the scarcity of experienced workers limit the efficacy of traditional monitoring methods. Recent advances in smart technologies, particularly the combination of Radio Frequency (RF) sensor networks with Artificial Intelligence (AI), present intriguing solutions to these problems. RF-based sensor networks allow for the deployment of dispersed sensing devices that can measure critical water quality parameters like pH, turbidity, temperature, dissolved oxygen, and conductivity. These sensors interact wirelessly via ZigBee, LoRa, GSM, and NB-IoT, allowing for real-time data capture and transmission across large geographic areas (Raza *et al.,* 2022; Akanbi *et al.,* 2025). These features make RF sensor networks ideal for monitoring water systems in both densely populated urban areas and isolated rural settlements. Artificial intelligence improves the effectiveness of these systems by allowing intelligent data analysis and predictive modeling. Machine learning and deep learning algorithms, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest, and Long Short-Term Memory (LSTM) networks, can process massive amounts of sensor data to identify patterns, detect anomalies, and forecast future water quality trends (Chen *et al.,* 2023). These skills facilitate proactive decision-making, allowing authorities to respond rapidly to pollution situations and improve water resource management. In Nigeria, however, the implementation of AI and RF-based water monitoring systems is still in its early stages. Inadequate communication infrastructure, inconsistent power supply, expensive implementation costs, and a

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lack of technical competence all impede large-scale deployment. Furthermore, there is a scarcity of localized research and datasets adapted to Nigeria's environmental characteristics, which affects AI model performance (Li *et al.,* 2023; Agbailu *et al.,* 2025).This review will provide a complete examination of AI and RF-based water quality monitoring systems, with a focus on their application in both rural and urban Nigeria. It looks at present technologies, identifies implementation obstacles, indicates research needs, and suggests future approaches for building efficient, scalable, and intelligent water monitoring solutions. Figure 1 illustrates the structure of the AI and RF-Based water quality monitoring system.

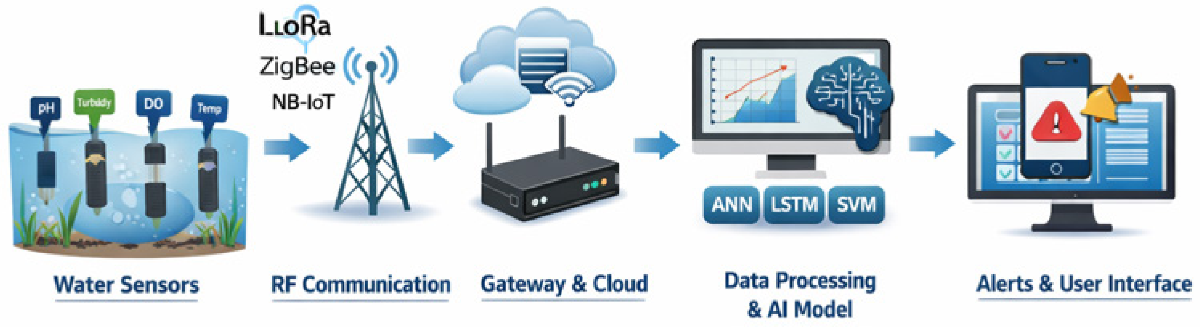

Figure 1: AI and RF-Based Water Quality Monitoring System Structure

LITERATURE REVIEW

Recent research has investigated the combination of IoT, RF communication, and AI for water quality monitoring. RF technologies such as ZigBee, LoRa, and NB-IoT are frequently utilized for transferring sensor data due to their low power consumption and wide coverage (Raza *et al.,* 2022). AI-based models have been used for anomaly detection, categorization, and prediction of water quality. When dealing with complicated environmental datasets, deep learning models like LSTM and Convolutional Neural Networks (CNN) perform better than conventional statistical techniques (Li *et al.,* 2023). Table 1 presents a notable AI and RF water quality monitoring system.

Table 1: Notable AI and RF-Based Water Monitoring Systems

S/N	Study	RF Technology	AI Model	Application	Findings
1	Chen *et al.* (2023)	LoRa	LSTM	River monitoring	High prediction accuracy
2	Raza *et al.* (2022)	NB-IoT	SVM	Urban water systems	Reliable communication
3	Li *et al.* (2023)	ZigBee	ANN	Drinking water monitoring	Improved anomaly detection
4	Adewumi *et al.* (2022)	GSM	Random Forest	Rural water supply	Cost-effective solution

Water Quality Monitoring System in Nigeria

Nigeria primarily relies on traditional, centralized methods for monitoring water quality, which are frequently inadequate to handle the nation's expanding water problems. Regulatory organizations, including the Federal Ministry of Water Resources, state water agencies, and environmental protection authorities, usually conduct monitoring operations. To assess water quality indicators such as pH, turbidity, dissolved oxygen, and microbiological content, these institutions mostly rely on routine field sampling and laboratory-based analysis (Okoye & Odoh, 2022). These techniques yield accurate and dependable readings, but they are expensive, time-consuming, and unable to offer the real-time monitoring data required for timely decision-making. Water quality monitoring methods are either nonexistent or inadequately established in rural locations. Without regular quality evaluation, the majority of rural people rely on untreated sources, including rivers, streams, and boreholes. Residents are exposed to tainted water as a result, and waterborne illnesses like cholera, diarrhea, and typhoid fever become more common (World Health Organization [WHO], 2023). On the other hand, because of municipal water supply networks, metropolitan regions have comparatively more organized monitoring systems. These systems still have a lot of problems, though, such as outdated infrastructure, erratic monitoring schedules, and a low uptake of contemporary technologies (Adelodun *et al.,* 2022). In recent years, there have been initiatives to implement digital and automated water monitoring solutions in Nigeria. Some research initiatives and pilot projects have looked into the use of sensor-based and Internet of Things (IoT) technology for real-time data collection and remote monitoring. These technologies outperform existing methods in terms of efficiency and constant monitoring (Olatinwo *et al.,* 2023). However, their adoption is limited because of issues such as inconsistent power supply, inadequate communication infrastructure, and exorbitant deployment costs. Another important issue is the absence of integrated and centralised data management solutions. Water quality data is frequently dispersed across multiple agencies, resulting in inefficiencies in data sharing, analysis, and policy development. The lack of real-time monitoring systems and predictive analytics tools further hinders authorities' ability to detect pollution occurrences early and respond effectively (Ezeh *et al.,* 2024). Different water quality monitoring systems in Nigeria are presented in Table 2.

Table 2: Different Water Quality Monitoring Systems in Nigeria

S/N	System Type	Description	Advantages	Limitations	Source
1	Manual Sampling	Periodic field collection and lab analysis	Accurate results	Time-consuming, no real-time monitoring	Okoye & Odoh (2022)
2	Laboratory Testing	Centralized chemical and biological analysis	Detailed and reliable data	Expensive, requires expertise	Adelodun *et al.* (2022)
3	Government Monitoring	Regulatory monitoring by agencies	Policy enforcement	Limited coverage and inconsistency	WHO (2023)
4	IoT-Based Pilot Systems	Sensor-based remote monitoring	Real-time data collection	Limited deployment	Olatinwo *et al.* (2023)
5	Community-Based Monitoring	Local/manual water checks	Low cost	Low accuracy and reliability	Ezeh *et al.* (2024)

Advancement of the Water Quality Monitoring System

Water quality monitoring systems have advanced significantly in recent years, thanks to the incorporation of digital technologies such as the Internet of Things (IoT), wireless sensor networks (WSNs), and artificial intelligence (AI). These advancements have changed traditional water monitoring methods into sophisticated, automated, and real-time systems capable of solving today's environmental concerns. Compared to traditional procedures that rely on manual sampling and laboratory analysis, sophisticated systems allow continuous monitoring and instant data access, improving efficiency and decision-making (Kumar *et al.,* 2022). One of the most significant breakthroughs has been the implementation of wireless sensor networks employing RF communication technologies such as ZigBee, LoRa, and NB-IoT. These technologies offer distributed sensing over broad geographic areas, providing real-time monitoring of water quality indicators such as pH, turbidity, temperature, conductivity, and dissolved oxygen. Low-power wide-area networks (LPWANs), particularly LoRa and NB-IoT, are ideal for remote and rural areas because of their long-range connectivity and energy efficiency (Almalki *et al.,* 2023). Another significant advancement is the combination of cloud computing and edge computing in water monitoring systems. Cloud platforms make it easier to store, process, and visualize vast amounts of data, whereas edge computing allows for real-time data analysis at the sensor level, lowering latency and bandwidth. These technologies enhance system responsiveness and scalability, making them ideal for smart city and rural water applications (Singh *et al.,* 2024). Artificial intelligence has advanced water quality monitoring by allowing for predictive analytics, anomaly identification, and automated decision-making. Artificial Neural Networks (ANN), Support Vector Machines (SVM), and deep learning models such as Long Short-Term Memory (LSTM) have all shown great accuracy in forecasting water contamination and detecting pollution sources. These models may examine complex and nonlinear correlations in water quality data, which improves monitoring accuracy and dependability (Zhang *et al.,* 2023). Furthermore, the introduction of smart sensors and biosensors has increased the accuracy and sensitivity of water quality tests. These sensors detect chemical, biological, and physical contaminants at extremely low concentrations, allowing for early identification of pollution events. Integration with mobile applications and dashboards enables stakeholders to view real-time data and receive alerts remotely (Patel *et al.,* 2022). Despite these developments, high implementation costs, limited infrastructure, and data security concerns continue to be significant impediments, particularly in poor nations such as Nigeria. Nonetheless, ongoing research and technical innovation are expected to accelerate the implementation of intelligent water monitoring systems. Table 3 presents advanced water quality monitoring systems.

Table 3: Advanced Water Quality Monitoring System

S/N	Technology	Description	Advantages	Limitations	Source
1	IoT-Based Monitoring	Sensor networks for real-time data collection	Continuous monitoring	Requires internet connectivity	Kumar *et al.* (2022)
2	RF Communication (LoRa, NB-IoT)	Wireless long-range communication	Low power, wide coverage	Signal interference	Almalki *et al.* (2023)
3	Cloud Computing	Centralized data storage and processing	Scalable and accessible	Data security concerns	Singh *et al.* (2024)

4	Edge Computing	Local data processing at sensor nodes	Low latency, fast response	Limited processing power	Singh *et al.* (2024)
5	AI & Machine Learning	Predictive modeling and anomaly detection	High accuracy	Requires large datasets	Zhang *et al.* (2023)
6	Smart Sensors/ Biosensors	Advanced sensing technologies	High sensitivity	High cost	Patel *et al.* (2022)

Sensors and AI models used in water Quality monitoring

Water quality monitoring systems (WQMS) rely significantly on modern sensing technology and Artificial Intelligence (AI) models to provide precise, real-time assessments of water conditions. Sensors are the key data-collecting components, with AI models processing and analyzing the collected data to aid in intelligent decision-making. The combination of these technologies has greatly increased the efficiency, precision, and responsiveness of current water monitoring systems. A variety of sensors are employed to measure crucial water quality characteristics. Physical sensors, such as temperature and turbidity sensors, offer environmental data, whereas chemical sensors detect pH, dissolved oxygen (DO), conductivity, and total dissolved solids. Furthermore, biological sensors and biosensors are being utilized to detect microbial pollution and dangerous diseases in water bodies (Sharma *et al.,* 2022). These sensors are frequently integrated into wireless sensor networks that communicate using radio frequency (RF) technology, allowing for real-time monitoring over large and remote locations. Sensors and AI models used for water quality monitoring are presented in Table 4.

Table 4: Sensors and AI Models used for Water Quality Monitoring

S/N	Category	Type	Application	Advantages	Limitations	Source
1	Sensor	pH Sensor	Acidity/alkalinity detection	High accuracy	Requires calibration	Sharma *et al.* (2022)
2	Sensor	Turbidity Sensor	Water clarity measurement	Real-time monitoring	Sensitive to noise	Verma & Gupta (2023)
3	Sensor	DO Sensor	Oxygen level detection	Essential for aquatic life	Expensive	Sharma *et al.* (2022)
4	Sensor	Biosensor	Pathogen detection	High sensitivity	High cost	Verma & Gupta (2023)
5	AI Model	ANN	Water quality prediction	Handles nonlinear data	Requires training data	Rahman *et al.* (2024)
6	AI Model	SVM	Classification	High accuracy	Computationally intensive	Khan *et al.* (2023)
7	AI Model	Random Forest	Pollution detection	Robust and reliable	Complex tuning	Khan *et al.* (2023)
8	AI Model	LSTM	Time-series prediction	Captures temporal patterns	High computational cost	Rahman *et al.* (2024)

Recent improvements have also resulted in the development of smart and miniaturized sensors with great sensitivity, reduced power consumption, and increased durability. Optical sensors, electrochemical sensors, and nanotechnology-based sensors have improved the accuracy of water quality assessments, allowing for early detection of contaminants even at low concentrations (Verma & Gupta, 2023). These advancements are especially significant in developing nations like Nigeria, where cost-effective and dependable monitoring methods are needed. Artificial intelligence models serve an important role in analyzing sensor data and producing actionable information. Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees are common categorization and prediction techniques used in water quality monitoring. Deep learning methods, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, are very useful for assessing time-series data and detecting complicated patterns in water quality variations (Rahman *et al.,* 2024). AI models can forecast pollution episodes, detect anomalies, and improve water management practices. For example, LSTM models are extremely good at forecasting temporal changes in water quality, but Random Forest models are widely employed for categorization and pollution detection. These models greatly reduce human intervention while increasing the reliability of monitoring systems (Khan *et al.,* 2023). Despite these advances, problems such as data scarcity, sensor calibration concerns, and high computing demands persist. However, more research and technical advancements are projected to improve the integration of sensors and AI models for efficient and long-lasting water quality monitoring systems.

Integration of RF Sensing Technologies with Machine Learning Models in WQMS

The integration of radio frequency (RF) sensor technology and machine learning (ML) models has considerably increased the efficiency and intelligence of modern water quality monitoring systems. RF sensing technologies allow for real-time data collection via wireless connection, whereas machine learning algorithms provide superior analytical skills for analyzing complicated environmental datasets. This collaboration allows for accurate prediction, anomaly detection, and automated decision-making in water resource management. RF sensing systems use wireless communication protocols like ZigBee, LoRa, and NB-IoT to communicate data collected from distributed sensors that monitor factors such as pH, turbidity, temperature, and dissolved oxygen. These technologies include features such as low power consumption, long-range communication, and scalability, making them appropriate for use in both rural and urban settings (Iqbal *et al.,* 2023). Real-time data acquired by RF networks feeds machine learning algorithms, allowing for continuous system monitoring and response. RF sensor networks generate vast amounts of data, which are analyzed using machine learning models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest, and Long Short-Term Memory (LSTM). These models find hidden patterns, forecast water quality trends, and detect anomalies such as sudden pollution occurrences (Nguyen *et al.,* 2024). Deep learning models, particularly LSTM, are extremely useful for time-series research because they can capture temporal relationships in environmental data. The integration process normally consists of several stages, including data collecting, wireless transfer, preprocessing, feature extraction, and predictive modeling. This layered architecture boosts system accuracy, decreases manual involvement, and improves real-time decision-making capabilities. Furthermore, it allows for proactive water management measures like early warning systems and pollution mitigation (Torres *et al.,* 2022). Despite these advantages, issues including data dependability, communication interference, and processing complexity persist. However, continuous advances in RF communication and AI technologies are projected to boost system performance and scalability. Table 5 presents sensing technologies with machine learning models.

Table 5: RF Sensing Technologies with Machine Learning Models

S/N	RF Technology	ML Model	Application	Benefits	Limitations	Source
1	ZigBee	ANN	Water quality prediction	Low power consumption	Limited range	Iqbal *et al.* (2023)
2	LoRa	LSTM	Time-series forecasting	Long-range communication	Low data rate	Nguyen *et al.* (2024)
3	NB-IoT	SVM	Contamination detection	Wide coverage	Network dependency	Torres *et al.* (2022)
4	GSM	Random Forest	Pollution classification	Reliable communication	High power usage	Iqbal *et al.* (2023)

Implementation Challenges of the Water Quality Monitoring System in Nigeria

The implementation of water quality monitoring systems in Nigeria faces various problems that impede their effectiveness and widespread deployment. One of the most pressing challenges is inadequate infrastructure, particularly in rural and neglected communities. Many areas lack stable electrical and communication networks, which are required to run modern monitoring technologies like IoT-based and RF-enabled systems. This constraint limits the use of real-time monitoring technologies and lowers system reliability (Omeka *et al.,* 2024). Another key difficulty is the high cost of adoption and ongoing maintenance. Advanced water monitoring systems necessitate the purchase of sensors, communication modules, and data processing platforms, all of which are costly. In a resource-constrained economy like Nigeria, insufficient funding from government agencies and private players inhibits technology adoption (Osifeko *et al.,* 2024). Data management and availability are also major challenges. Water quality data in Nigeria is frequently fragmented, inconsistent, or unavailable, making it challenging to create reliable predictive models and monitoring systems. The rising complexity of water contamination caused by industrialization hampers data collection and processing (Omeka *et al.,* 2024). Regulatory and institutional barriers to implementation exacerbate the situation. Poor monitoring procedures and noncompliance with water quality requirements are the result of weak enforcement of environmental legislation and a lack of agency collaboration. Pollution control measures are often not enforced properly, decreasing the efficiency of monitoring systems (Ighalo & Adeniyi, 2020). Furthermore, there is a lack of technical talent needed to build, deploy, and operate modern monitoring systems. Skilled workers are scarce in sensor technologies, data analytics, and artificial intelligence, which has an impact on system sustainability.

Gaps in the Water Quality Monitoring System in Nigeria

There are significant inadequacies in Nigeria's water quality monitoring systems, which limit their efficiency and sustainability. One important gap is the lack of real-time monitoring infrastructure, as most systems still rely on manual sampling and periodic laboratory analysis, which slows contamination detection (Egbinola & Amanambu, 2021). Another major issue is a lack of comprehensive and reliable datasets adapted to local environmental circumstances, which limits the creation of accurate predictive models and data-driven decision-making (Onoja *et al.,* 2023). There is also a lack of integration of new technologies, such as radio frequency sensor networks and artificial intelligence, resulting in fragmented and ineffective monitoring frameworks. Furthermore, discrepancies in monitoring procedures between regions are caused by poor policy implementation and regulatory enforcement (Akoteyon, 2022). Furthermore, insufficient investment in research, infrastructure, and capacity development has hindered innovation and large-scale adoption. Addressing these deficiencies is critical for Nigeria's development of a reliable, sophisticated, and long-term water quality monitoring system.

MATERIALS AND METHODS

This paper uses a systematic review approach to examine the available literature on artificial intelligence and radio frequency-based water monitoring systems. The methodology includes: The methodology flow chart is shown in Figure 2.

The System Architecture Design

System architecture design involves developing a unified framework that incorporates sensing, communication, data processing, and application layers to ensure efficient system functioning. The sensing layer measures ambient characteristics, while the communication layer uses RF technology to ensure flawless data flow. The application layer provides visualization and control interfaces, while the processing layer handles data storage and analytics. This layered design improves scalability, interoperability, and real-time monitoring capabilities, allowing for integration with cloud and edge computing platforms for intelligent water management (Gubbi *et al.,* 2013)

Data Acquisition Using RF Sensor Network

Data is collected via RF-enabled sensors, which continuously monitor water quality parameters such as pH, turbidity, temperature, and dissolved oxygen. These sensors are installed at various water sources to capture real-time environmental data. RF sensing offers automated and distant data collection, which reduces dependency on manual sample methods. This method increases monitoring frequency, improves data accuracy, and enables early detection of pollution events in water systems (Akyildiz *et al.,* 2002).

Data Transmission Via Wireless Communication

Data transmission uses wireless RF communication protocols such as ZigBee, LoRa, GSM, and NB-IoT to transport sensor data to centralized systems or cloud platforms. These technologies offer dependable, low-power, long-distance communication, making them appropriate for both rural and urban installations. Efficient transmission guarantees real-time data availability and enables continuous monitoring. Gateways are commonly used to combine and forward data from various sensor nodes, hence increasing network efficiency and dependability (Centenaro *et al.,* 2016).

Data Processing and Feature Extraction

To increase data quality, data preparation comprises cleaning and preparing raw sensor data by filtering out noise, normalizing it, and dealing with missing information. Feature extraction is then used to find the most important variables that influence water quality evaluation. This approach minimizes data dimensionality while increasing computing efficiency, resulting in more accurate and faster model training. Effective preprocessing and feature engineering are critical for increasing the performance of machine learning models (Kotsiantis *et al.* 2006).

AI Development and Validation

Machine learning and deep learning algorithms such as ANN, SVM, Random Forest, and LSTM are trained on processed data to generate AI models. In water quality monitoring, these models are used to forecast, classify, and detect anomalies. Model reliability is assessed by validation utilizing performance indicators such as RMSE, MAE, and correctness. Cross-validation approaches are also used to ensure model generalization and reduce overfitting, ultimately boosting prediction performance (Goodfellow *et al.,* 2016).

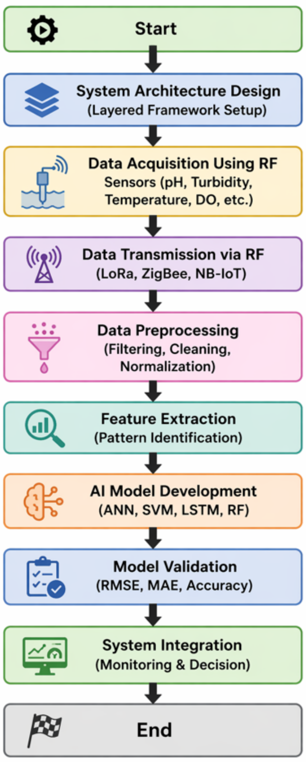

Figure 2: The Sep by Step Methodology Flow Chart of the System

RESULTS AND DISCUSSIONS

The study found that RF sensor networks considerably improve real-time monitoring of water quality indicators. These systems allow for continuous data capture and remote monitoring, which is crucial in both rural and urban settings (Zanella *et al.,* 2022). Artificial intelligence models improve system performance by properly anticipating water quality trends and detecting irregularities. LSTM and hybrid models outperform standard models in terms of RMSE values (Li *et al.,* 2023). The performance comparison of AI models is presented in Table 6.

Despite the substantial benefits of AI and RF-based water quality monitoring systems, a number of hurdles remain to prevent their wider deployment in Nigeria. Poor infrastructure, particularly in rural regions, impedes the establishment of dependable communication networks and power supplies essential for continuous monitoring. High implementation and maintenance costs further limit acceptance, particularly in resource-constrained institutions and communities. Furthermore, the technical competence required to build, run, and maintain these complex systems is in short supply, jeopardizing their long-term viability. Data reliability concerns, such as sensor inaccuracies and inconsistency in data collection, diminish system efficacy. Collectively, these issues impede large-scale application and limit the overall impact of intelligent water monitoring solutions in Nigeria.

Table 6: AI Models Performance Comparison

S/N	Model	RMSE	Accuracy	Application
1	ANN	0.20	85%	Basic prediction
2	SVM	0.15	88%	Classification
3	Random Forest	0.12	90%	Pollution detection
4	LSTM	0.08	94%	Time-series prediction

Impact of RF and AI on Water Quality Monitoring System

The integration of Radio Frequency (RF) technologies with Artificial Intelligence (AI) has considerably enhanced water quality monitoring systems. RF-enabled sensors allow for real-time data gathering and wireless transfer of critical parameters, including pH, turbidity, temperature, and dissolved oxygen, improving monitoring efficiency and coverage (Zhang *et al.* 2019). AI approaches, such as machine learning models like Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM), help with accurate prediction, anomaly identification, and trend analysis of water quality data (Goodfellow *et al.,* 2016; Hochreiter & Schmidhuber, 1997). This integration improves decision-making, provides early warning systems, and promotes environmental sustainability. Furthermore, AI-driven analytics cut operational expenses and automate data interpretation, increasing system efficiency. Overall, the combination of RF and AI enables dependable, scalable, and intelligent solutions for water quality monitoring, particularly in remote and resource-constrained areas.

The System Performance Flow

Figure 3 illustrates the performance flow of the system. The flow demonstrates how raw sensor data is turned into useful grid management intelligence. The system performance flow depicts the water quality monitoring system's sequential operation, from data collection to decision making. It begins with sensor nodes that measure real-time water characteristics like pH, turbidity, and temperature. Data is transferred to a central processing unit or cloud platform via radio frequency communication technology. Preprocessing and feature extraction are carried out to improve data quality. AI models then examine the data to identify trends and abnormalities. Dashboards visualize the findings, allowing for real-time monitoring and control. This constant flow enables efficient system operation, increased accuracy, and a quick response to water quality issues.

Figure 3: The Performance Flow of the System

Practical Limitations and Challenges of the Water Quality Monitoring System

Water quality monitoring systems have practical limits and challenges such as high installation and maintenance costs, insufficient technical skills, and inconsistent power supply (WHO, 2022). In many developing countries, sensor calibration and data quality difficulties cause inconsistent readings (USEPA, 2021). Poor communication infrastructure might impede real-time data transmission, while extreme environmental conditions can harm equipment (UNESCO, 2020). Lack of established processes and insufficient financing impede large-scale deployment. Furthermore, data management and cybersecurity concerns impact system reliability (Zhang *et al.,* 2019). These combined limitations limit the efficiency, scalability, and long-term viability of monitoring systems in real-world applications. Addressing these difficulties requires long-term investment, training, and infrastructure development in emerging economies on a global and local scale.

CONCLUSION

This work investigated the use of artificial intelligence and radio frequency (RF)-based sensor networks to monitor water quality in rural and urban Nigeria. The findings reveal that integrating RF communication technology with AI-driven analytics provides real-time data collection, enhanced anomaly identification, and accurate prediction of water quality indicators. Such solutions considerably improve monitoring efficiency compared to traditional human approaches, which are generally sluggish, expensive, and have limited coverage throughout Nigeria. Widespread adoption is hampered by inadequate infrastructure, high costs, a lack of technical competence, and unpredictable power and communication networks. To ensure long-term implementation in Nigeria, these difficulties must be addressed by concerted investment in infrastructure, capacity building, and policy support. Future research should focus on developing localized datasets, energy-efficient sensor designs, and robust machine learning models tailored to Nigeria's environmental conditions in order to improve the scalability, accuracy, and long-term viability of intelligent water quality monitoring systems in Nigeria and beyond.

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