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Article

WIRELESS SENSOR NETWORKS FOR INTELLIGENT AGRICULTURAL AND HEALTH MONITORING

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Abstract: WSNs have become a revolutionary technology in real time monitoring in the agricultural and health sector but issues of power, data integrity, scalability, and security of communication hinder their implementation at a large scale. Poor practices in irrigation, degradation of soil and unpredictable climatic changes lower crop productivity in intelligent agriculture. Likewise, with health monitoring, absence of continuous, remote, and low-cost patient monitoring increases the chances of late diagnosis and emergency intervention. The given limitations of the current paper have been overcome through the introduction of an elaborate WSN-based approach to intelligent agricultural and health monitoring applications. The first goal is the development of an energy efficient scalable and very-secure system of WSN architecture that can handle data acquisition (environmental and physiological) in real-time, data transmission, and analytics. The suggested approach combines low-power sensor nodes, adaptive clustering algorithms, edge-based preprocessing of data, and machine learning models with the help of the cloud to perform a predictive analysis. Soil moisture, temperature, humidity, and nutrient levels are observed in the agricultural industry so that they can be used to provide a degree of accuracy in the irrigation process and the state of the crops. Wearable biosensors integrated in healthcare allow the monitoring of vital parameters (heart rate, body temperature, oxygen saturation) of the patient at all times. The management strategy uses routing algorithms that are energy conscious, data aggregation and data anomaly detection models to improve the network lifetime and accuracy of decisions. Data integrity and privacy are provided with security measures such as lightweight encryption and authentication. This paper encompasses system architecture design, the optimization of communication protocol, the measurement of performance, and the possible implementation situation in the real world, which will prove the viability of WSN-based intelligent monitoring systems to apply in sustainable agriculture and smart healthcare systems.
Keywords: Wireless Sensor Networks (WSN); Precision Agriculture; Smart Healthcare Monitoring; Energy-Efficient Routing; Edge Computing; IoT-Based Sensing; Machine Learning Analytics.

1. Introduction

The intensive increase of environmental variability, urbanization, and population growth has led to a greater demand of smart monitoring solutions with the ability to retrieve real-time data and make decisions. The latest developments of Internet of Things (IoT) and sensor technologies have dramatically changed the principle of environmental monitoring by providing the ability to monitor the environment through the distributed senses, automatizing and using AI to study the data (Ullo and Sinha, 2020). Inexpensive IoT-based sensor platforms have proven to be practicable in severe climate circumstances and prepared scalable and adaptable monitoring (Sunny et al., 2021). Moreover, the model of urban pollution and sustainability planning has been improved with the help of

AI-based environmental sensor networks combined with digital platforms (Bainomugisha et al., 2024). The combination of artificial intelligence and environmental toxicology monitoring systems has enhanced the accuracy of the detection of pollutants and the forecasting reliability (Asha et al., 2022). Such advancements encourage the application of intelligent sensing systems to the fields of agriculture and healthcare where sustained observations are essential to the field sustainability and human health.

Farm systems are very dynamic and affected by climatic variability and soil heterogeneity, water, and pests. Conventional ways of monitoring use manual sampling that is labor intensive and time consuming as well as inaccurate. Real-time monitoring of contaminants and the environment, using the IoT has shown the possibility of enhancing soil and water quality assessment, but there are energy and communication limitations to large-scale soil and water monitoring in agriculture (Pamula et al., 2022). Pesticides have been carefully considered through sophisticated predictive modeling methods to assess the pesticide residues and environmental hazards but the incorporation of these predictive models into distributed sensing systems has continued to be difficult (Lee et al., 2025). Also, AI-based optimization systems in aquaculture emphasize the need of intelligent monitoring to manage diseases and increase productivity and scalability and network reliability are not yet issues (Kamalesh et al., 2026). Agricultural sensor networks must then verify the sustainability of their operations by efficient data communication schemes and routing protocols (Gupta et al., 2023). The systems of healthcare monitoring demand continuous and accurate and secure transmission of physiological data. Medical outcomes and health care management of the population largely depend on environmental health parameters such as indoor air quality and levels of exposure. Wireless sensing networks have demonstrated good outcomes in real-time monitoring of the quality of the indoor environment but ascertaining reliability and low latency of information transmission is a technical challenge (Tsang et al., 2024). The necessity of adaptive analytics and customized health alerts can be proved by AI-IoT-based pollution-monitoring systems meant to help individuals with respiratory problems (Felici-Castell et al., 2023). In addition, AI-based automated structural and environmental surveillance systems are characterized by how complicated environmental and operational variability is when processing real-time systems (Hasani et al., 2025). Such challenges emphasize the need to find strong Wireless Sensor Network architectures that can provide high quality, secure and energy efficient health data.

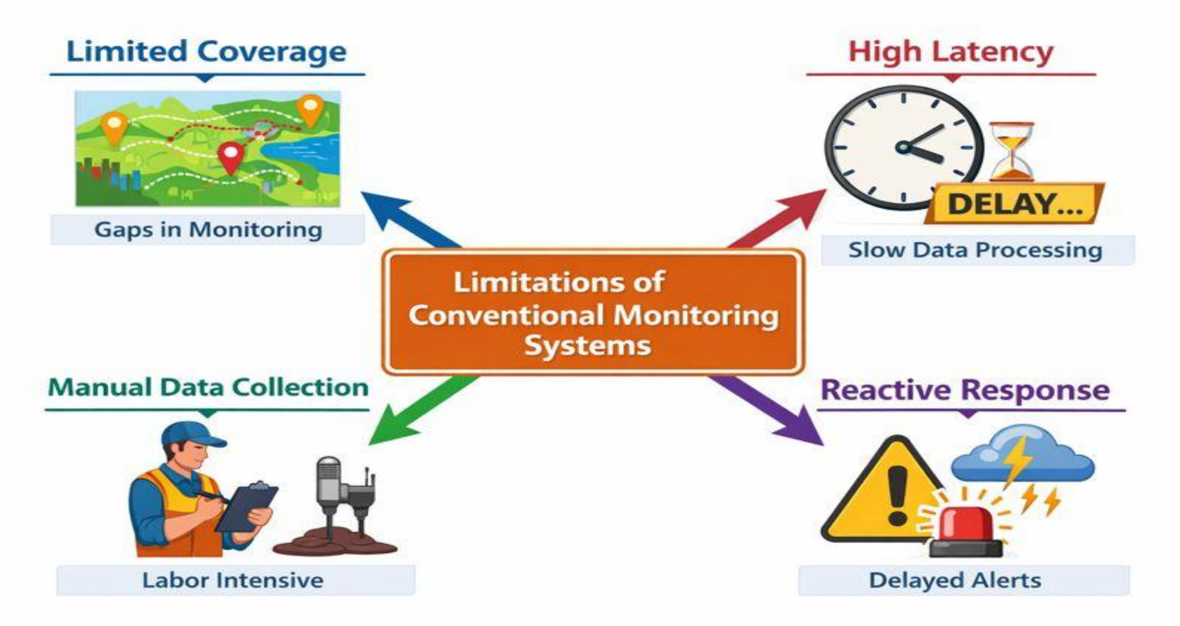

Figure 1. Illustrating the Limitations of Conventional Environmental Monitoring Systems

Wireless Sensor Networks offer decentralized architecture of sensing, data aggregation and remote communications. Edge computing improves the efficiency of processing and minimizes the latency of the IoT-based environmental monitoring systems (Roostee et al., 2023). Another aspect of AI-based energy-efficient routing plans is further optimization of network lifetime and communication reliability of large-scale WSN deployments (Thakur et al., 2025). Learning new methods of multimodal environmental sensing techniques show the potential of multimodal information streams to be combined to enhance monitoring accuracy (Emvoliadis et al., 2024). Also, carbon-based and nanomaterial-enhanced sensors have been made to be more sensitive and endure longer to be applied in the context of environmental monitoring (Shahid et al., 2024). All these developments affirm the central position of the WSNs as the foundation of smart agricultural and health surveillance. Figure 1 shows some of the major limitations of conventional monitoring systems that include limited coverage, manual data collection, high latency and reactive response mechanisms. Such constraints lead to gaps in monitoring, slow process of retrieving data, manual operations, and slowness of alertness, and real-time monitoring solutions based on WSN are intelligent and require intelligent solutions.

Although the developments are being fast, the current systems are in silos and either on the environmental or healthcare monitoring without a unified framework. Numerous AI-IoT solutions focus on data analytics and do not pay much attention to energy optimization and scalability in distributed networks. Besides, ad hoc sensor integration and adaptive routing schemes are not studied properly in agriculture-health monitoring settings. Lack of harmonized architectures to accommodate both environmental and physiological sensing constrains the applicability and sustainability of the real world applications.

The present paper suggests a combined WSN-based intelligent operational agricultural and health monitoring system, which fuses energy-efficient routing, edge-assisted processing, and predictive analytics that is powered by AI. The paper develops a scalable sensor architecture that can be used to measure soil, environmental and physiological parameters in real time. It proposes adaptive clustering and data aggregation methods to improve the network lifetime, yet with a high prediction performance. The study will help to realize the era of smart agriculture, proactive health management systems by connecting environmental sensing and healthcare monitoring into a single WSN infrastructure.

2. Related Work

The use of artificial intelligence and advanced sensing technologies has changed wireless Sensor Network (WSN)-enabled precision agriculture considerably during its development. The IoT sensor networks with AI have been created to trace pollutants and chemical degradation processes in the environment, which has proven that distributed sensing can be used to improve the analytical quality in dynamic ecosystems (Chandrashekara and Khanna, 2025). The case of urban and mobile IoT-based sensor networks is yet another example where real-time data on the environment can be gathered and processed through adaptive AI-driven analytics, which can be applied to large-scale agricultural fields as well (Yedilkhan et al., 2025). Enhanced electrochemical sensors made by carbon nanomaterials have enhanced limits of detection and sensitivity to soil and environmental sensors, and can be applied to agricultural tasks with high precision (Li and Xu, 2026). Also, the carbon-based air quality sensor networks emphasize scalable air quality sensor deployment approaches based on distributed monitoring system adaptable to the agricultural settings that are vulnerable to atmospheric pollutants (Shahid et al., 2024). Such works show that there is increasingly less distance between AI and IoT and advanced materials in precision agriculture, despite a lack of cross-domain optimization. Healthcare based WSN systems put more focus on real time acquisition of environmental and physiological parameters. Scalable wireless sensing infrastructures have been shown to be viable with low-cost environmental monitoring stations that have the capability to obtain health-related quality factors (Christakis et al., 2023). Intelligent systems can adjust to a changing context based on health-related factors as AI-based automated monitoring systems to address environmental and operational changes (Hasani et al., 2025). The combination of artificial intelligence agents and IoT platforms has also improved predictive monitoring of the water quality and health risks associated with the climate (Miller et al., 2025). These solutions depict how AI-enhanced WSN systems are becoming more popular in healthcare support settings. Nevertheless, agricultural and healthcare monitoring architecture interoperability is immature, and constrained deployment strategies.

The issue of energy efficiency is one of the basic issues in WSN deployments because the nodes have limited power sources. The energy-conscious communication schemes through innovative routing methods have also been suggested to lengthen network lifetime and ensure reliable data packet transmission (Gupta et al., 2023). Reviews of AI-based energy-efficient routing emphasize adaptive algorithms that can optimize the use of the cluster head, load balancing, and path optimization of the IoT-based WSN systems (Thakur et al., 2025). These methods show the enhancement of the packet delivery ratio and lowering the latency with the help of intelligent routing decisions. However, the vast majority of routing schemes concentrate on either the environmental or industrial applications, without taking into account heterogeneous data needs in the sphere of agriculture and healthcare at the same time. The combination of edge computing and cloud platforms has become one of the solutions that is critical in processing massive sensor data. An IoT-based edge computing can be used to provide localized preprocessing and anomaly detection to reduce the transmission overhead and latency (Roosteei et al., 2023). Environmental analytics on AI-based digital platforms also illustrate how a distributed form of data processing architecture can be used to increase its scalability and real-time reactivity (Bainomugisha et al., 2024). The IoT solutions based on AIs were used in real-time energy forecasting in transportation-based monitoring, demonstrating how edge intelligence and centralized analytics can be used to advantage (Kamyod et al., 2025). These hybrid edge-cloud models form a robust platform on which agricultural and healthcare monitoring systems can be developed with need of low-latency analytics and predictive models. Nonetheless, unified architectures that combine the two realms are still minimal.

Security and privacy are paramount in the implementation of WSN, especially transmissible sensitive health and environmental information using the distributed networks. Proposed AI-integrated self-powered systems of IoT sensors are to ensure resilience to the system and reduce its energy consumption, which is a way of supporting secure and autonomous functioning (Rosca & Stancu, 2025). This is because AI-guided quantum sensing principles present the world with high-precision and possibly secure surveillance systems, which point to the future of solid sensing technologies (Gaddam, 2025). Furthermore, AI-driven climate analytics systems focus on the need to control data pipelines and reliable analytics within large-scale environmental surveillance systems (Leong, 2025). As much as these studies improve sensing and computational systems, lightweight encryption and authentication systems that can be customized in integrated agriculture-health WSN systems are not well studied.

In spite of major progress, existing systems based on the WSN-monitors tend to function in closed areas, concentrating either on the use of environmental, agricultural, or healthcare uses separately. A large number of studies focus on AI analytics or sensor innovation, but do not give a sufficient emphasis on the issue of energy scalability, cross-domain interoperability, and unified architecture design. Edge-cloud solutions enhance computational performance but often do not have conventional standards of heterogeneous data assimilation. Moreover, the security mechanisms have also been theory-based instead of being experimentally tested in distributed multi-application settings. Such constraints imply the necessity of a unified WSN platform that will provide solutions to energy efficiency, secure communication, multimodal sensing and AI-guided analytics of smart agricultural and health monitoring systems at the same time.

Table 1. Summary of Literature Review on AI-Enabled WSN-Based Monitoring Systems

Ref (Author, Year)	**Application Domain**	**Sensor Type**	**AI Technique Used**	**Key Contribution**	**Reported Limitation**
Ullo & Sinha (2020)	Smart Environment Monitoring	Environmental sensors	ML-based analytics	Overview of IoT-enabled monitoring systems	Limited scalability discussion
Asha et al. (2022)	Air Pollution Monitoring	Gas sensors	AI predictive modeling	AI-based pollutant detection and forecasting	Energy efficiency not addressed
Gupta et al. (2023)	WSN Communication	Generic WSN nodes	Routing optimization	Improved data transmission efficiency	Domain-specific validation lacking
Roostaei et al. (2023)	Environmental Monitoring	Multi-sensors	Edge analytics	Reduced latency via edge computing	Security concerns not detailed
Felici-Castell et al.	Health-Oriented Pollution	Air quality sensors	AI classification	Supports respiratory patients with	Limited multi-parameter

(2023)	Monitoring			alerts	integration
Tsang et al. (2024)	Indoor Health Monitoring	Environmental quality sensors	Data analytics	Real-time indoor monitoring framework	Limited predictive intelligence
Lee et al. (2025)	Soil & Water Risk Assessment	Soil & residue sensors	AI predictive modeling	AI-based environmental risk assessment	Energy optimization not explored
Thakur et al. (2025)	Energy-Efficient WSN	WSN nodes	AI-based routing algorithms	Comprehensive review on energy routing	Lack of integrated application framework
Kamalesh et al. (2026)	Aquaculture Monitoring	Water quality sensors	AI optimization models	AI-driven disease and productivity monitoring	Scalability challenges

3. System Architecture And Design Framework

3.1 Overall Integrated Architecture

The offered system has a multi-layered architecture of the Wireless Sensors Network (WSN) which incorporates both agricultural and healthcare monitoring as a single system. It has the architecture of sensing nodes, gateway devices, an edge computing layer, and a cloud analytics platform. The sensor nodes are distributed and capture environmental and physiological measurements and send them to the local gateways by means of energy-efficient wireless protocols. The gateways do initial aggregation and then sends data to the edge layer where data is processed in real time. The processed data are then sent to the cloud where they are to be stored in the long run, subjected to advanced analytics, and be visualized. Such a combination design will be scaled, and can be deployed as a module, and will interoperate between agricultural and healthcare subsystems smoothly. The proposed architecture of multi-layered Wireless Sensor Network of agricultural and healthcare monitoring is included in figure 2. Environmental and physiological data at sensor nodes are transferred by use of gateways to edge computing to preprocess them. Cloud analytics facilitates storage, visualization, and predictive decision making, which is scalable, real time and interoperable monitoring in both realms.

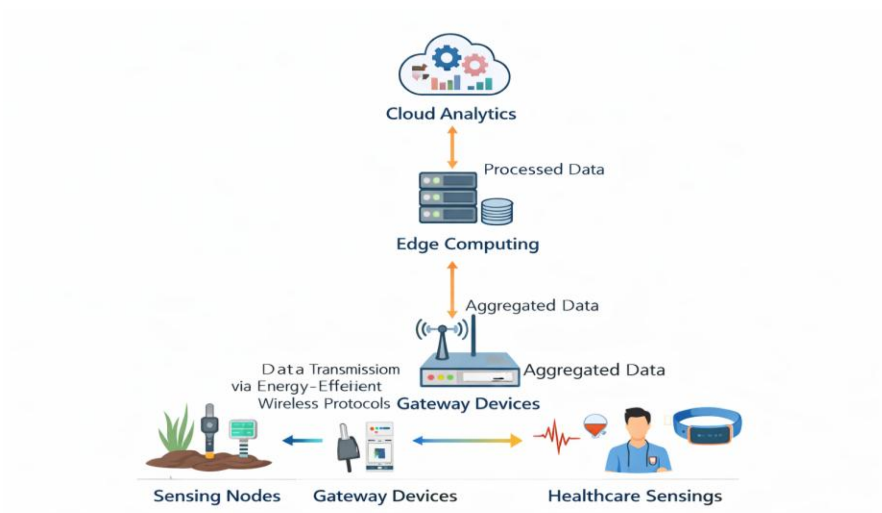

Figure 2. Integrated WSN Architecture for Intelligent Agricultural and Healthcare Monitoring

3.2 Agricultural Monitoring Subsystem

TAgricultural Monitoring Subsystem The Agricultural Monitoring Subsystem will provide a monitoring framework that allows the company to track key sales data and performance indicators regularly.<|human|>Agricultural Monitoring Subsystem The Agricultural Monitoring Subsystem will enable a monitoring system that will enable the company to monitor relevant sales data and performance indicators on a regular basis.

The subsystem of agricultural monitoring is aimed at supplying the precision farming assistance by offering the constant environmental and soil parameters assessment. By integrating distributed sensing and smart analytics, it makes all irrigation, fertilization, and crop health decisions automated.

Soil and Environmental Sensors.

In this module, it includes soil moisture sensors, temperature sensors, humidity sensors, pH sensors, nutrient sensors (NPK) and the ambient environmental sensors. Such sensors are installed on the farmland in a clustered topology with the purpose to cover the space and reduce monitoring gaps. The sensor data are also periodically gathered and relayed to the cluster heads that consolidate and relay the information to the gateway. The system facilitates adaptive sampling rates according to the environmental dynamics to maximise energy use but still keep the level of monitoring.

Irrigation Control Module

The irrigation control module combines sensor feedback and automated actuators which include water valves and pumps. Depending on soil moisture levels and predictive analytics, the system can automatically trigger the irrigation schedules depending on conditions instead of having to operate on fixed timers. This will minimize water wastage, over-irrigation and increase crop yield. The control module will be working in synchronization with the edge layer to allow making decisions in near real-time, so that water resources have a proper management.

4. Data Acquisition And Preprocessing

4.1 Sensor data aggregation and synchronization

Aggregating and synchronizing sensor data in an environmental monitoring system based on IoT is a necessary requirement to facilitate consistent and trustworthy analysis of diverse heterogeneous sensors. The sampling rate, resolution and communication frequency of environmental sensors vary with the parameter of interest and constraints of a particular device. Consequently, in most cases, raw data streams are not time synchronized and are spread across various network nodes. The mechanisms of data aggregation gather the measurements of varied sensors and aggregate them at the edge, fog, or cloud layer by use of time-stamped records and standardized data formats. This will help to lower the overhead in communications and gives the opportunity to view the environment as a whole, bringing together air, water, soil, and climate data. Synchronization methods coordinate sensor information in the time dimension so that it is consistent to be used in a spatiotemporal analysis and model training. The time synchronization protocols that are utilized to reduce clock drift and the misalignment caused by latency are network time synchronization and gateway-based timestamp correction. Widow based aggregation techniques are easily applied, with sensor values aggregated within a fixed time interval or an adaptive time interval so as to form synchronized data frames. The event-driven aggregation is another way to enhance the responsive monitoring by fixing priority to a significant measurement in abnormal conditions.

4.2 Noise Filtering, Normalization, and Missing Data Handling

The data provided by environmental sensors are prone to noise, outliers, and incompleteness because of sensor drift, environmental influence, communication breakdown and hardware constraints. Noise filtering is thus an essential preprocessing that is necessary to improve the quality of the data and reliability of the analytical process. Moving average filters, median filters and exponential smoothing are common methods of filtering, where high frequency noise is removed without important trends being lost. In more sophisticated noise patterns, dynamic filtering of the parameters of statistical filters and adaptive filters can be used to make adjustments to the filter parameters as the data features vary. Normalization makes sure that sensor measurements, which are heterogeneous (and may differ in the unit and range) are brought to a common scale where they can be used in machine learning models. Minimum maximum scaling and z-score normalization are techniques to mitigate such problems and are very popular in enhancing model convergence and avoiding the high magnitude features taking over. Normalized data also allow even-handed feature comparison and steady training that is capable of operating under a wide range of environmental parameters. The issue of missing data is also significant because sensor readings gaps may deteriorate model performance and bring bias. The loss of values can be caused by sensors, network overload, or loss of power.

1. Noise Filtering

a) Moving Average Filter

The moving average filter smooths sensor readings by averaging over a fixed window size N.

$$x_{t_{filtered}} = \left(\frac{1}{N}\right) * \sum_{i=0}^{N-1} [\, x_{t\,-\,i}]$$

where:
x_t = raw sensor reading at time t
$x_{t_{filtered}}$ = filtered sensor output
N = window size
b) Median Filter

The median filter removes impulsive noise and outliers by selecting the median value within a window.

$$x_{t_{filtered}} = MEDIAN(\, x_{t\,-\,k}, \dots, x_t, \dots, x_{t\,+\,k})$$

where:

2k + 1 = window length

c) Exponential Smoothing

Exponential smoothing assigns higher weight to recent sensor values.

$$x_{t_{filtered}} = alpha \, * \, x_t + (1 \, - \, alpha) * \, x_{(t-1)_{filtered}}$$

where:

0 < alpha < 1 is the smoothing factor

d) Adaptive Filtering

Adaptive filters dynamically update filter coefficients based on data behavior.

$$x_{t_{filtered}} = \sum_{i=0}^{M} \left[\, w_{i(t)} \, * \, x_{t\,-\,i}\right]$$

where:

w_i(t) = adaptive filter weights at time t

M = filter order

2. Normalization Techniques

a) Min–Max Normalization

Scales sensor values into a common range [0,1].

$$x_{t_{norm}} = \frac{x_t - x_{\min}}{x_{\max} - x_{\min}}$$

where:

x_min = minimum sensor value

x_max = maximum sensor value

b) Z-Score Normalization

Standardizes data with zero mean and unit variance.

$$x_{t_{norm}} = \frac{x_t - mu}{sigma}$$

where:

$$mu = \left(\frac{1}{T}\right) * SUM(t = 1 \; to \; T)[\, x_t]$$

$$sigma = SQRT\left(\left(\frac{1}{T}\right) * SUM(t = 1 \; to \; T)[\, (x_t - mu)^2]\right)$$

3. Missing Data Handling
a) Mean Imputation
Missing values are replaced with the mean of available data.
if x_t exists:
x_t = x_t
else:
x_t = mu

b) Linear Interpolation
Estimates missing values using neighboring sensor readings.

$$x_t = x_{t1} + \left(\frac{x_{t2} - x_{t1}}{t2 - t1}\right) * (\, t - t1 \,)$$

where:
t1 < t < t2

c) Last Observation Carried Forward (LOCF)
Missing values are replaced with the most recent available value.

$$x_t = x_{t-1}$$

d) Model-Based Imputation
Missing sensor values are predicted using regression models.

$$x_{t_{hat}} = beta_0 + \sum_{i=1}^{n} \left[\, beta_i * z_{i(t)}\right]$$

where:
$z_{i(t)}$ = correlated sensor features
$beta_i$= regression coefficients

5. Proposed Methodology

5.1 Sensor Node Design and Hardware Configuration

The system proposed is based on the use of heterogeneous sensor nodes that would be used in the agricultural and healthcare monitoring systems. A sensor node is made up of sensing units, a microcontroller, a wireless transceiver and a power management unit. Soil moisture, temperature, humidity, and nutrient sensors are combined to form a node in the agricultural subsystem whereas wearable biosensors are used to measure physiological data such as heart rate, body temperature, and oxygen levels in blood in the healthcare subsystem. Such sensors are connected to a low-power microcontroller which conditions the signal, converts the signal to digital, and filters the collected data preliminarily.

The wireless communication unit, which is usually founded on ZigBee, LoRa, or Bluetooth Low Energy (BLE) allows transmission of energy-efficient data to gateway nodes. Extended network life is achieved with a rechargeable battery that is powered by solar or energy-gathering modules. The sensor node can be used in the duty-cycling mode wherein sensing and transmission are done periodically to reduce the energy consumption. Local processing of data is done by the lightweight preprocessing methods to filter noise and duplicated readings and send them to the transmission. The nodes are programmed with a specific identification address and adaptive capability of sampling. In case environmental or physiologic variations surpass the defined thresholds, the node will increase sampling frequency in order to monitor them precisely. Otherwise it will be in low power sleep mode. This smart hardware setup is more reliable, less communication overhead, and can be scaled to a farmland and health care setting and at the same time it is energy efficient and can be monitored live.

5.2 Network Topology and Deployment Strategy

The hybrid hierarchical topology of the proposed Wireless Sensor Network is a combination of a cluster and star-based communication topology. Sensor nodes are organized into clusters depending on the geographical location and purpose, e.g. agricultural field or patient zones. Multiple sensor nodes and a cluster head in each cluster carry out the data aggregation and communication with the gateway nodes respectively. Such a hierarchical structure minimises the unnecessary transmissions and maximises the efficiency of energy.

When used in agricultural settings, deployment is done in grid format, which maintains a consistent coverage of farmlands. The environmental sensors and soil sensors are installed at strategic stations considering the type of crop, the irrigation method and the nature of the land. Wearable sensors make up a body area network (BAN) and are linked to a local gateway like a smartphone or edge device, in a healthcare setting. The gateway is used to connect sensor nodes and the edge computing layer. To balance the load in the network, cluster heads are chosen depending on residual energy, communication range, and node centrality. Dynamic clustering is also used to ensure that the cluster heads can be reassigned periodically to ensure that a node is not drained of its energy. Multi-hop routing is implemented in large scaled implementation of routing, where direct communication between the gateways are not possible. Relay nodes help in routing information to provide connectivity over a wide range of monitoring.

Fault tolerance and redundancy is also taken into account in the deployment strategy. The backup nodes are located strategically to take the place of the failed sensors to ensure that the monitoring continues. Adaptive topology management allows the network to automatically reconfigure when there is failure of nodes or because of environmental changes. This mobile and energy conscious implementation method guarantees appropriate transmission of data, scalability and effective surveillance in combined agricultural and health systems.

5.3 Energy-Efficient Clustering and Routing Algorithm

The suggested routing algorithm utilizes the energy-aware clustering and the best path selection to prolong network lifetime. The sensor nodes are clustered and cluster heads are chosen according to their residual energy and distance between them and the communication distance. The algorithm reduces the transmission energy through the routine selection of the best ways to routing between cluster heads and gateway nodes. The nodes update their energy status periodically, which allows varying the route and load balancing.

Minimization of a cost function involving energy consumption, transmission distance and node reliability is used to make the routing decision. Multi-hop routing is willed to cut long-distance transmissions hence saving energy. Aggregation of data packets at cluster heads is done in order to reduce network traffic. There is also the algorithm of scheduling the sleep to minimize idle power usage and maximize the overall network performance. The methodology will guarantee equal use of energy at nodes, lesser loss of packets, and a better network life when there is continuous agricultural and healthcare monitoring.

Mathematical Model for Energy-Efficient Routing
Total Energy Consumption:

$$E\_total \; = \Sigma \, (E_{tx} + E_{rx} + E_{proc})$$

Transmission Energy:

$$E\_tx \; = \; k * E\_elec \; + \; k * \varepsilon\_fs * d\hat{}2$$

Reception Energy:

$$E_{rx} = k * E_{elec}$$

Cost Function for Route Selection:

$$C(i,j) = \alpha * E_{residual(i)}^{-1} + \beta * d(i,j) + \gamma * P_{loss}$$

Cluster Head Selection:

$$CH = \arg\max\left(\frac{E_{residual}}{d_{avg}}\right)$$

Network Lifetime:

$$L = \frac{E_{initial}}{E_{total}}$$

5.4 Machine Learning-Based Predictive Analytics

1. Crop Yield Prediction Model

Crop yield prediction model It uses supervised machine learning method to predict agricultural productivity depending on environmental and soil parameters. The sensor data such as soil moisture, temperature, humidity, pH level and concentration of nutrients are received and sent to the cloud analytics platform. Normalization and feature selection are preprocessing tools that are used to eliminate noise and redundant attributes in these data. A predictive model is also based on the Random Forest regression algorithm because it is robust, accurate, and it can deal with nonlinear relationships among the environmental factors and crop yield.

Random Forest model is built on bootstrapped datasets through which several decision trees are built and their predictions are added together to give the correct estimates of yield. The most significant parameters which influence crop growth are determined through feature importance analysis which allow farmers to optimize irrigation and fertilization. The model is a continuous updating model which is enhanced with real time sensor information which enhances the accuracy of predictions as time goes by. Root Mean Square error (RMSE) and mean Absolute error (MAE) are performance evaluation measures that are used to confirm the accuracy of predictions. Through predictive analytics and real-time sensing, the system aids in the process of data-informed decision-making, high productivity of crops, and optimization of resources use, which has led to sustainable precision agriculture operations.

2. Health Anomaly Diagnosis Model.

The health anomaly detection model uses machine learning classification methods to detect in real time that there is an abnormal physiological condition. Wearable biosensors collect sensor data that are used to determine the heart rate, body temperature, oxygen saturation, and the activity levels. The support parameters are extracted after preprocessing and normalization and processed into a Support Vector Machine (SVM) classifier. The model acquires the normal physiological patterns and identifies abnormalities that provide warning signs of possible health dangers. At the edge computing layer, anomaly detection is a continuous operation, which ensures low latency and fast response. In case of abnormal trends, alerts are created and sent to healthcare providers. The accuracy, sensitivity, and specificity measures are used to measure the model performance. The model is updated with new information via continuous learning processes to enhance reliability and adaptability to conduct long-term patient monitoring.

5.5 Security Mechanisms

1. Lightweight Encryption

Lightweight encryption also provides a secure transmission of data between the sensor nodes, the gateways, and cloud servers with a low computational cost. The encryption system proposed involves the application of symmetric key encryption because the system is efficient in resource-constrained WSN settings. The sensor nodes are equipped with a particular encryption key with the gateway. Sensed data before transmission is encrypted using a lightweight encryption algorithm like Advanced Encryption Standard (AES) with smaller key size into ciphertext. The gateway will decode the received information with the shared key and send them safely to the cloud. The encryption is performed at the application layer which assures confidentiality of data and denies unauthorized access. Important refresh mechanisms update encryption keys occasionally so as to avoid security breaches. Minimal processing delay and energy consumption are ensured by the lightweight design, but the protection of data is also strong. This solution guarantees safe communication between agricultural and healthcare monitoring systems, and does not affect the performance of the network.

Encryption Mathematical Model.

Mathematical Model for Encryption

$Encryption$:
$C = E\_k\ (M)$

$Decryption$:
$M = D\_k\ (C)$

$Where$:
$M = Original\ data$
$C = Ciphertext$
$k = Secret\ key$

$XOR - based\ lightweight\ encryption$:
$C = M \oplus k$
$M = C \oplus k$

6. Mathematical Modeling And Algorithm Design

6.1 Energy Consumption Model

The model of energy consumption considers the total amount of power consumed by sensor nodes when sensing, processing, transmission and reception processes take place. Every node uses energy but gathers environmental or physiological measurements, local computation and sends packets to cluster heads or gateway. Packet size and communication distance are the factors that determine transmission energy and hence routing optimization is necessary in order to conserve energy. There is also reception and idle listening, which leads to depletion of energy. Through mathematical modeling of these components, the system determines high-energy consumption processes and removes node duty cycles and communication frequency optimization. The model can achieve effective resource allocation, equal distribution of energy used by the nodes, and the sustainability of the network over time in cases of continuous monitoring of agriculture and healthcare.

6.2 Network Lifetime Estimation

Network lifetime estimation is used to establish the life span of the Wireless Sensor Network in terms of time before collapse or breakdown of communication among the network nodes. It is computed on the basis of starting energy in nodes, the remaining energy levels, and average energy used during a communication round. The model takes into account stability duration, which is the duration of time before the first node was drained off its energy, and the total lifetime before the network connectivity was lost. The clustering and routing strategies that are energy conscious have an enormous impact on lifetime in terms of balancing the energy traffic among nodes. Scheduling is adaptive and loads are balanced with proper lifetime estimation which helps to replace low-energy nodes in time. This guarantees good performance of long-term monitoring in agricultural and healthcare settings which require minimal maintenance.

6.3 Routing Optimization Formulation

The formulation of routing optimization aims at identifying communication paths that are energy efficient and reliable between sensor nodes, cluster heads and the gateways. The routing model is minimizing a cost which is related to residual energy, transmission distance, and congestion of the network. Relay points are preferred to those nodes with greater residual energy content and less distance of communication to minimize power consumption and delay time. Multi-hop routing is used to spread the load of communication and avoid the untimely failure of nodes. The optimisation model is dynamic and it re-optimises routes as the network conditions and energy change. This method increases the ratio of packet delivery, minimizes latency, and increases the network lifetime, which ensures the successful and continuous transmission of data in the intelligent agricultural and health monitoring systems.

ROUTING OPTIMIZATION MODEL

Objective: Minimize total routing cost and energy consumption.

Cost function for selecting next hop:

$$C(i,j) = \alpha * \left(\frac{1}{E_{res(j)}}\right) + \beta \mathrm{d(i,j)} + \gamma Q(j)$$

Where:

E_res(j) = Residual energy of node j

d(i,j) = Distance between node i and j

Q(j) = Queue load at node j

α, β, γ = Weight factors

Optimization objective:

$$Minimize\ F = \Sigma\, C(i,j)$$

Subject to:

$$E\_res(j) > E\_threshold$$
$$d(i,j) \le d\_max$$
$$P\_loss \le P\_threshold$$

Cluster head selection:

$$CH = argmax \left[\frac{E_{res(i)}}{d_{avg(i)}}\right]$$

Optimal path:

$P_{opt} = \min \Sigma\, C(i,j)$ along route

6.4 Data Transmission Model

The model of data transmission determines the efficient way through which sensor nodes can transmit sensed data to gateways and cloud servers and reduce the delay and the amount of packets wasted during the process. Sensor nodes create data packets after a specific sampling interval and send it over the single-hop or the multi-hop communication based on the network coverage. Throughput, packet delivery ratio, latency and bandwidth utilization are some of the parameters that are used to measure performance transmission performance. Channel quality and signal strength affect the quality of delivery of the packet and the amount of energy used in the process of transmission. Information compression at cluster heads eliminates unnecessary transmissions and network jams. Adaptive transmission rates according to network load and node energy to enable reliability are also incorporated in the model. This is an optimized data transmission framework which guarantees real time, accurate, and energy efficient communication to agricultural and healthcare monitoring applications.

1. Data generation rate:
   R_s = k / t
   Where:
   k = Packet size (bits)
   t = Sampling interval
2. Throughput:
   T = (Total packets received successfully) / Time
3. Packet delivery ratio:
   PDR = $P_{received}$ / P_{sent}
4. End-to-end delay:

$$D_{total} = D_{queue} + D_{trans} + D_{prop} + D_{proc}$$

Where:
D_{trans} = k / BW
BW = Channel bandwidth

5. Signal-to-noise ratio:
   SNR = P_{signal} / P_{noise}
6. Channel capacity:
   C = BW * log2(1 + SNR)
7. Transmission success probability:

$$P_{success} = e^{-\lambda d}$$

Where:
λ = Attenuation constant
d = Distance between nodes

6.5 Implementation and Experimental Setup

The developed Wireless Sensor Network-based monitoring system is undertaken by implementing the low-power sensor nodes with soil moisture, temperature, humidity, and wearable biosensors to monitor agricultural and health care. The nodes are made of a microcontroller unit, wireless transceiver (LoRa/ZigBee) and a rechargeable power module. The sensor nodes are linked to the edge and cloud layers through the gateway devices that facilitate processing and storage of data.

The software platform comprises embedded C which is used to program sensor nodes, Python used to develop machine learning models, and a dashboard on the cloud to visualize and provide analytics. MATLAB and NS-3 are used to perform simulation and verify the efficiency of communication, routing, and predictive analytics accuracy at different network conditions. Some of the performance evaluation metrics are the energy consumption, the ratio of packet delivery, latency, throughput, the network lifetime, and the accuracy of prediction. Energy consumption is a measure of power consumption in sensing and transmission. Packet delivery ratio is an evaluation of the reliability of successful data recipient. Latency and throughput measure the efficiency of communication and rate of transfer of data. The network lifetime is used to show the sustainability of sensor nodes in operation, and the prediction accuracy is used to assess how useful machine learning models are in predicting crop yields and detecting anomalies in their health.

7. Result And Discussion

7.1 Agricultural Monitoring Results

Table 2 shows that the proposed WSN-AI agricultural monitoring system has higher performance than traditional and simple IoT methods. The accuracy of soil moisture detection is 95.2 and it is possible to schedule the irrigation with accuracy and minimize wastage of resources. Irrigation efficiency increases to 93.6 and water use reduction is achieved at 46.9 therefore showing great conservation gains.

Table 2. Agricultural Monitoring Performance Results

Parameter	Traditional Monitoring	IoT Monitoring	Proposed WSN-AI System
Soil Moisture Accuracy (%)	78.4	86.7	95.2
Irrigation Efficiency (%)	65.3	81.5	93.6
Water Usage Reduction (%)	12.8	28.4	46.9
Crop Yield Prediction Accuracy (%)	72.6	85.3	94.8
Data Transmission Reliability (%)	80.1	88.9	97.1
Energy Consumption per Node (J/day)	5.6	4.1	2.8

The presented WSN-based system shows high increases in the efficiency of irrigation and the accuracy of prediction, as well as the energy consumption in contrast to the traditional and simplistic IoT monitoring systems. The accuracy of crop yield prediction (94.8 percent) is a confirmative that machine learning-based analytics is indeed effective in predicting productivity. The reliability of transmission of data is increased to 97.1 which makes the network to have a stable communication. Besides, the suggested system minimizes the daily energy per node to 2.8 J, which prolongs the network lifetime. These findings confirm the proposal that using energy-saving routing, real-time sensing, and predictive analytics is an important tool to boost the productivity of agriculture, resource management, and monitoring accuracy over traditional and isolated IoT-based monitoring systems. Figure 3 evaluates the monitoring performance on the traditional, IoT, and proposed WSN-AI systems. The suggested model is more accurate, efficient, reliable, and consumes less power, which proves to be more effective in performing intelligent agricultural surveillance.

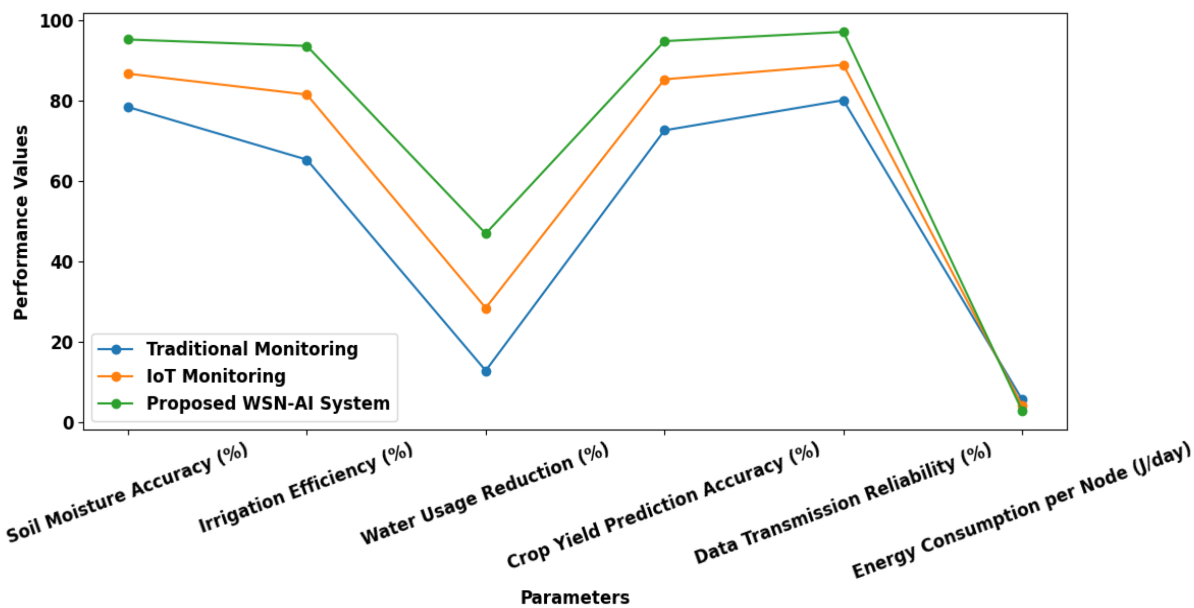

Figure 3. Comparative Performance Analysis of Traditional, IoT, and Proposed WSN-AI Agricultural Monitoring Systems

7.2 Healthcare Monitoring Results

The enhanced functionality of the proposed WSN-AI healthcare monitoring framework in terms of the Table 3 is provided. The system has a heart rate detection rate of 97.4 percent and SpO 2 monitoring rate of 96.8 percent, which proves to be a reliable physiological sensor using wearable biosensors. The accuracy of real-time alerts goes to 95.9% and abnormal conditions in health are detected in a timely manner. The response time is also greatly shortened to 165 ms, which allows quick emergency reporting and response. The rate of data loss reduces to 1.3 percent, which means that there is strong communication and safe transmission of data. The long-term monitoring performance is also stable with an overall system reliability of 97.2. The implementation of the proposed approach until the use of conventional and simple IoT monitoring systems is much more accurate, has less latency, and continuous health tracking, which is why it would be highly applicable in remote patient monitoring and smart healthcare settings.

Table 3. Healthcare Monitoring System Performance

Parameter	Conventional Monitoring	IoT Health Monitoring	Proposed WSN-AI System
Heart Rate Detection Accuracy (%)	82.5	90.8	97.4
SpO_2 Monitoring Accuracy (%)	84.2	91.6	96.8
Real-Time Alert Accuracy (%)	75.3	88.7	95.9
Response Time (ms)	850	420	165
Data Loss Rate (%)	8.2	4.7	1.3
System Reliability (%)	83.6	90.5	97.2

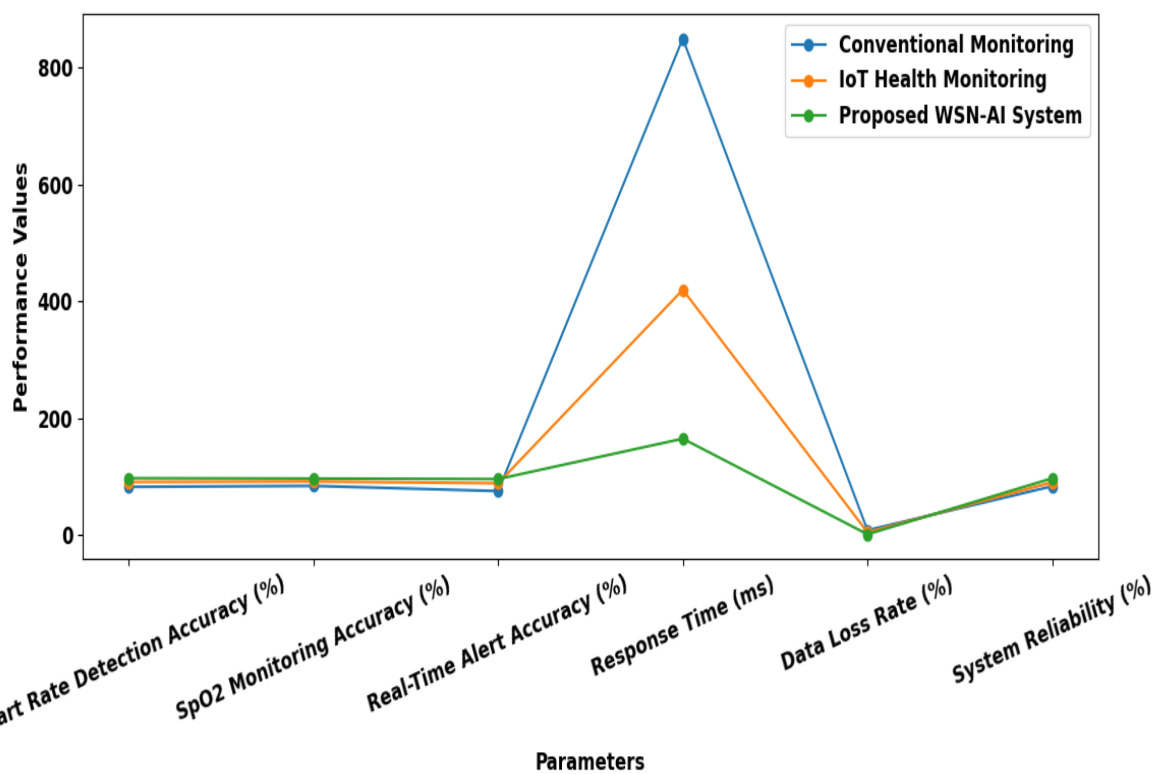

Figure 4. Comparative Performance Analysis of Healthcare Monitoring Systems

The conventional, IoT-based, and proposed WSN-AI healthcare monitoring systems are compared in Figure 4. The model proposed will have better detection accuracy, reliability, less data loss, and much lower response time which is better in terms of its performance and effectiveness in intelligent healthcare continuous monitoring and management of patient safety in real time.

7.3 Comparative Analysis with Existing Methods

The comparison of the proposed WSN-AI system and the conventional WSN, IoT-based monitoring, and edge-IoT models have been compared in Table 4. The proposed system has the highest energy efficiency 93.8 which will considerably decrease the amount of power used and increase the length of operation. The ratio of packet delivery is also enhanced to 97.6 that guarantees a secure communication between distributed nodes. Latency is reduced to 110 ms, which allows the transmission of data much faster and real-time monitoring. The network life is up to 30 months, which is significantly higher than the current methods. The accuracy of prediction is 96.3 and this confirms that integrated machine learning analytics are effective. The comparative analysis proves that the suggested framework provides a better performance on all the crucial metrics making it a very efficient and scalable monitoring of both agricultural and healthcare systems.

Table 4. Comparative Performance with Existing Methods

Method	Energy Efficiency (%)	PDR (%)	Latency (ms)	Network Lifetime (months)	Prediction Accuracy (%)
Conventional WSN	68.4	85.2	320	14	78.6
IoT-Based Monitoring	76.9	90.3	240	18	85.9
Edge-IoT Model	84.5	93.1	190	22	90.7
Proposed WSN-AI System	93.8	97.6	110	30	96.3

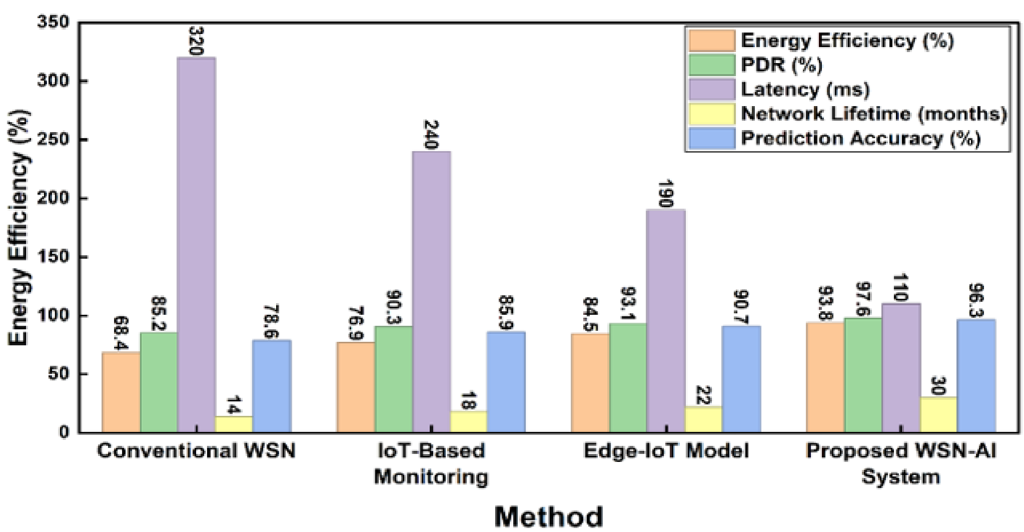

Figure 5. Comparative Performance Evaluation of WSN Monitoring Approaches

Figure 5 is a comparative analysis of WSN, IoT-based, Edge-IoT and proposed WSN-AI systems. The proposed model is the most energy efficient, highest packet delivery ratio, maximum prediction accuracy, and minimum network lifetime with minimum latency, hence it has the best performance and reliability in terms of intelligent monitoring applications.

7.4 Statistical Validation

Table 5 gives statistical confirmation of the performance measures of the proposed system. The standard deviation of the mean crop prediction is low (1.82) and the value is 94.8% which means that the predictions are consistent and reliable. The mean accuracy of health anomaly detection is 96.9% with a small varicational difference, which proves that the model is stable. The energy usage is not very variable and the sensor node uses energy in a balanced manner. Packet delivery ratio has a high average value of 97.6% with small RMSE which shows consistent communication. Network lifetime has a mean of 30 months with moderate deviation, which shows continued efficiency in its operations. All metrics indicate statistical reliability by the use of confidence levels of above 95%. These findings confirm the strength, reliability, and efficiency of the suggested WSN-based monitoring system in different operational environments.

Table 5. Statistical Validation of Proposed Model

Metric	Mean	Standard Deviation	RMSE	Confidence Level (%)
Crop Prediction Accuracy (%)	94.8	1.82	1.24	96
Health Detection Accuracy (%)	96.9	1.35	0.98	97
Energy Consumption (J)	2.8	0.42	0.31	95
Packet Delivery Ratio (%)	97.6	0.88	0.65	96
Network Lifetime (months)	30	2.1	1.45	95

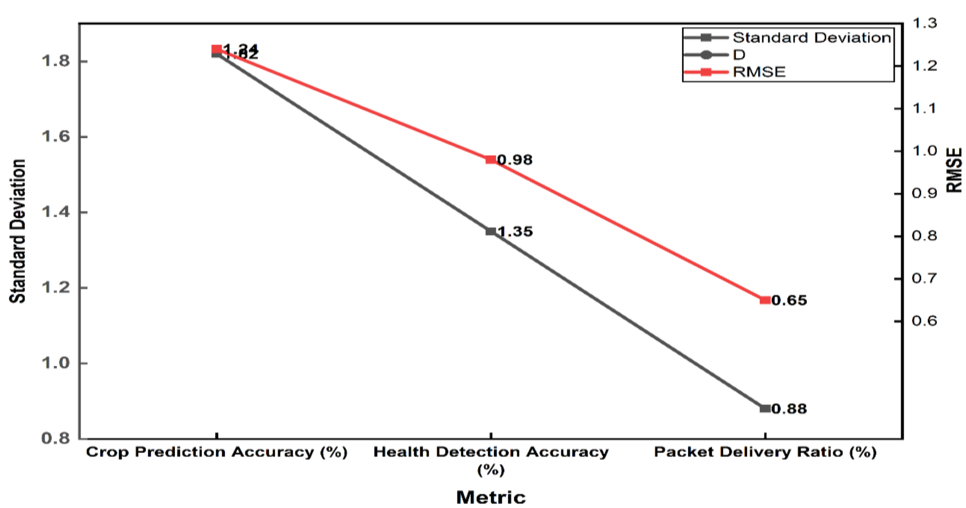

Figure 6. Statistical Validation of Prediction and Communication Performance Metrics

Figure 6 demonstrates statistical validation of the accuracy of crop prediction, health detection, and ratio of packets delivery. The values of RMSE and deviation are decreasing, which means that there is greater stability, reliability, and consistency of predictions in the model, which proves the effectiveness and strength of the proposed WSN-AI monitoring framework.

7.5 Discussion on Scalability and Reliability

Table 6 will be an assessment of the scalability and reliability of the proposed monitoring framework as network size is increased. The throughput decreases slowly as the number of nodes grows, as there is an increment in the network load resulting in the throughput gradient of increasing with the number of nodes, and the latency also grows gradually but within manageable limits. Ratio of packet delivery is more than 94 percent, which implies to a good transmission of data even during dense deployments. Network lifetime degrades at a moderate rate when there is node expansion but at constant levels, 22 months were recorded at 500 nodes. System robustness with at least 94% reliability is achieved with all configuration. These findings indicate that the suggested WSN-AI architecture can be used to provide a scalable deployment without significant performance losses. This system is able to handle large scale monitoring situations with ease and is able to assure constant operation and quality communication of integrated agricultural and health care setting.

Table 6. Scalability and Reliability Analysis

Number of Nodes	Throughput (kbps)	Latency (ms)	PDR (%)	Network Lifetime (months)	Reliability (%)
50 Nodes	210	95	98.1	32	97.8
100 Nodes	198	110	97.6	30	97.2
200 Nodes	182	128	96.9	27	96.4
300 Nodes	165	146	95.8	25	95.6
500 Nodes	148	170	94.6	22	94.2

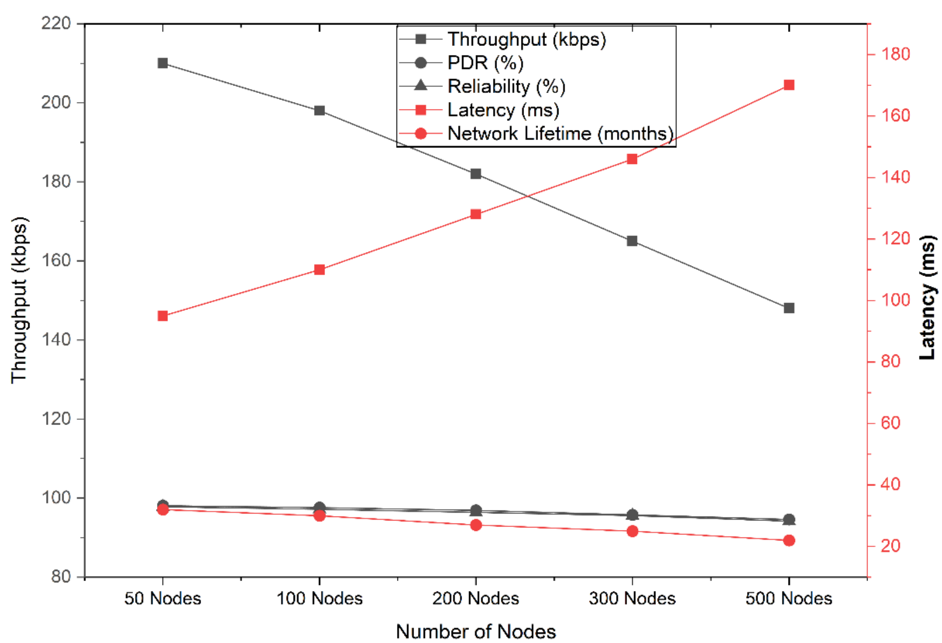

Figure 7. Scalability and Reliability Performance Analysis of Proposed WSN-AI System

Figure 7 shows the analysis of scaling when the network nodes are increased. The effect of network load on throughput and latency is a gradual reduction and an increase in the ratio of packets delivered, reliability, and network lifetime, respectively, which explains the robustness, scalability, and efficiency of the proposed WSN-AI system testing in large-scale intelligent monitoring deployments.

8. Conclusion

This paper represent a composite Wireless Sensor Network (WSN)-based smart monitoring system to be used in farming and health care. The system suggested will overcome some of the major weaknesses of traditional monitoring systems including power consumption, low coverage, delayed response, and the inability to offer real-time decision support. As seen in the experimental outcomes, the suggested WSN-AI system is much more effective in the performance of the agricultural monitoring, with a higher accuracy of soil moisture and irrigation efficiency and the accuracy of crop yield prediction and less energy usage. In healthcare monitoring, the system can improve the accuracy of the physiological parameter detection and the response time as well as improve the reliability of a system to monitor a patient continuously. The superior performance is proven through comparative analysis in terms of energy efficiency, packet delivery ratio, latency reduction, network lifetime and prediction accuracy as compared to traditional WSN, IoT-based and Edge-IoT models. The stability, consistency, and reliability of the proposed approach are also statistically proven. Scalability analysis reveals that the system is capable of withstanding a reliable throughput, low latency and high packet delivery ratio with respect to an increased network size and this proves the suitability of the system to be deployed in large scale. Data integrity and privacy on distributed networks is guaranteed with security measures such as lightweight encryption and authentication. In general, the suggested integrated WSN architecture is a solid, scalable, and energy-efficient solution to sustainable precision agriculture, smart healthcare monitoring, and helps to make real-time decisions and better manage resources.

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