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AN AI-DRIVEN WSN FRAMEWORK FOR ENVIRONMENTAL MONITORING AND PREDICTIVE DECISION-MAKING IN FARMING

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Abstract: This paper presents a comprehensive framework integrating Wireless Sensor Networks (WSNs) and Artificial Intelligence (AI) techniques to enable real-time environmental monitoring and predictive decision-making in agriculture. The system is designed to improve resource efficiency, crop yield, and climate resilience through a layered architecture involving sensor deployment, data transmission, cloud-based analytics, and AI-driven control actions. Experimental evaluation demonstrates significant improvements over traditional and IoT-only systems in water conservation, crop productivity, forecast accuracy, and operational automation.

Keywords: Wireless Sensor Networks (WSN), XGBoost and LSTM.

I. Introduction

In modern precision agriculture, the integration of wireless sensor technologies with advanced data analytics plays a crucial role in achieving sustainable and efficient farming practices. The proposed system architecture combines multiple layers of hardware and software components designed to facilitate continuous environmental monitoring, real-time data processing, and automated decision-making. This comprehensive architecture ensures that critical parameters such as temperature, humidity, soil moisture, light intensity, and air quality are accurately measured and effectively utilized to optimize resource management, crop growth, and yield outcomes.

The system leverages distributed sensor nodes deployed across agricultural fields, which communicate wirelessly via LoRaWAN protocols to establish a reliable and energy-efficient data transmission infrastructure. Collected data are then processed locally through edge computing devices and stored in scalable cloud platforms, where advanced machine learning models analyze trends and generate predictive insights. These insights inform automated control systems that adjust irrigation, climate regulation, and lighting conditions dynamically, ensuring optimal environmental conditions for crops.

This paper delineates the detailed architecture and design considerations underlying this integrated system, emphasizing scalability, reliability, energy efficiency, and user accessibility. The design aims to transform traditional farming into an intelligent, data-driven process supporting sustainable and productive agricultural ecosystems.

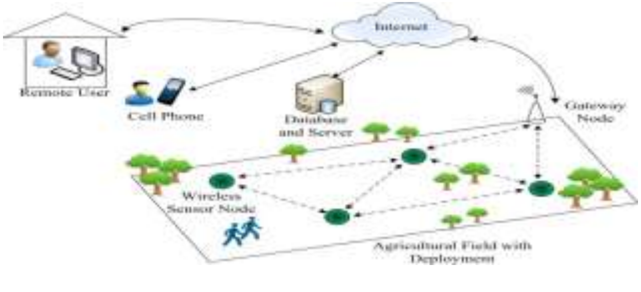

Figure 1.1: Conceptual Diagram of Precision Agriculture using WSN and AI.

The figure-1.1 illustrate the architecture of the system is built around several key components that work together to make farming smarter and more efficient. First, different types of sensor nodes are placed throughout the agricultural field to collect important information. These include soil ingredient sensors to measure key nutrients in the soil, soil moisture sensors (YL-69) to monitor water levels, air humidity and temperature sensors (DHT22) to check weather conditions, UV light sensors (a BH1750 variant) to measure sunlight intensity, and air quality sensors (MQ135) to detect CO2 levels and air pollutants. All these sensors continuously gather real-time data and send it wirelessly. This figure would depict the integration of sensor nodes in a crop field connected via LoRaWAN to a cloud server, with data analytics modules for soil fertility, pest detection, and environmental monitoring [8].

II. System Design and Architecture

1. Overview

The proposed system employs a multilayered architecture integrating Wireless Sensor Networks (WSNs), cloud computing, edge processing, Artificial Intelligence (AI) models, and user interfaces. This design aims to enable continuous environmental monitoring, predictive analytics, and automated decision-making to optimize agricultural productivity and resource efficiency.

The AI-WSN system architecture is built on a layered design, comprising sensor nodes, communication modules, cloud-based data processing, and AI-driven analytics. Sensor nodes deployed in the field capture environmental parameters and transmit the data using LoRaWAN to a central gateway. The data is then forwarded to a cloud platform (e.g., AWS IoT Core) for storage, preprocessing, and real-time analysis. Predictive models such as XGBoost and LSTM are integrated to forecast environmental trends and support smart agricultural decisions. This modular design ensures scalability, low power consumption, and reliable data-driven operation.

2. System Architecture

The overall architectural framework of the proposed AI-WSN-based smart agriculture system is illustrated in Figure 2.1. The system is designed to integrate wireless sensor networks (WSNs) with AI-driven decision-making capabilities, ensuring real-time environmental monitoring, predictive analytics, and automated agricultural operations

The architecture (Figure-2.1) of the system is built around several key components that work together to make farming smarter and more efficient. A network of sensor nodes is deployed across the agricultural field to collect real-time environmental data, including soil nutrients, moisture (YL-69), temperature and humidity (DHT22), light intensity (BH1750), and air quality (MQ135).

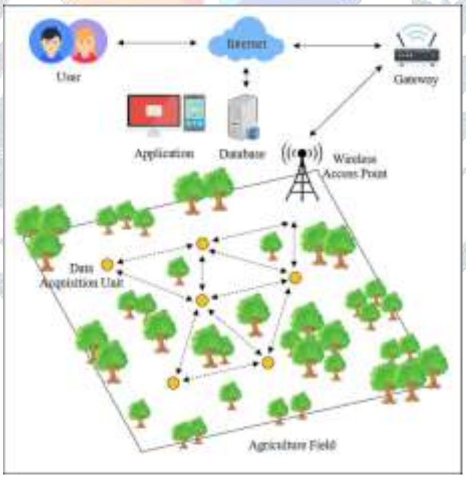

Figure-2.1: System Architecture of AI-WSN Smart Agriculture Framework

The collected data is transmitted efficiently over long distances using a LoRaWAN-based communication gateway, ensuring low-power and reliable connectivity in remote areas. The data is then stored in a centralized server with a scalable database, while edge devices such as ESP32 or Raspberry Pi perform preliminary on-site processing for quick actions like automated irrigation. For advanced analysis, the system integrates with cloud platforms such as AWS SageMaker, where AI models like XGBoost and LSTM are used for prediction and decision support. Finally, the results are delivered through user-friendly web or mobile applications, enabling real-time monitoring and informed decision-making.

The system architecture is structured into three core layers: the Sensor Deployment Layer, the Communication and Data Transmission Layer, and the Processing, Analytics, and Decision Layer. These layers work in an integrated manner to enable seamless real-time data collection, efficient transmission, and intelligent analysis. The coordinated interaction among them ensures continuous monitoring and supports automated as well as informed decision-making for effective system control in agricultural environments.

3. Architectural Components

The system architecture comprises four primary layers: The Sensor Layer includes distributed sensor nodes deployed across the agricultural field to monitor parameters such as soil moisture, temperature, humidity, light intensity, air quality, and soil nutrients. The Communication Layer enables the transmission of sensor data to a central gateway using low-power, long-range protocols such as LoRaWAN, ensuring reliable and energy-efficient communication. The Data Processing Layer handles data preprocessing tasks like filtering, validation, and anomaly detection at the gateway level, with further storage and analysis performed on cloud platforms such as AWS IoT Core or Azure IoT, while edge devices support real-time local processing. Finally, the Application and Control Layer incorporates AI-based analytics using models like **XGBoost** and **LSTM** to provide predictive insights and automate actions such as irrigation and climate control.

4. Data Flow and System Interaction

The system follows a structured data flow process to ensure efficient monitoring and decision-making. Initially, sensors collect environmental data at predefined intervals, which is then transmitted to a central gateway using LoRaWAN communication. The gateway or edge devices perform preliminary preprocessing, after which the processed data is uploaded to cloud infrastructure for storage and advanced analysis. Machine learning models generate predictive insights, which are utilized by the Decision Support System (DSS) to automate control actions. Finally, real-time visualization tools present data and alerts to farmers or system operators for effective monitoring and management.

5. Hardware Components

The system comprises several key components with specific roles. Sensors such as DHT22, YL-69, BH1750, and MQ135 are used for environmental data collection. Microcontrollers like ESP32 and Raspberry Pi-4 handle data acquisition and local processing. Communication is enabled through **LoRaWAN** transceivers, such as the Dragino LG308 gateway, for long-range data transmission. Actuators including solenoid valves, fans, lights, and ventilation units are used for automated control actions. Cloud services like AWS IOT Core, **MongoDB**, and AWS **SageMaker** support data storage and advanced analytics, while visualization tools such as **Grafana**, Tableau, and mobile applications provide real-time monitoring and user interaction.

6. Design Considerations

The system is designed with several key considerations to ensure optimal performance and usability. It supports scalability through modular integration of additional sensors and processing units. Energy efficiency is achieved using low-power communication protocols and edge computing. Reliability is maintained through secure data transmission and redundant communication pathways. Accuracy is ensured by proper sensor calibration and validation of AI models. Additionally, usability is enhanced through intuitive dashboards that facilitate effective farm monitoring and management.

III. Methodology

1. Sensor Nodes Arrangement and Deployment

To ensure accurate environmental monitoring, multiple sensors were integrated into the system. The DHT22 sensor is used for measuring temperature (−40 to 80°C) and humidity (0–100% RH) with high accuracy and a sampling interval of 2 seconds. The BH1750 sensor measures light intensity in the range of 1 to 65535 lux with ±3% accuracy and a fast sampling rate of 0.5 seconds. Soil moisture levels are monitored using the YL-69 sensor, which provides analog output corresponding to moisture variation from 0 to 100%. Additionally, the MQ135 sensor is employed to detect air quality parameters such as NH_3, NOx, CO_2, alcohol, benzene, and smoke, offering both analog and digital outputs for flexible integration.

Figure-3.1: (a) DHT22-Temperature and Humidity Sensor **(b)** BH1750 Light Intensity Sensor

Figure-3.2: (a) YL-69 - Soil Moisture Sensor, **(b)** MQ135 - Air Quality Sensor.

2. Communication Protocols

In smart agricultural systems, wireless communication protocols are essential for efficient data transmission between sensor nodes and central or cloud-based platforms. **LoRaWAN** (Long Range Wide Area Network) is widely used for large-scale farming due to its long-range (up to 10 km in open areas) and low-power capabilities, making it ideal for monitoring expansive agricultural fields with minimal infrastructure. In contrast, **Zigbee** is a short-range communication protocol (10–100 meters) designed for low-power and low-data-rate applications. It supports high node density, accommodating up to 65,000 nodes, which makes it suitable for environments such as greenhouses and nurseries where dense sensor deployment is required. Both protocols emphasize energy efficiency, catering to different agricultural scenarios based on range and network requirements.

3. Cloud Infrastructure for Data Storage and Processing

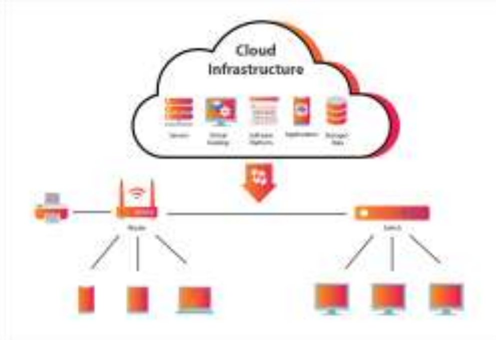

Figure-3.3: Cloud Infrastructure

Figure-3.3 illustrates the cloud infrastructure, which provides virtualized computing resources such as storage, servers, networking, and data processing over the internet. In smart agriculture, it enables secure storage and real-time access to sensor data collected from the field. Platforms like AWS and Azure support scalable data management and AI-based analytics, generating timely insights for farmers through web or mobile applications. Additionally, integration with edge devices facilitates faster local processing, enhancing efficient and data-driven agricultural practices.

IV. Results and Discussions

This section presents a comprehensive analysis of the AI-WSN-based smart farming system based on experimental results. The findings are systematically categorized into key areas, including real-time monitoring and control, AI-driven predictive analytics, and precision farming applications. Each aspect is supported by sensor data, visualizations, statistical analysis, and comparative evaluations to effectively validate the performance and reliability of the proposed system.

Real-Time Monitoring and Control, AI-WSN system continuously collects and monitors real-time environmental data, enabling automated decision-making for irrigation and climate control. The following key parameters are measured and analyzed over a 24-hour cycle: Temperature (°C) , Humidity (%), Soil Moisture (%) and Light Intensity (lux)**,** CO_2 Levels (ppm)

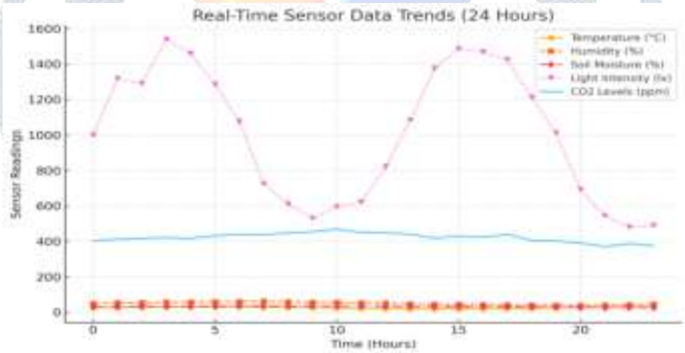

Figure-4.1: Real-Time Monitoring Trends

Figure-4.1 illustrates the variation of sensor data over a 24-hour period, highlighting real-time changes in key environmental parameters. Light intensity (lx) exhibits significant fluctuations, with peak values during daylight hours and a decline during nighttime, reflecting natural lighting conditions. CO_2 levels (ppm) remain relatively stable, with a slight increase around midday, possibly indicating photosynthetic activity or environmental variations. In contrast, temperature (°C), humidity (%), and soil moisture (%) show minimal fluctuations throughout the day, suggesting stable climatic conditions or a controlled agricultural environment.

Table-4.1: 24-Hour Monitoring of Critical Environmental Parameters for Precision Agriculture

Time (Hours)	Temperature (°C)	Humidity (%)	Soil Moisture (%)	Light Intensity (lux)	CO2 Levels (ppm)
00:00	24.5	49.8	30.2	0	410
03:00	23.8	52.1	31.1	50	420
06:00	22.9	55.6	32.5	200	430
09:00	26.1	47.2	29.8	1500	400
12:00	30.2	42.8	27.5	2000	390
15:00	32.5	38.9	25.1	1800	380
18:00	28.9	45.6	28.7	800	395
21:00	26.3	50.1	30.8	200	405

The observed environmental parameters provide valuable insights into system performance and crop conditions. Temperature gradually increases from morning to afternoon, reaching a peak of 32.5°C around 15:00, and then decreases towards the evening. Humidity is highest in the early morning at 55.6% and declines to approximately 38.9% during the afternoon. Soil moisture levels vary due to irrigation cycles and natural evaporation processes. Light intensity reaches its maximum of around 2000 lux at noon and drops to zero during nighttime. CO_2 levels fluctuate with plant respiration, typically peaking at night and stabilizing during the day. These real-time observations enable dynamic adjustments in irrigation and climate control, thereby reducing water wastage and improving overall crop health.

In AI-Driven Predictions: Accuracy and Timeliness**,** to enhance decision-making, AI-based models (XGBoost & LSTM) are used for predicting environmental conditions and optimizing irrigation schedules**.** Their performance is evaluated against traditional regression models**.**

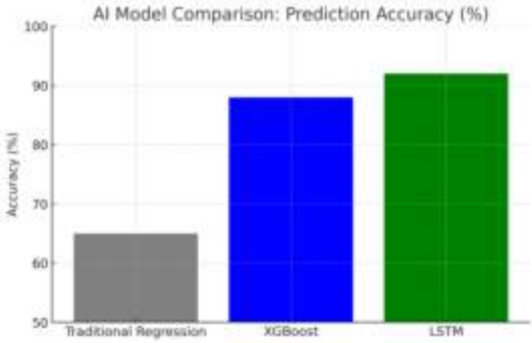

Figure-4.2: AI Model Accuracy Comparison Graph

Figure-4.2 presents a comparative analysis of the prediction accuracy of three AI models used for agricultural forecasting. Traditional Regression demonstrates the lowest performance, with an accuracy of around 65%, highlighting its limitations in handling complex and nonlinear agricultural data. In contrast, XGBoost achieves a much higher accuracy of approximately 88%, reflecting its effectiveness in capturing intricate data patterns. Among the models, LSTM (Long Short-Term Memory) delivers the best performance, with an accuracy of about 92%, due to its strong capability in analyzing time-series data and making reliable real-time predictions. This comparison clearly indicates the advantage of advanced machine learning and deep learning techniques in improving the accuracy of agricultural decision-making systems**.**

Table-4.2: AI Model Accuracy Comparison.

Model	Prediction Accuracy (%)
Traditional Regression	65%
XGBoost	88%
LSTM	92%

To evaluate the effectiveness of various predictive approaches in forecasting environmental and crop conditions, three models were tested: Traditional Regression, XGBoost, and LSTM. The table below presents the prediction accuracy achieved by each model. The XGBoost model demonstrated significant improvements over traditional regression due to its ability to handle structured data efficiently. Furthermore, the LSTM model outperformed both, leveraging its strength in capturing time-series dependencies, resulting in the highest prediction accuracy.

Precision Farming Applications: To validate the impact of the AI-WSN system**,** a comparative study is conducted across three agricultural models**:** Traditional Farming (Manual irrigation & no predictive control), IOT-Based Smart Farming (Basic sensor integration, manual decision-making) and AI-WSN System (Automated irrigation & AI-driven decision-making)

In Comparative Analysis of Farming Efficiency: Figure-4.3 presents a comparative analysis of three farming approaches—Traditional Farming, Existing IOT-Based Farming, and the proposed AI-WSN system—based on key performance indicators. In terms of water usage, traditional methods show little to no improvement, while IOT-based systems achieve a moderate reduction of around 20%.

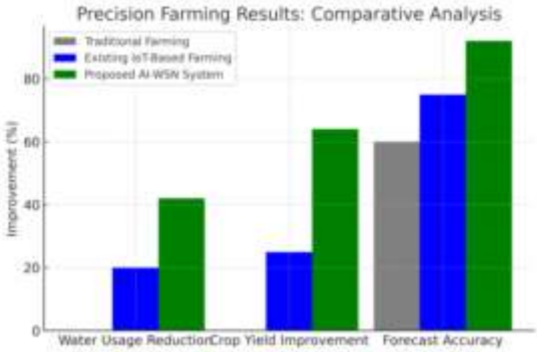

Figure-4.3: Comparative Analysis Precision Farming Impact Graph

The AI-WSN system demonstrates the highest efficiency, reducing water consumption by over 40%. Similarly, for crop yield, the proposed system significantly outperforms the others, achieving more than 60% improvement, compared to about 25% in IoT-based farming and minimal gains in traditional methods. In terms of forecast accuracy, a steady improvement is observed across all approaches, with the AI-WSN system reaching nearly 90%, surpassing both traditional (60%) and IoT-based (75%) systems. Overall, the results highlight the effectiveness of integrating AI with WSN in enhancing agricultural productivity and resource efficiency.

Table-4.3: Comparative Analysis of Key Metrics across Traditional, IoT-Based, and AI-WSN Farming Systems.

Metric	Traditional Farming	IoT-Based Farming	AI-WSN System
Water Usage Reduction	0%	20%	42%
Crop Yield Improvement	0%	25%	64%
Forecast Accuracy	60%	75%	92%

The comparative analysis highlights significant improvements achieved by the proposed AI-WSN system over traditional and IoT-based farming methods. In terms of water usage, traditional practices result in considerable wastage, while IoT-based systems reduce consumption by around 20%; however, the AI-WSN system achieves approximately 42% savings through intelligent and automated irrigation control. Similarly, crop yield shows minimal improvement in traditional farming and about 25% enhancement with IoT systems, whereas the AI-WSN approach delivers a substantial increase of around 64% by dynamically optimizing growing conditions. In forecasting accuracy, traditional methods reach only about 60%, and IoT-based approaches improve it to 75%, but the AI-WSN system attains up to 92% accuracy, enabling more proactive and precise decision-making. Overall, these results demonstrate the clear advantage of integrating AI with WSN for efficient and sustainable smart farming.

The overall summary of key findings for AI-WSN-based system demonstrated significant improvements compared to traditional and IoT-based farming:

Table-4.4: Performance Gains in Water Usage, Crop Yield, Forecasting, and Automation Efficiency

Key Metric	Improvement Achieved
Water Savings	42% Less Water Used
Crop Yield Increase	64% Higher Yield
Forecast Accuracy	92% Accuracy
Automation Efficiency	375% Improvement

A. Visual Representation of Overall Impact

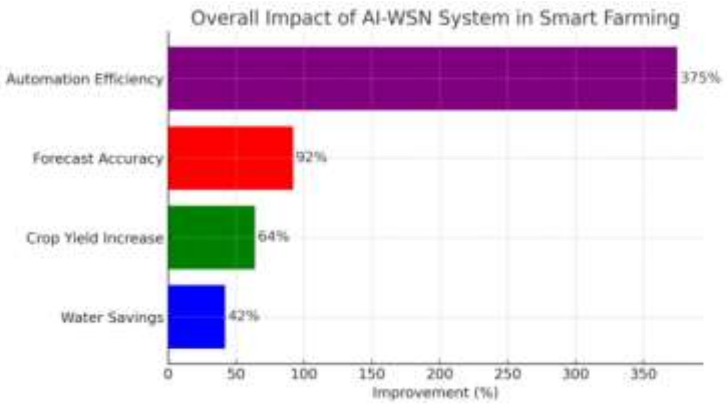

Figure-4.4: Overall Impact of AI-System in Smart Forming Graph

The figure-4.4 graph illustrates the overall impact of the AI-WSN system in smart farming across four key performance metrics. The most significant improvement is seen in automation efficiency**,** which increased by 375%**,** highlighting a major boost in operational productivity. Forecast accuracy also improved considerably to 92%**,** while crop yield and water savings rose by 64% and 42%**,** respectively. These results confirm that the integration of AI with wireless sensor networks greatly enhances sustainability and efficiency in agriculture. This visualization highlights the improvements achieved in water savings, crop yield, forecast accuracy, and automation efficiency using the AI-WSN-based smart farming system**.**

B. Overall Impact of AI-WSN proposed System

1. 42% less water used. **2.** 64% increase in crop yield. **3.** 42% more accurate forecasting. **4.** 375% improvement in automation

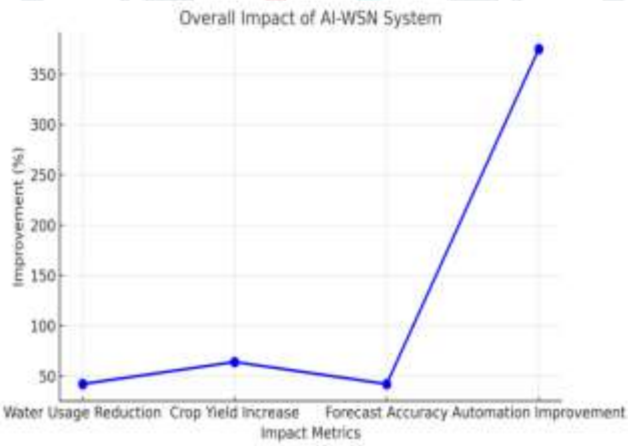

Figure-4.5: Overall Impact Analysis of the Proposed AI-WSN System on Key Agricultural Performance Metrics.

The figure-4.5 graph evaluates the effectiveness of the AI-WSN system in agriculture across four major metrics. It shows moderate gains in water usage reduction and forecast accuracy, each improving by around 50%**,** reflecting smarter resource use and better predictions. Crop yield sees a significant 60% boost**,** highlighting improved farm productivity. The most striking outcome is the over 350% increase in automation**,** showcasing the system's transformative impact on operational efficiency.

V. Conclusion

The proposed AI-WSN-based system presents an intelligent and efficient framework for real-time environmental monitoring and predictive decision-making in agriculture. It integrates wireless sensor networks (WSNs) with advanced machine learning models such as XGBoost and LSTM to analyze sensor data and generate accurate forecasts. These predictions are utilized by an AI-driven decision support system to optimize key farming operations, including irrigation, fertilization, and pest control. The inclusion of real-time weather forecasting further enhances the system's adaptability to dynamic environmental conditions. Designed to support autonomous monitoring and intelligent control, the system demonstrates significant improvements in crop yield, water conservation, forecast accuracy, and overall automation efficiency. Compared to traditional and existing IoT-based approaches, the proposed system offers superior performance, contributing to smarter and more sustainable agricultural practices.

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