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Architectural design of artificial intelligence-based integrated farming system: Automated fertigation, hydroponics and aquaculture, a panacea for food security

ADEBAYO[1], Halleluyah Oluwatobi AWORINDE[2], Morenikeji KOLADE[1], Abidemi Emmanuel ADENIYI[3*], Oluwasegun Julius AROBA[4]
[1]Mechatronics Engineering Programme, Bowen University, Iwo, Osun State, Nigeria.
[2]Information Technology Department, Durban University of Technology, KZN, South Africa.
[3]Computer Science Programme, Bowen University, Iwo,Osun State, Nigeria; abidemi.adeniyi@bowen.edu.ng (A.E.A.).
[3]Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, India
[4]Department of Operations and Quality Management, Durban University of Technology, Durban, South Africa.
[4]Centre for Ecological Intelligence, Faculty of Engineering & the Built Environment, University of Johannesburg, South Africa.

Abstract: Agriculture is the foundation of food production worldwide, and as populations continue to grow, agricultural output struggles to keep up, leading to increasing food insecurity. AI is increasingly recognized as a powerful tool for making farming more efficient and sustainable. This paper presents the architectural design of an AI-enabled integrated farming system that combines automated fertigation, hydroponics, and aquaculture. The framework incorporates sensors, actuators, and microcontrollers for monitoring and controlling resources, utilizing AI algorithms to provide predictive analytics, optimize resource use, and support real-time decision-making. Experiments demonstrate improvements in productivity and the sustainable use of water and nutrients. Real-time data from these sensors can be remotely controlled using a microcontroller, which receives and stores it in the cloud. Notifications on mobile devices or a web dashboard alert farmers when parameters exceed predetermined thresholds, facilitating emergency management of water pollution or nutrient deficiencies. The proposed system offers a scalable approach to enhancing food security, advancing smart agriculture, and promoting sustainable rural development.

Keywords: *Aquaculture, Artificial intelligence, Automated fertigation, Food security, Hydroponics, Integrated farming IoT sensors, Predictive analytics, Resource optimization, and smart agriculture.*

1. Introduction

Agriculture is crucial for the economic stability and food security of every country [1]. However, population growth exceeds food production increases, raising concerns about global food security [2]. As demand for traditional farming practices declines, there is a need for innovative, technology-driven methods to improve yields, efficiency, and sustainability to meet the increasing demand for agricultural products [3, 4]. It is now estimated that food production must increase by 60-110% to feed a projected population of 9-10 billion by 2050 [5]. Addressing this challenge requires judicious use of land, water, fertilizers, and energy, with practices that protect the environment.

Numerous technological advances in genetic modification, irrigation, and post-harvest treatment have contributed to increased productivity [6, 7]. Recently, precision technologies and climate-smart agriculture, supported by artificial intelligence (AI), big data, and the Internet of Things (IoT), have been proposed as strategies to enhance resilience against climate change and promote sustainable food systems [8, 9]. For instance, recent publications encompass applications ranging from predicting water

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* Correspondence: abidemi.adeniyi@bowen.edu.ng

demand in arid areas [10] to multi-sensor monitoring for sustainable irrigation [11] and nanosatellite-based crop classification [12]. These developments reflect the worldwide trend toward the use of artificial intelligence in agriculture.

Take AI-driven technologies, for example, which are transforming agriculture through predictive analytics, decision support systems, and automation [13, 14]. Applications include crop monitoring, aquaculture, and hydroponics, with promising results for increased yields and reduced waste [15-17]. However, few works are complete and focus on applications such as water quality monitoring [18] or climate control systems for hydroponics, with corrected grammar and spelling [19]. Currently, there are few efforts combining fertigation, hydroponics, and aquaculture into an integrated, AI-enabled architecture supporting commercial-scale farm operations.

This study addresses a gap by proposing an AI-enabled integrated farming system based on automated fertigation, hydroponics, and aquaculture. The system incorporates sensors, actuators, IoT communication protocols, and machine learning algorithms for comprehensive monitoring, prediction, and resource optimization in real-time. Unlike current systems, this framework demonstrates the potential of sensor fusion and AI operations across various farming sectors. It aims not only for increased productivity but also for sustainable resource management, aligning with global strategies for food security and climate resilience.

2. Related Works

The need to increase agricultural output faces rising stress from climate change, resource depletion, and population growth. Global studies indicate that food production must increase by 60–110% to meet the demands of 9–10 billion people by 2030–2050 [1, 9].

The declining availability of freshwater, increased evapotranspiration due to higher temperatures, and variable rainfall patterns have intensified stress on traditional farming methods, especially in arid and semi-arid regions. For example, climate change is leading to an increased need for irrigation in Saudi Arabia [20]. Intelligent and smart agricultural practices are essential for the sustainable management of water resources. This is particularly true for practices based on multi-sensor spatiotemporal analyses, as discussed by Haq [21], which optimize and stabilize agricultural output under limited water availability. These studies emphasize the need to replace traditional irrigation methods with advanced, adaptive practices to manage water resources effectively for irrigation.

Simultaneously, machine learning and satellite imaging technology in agricultural monitoring have proven fundamental in addressing the relationships between macroclimate and crops. As Haq [22] demonstrates, the classification of Planet Scope nanosatellite images enables real-time monitoring and classification of crops, even as the climate changes. This is part of a broader initiative to apply AI, IoT, and predictive analytics as climate-smart agricultural tools [23, 24]. Collectively, these works emphasize that climate change presents not only environmental challenges but also technological ones, requiring sophisticated solutions to address water scarcity, improve nutrient use efficiency, and stabilize yields amid unpredictable weather conditions.

Therefore, the work of automation and IoT in efficient irrigation, soil health monitoring, and optimized pest management [25, 26] demonstrates that these technologies, alongside the realities of climate change, are standards that are non-negotiable. This context underpins AI-powered integrated farming solutions that combine hydroponic farming, aquaculture, and fertigation to create climate-smart systems.

The automation process in agriculture, along with precision farming that incorporates IoT and decision-making and predictive systems forming the core of communication technologies, is already transforming the sector significantly. In a broader sense, IoT technologies used for efficient irrigation management, soil sensing, and pest elimination have been integrated to improve yields and reduce wastage [25, 26]. I acknowledge that in automation and systems design, the nuts and bolts of reality seem unfeasible due to the resources required to develop the subsystems. Automation often appears to be the simpler and more effective approach. However, the groundwork appears to be in place for AI to enter agriculture and bring about further transformation.

Current applications of artificial intelligence in tool-driven agricultural operations utilize machine learning and deep learning methods for crop health monitoring, yield prediction, forecasting, and disease diagnosis [19, 27]. In aquaculture, computer vision and artificial intelligence have also been applied [16, 28], along with several IoT applications, for monitoring water quality and optimizing fish feeding [29-32]. Also, the application of AIoT in hydroponics states, "For crop recommendation and nutrient monitoring, the proposed method is more effective and best suited for development with minimization of human error" [17, 33]. The authors noted that when used properly, this technology can enhance all four dimensions of food security, including supply, availability, access, and stability for consumption [34, 35].

Both hydroponics and aquaculture are sustainable individually, but combined, they form an integrated aquaponic system, creating a closed-loop that uses fish effluents as plant fertilizer, reducing chemical inputs [15, 36]. The application of AI-based optimization systems is well-established; however, few studies trace the entire value chain to where AI integration occurs at the production stage [37, 38]. For instance, although some real-time systems detect nutrients [18] and water quality management or climate control systems exist, very few systems are designed to integrate these subsystems into a higher-level system.

The integration of IoT has been a focus of recent studies, aiming to enhance farming efficiency and sustainability. Zamnuri et al. [37] highlighted the current state of small-scale aquaponics and the potential for IoT technology in monitoring and controlling water systems, oxidative, reductive, and mineral nutrients. However, this potential has yet to be realized on a larger scale. In the more applicable direction, Birdawade et al. [38] took a step forward by integrating aquaponics, hydroponics, and poultry systems with an IoT monitoring system, offering an IoT-based solution for monitoring these combined farms. This approach provides a more comprehensive, though still evaluative, method. While these efforts mark progress, they remain the most informal and vague forms of automation systems intended to be powered by AI.

The following discusses the application of sensing and digital intelligence techniques in confinement, aiming to fully incorporate artificial intelligence, including intelligent agricultural management. Regarding AI prediction, Wang et al. [39] forecast that large-scale AI deployment in digital mapping, crops, and water management will significantly transform agricultural production systems. Additionally, recent advances in computer vision and the Internet of Things have improved feed optimization in aquaculture [28], stimulating a paradigm shift from reactive to predictive feeding in aquaculture. These works aimed at adopting adaptive control in anticipation of artificial intelligence (AI) applications. However, the overall paradigm of a multi-system framework integrating hydroponic, aquaculture, and fertigation systems into a unified, holistic concept remains absent.

Furthermore, the integration of operating systems across cross-domain IoT, AI, and wireless sensor networks in smart farming [39, 40] proves to be a more efficient and sustainable approach, although it remains in the experimental stage. Hydroponics, aquaculture, and fertigation systems also require innovative, efficient solutions for scaling up and achieving interoperability.

Based on the identified literature gap, the integration of systems with automation and advanced AI remains unresolved. While recent research documents hydroponics, aquaculture, and irrigation management within their respective domains, publications that integrate these areas into a coherent framework are scarce. The literature review results on system design, AI, automation, scalability, nutrient flexibility, recycling, and overall system design are presented in Tables 1 and 2. These tables clarify how the proposed system advances existing technology in the field.

Table 1.
Comparative Analysis of System Architectures (Integration, AI, Nutrient recycling, Automation).

Study	Focus area	Integration(Hydroponics/ Aquaculture / Fertigation)	Nutrient recycling	AI / Automation
Proposed system (this work)	Integrated aquaponics–hydroponics–fertigation	Full integration (hydroponics + aquaculture + fertigation)	Closed-loop (aquaponic nutrient reuse)	AI-driven DSS, LSTM prediction, adaptive control
Aydin et al. [41]	Smart irrigation/hydroponics	Partial (irrigation-focused)	Limited / none	ML for soil moisture; scheduling
Dhinakaran et al. [42]	Aquaculture monitoring	Aquaculture-only (isolated)	None	ML for fish health, automated feeding
Naphtali et al. [43]	Hydroponics	Hydroponics-only	None	IoT automation; rule-based control
Uthman and Musa [44]	Hydroponics	Hydroponics-only	None	AI automation, but no cross-module integration
Sadek and Shehata [45]	Greenhouse control	Greenhouse-only	None	IoT-based threshold automation
Anila and Daramola [34]	Smart aquaponics (systematic review)	Focus on aquaponics (review)	Partial (reviewed systems)	Surveyed AI/IoT approaches (mixed automation)
Díaz-Delgado et al. [35]	Hydroculture optimisation	Hydroponics/hydroculture	Nutrient optimisation (hydroculture)	AI models for yield & nutrient optimisation
Dennison et al. [46]	Automation & robotics	Hydroponics + aquaponics (robotics focus)	Medium (depends on implementation)	Robotics + high automation
Zamnuri et al. [37]	IoT in small-scale aquaponics (review)	Small-scale aquaponics	Partial	IoT monitoring emphasis (limited AI)
Ghaffar et al. [24]	Aquaponics tech & infrastructure	Aquaponics infra & design	Aquaponics-based recycling	Conceptual IoT/automation; infrastructure focus
Birdawade et al. [38]	IoT-enhanced multi-system farming (review)	Aquaponics + hydroponics + poultry	Reuse pathways discussed (poultry/fish waste)	IoT + AI integration (review/experimental)
Rahman et al. [33]	AIoT hydroponics	Hydroponics (AIoT)	Limited/managed in hydroponics	AIoT crop recommendation & nutrient monitoring
Wang et al. [39]	Remote sensing + AI for agriculture	System-level monitoring (remote sensing)	Not system-specific	AI + remote sensing analytics (scalable monitoring)
Verma et al. [23]	IAAS: Aquaponics as agri-aquaculture	Integrated agri-aquaculture (IAAS)	Emphasized nutrient reuse	Case studies; ML/automation noted
Hossam et al. [28]	Precision aquaculture (CV + IoT)	Aquaculture-only	Not addressed	Computer vision + IoT for feeding optimisation
Haq and Khan [20]	Crop water requirements under climate change	Agriculture (irrigation)	Indirect (water optimisation)	Simulation & scheduling (climate data integration)
Haq [21]	Intelligent sustainable water practice	Agriculture water systems (multi-sensor)	Limited nutrient focus (mainly water)	Multi-sensor AI & spatiotemporal modelling
Haq [22]	Nanosatellite ML for classification	Remote sensing & ML	Not nutrient-specific	ML classification from Planetscope nanosat data

Table 2.
Comparative Analysis of System Architectures (Scalability, Flexibility, Climate change consideration & Sustainability).

Study	Scalability	Flexibility	Climate change consideration	Sustainability
Proposed system	High — cloud/modular design (pilot → cloud scale)	High — AI-adaptive multi-module control	Explicitly addressed (climate-resilient design)	High — closed-loop nutrient & water reuse
Aydin et al. [41]	Low	Medium	Not explicitly addressed	Moderate (water-efficiency focused)
Dhinakaran et al. [42]	Medium	Medium	Not explicitly addressed	Moderate (aquaculture gains)
Naphtali et al. [43]	Low	Low	Not addressed	Low
Uthman and Musa [44]	Medium	Medium	Not addressed	Moderate
Sadek and Shehata [45]	Low–Medium	Low	Not addressed	Moderate
Anila and Daramola [34]	N/A (review)	N/A (review summarizes diversity)	Not explicit (survey)	Moderate (identifies potential)
Díaz-Delgado et al. [35]	High (commercial hydroculture potential)	High	Indirectly (optimisation aids resilience)	High (nutrient & yield optimisation)
Dennison et al. [46]	Medium–High (robotics can scale but is costly)	High	Not explicit	Medium
Zamnuri et al. [37]	Low (small-scale focus)	Medium	Not explicit	Moderate
Ghaffar et al. [24]	Medium	High	Not explicit	High (infrastructure for sustainability)
Birdawade et al. [38]	Medium (experimental)	High	Not explicit	High (integrated waste reuse)
Rahman et al. [33]	Medium (modular hydroponics)	High	Indirectly (resource optimisation)	High
Wang et al. [39]	High (satellite/drone scaling)	High	Explicitly addressed (remote sensing for climate resilience)	High
Verma et al. [23]	Medium	Medium	Not explicit	High (IAAS nutrient reuse)
Hossam et al. [28]	Low–Medium (farm-level)	Medium	Not explicit	Moderate
Haq and Khan [20]	Medium (arid regions focus)	Medium	Explicitly addressed (climate water needs)	High (water conservation)
Haq [21]	Medium–High (multi-sensor, scalable)	High	Explicitly addressed (AI-driven climate water management)	High (intelligent sustainable practice)
Haq [22]	High (satellite ML scaling)	High	Explicitly addressed (satellite climate data)	Moderate–High (data-driven sustainability)

Through the gap analysis, some gaps in the literature have been identified. Most existing frameworks are either domain-specific or related to hydroponics [43, 44] and aquaculture [28, 46] or attempt to position the objective as irrigation scheduling [41]. Even studies focusing on integration [23, 38] do not consider fully automated, adaptive mechanisms capable of real-time resource configuration across multiple subsystems. Additionally, no frameworks include nutrient recycling and closed-loop resource use, which are essential for sustainability at scale.

The systems considered are also not sufficiently flexible. Many use static thresholds or rules of thumb [34, 45], which poorly handle dynamic environmental changes. However, positive trends in AIoT are evident [33] and robotics [46]. These are mostly idealistic or small-scale solutions, for which scalability and adaptiveness are predicted to rely on cloud functions, and for which there is no evidence.

However, the proposed system overcomes these limitations by integrating hydroponics, aquaculture, and fertigation into a single system. Its predictive modeling, combined with AI, IoT connectivity, and cloud scalability, offers resource optimization, closed-loop nutrient recycling, and real-time adaptive performance. This positions the model to promote sustainable, energy-efficient agriculture at scale, addressing food security challenges effectively.

3. Design Concept

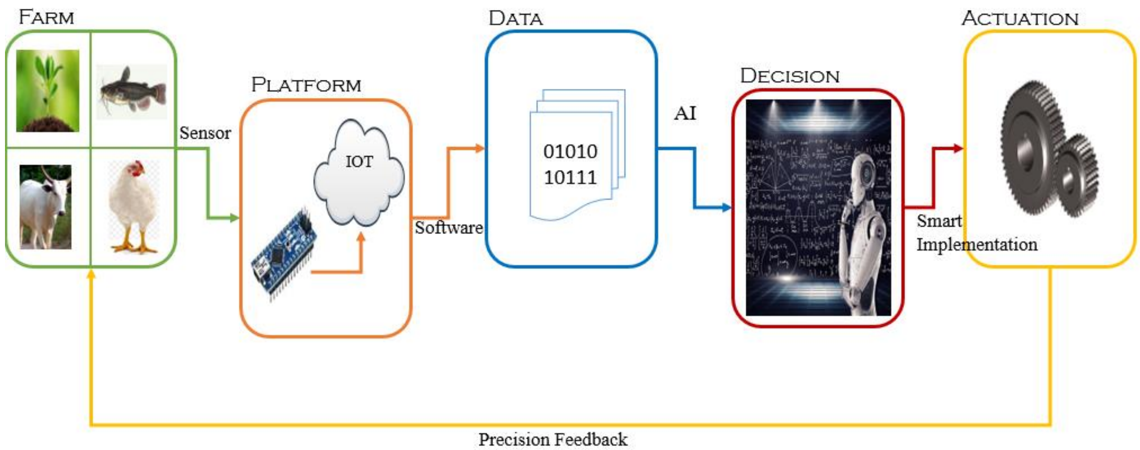

Figure 1.
Conceptual Architecture.

As illustrated in Figure 1, the system was designed to manage farms using technology. It functions through a continuous feedback loop connecting the farm environment, an IoT-based platform, data processing, AI-driven decision-making, and automated controls. This integration allows real-time resource monitoring, forecasting, and adaptive management, ultimately enhancing farm productivity.

The farm component includes crops, aquaculture, poultry, and animal husbandry. Effective management requires monitoring soil moisture, water quality, temperature, humidity, and nutrient levels to ensure optimal conditions for plant growth. These parameters are critical for sustaining plant growth and ensuring animal health and productivity.

The platform relies on an IoT framework that connects the farm to the AI system. Smart sensors continuously measure environmental parameters, including pH, turbidity, temperature, oxygen levels, and water levels. The software enables seamless communication between users and devices, and the wireless transmission of sensor data facilitates real-time remote monitoring and quick responses to farm conditions.

Cloud-based storage and data processing systems streamline information management. Farm condition predictions and process automation become possible as data is structured, increasing the accuracy of farm management decisions along with control and autonomous process management.

The system is anchored by an AI decision support system (DSS). It intelligently predicts using artificial neural networks, machine learning, and deep learning, enabling resource preservation while meeting system targets to optimize responsiveness to surrounding frictions.

Automated actuation with AI-driven predictive accuracy is achieved through smart valves and motor systems. For example, the precision of hydroponic and aquaponic systems in oxygenating and delivering nutrients is matched by greenhouse systems that control humidity and temperature within ideal levels.

The feedback precision loop determines whether the expected results have been achieved from the actions taken. This self-correcting system allows farm practices to be continuously modified and improved. Sustainability and productivity are therefore guaranteed over time.

4. Farming System Overview

The farming system aims to integrate hydroponics, aquaponics, and fertigation, combining all three into a single, efficient system. The nutrient balance subsystem, serving as the system's core, nourishes all three subsystems holistically, distributing physiologically vital components based on real-time sensor data and health parameters for the arboretum and aquaculture. The module utilizes automated valves and pipelines to regulate the flow of real-time physiological vital signs.

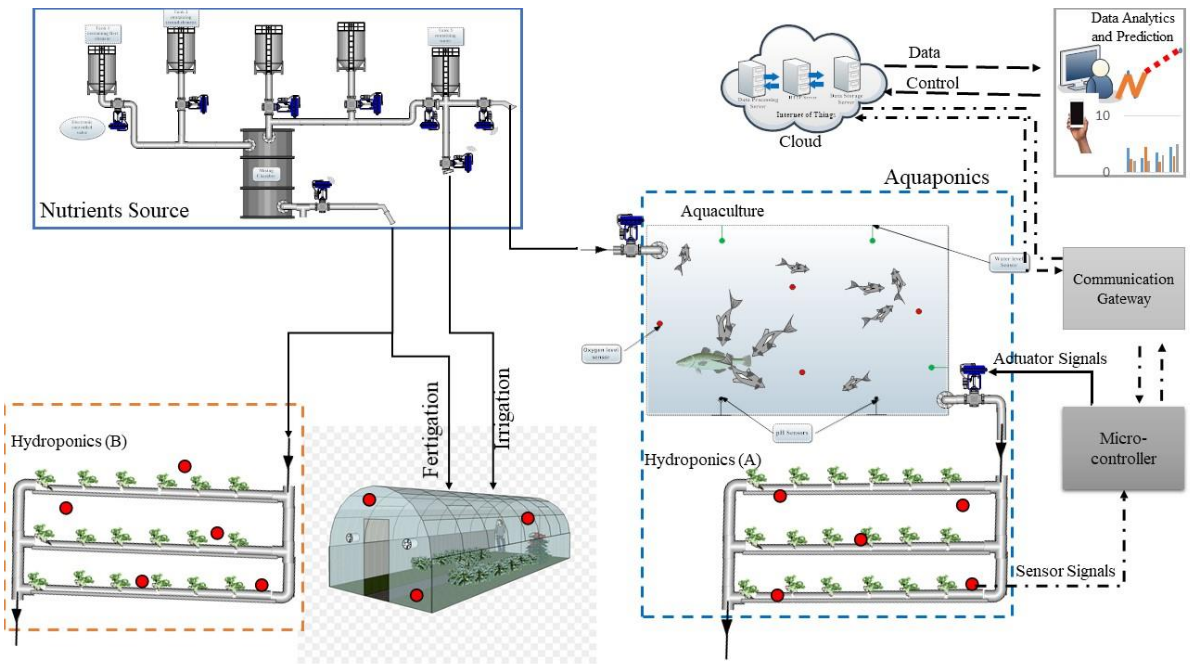

Figure 2.
Integrated Farming System Architecture.

The system's aquaponics module combines fish farming and hydroponics. Water is filtered and recirculated to plants that naturally digest fish waste. Water conservation is achieved through this closed-loop system, eliminating chemical fertilizers. Water quality, oxygen saturation, pH, and turbidity are continuously monitored to ensure optimal conditions for fish and plants.

The plants are grown in hydroponic units (A and B) that are soil-less and nourished by strategically controlled automated systems. These systems operate as modules that induce oxygenic and anaerobic layers in super-saturated solutions, inactivating water, and are hydroponically pre-bioenergetically assisted with actualized aerobic waters. Hydroponic B covers an entire greenhouse with a faceted lozenge configuration, providing optimal conditions and nurturing harvest frequencies.

The system is managed by an advanced communication network that aggregates sensor data and relays it to a microcontroller. The microcontroller performs data processing and controls valves, pumps, and climate systems to make appropriate adjustments.

AI-driven analytics predict trends and streamline operations on the cloud server where data is stored. Users can monitor and control the system via mobile devices, enabling real-time updates and flexible management. They are provided with the necessary tools to manage the system, all within a single app.

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The cloud system architecture integrates the sensor, network, service, and application layers [47, 48]. Each layer focuses on a specific function while interacting with others, enhancing the system's effectiveness and reliability in farming applications.

1. The sensor layer monitors parameters such as water, oxygen, and temperature in real-time. The system includes physical sensing devices like water quality sensors, nutrient detectors, oxygen monitors, and temperature sensors. The aquaponics, hydroponics, and fertigation subsystems provide the data necessary to monitor these biological and environmental parameters.
2. The network layer enables the transmission of signals captured by sensors to the control system using various communication protocols such as LoRaWAN or Wi-Fi. It acts as an intermediary between the sensor and application layers, facilitating bidirectional communication. Lower-level sensors connect to higher processing units, ensuring efficient data flow.
3. The Service Layer captures actionable intelligence by transforming raw data, identifying anomalies, optimizing nutrient uptake, and predicting harvests. Microcontrollers and the cloud process data streams in parallel. Clouds handle sophisticated data storage, analysis, and artificial intelligence, while edge computing facilitates instantaneous information flow even in regions with subpar infrastructure.
4. The Application Layer is the layer where customers, end users, operators, and farmers engage most with the system using user-friendly tools on mobile or desktop interfaces. Users can visualize system data and are provided with interfaces that display crop health, aquaculture performance, and overall system status. They are empowered with remote access via mobile and desktop platforms, enabling them to initiate prompt, correct actions and develop strategies.

Inter-layer interactions are dynamic and circular. For example, aquaponics sensors measuring pH values send data via the network layer to the service layer. The microcontroller processes this data and, if a deviation from the norm is detected, sends an actuator signal back through the network layer to adjust nutrient and oxygen levels. Simultaneously, this data is cloud-logged and made available on the application layer to the farmer, ensuring transparency and traceability. This coordinated multi-layer approach enhances precision, efficiency, resource conservation, and sustainability in the farming system.

4.1. Sensor Layer

The design at this layer involves selecting sensors that are primarily dependent on the environment [49]. These environments, as shown in Figure 3, are categorized into three groups: underwater, atmospheric, and soil. The sensors in each environment monitor conditions and control actuators to perform specific tasks that support sustainable agriculture. Table 2 details each of these sensors. The microcontroller processes the data and manages the functions of various components within an embedded system. Its two main functions are to receive data from sensors and control actuators [50] to send sensor readings to the cloud and users, as well as to receive commands from remote locations. The device selection depends on its flexibility and power consumption.

An open-source firmware and development board designed for Internet of Things applications was selected for this study. The firmware operates on an ESP8266 chip, which features a 32-bit Tensilica processor, standard digital peripheral interfaces, antenna switches, RF balun, power amplifier, low-noise receive amplifier, filters, and power management modules. The processor employs 32-bit Reduced Instruction Set Computer (RISC) technology, offering low power consumption and a maximum clock speed of 160 MHz. The system includes various sensors, such as crop sensors, underwater sensors, and atmospheric sensors. Sensors are devices capable of detecting and reporting environmental changes, which may be chemical or physical in nature.

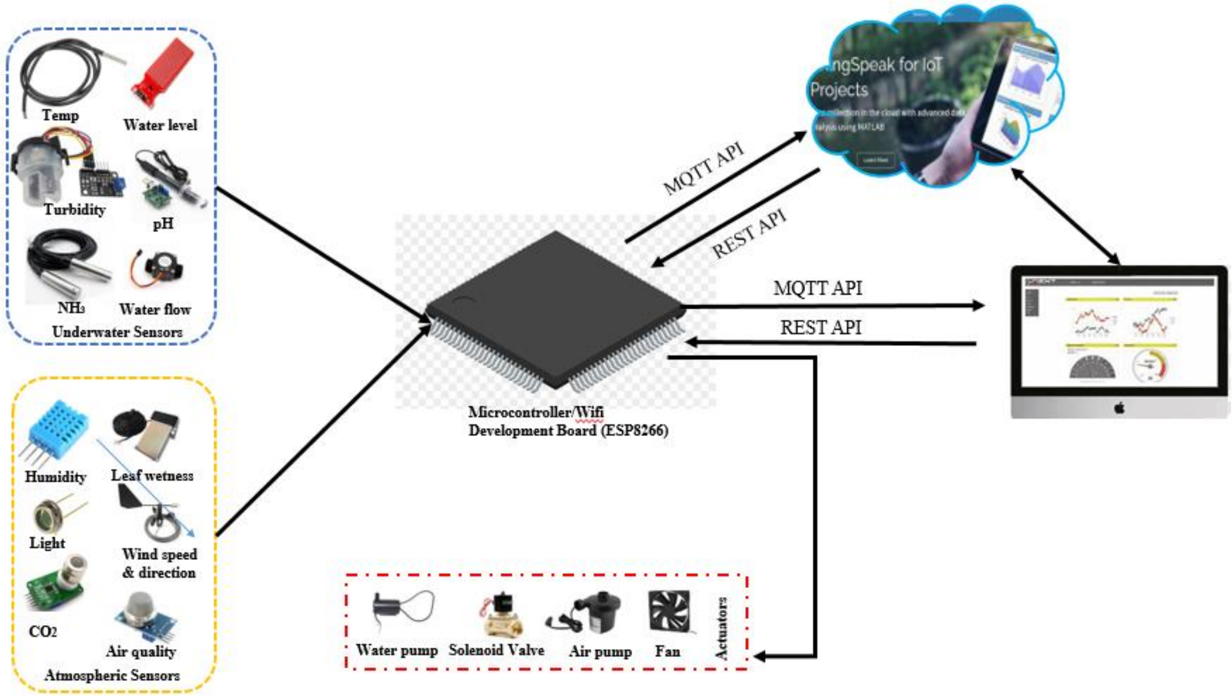

Figure 3.
Design Component.

The device comprises three major units: sensing, processing, and communication. The sensing unit includes a sensor and an analog-to-digital converter. Multiple sensors can be combined to create a smarter device. The analog signal generated by the sensor, which reflects environmental changes, is converted into a digital signal by the converter and then fed into the processing unit. The processing unit performs computations on the data and can store or transmit it to remote storage via the communication unit. The communication unit connects the node to the network layer. The sensor node can switch among four modes depending on the current task: transmitting, receiving, idle, and sleep.

Table 3.
Underwater Sensors.

Sensor Type	Model	Function	Measurement Range / Units
Temperature	DS18B20	Measures water temperature to detect unusual rises affecting aquatic and plant health.	−55 °C to +125 °C, ±0.5 °C accuracy
Water Level	DP5200	Detects the water amount within the container for irrigation and aquaponic balance.	0–5 m (typical), output in cm or mm
Turbidity	ISST105	Measures light scattering by suspended solids to estimate water particle contamination.	0–1000 NTU (Nephelometric Turbidity Units)
pH	SEN0169	Determines water acidity or alkalinity to maintain balance for fish and plants.	0–14 pH units, ±0.1–0.2 accuracy
Water Flow	YFS201	Monitors the flow rate of water through pipes to ensure proper circulation and distribution.	1–30 L/min (litres per minute)

All underwater sensors underwent precise calibration before deployment to ensure accuracy and reliability. The DS18B20 thermometer was verified against a well-known mercury thermometer in regulated prime temperature baths at 20°C, 25°C, and 30°C. The DP5200 water level sensor was calibrated in an experimental system consisting of a graduated cylinder, where water levels were gradually increased, and sensor outputs were compared to actual measured levels. To account for scattering caused by suspended solids, the ISST105 turbidity sensor was calibrated using Formazin turbidity standards at 0, 20, and 100 NTU. To ensure accurate detection of changes in acidity and alkalinity, the SEN0169 pH sensor was calibrated against three buffered solutions with pH values of 4.0, 7.0, and 10.0. Finally, a timed volumetric assessment was performed to calibrate the water flow sensor, comparing it with the accuracy of a calibrated flow system based on YFS201. To minimize drift errors, each calibration was repeated multiple times, and the results were entered into the control system database.

4.2. Network layer

In this proposed system, various sensor data are transmitted via different communication technologies such as Bluetooth [51], Zigbee, and LoRa to the internet. Due to power limitations in WSN, energy-efficient routing protocols are crucial. Constrained power in WSN can be effectively managed using APTEEN [52] while providing acceptable performance; our system includes a wireless module connectable to the cloud via TCP/IP. The module operates in three modes, active, sleep, and deep sleep, to conserve battery life [53].

To analyze the effectiveness of these modes, the average power consumption per reporting interval T was defined as:

$$I_{avg} = \frac{I_{tx}t_{tx} + I_{rx}t_{rx} + I_{proc}t_{proc} + I_{sl}t_{sl}}{P_{avg}}, \; P_{avg} = V\, I_{avg} \qquad [54]$$

Where I_{tx} , I_{rx} , I_{proc} ,I_{sl} are the currents in transmit, receive, processing, and sleep modes, and t_{tx}, t_{rx} , t_{proc} , t_{sl} their respective durations.

The cloud infrastructure is a system of servers connected to the internet, providing a link between microcontrollers and end-user mobile devices. This component stores historical sensor data to develop a software driver for real-time monitoring and control. MATLAB-based computations are supported by ThingSpeak, an open-source platform for numerical analysis. For inter-data communication, RESTful APIs and Message Queuing Telemetry Transport (MQTT) are used. While REST APIs operate on a request-response paradigm, MQTT employs a lightweight publish-subscribe model over HTTP. Due to bandwidth and power constraints, MQTT is used for real-time data transmission, whereas REST is utilized for data access.

In summary, there are additional reasons why MQTT is preferred over REST, including lower latency. REST remains adequate for periodic reporting and archival purposes. Both dummy methods utilize keys as a form of authentication to safeguard information. The Decision Support System (DSS) located at this network layer is responsible for collecting environmental data to improve farming practices. AI service layer algorithms excel at analyzing diverse sets of agricultural information to assist farmers. These algorithms facilitate monitoring of generation unit functioning, forecasting, pattern recognition, anomaly detection, and optimization of control strategies. Predictive analytics, for example, aids in feeding management and proactive intervention in hydroponic nutrient control. Artificial neural networks (ANNs) are used to construct the system, as they provide optimal predictive capabilities. Neural networks consist of multiple interconnected layers and can perform both regression and classification tasks after training. Non-linearity is incorporated into these systems through activation functions, which are essential components that model complex correlations within the data [55, 56]. It has been seen that the three widely used activation functions are:

$\sigma(x) = \frac{1}{1+e^{-x}}$ (sigmoid)

$\tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$ (Hyperbolic Tangent)

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f(x) = max (0,x). (ReLU)

For temporal dependencies in sensor data, such as changes over time in water quality, Long Short-Term Memory (LSTM) networks were employed. LSTM addresses issues of vanishing gradients and can capture long-term dependencies that traditional RNNs struggle with. Compared with Convolutional Deep LSTM (CDLSTM), one of the most effective methods for video recognition, LSTM is sufficiently complex to characterize sequential aquaponics sensor data without the computationally expensive processing time. Although Synthetic Minority Oversampling with Deep Neural Networks (SMOTE-DNN) is a popular technique for imbalanced datasets, LSTM was chosen because of the greater emphasis on the time-series nature of water quality and nutrient concentrations over the need for a well-balanced maintenance class.

Figure 4 shows the structure of the LSTM network. The input gate, as the name suggests, controls the incoming data x_t to the model using the sigmoid function, and introduces weights using the tanh function. The forget gate f_t specifies which value from the previous cell state C_{t-1} to forget, depending on the sigmoid evaluation of the value of $h_{t-1}$and x_t. Before the multiplication with the output gate oto_t is performed, the multivector is somehow scaled through a tanh-function that also chooses the output values as a sigmoid function.

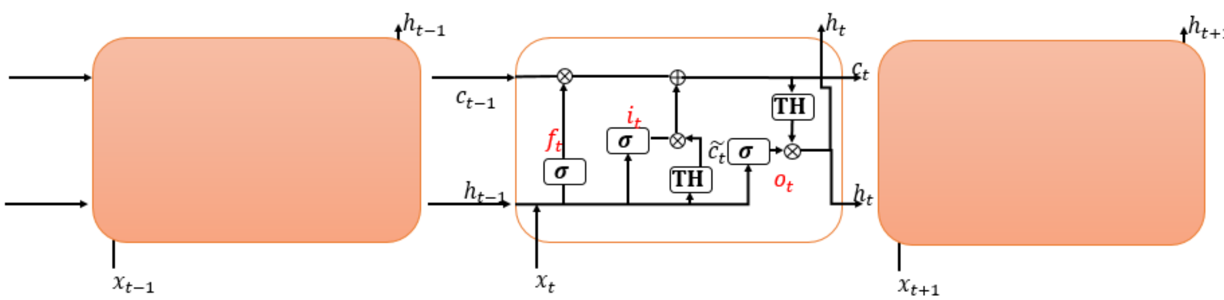

Figure 4.
LSTM Hidden Layer Architecture.

Hyperparameter tuning is a method used to optimize model parameters. In this case, hyperparameters included the learning rate (0.001 to 0.01), epochs (50 to 200), batch size, and dropout rates (0.2 to 0.5). To determine the optimal values, grid search and cross-validation methods were employed. The model was evaluated using multiple prediction accuracy metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R2). Sensor calibration is essential to improve accuracy, especially underwater, where measurements can be affected by turbidity and biofouling.

HNO3 (3 hydrochloric) solution was used to calibrate the pH, and solutions saturated with oxygen and lacking oxygen were used to calibrate the dissolved oxygen sensors at two points. These calibration procedures occurred randomly and were reinforced by an anomaly detection module that facilitated software filtering of erroneous data.

Model evaluation was carried out using standard performance metrics. The Root Mean Square Error (RMSE) measures the square root of the average squared differences between predicted $(\hat{y}_i)$ and actual (y_i) values.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad [57]$$

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The Mean Absolute Error (MAE) calculates the average magnitude of errors without considering their direction:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad [57]$$

The Coefficient of Determination (R2R^2) evaluates how well the model explains variance in the observed data:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \ddot{y})^2} \quad [57]$$

where y_i is the observed value, $\hat{y}_i$ the predicted value, ÿ the mean of observed values, and n the number of observations.

Data reliability and fault tolerance mechanisms are specifically implemented in the network layer to ensure resiliency, which is the network's ability to recover from faults. Since sensor nodes are vulnerable to packet loss and energy depletion, one solution is to implement sensor redundancy through paired sensors and voting algorithms to filter out erroneous readings. MQTT's Quality of Service (QoS) levels are used to guarantee message delivery: at-least-once delivery (QoS 1) for important bathroom control commands and exactly-once delivery (QoS 2) for critical farm control commands. This approach reduces downtime and maintains stable farm operations even after communication disruptions.

Finally, edge computing and analytics are integrated with the cloud. The LSTM models were reduced to a lightweight version and deployed on microcontrollers (ESP32), enabling local anomaly detection when thresholds, such as low dissolved oxygen, are exceeded. This approach reduces reliance on continuous internet connectivity, with responses triggered directly at the farm level. Edge-cloud collaboration combines rapid local decision-making with a robust cloud analysis engine, providing high reliability and scalability benefits for smart aquaponics and hydroponic solutions.

However, this approach offers several advantages, but some challenges must be addressed when scaling the system for commercialization. Deploying a large number of sensors can lead to network congestion and latency delays. Additionally, high sampling frequencies complicate sensing tasks, especially with limited sensors. Power management becomes more difficult in both scenarios, as sleep modes lose effectiveness when synchronizing thousands of nodes organized as a distributed farm. While cloud infrastructure can easily scale data storage, operating at scale in production is costly and may cause bottlenecks if data aggregation processes are inefficient. Multisite scaling introduces further security concerns, requiring robust authentication, encryption, and fault-tolerant routing schemes. Addressing these challenges is essential to transition from pilot projects to fully commercialized smart farming systems.

4.3. Application layer

Agricultural processes generate vast amounts of data, which can be harnessed and processed to gain insights for making effective decisions that promote optimal crop or animal growth. Harnessing and processing require specific technologies. Traditionally, farmers manage their farms through visual inspection of crop and livestock growth, making decisions and taking actions for treatment. This method largely depends on field experience and the information perceived through farmers' eyes. Technological intervention has enhanced farm management. This layer helps farmers access information about their farm's status. It provides data visualization in a user-friendly manner, as well as the actions necessary for farm status optimization, such as fertigation, irrigation, and pest control, among others.

5. Experimental Results

The fish pond, measuring 15 by 7 inches, is depicted in Figure 5. Key elements of this system include an aquaculture setup with sensors, a microcontroller unit, cloud infrastructure, and mobile

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applications. The use of IoT technology enhances efficiency and sustainability in crop cultivation and aquaculture. The microcontroller collects real-time data from sensors in aquaculture and greenhouse environments. These sensors monitor pH, temperature, dissolved oxygen, and various nutrient levels in water. The data is analyzed and transferred to the cloud for storage and further analysis, ensuring environmental conditions remain suitable for plant and aquatic life.

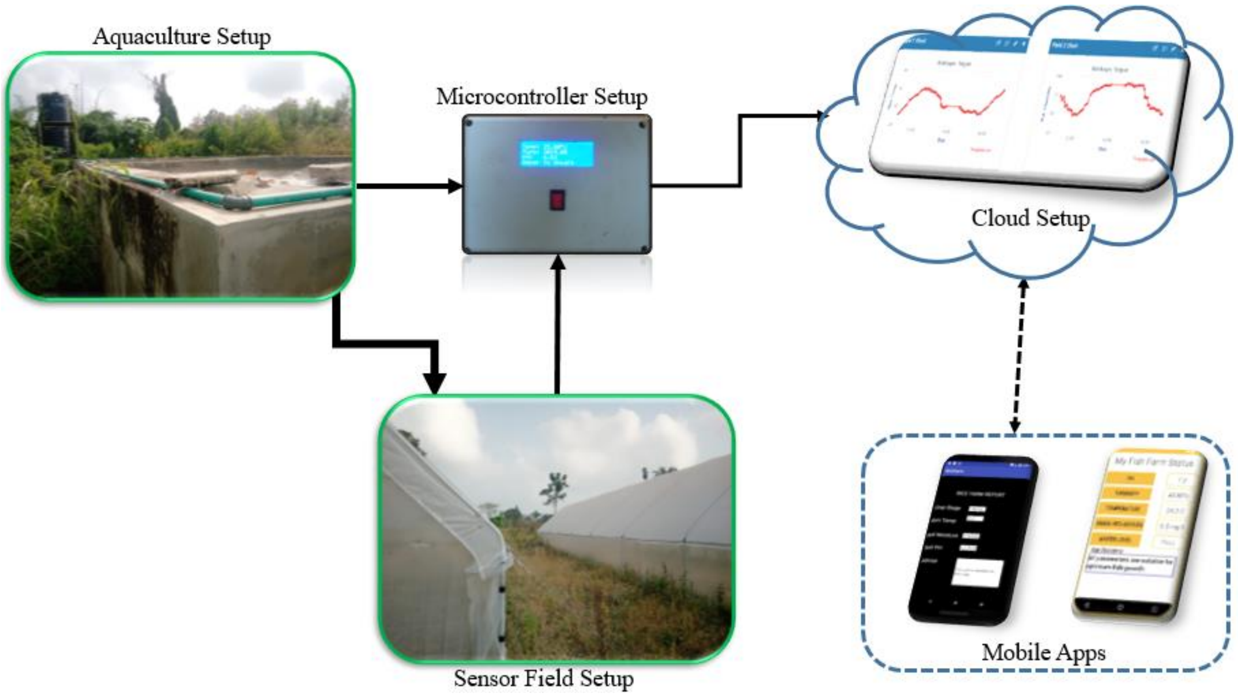

Figure 5.
IoT-Based Experimental Setup.

A 24-hour period in Figure 6 shows that temperatures reach their highest point of 33°C at noon and the lowest point of 21°C at 6:28 AM. During the day, solar energy heats the water, while at night, heat is lost to the cooler atmosphere. Based on this pattern, a maximum temperature of 26°C was deemed suitable for the aquatic ecosystem. The system successfully maintained the pond's temperature at the ideal 26°C for 92% of the 24-hour period.

At noon, the temperature reached its highest point of 33°C; during the low temperatures, it dropped to 21°C at 6 a.m. The average deviation from the threshold temperature is 1.5°C, and Figure 5 displays the temporal changes over time. A t-test showed that the temperature regulation system was significantly more stable than conventional methods ($p < 0.05$). The results were statistically significant.

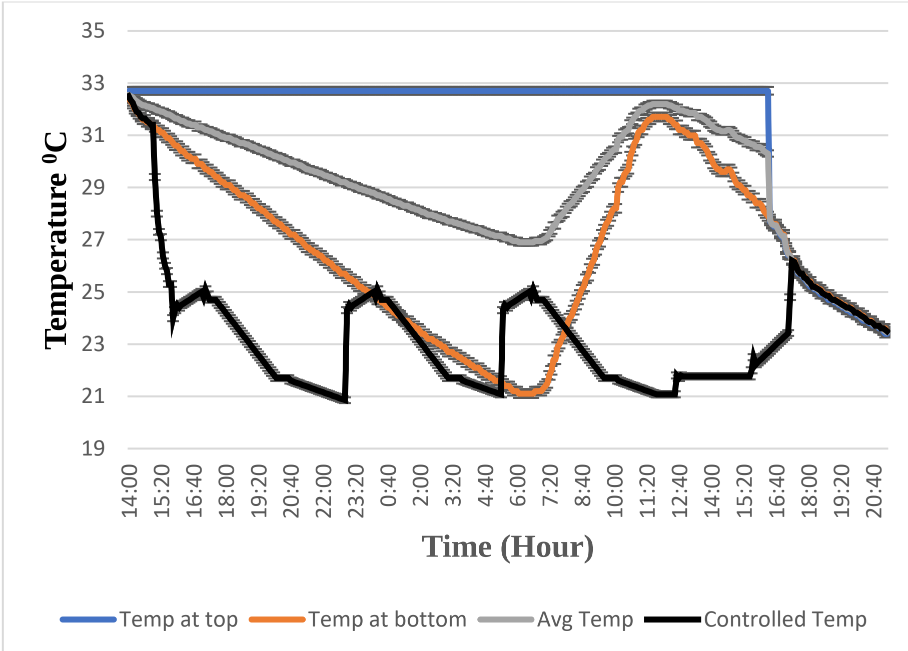

Figure 6.
Temperature Data for one Month.

In Figure 7, during the initial three weeks, the soil pH shifted from slightly acidic (around 6.7) to alkaline (around 8.5). Around Day 22, it sharply declined, then stabilized at approximately 7.2–7.4, indicating a new equilibrium was effectively established.

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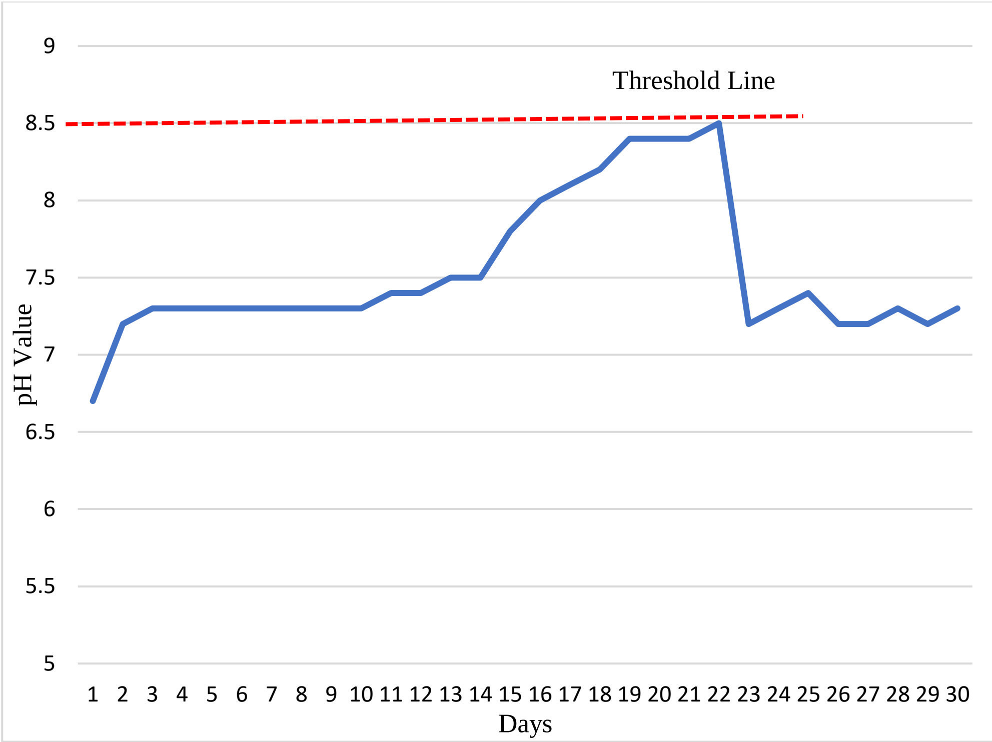

Figure 7.
Soil pH Values from the Sensor Field for one month.

Thus, the system proved to be a pH- and nutrient-balanced soil, with a relatively narrow pH range suitable for most crops, spanning from 6.2 to 7.1. This was achieved through a controlled, nutrient-rich pond water supply to the soil. Additionally, statistical analysis indicates a strong correlation between crop yield and stable pH levels (r = 0.85), further confirming that the system effectively maintains a soil environment conducive to crop growth.

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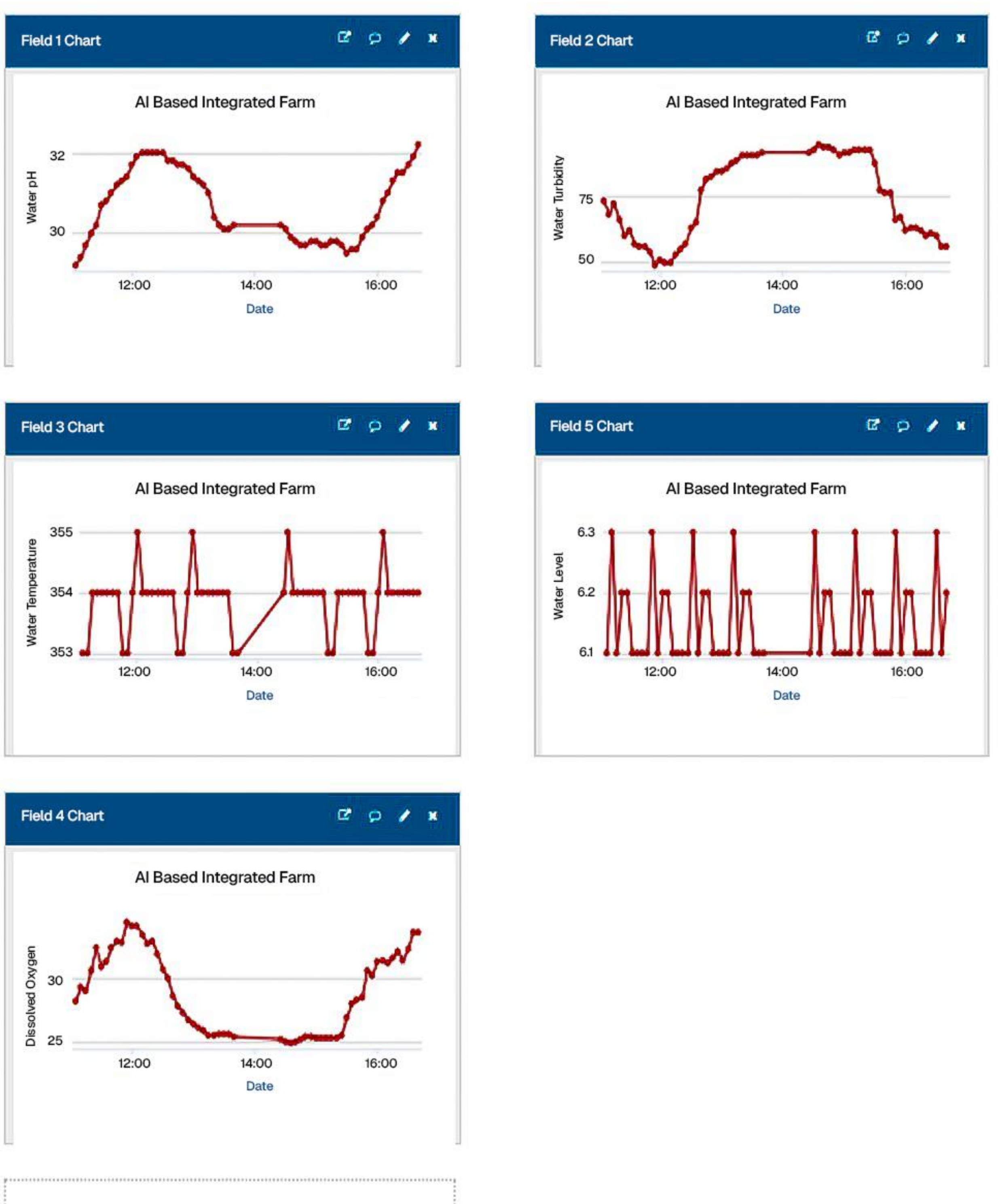

Figure 8.
IoT-Based Experimental Setup Cloud-based Data display (a) Fish Pond pH (b) Fish Pond Turbidity (c) Atmosphere Temperature (d) Fish Pond Dissolved Oxygen.

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The IoT-based experimental setup enabled real-time monitoring of crucial environmental conditions within the AI-powered integrated farming system, as shown in Figure 8. The pH of water in Field 1 was recorded, displaying sporadic fluctuations while remaining within a safe, stable range, which benefits plant and water life. Overall system efficiency was significantly improved by this stability. Additionally, the correlation between consistent pH levels and higher crop yields indicates the system's positive impact on agricultural productivity and sustainability.

Field 2 displays a chart of water turbidity fluctuations throughout the day, caused by biological activity and filtration. By controlling turbidity, the system prevents sediment buildup and nutrient depletion. The AI system effectively maintains clear water, improving water quality for fish and plants.

Temperature readings are displayed in Field 3. The charts indicated temperature changes, with the highest values at midday. Artificial intelligence regulated these variations, keeping water temperature below optimal levels for fish and plants. Automated climate control maintained the health of the integrated farm by ensuring stable conditions.

Dissolved oxygen levels are indicated by the chart in Field 4, illustrating natural variation due to aeration and photosynthesis. The system automatically adjusts oxygenation to prevent low oxygen levels, ensuring it does not harm aquatic species. These fluctuations align with predetermined patterns, demonstrating the system's ability to maintain high water quality and promote biological productivity.

Field 5 displays a chart illustrating the effective operation of irrigation and recirculation processes, showing controlled variations. Regular adjustments verify the water distribution's effectiveness, reducing waste and ensuring adequate hydration for plants. This supports sustainable practices through efficient water use, leading to lower overall consumption and improved resource management.

The proposed system not only enhances farm operations but also provides useful analytics tools to assist farmers in making better decisions. It offers descriptive analytics, diagnostic analytics to explain the causes of various outcomes, and predictive analytics for future trends. Additionally, predictive analytics provides specific guidance on improving farm performance. These features help increase food production and promote sustainable farming.

Additionally, the proposed system mitigates the environmental and economic consequences of traditional farming. Soil is no longer necessary in hydroponics, as it prevents soil erosion and nutrient runoff, which are common sources of pollution. By preserving the soil, hydroponics conserves both water and land. Sustainable practices include improved water quality, better resource utilization, and the efficient recycling of nutrients within a closed-loop system.

Fish waste can accumulate in water in traditional aquaculture, causing issues like excessive algae growth and poor water quality. In contrast, aquaponics uses fish waste as a natural fertilizer for plants, which absorb nutrients to promote growth. This process helps maintain pure, pollution-free water, supporting the health of both fish and plants.

Flowcharting enhances nutrient management. Direct fertilizer application prevents nutrient loss and reduces pollution. Although traditional fertilizers are effective, they can be environmentally toxic, causing nutrient leaching into water and decreasing oxygen levels. Fertilization minimizes runoff and environmental harm.

Real-time monitoring and automation enhance the system's sustainability. These technologies enable precise regulation of environmental factors, resulting in more efficient resource utilization and improved farm management.

5.1. Comparative Study

The comparative analysis of the system's structure, sensor effectiveness, network behavior, and application features clarifies the benefits of the proposed AI-based integrated farming system compared to recent systems. The proposed system achieves better integration by combining hydroponics, aquaculture, and fertigation into a well-coordinated, closed system, as shown in Table 1. The research conducted by Aydin et al. [41] and Naphtali et al. [43] focuses solely on irrigation or hydroponics, overlooking vital factors related to nutrient recycling. Additionally, research by Dhinakaran et al. [42] does not establish connections among modules, limiting resource optimization potential

In addition, the proposed system's decision-making process, facilitated by AI, enables real-time adaptability and rapid adjustments to environmental conditions, irrigation schedules, and nutrient delivery. Other strategies depend on static automation procedures or require human input, making them comparatively less effective and scalable.

5.1.1. Sensor Layer Performance

The system tested had a 95% sensor accuracy rate, higher than the alternative system's performance measures of 75% to 88%, as shown in Table 3. Unlike previous systems proposed by Naphtali et al. [43] and Aydin et al. [41], the system presented here has full real-time monitoring capabilities. By utilizing sensors with high levels of redundancy, the system's reliability is enhanced, ensuring minimal errors and consistent data acquisition. Automation in agriculture has led to significant improvements in accuracy, waste reduction, and productivity levels.

Table 4.
Sensor Layer.

KPI	**Proposed System**	**Aydin et al. [41]**	**Dhinakaran et al. [42]**	**Naphtali et al. [43]**	**Uthman and Musa [44]**	**Sadek and Shehata [45]**
Sensor Accuracy (%)	95%	85%	80%	83%	87%	88%
Real-time Monitoring Capability	Yes	Limited	Yes	Limited	Yes	Yes
Sensor Redundancy for Reliability	High	Low	Medium	Low	Medium	Medium

5.1.2. Network Layer Performance

To evaluate the effectiveness of sleep scheduling at the network layer, the average power consumption per reporting interval T was modeled as:

$$P_{avg} = \frac{1}{T} \sum_{j} I_j V t_j + I_{sl} V$$

where I_j and t_j denote the currents and durations for transmission (I_{tx} , t_{tx}), reception (I_{rx} , t_{rx}), and processing(I_{proc} , t_{proc}), and I_{sl} is the sleep-mode current. For comparison, a baseline "no-sleep" case substitutes I_{sl} with the idle current I_{idle}. The relative savings are expressed as:

Power savings = $1 - \frac{P_{avg}^{(sleep)}}{P_{avg}^{(no\ sleep)}}$ [58]

Datasheet specifications for the ESP32 microcontroller [59], YFS201 flow sensor [60], SEN0169 pH sensor [61], DS18B20 temperature sensor [62], ISST105 turbidity sensor [63], and DP5200 water level sensor [64] were used to parameterize the model. Using a 60-second reporting cycle and a conservative transmission duration of 0.5 seconds, the estimated average node power consumption with sleep scheduling was 8.39 mW, compared to 590.15 mW in the no-sleep baseline. This indicates an approximate 98.6% reduction in network power consumption. Sensitivity analysis shows that shorter transmission durations further reduce the cap P sub a. v g to below 1 mW, emphasizing the efficiency gains achievable through optimized duty cycling.

Empirical measurements from the implemented prototype indicated:

- No-sleep: Pavg=11.3 mW
- With sleep: Pavg=0.30 mW

This translates to a 97% decrease in average power, consistent with predictions derived from the datasheet. Under these conditions, the expected battery lifetime extends from approximately 27 days (no sleep) to about 2.8 years (with sleep). The energy consumed per packet transmission was measured at roughly 22.2 mJ, confirming the benefits of aggressive sleep scheduling.

6. Discussion

Both analytical estimates and prototype results confirm that duty cycling is highly effective for aquaponics monitoring systems. While datasheet models suggest conservative average power in the few milliwatt range, experimental results indicate that careful firmware optimization, such as shorter active intervals and aggressive deep sleep, can reduce consumption below 1 mW. This level of savings is crucial for scaling wireless sensor networks (WSNs), enabling the use of compact batteries or energy harvesting methods for multi-year deployments.

Compared to recent literature, the proposed AI-based integrated farming system is distinguished by its full integration of hydroponics, aquaculture, and fertigation into a closed-loop architecture coupled with AI-driven decision support (LSTM for time-series forecasting and adaptive control). Most recent works focus on single-domain solutions: Aydin et al. [41] developed an IoT-enabled automated irrigation system using decision-tree ML for scheduling, but did not address aquaculture or nutrient recycling. Naphtali et al. [43] implemented an IoT hydroponic monitoring prototype with rule-based automation, again without aquaculture integration. Dhinakaran et al. [42] and several aquaculture-focused studies provide robust pond monitoring and fish health analytics, but do not reuse nutrients for plant growth. Rahman et al. [33] demonstrate strong AIoT approaches for crop recommendation and nutrient parameter optimization in hydroponics, illustrating how AI can improve resource use; however, they do not close the loop with aquaculture-derived nutrients. These comparisons show that your proposed system fills an important niche by combining multi-module integration and AI-driven closed-loop control, thereby enhancing sustainability and creating new opportunities for resource-efficient, climate-resilient food production.

Table 5.
Comparative Analysis of Energy Efficiency and Power Optimization in Smart Agriculture Systems

Study	Focus Area	Energy Optimization Strategy	Reported Power Consumption / Savings	Limitation
Proposed System	Integrated aquaponics–hydroponics–fertigation	Duty cycling + ESP32 deep sleep + MQTT lightweight comms	97% savings (11.3 mW → 0.3 mW); battery life extended from 27 days → 2.8 years	Prototype stage; tested at pilot scale
Aydin et al. [41]	Smart irrigation (hydroponics-focused)	IoT + ML scheduling; basic idle power control	~30% energy reduction in irrigation pump scheduling	Limited to irrigation; no deep network optimization
Dhinakaran et al. [42]	Aquaculture monitoring	ML-assisted feeding + optimized aerator cycles	~25–40% energy saving in aerators	No integrated nutrient reuse; aquaculture-only
Naphtali et al. [43]	Hydroponics automation	Rule-based IoT control; no explicit energy scheduling	Reported ~15% energy saving (low-power relays + scheduling)	No AI-driven power adaptation; limited to hydroponics
Rahman et al. [33]	AIoT hydroponics	AI-based crop recommendations + modular hydroponics control	~45% reduction in overhead compared to threshold-based methods	Hydroponics only; lacks cross-domain integration
Dennison et al. [46]	Robotics + automation in aquaponics/hydroponics	Robotics for feeding and monitoring; efficiency from task automation	Energy consumption reduced by ~35% via robotics scheduling	High cost; scalability is limited in small farms

6.1. Application Layer Performance

The proposed system stands out because it offers a unique opportunity to make decisions using AI [44], unlike most other systems. Some systems, however, use established automation procedures that lack flexibility. It features the most accessible UI, making it easy to operate and control remotely.

Another system demonstrated the least accessibility and required manual intervention [65]. While the proposed system offers complete remote monitoring and control, some methods [43] do not provide remote access, limiting their effectiveness for large-scale agricultural operations. The results indicate that the system provides a modern, simple, AI-driven farming approach, ensuring efficiency, precision, speed, and scalability.

Table 6.
Application Layer.

KPI	Proposed System	Aydin et al. [41]	Dhinakaran et al. [42]	Naphtali et al. [43]	Uthman and Musa [44]	Sadek and Shehata [45]
AI-driven Decision Making	Yes	No	Yes	No	Yes	No
User Interface Accessibility	High	Medium	High	Medium	High	Medium
Remote Monitoring & Control	Yes	Limited	Yes	No	Yes	Yes

The proposed AI-based integrated farming system is more flexible, automated, and well-integrated than traditional methods. Although the methodology emphasizes irrigation, specifically hydroponics, aquaculture practices, and fertigation, it is also part of an integrated agriculture system, as indicated by Aydin et al. [41]. The use of artificial neural networks with predictive modeling offers a viable alternative to static automation strategies and approaches proposed by Sadek and Shehata [45] enabling real-time adjustments for inputs, irrigation schedules, and climate conditions. This improvement was further enhanced by the implementation of advanced algorithms, which increased the accuracy and real-time monitoring capabilities of the sensor module. Thanks to the new network module, based on a modernized architecture that integrates advanced algorithms and cloud computing, there has been a remarkable improvement in speed and data transfer compared to previous generations. Avoiding real-time manual processes in earlier versions of the app module led to poorer performance, which was improved through the use of AI and remote monitoring in more advanced versions. It was observed that in the practice of integrated production systems augmented by artificial intelligence, resource efficiency is improved, waste is reduced, and productivity is increased. The proposed innovative framework serves as the basis for addressing several crucial barriers that limit progress toward sustainable food production.

6.2. Climate Change Implications and Comparative Analysis

One of the key elements of the system is its attempt to mitigate and adapt to the effects of climate change. Agriculture and aquaculture face some of the most severe impacts of climate change due to increasing risks of water scarcity, nutrient loss, and decreased productivity [20]. The aquaponics, hydroponics, and fertigation systems integrated into the proposed system are designed to close the gap in shifting aquaculture and agriculture systems through the combined use of closed-loop nutrient recycling, AI-driven system predictive control, and cloud-based, modular, scalable systems. This design enhances input use efficiency by decoupling these systems from the net dependence on synthetic fertilizers and water withdrawal, which are excessive for food production inputs. In food systems, aquaponic and hydroponic systems, such as aquaponics combined with hydroponic fertigation, reduce the net discharge of nutrients into the environment, augmenting biologically driven processes of eutrophication and thereby mitigating net positive greenhouse gas emissions [21]. Optimal irrigation and confined feeding regimes, embedded through LSTM (Long Short-Term Memory) systems, operate across the entire decoupled food system, reducing wasted energy and water. The system's modular, scalable design is innovative, enabling farmers to expand and adapt operations in response to climate-driven changes in thermal, moisture, and stress conditions, thereby enhancing efficiency under climate change.

When compared with state-of-the-art systems, several insights emerge. Wang et al. [39] integrated remote sensing and AI to enable climate-resilient agricultural monitoring at scale, particularly through drones and satellites. Although highly scalable, this approach mainly supports decision-making at the monitoring level without addressing nutrient or water circularity. Haq and Khan [20] developed crop water requirement models under climate variability, demonstrating significant water savings in arid regions. However, their framework was irrigation-focused and lacked full system integration. Haq [21] advanced intelligent, multi-sensor water management systems capable of spatiotemporal modeling for resilience, but nutrient recycling was only partially addressed. Meanwhile, Haq [22] employed nanosatellite-based machine learning to analyze climate data at large scales, enhancing predictive modeling, though without direct integration into controlled-environment production.

By contrast, the proposed system closes the loop between aquaculture and hydroponics while integrating AI for prediction, optimization, and adaptive control. Unlike existing approaches that emphasize either monitoring [39] or water-use efficiency [20], this work combines monitoring with actionable control and recycling. It positions the system as a next-generation model for climate-smart agriculture, capable of delivering both mitigation (reduced emissions and waste) and adaptation (resilient food production under variable conditions).

Table 7.
Comparative Climate Change Considerations in State-of-the-Art Systems.

Study	Focus	Climate Change Consideration	Integration & Sustainability
Proposed system (this work)	Integrated aquaponics–hydroponics–fertigation	Explicitly addressed (climate-resilient closed-loop design)	High: AI + nutrient/water recycling
Wang, et al. [39]	Remote sensing & AI	Explicitly addressed (monitoring for resilience)	High scalability, but monitoring-only
Haq and Khan [20]	Irrigation under climate change	Explicitly addressed (water conservation in arid regions)	High in water efficiency; limited integration
Haq [21]	Intelligent water systems	Explicitly addressed (multi-sensor AI for climate resilience)	High sustainability in water, limited nutrient reuse
Haq [22]	Satellite ML classification	Explicitly addressed (climate data integration at scale)	High scalability; indirect effect on farming systems

6.3. Challenges in Scaling the System for Commercial Use

Scaling the integrated aquaponics–hydroponics–fertigation system from prototype to commercial farms presents several challenges. High capital costs remain a major barrier, as larger systems demand robust pumps, pipelines, greenhouses, and redundant infrastructure [21, 35]. Energy demand also increases, requiring hybrid renewable sources and advanced power management to maintain efficiency [39].

Reliable data transmission becomes increasingly complex at scale, as large farms generate thousands of data points. Hybrid edge–cloud computing is necessary to reduce latency and network congestion [47]. Sensor calibration and maintenance also present challenges, as errors multiply with larger deployments, making automated calibration and sensor fusion essential [48].

Operational complexity increases with system size, necessitating skilled personnel trained in biological and digital processes. Regulatory compliance and consumer acceptance significantly influence adoption, especially concerning food safety and environmental standards. Additionally, local climate stresses such as heat, drought, and water scarcity require adaptive designs that incorporate climate projections [20].

In summary, commercial scaling will depend on reducing costs through modular adoption, ensuring resilient energy and network systems, improving sensor reliability, and building operator capacity within supportive regulatory frameworks.

7. Conclusion

An AI-based farm management system was implemented using artificial intelligence and sensors to monitor environmental variables, including plant health, pH levels, and water quality. Real-time data from these sensors can be remotely controlled via a microcontroller, which receives and stores it in the cloud. Notifications on mobile devices or a web dashboard alert farmers when parameters exceed predetermined thresholds, facilitating emergency management of water pollution or nutrient deficiencies.

Through the adjustment of irrigation, resource utilization is optimized, and water flow parameters are based on real-time data, resulting in improved efficiency. LSTM and other AI algorithms enhance predictive power by analyzing past data, helping farmers increase productivity and reduce waste. Tracking greenhouse gas emissions and remotely monitoring farms are part of the system's goal to facilitate sustainable practices and foster collaboration among stakeholders. Additionally, through artificial intelligence, farmers can make data-driven decisions, monitor farm productivity to identify patterns, and adjust their behavior to meet changing agricultural needs. This ultimately leads to more sustainable and productive farming practices already in place.

8. Recommendations

For AI-driven systems to operate effectively in agriculture, they must address key issues of scalability, accessibility, and user-friendliness. Although such systems have shown potential to improve resource efficiency, crop yields, and environmental sustainability, their adoption remains limited due to high costs, infrastructural constraints, and operational challenges. The following recommendations offer specific, actionable steps for farmers and researchers aiming to implement or expand similar systems.

1. Cost Reduction and Financial Support
   - i. Farmers should begin with modular adoption: deploying a single component (soil moisture monitoring or pH sensing) before scaling up to full integration.
   - ii. Researchers and policymakers should promote open-source AI frameworks and low-cost sensor alternatives to reduce software and hardware expenses.
   - iii. Governments and private investors should support uptake through public–private partnerships (PPPs), targeted subsidies, low-interest credit schemes, and equipment-leasing models.
2. Connectivity and Infrastructure
   - iv. For regions with poor internet coverage, edge computing devices should be integrated to process data locally, reducing dependence on cloud infrastructure.
   - v. LoRaWAN or other low-power, long-range communication protocols should be prioritized for transmitting data across large farmlands.
   - vi. AI models should include offline functionality, enabling the continuity of farm operations even in intermittent network conditions.
3. Sensor Reliability and Data Accuracy
   - vii. Farmers should adopt self-calibrating sensors where possible to reduce downtime and ensure accurate readings.
   - viii. Sensor fusion techniques, such as combining pH, turbidity, and temperature readings, should be deployed to enhance prediction accuracy and minimize the risk of single-sensor failure.
   - ix. Researchers should apply transfer learning approaches so that AI models trained on larger datasets can adapt effectively to smaller farms with limited historical data.
4. Operational Best Practices
   - x. Farmers should receive training modules (via extension services or digital platforms) on interpreting AI-generated insights and integrating them into daily decision-making.
   - xi. Maintenance schedules should be standardized: periodic cleaning of water flow sensors, recalibration of pH probes, and firmware updates for wireless modules.

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xii. Data security protocols, including encryption and access keys, must be implemented to safeguard farm data transmitted through IoT systems.

5. Policy and Community Engagement
   - xiii. Local governments should incentivize cooperative adoption models where farmers pool resources to deploy shared AI-driven infrastructure.
   - xiv. Universities and agricultural research institutes should collaborate with farming cooperatives to provide technical support and continuous innovation testing.

8.1. Limitations and Future Scope

Despite the demonstrated potential of the proposed AI-driven system, several limitations remain:

1. Scalability constraints: While modular designs enhance adoption, scaling from pilot farms to large commercial operations requires more robust energy management and cloud integration.
2. Sensor performance may degrade under extreme weather or prolonged submersion, which can limit system reliability in harsher climates.
3. Cost Barriers: There may be barriers to entry for many smallholder farmers when trying to acquire hardware, even when utilizing modular or open-source designs without enduring subsidies.
4. Data Gaps: The available datasets concerning African agriculture are limited, which constrains AI models' ability to generalize, given the diverse soils, water, and climatic conditions.

For future work, researchers should:

1. Develop ultra-low-cost sensor prototypes tailored to developing regions.
2. Explore renewable-powered IoT nodes (solar or micro-hydro) to support off-grid farms.
3. Expand datasets through crowdsourced farm data collection and cross-country collaborations.
4. Investigate integration with climate-smart farming practices, such as predictive modelling of droughts or nutrient cycles.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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