Artificial intelligence of things solution for Spirulina cultivation control

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ABSTRACT

In the evolving field of Spirulina cultivation, the integration of the internet of things (IoT) has facilitated the optimization of spirulina growth and significantly enhanced biomass yield in the culture medium. This study outlines a control open-pond system for Spirulina cultivation that employs generative artificial intelligence (AI) and edge computing within an IoT framework. This transformative approach maintains optimal conditions and automates tasks traditionally managed through labor-intensive manual processes. The system is designed to detect, acquire, and monitor basin data via electronic devices, which is then analyzed by a large language model (LLM) to generate precise, context-aware recommendations based on domain-specific knowledge. The final output comprises SMS notifications sent to the farm manager, containing the generated recommendations, which keep them informed and enable timely intervention when necessary. To ensure continued autonomous operation in case of connectivity loss, pre-trained TinyML models were integrated into the Raspberry Pi. These models display alarm signals to alert the farm owner to any irregularities, thereby maintaining system stability and performance. This system has substantially improved the growth rate, biomass yield, and nutrient content of Spirulina. The results highlight the potential of this system to transform Spirulina cultivation by offering an adaptable, autonomous solution.

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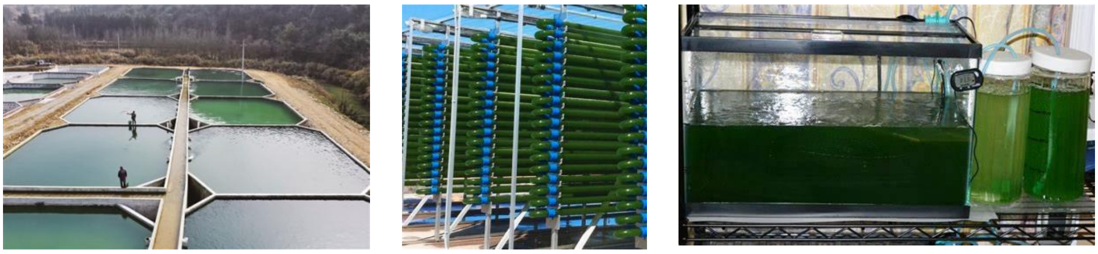
1. INTRODUCTION

Spirulina (*Arthrospira platensis*) is a blue-green algae [1] recognized for its nutritional benefits and high protein content (50%-70% of dry weight) [2], [3]. In addition to its rich source of vitamins, minerals, and bioactive compounds such as carotenoids [4], [5] and antioxidants, it is used in food, cosmetics, and as a dietary supplement, even supporting astronauts on long space missions [6], [7]. Due to its well-established commercial production, Spirulina is cultivated in several countries, including the United States, Thailand, China, India, Taiwan, Pakistan, and Burma [8]. Additionally, effective management of spirulina cultivation is necessary to achieve high yields and produce a quality product. Among the many cultivation methods, three are particularly popular: open-pond systems [9], photobioreactors (PBRs) [10], and home cultivation kits. Figure 1 shows each of the three systems used for the cultivation of Spirulina. Open-pond systems, as shown in Figure 1(a), are the most widely used. Typically, these systems utilize tanks that expose Spirulina to natural sunlight, thereby reducing investment and maintenance costs. These systems are notable for their scalability and simplicity, which make them a particularly well-suited solution for farmers. However, these systems are prone to contamination and sudden changes in environmental conditions. Figure 1(b) illustrates photobioreactors (PBRs), which use a more controlled approach with closed systems, such as tubular, flat-panel, or columnar configurations. This method carefully controls light, temperature, and nutrient supply. Therefore, there is a reduction in contamination risk and a continuous controlled production of the product throughout the year. This is also widely applied in high-production and quality spirulina, which requires a higher initial investment and associated running maintenance. Home cultivation kits are used for indoor cultivation in home settings and come with basic environmental controls to simplify the growing process for individuals and small-scale growers, as illustrated in Figure 1(c).

Typically, Spirulina is cultivated in open ponds and then transferred to PBRs for later growth stages, leveraging the cost-effectiveness of open ponds and the high productivity and control of PBRs. Efficient management and control of Spirulina cultivation through these methods ensure high-quality production, reinforcing Spirulina's viability and value as a nutrient-dense food source and sustainable solution for nutraceutical applications.



(a) (b) (c)

Figure 1. Different methods to cultivate Spirulina (a) open pond systems, (b) photobioreactors (PBRs), and (c) home cultivation kits

Furthermore, in open-pond systems, manual control of key parameters such as pH, temperature, and nutrient concentrations is laborious and prone to human error, leading to variations in growth rates, differences in quality, and increased operational costs. To address these limitations, this study proposes an artificial intelligence of things (AIoT) -enabled solution that enables precise monitoring, autonomous regulation, and optimization of growth conditions to enhance biomass yield and nutrient content. The proposed system integrates sensors enabled with IoT, real time data analytics, and machine learning models to control key parameters such as temperature, pH, and nutrient levels. It applies automation and AI-based insights to reduce the chances of risks linked to human error, ensure the best conditions for growth, and provide remote management. Moreover, this work addresses key limitations of existing systems, such as unstable internet connectivity in coastal regions and the lack of autonomous operation during network loss.

This work is organized as follows: Section 2 reviews related works and compares them with other articles. Furthermore, section 3 explores the background of Spirulina, highlighting its importance and optimal growth requirements. Section 4 discusses the project process, including the description of the data set and the data processing from collection to analysis. Next, in section 5, we present a complete system overview that explains the proposed system and the data flow diagram to fully grasp the general operations of the system. Section 6 elaborates on the results of this system, followed by discussion and conclusion in sections 7 and 8, respectively.

2. RELATEDWORKS

In recent years, several works have showcased the potential of IoT in enhancing Spirulina cultivation. Research has focused on the implementation of technology to improve Spirulina cultivation. Initially, we explored general information using the keyword "Spirulina cultivation". As we narrowed our focus to IoT and AI applications for real-time monitoring and automation, we filtered out papers on Spirulina cultivation systems or included a chapter discussing Spirulina cultivation systems. Of these, 5 papers were the most related. This section will discuss each proposal and compare it with our solution as shown in Table 1.

Aquino *et al.* [11] present a vision-based closed Spirulina cultivation system integrating RGB/lux sensors with pH and temperature monitoring, combined with an artificial neural network (ANN) for growth prediction. This method enables reliable estimation of cell density without direct sampling. Similar to the proposed system, it applies sensor-driven monitoring to improve Spirulina growth. However, while it predicts biomass trends, it lacks adaptive decision-making. By contrast, the proposed framework employs generative artificial intelligence (AI) and TinyML to not only predict but also generate context-aware recommendations and enable autonomous control.

Table 1. Comparative evaluation of Spirulina cultivation systems (IoT, AI, and AIoT approaches)

Metric	A vision-based closed spirulina (a. platensis) cultivation system with growth monitoring using artificial neural network [11] (2018)	Smart micro farm: Sustainable algae spirulina growth monitoring system [12] (2018)	Development of smart algae pond system for microalgae biomass production [13] (2021)	IoT-based closed algal cultivation system with vision system for cell count through ImageJ via Raspberry Pi [14] (2021)	Evaluation of real- time monitoring on the growth of Spirulina Microalgae: Internet of Things and Microalgae Technologies [15] (2024)
IoT availability	Partial (pH, temp, DO via Arduino; local)	Yes (Arduino+GSM)	Yes (multi-sensor ESP32 cloud)	Yes (RPicamera+sen sors)	Yes (ThingSpeak IoT)
AI availability	Yes (ANN from RGB & lux)	No	No	No (ImageJ, rule-based)	No
Sensor types monitored	Temp, pH, DO, RGB & lux	Temp, pH, light, water level	Temp, pH, CO_2, turbidity, light, velocity	Temp, pH, light, camera imaging	Temp, light, water level, absorbance (TCS3200)
Real-time data availability	No	Yes (GSM SMS alerts)	Partial (local + DB)	Yes (RPi + online)	Yes (ThingSpeak cloud)
Data transmission latency	N/A	Higher (SMS)	Low (ESP32 → MySQL)	Low (RPi Wi-Fi)	Low (ESP8266 → ThingSpeak)
Prediction accuracy (%)	ANN MSE = 0.00478	N/A	N/A	N/A	N/A
Energy consumption (kWh)	N/A	N/A	Paddlewheel 0.5 → 0.2	N/A	N/A
User interface quality	LCD alerts	SMS alerts	Local + DB logging	Web dashboard (RPi)	Cloud dashboard + mobile
Scalability	Lab-scale 10L	Small-scale farm	Prototype raceway pond 120L	Lab-scale 5–10L	Lab-scale 10L
Implementation Cost	Not discussed	Arduino + GSM	Energy savings from paddlewheel	RPi setup	Low-cost Sensors (¡$250
Growth rate (day^{-1})	0.0519 vs 0.0372	N/A	N/A	N/A	N/A
Cultivation system type	Closed pond (PBR-like)	Open pond (micro farm)	Raceway ponds (open)	Closed pond (RPi monitored)	Photobioreactor (lab-scale)

Ariawan and Makalew [12] describe a smart micro farm using Arduino-based sensors (pH, light, temperature) and GSM modules to deliver threshold-based SMS alerts. This system provides an early, low-cost IoT application that makes Spirulina monitoring more accessible. Like the proposed design, it emphasizes real-time tracking of key growth parameters. The difference lies in adaptability: this system is reactive and manual, while the proposed solution integrates LLMs and TinyML to deliver proactive, context-aware recommendations and maintain functionality offline, advancing from monitoring to intelligent intervention.

Hermadi *et al.* [13] develop a smart pond system with ESP32 sensors measuring environmental parameters (temperature, pH, CO2, turbidity, light, water velocity), integrated with automated paddlewheel control for energy efficiency. Similar to the proposed system, it integrates IoT for continuous monitoring and automated adjustments. However, it lacks adaptive intelligence and deeper data analysis. The proposed framework expands this by embedding generative AI and TinyML, transforming sensor-based automation into an intelligent, knowledge-driven cultivation process.

Tolentino *et al.* [14] propose an IoT-based closed algal cultivation system that combines Raspberry Pi imaging with ImageJ software for cell count estimation. This vision-based method enhances biomass tracking accuracy at low cost. Like the proposed design, it exploits digital imaging and IoT integration to improve Spirulina monitoring. However, its reliance on static, rule-based image analysis limits adaptability in dynamic conditions. The proposed system addresses this by incorporating LLMs and TinyML, enabling adaptive reasoning and real-time recommendations beyond static analysis.

Lim *et al.* [15] present a cloud-based monitoring system (ThingSpeak) integrated with IoT sensors (e.g., optical density, temperature), offering scalable real-time Spirulina growth tracking. Its strength is enabling efficient, remote supervision. Similar to the proposed work, it leverages IoT connectivity to enhance cultivation oversight. However, it lacks AI-based recommendations and autonomy. In contrast, the proposed framework integrates LLM analytics and TinyML edge resilience, elevating monitoring into a fully adaptive, autonomous cultivation management system.

In all reviewed studies, IoT-based monitoring of Spirulina cultivation has advanced significantly, yet a critical gap persists in the absence of AI-driven autonomous decision-making frameworks. While existing systems effectively collect and transmit environmental data, they fall short of leveraging advanced generative AI or large language models (LLMs) to provide adaptive, context-aware recommendations. Moreover, most solutions remain limited to small-scale prototypes, lacking scalability, resilience to connectivity loss, and integration of edge intelligence for uninterrupted operation. This gap highlights the need for research that bridges IoT sensing with autonomous AI reasoning, ensuring both real-time optimization of growth conditions and practical applicability in real-world Spirulina farming. This project aims to bridge these gaps by leveraging LLMs for dynamic and context-aware decision-making, deploying offline operations to address communication instability, and considering robust communication, especially in coastal areas.

3. BACKGROUND

To fully understand the system, it is important to cover the origins of Spirulina, the ideal cultivation conditions, and the significant role of IoT technology in enhancing its growth, productivity, and sustainability.

3.1. Origins and nutritional benefits of Spirulina

Spirulina is a microscopic aquatic organism of the cyanobacteria group. It is scientifically classified under the genus Arthrospira platensis [16]. This microalga has a characteristic spiral shape as depicted in Figure 2, consisting of 5 to 7 spirals typically 3 to 8 μm in diameter. It appears in the form of microscopic filaments made up of juxtaposed cells. The length of the filament and the number and density of the coils for each filament vary depending on the age of the microalgae and the cultivation conditions. Its reproduction is asexual and occurs through filament division [17].

In the mid-20th century, researchers rediscovered Spirulina in Europe and the U.S. [18]. Global interest has recently increased, particularly in Chad, where production has increased significantly. In Tunisia, Spirulina was first discovered in Lake Tunis in 1978 and later in Chatt el Jerid in 1997. There are also promising strains near Sfax and Hergla, indicating the potential for larger cultivation.

Figure 2. Spirulina under view x100 magnification

3.2. Optimal Spirulina cultivation conditions

Certain conditions are required to ensure optimal Spirulina growth [19], [20]. The water used for the culture medium should be seawater enriched with mineral salts to provide Spirulina with the necessary chemical elements [21], [22]. The temperature of the culture liquid directly influences the multiplication rate of Spirulina and the reproduction stability, with significant growth occurring only above 20 °C. In 1975, Pirt asserted that the optimum water temperature for cultivation is between 35 °C and 37 °C [23]. Light is essential for synthesizing organic matter from simple mineral elements, and the required light intensity varies greatly depending on the culture's depth and the algae's density [24]. The optimal pH of the culture medium should be at least 9; if it is too low, the culture may not start well, with clumps forming or Spirulina precipitating at the bottom [25], [26]. The main carbon source of Spirulina is carbon dioxide gas, and productivity can be increased by injecting pure carbon dioxide directly into the culture [27]. A certain level of conductivity in the water is also required, estimated to be between 15 and 35 g/l, along with a mix of other elements such as sodium bicarbonate, potassium nitrate, and sodium phosphate [27]–[29].

3.3. The impact of IoT technology on Spirulina cultivation

IoT technology is revolutionizing Spirulina cultivation by enabling real-time monitoring and control of critical parameters, as discussed in Section 1. This advancement allows for timely adjustments to optimize growth and productivity while identifying and addressing abnormalities in the cultivation process [12]. IoT sys tems enhance the growth rate and yield of Spirulina and contribute to significant environmental and economic improvements.

- Environmental benefits: IoT-enabled processes improve efficiency and sustainability, reducing resource wastage and increasing productivity. By incorporating clean energy sources like solar power, IoT can lower the carbon footprint of Spirulina cultivation. Additionally, mixotrophic cultivation techniques utilizing wastewater nutrients and solar energy contribute to sustainable and environmentally friendly practices [30].
- Economic implications: The integration of IoT in Spirulina cultivation boosts efficiency and productivity, addressing food security and resource limitations in agriculture. Automation and monitoring capabilities enabled by IoT can reduce labor expenses while increasing the value of the product, thereby offering substantial economic benefits [31], [32].

However, the successful integration of IoT in Spirulina cultivation is not without challenges. Issues such as interoperability, affordability, device power consumption, bandwidth, latency, and data processing must be carefully managed to ensure effective implementation [33], [34]. Our AIoT system addresses these challenges by combining IoT with machine learning models, enhancing system responsiveness and reliability. Through its offline capabilities and TinyML models, the system autonomously adjusts key parameters and maintains operations even during network disruptions. Furthermore, the lightweight nature of the message queuing telemetry transport (MQTT) protocol allows the system to operate efficiently in environments with limited bandwidth, such as coastal areas where internet connectivity may be slow or unstable. This approach reduces the dependency on constant connectivity, mitigates data processing challenges, and ensures consistent and efficient cultivation, making the process more resilient and sustainable.

4. METHOD

The AIoT system for Spirulina cultivation control consists of several key procedures.

4.1. Dataset description

After collaborating with Bio Algues Tunisie, a specialized Spirulina farm and laboratory, we received precise measurements for each condition they use in their cultivation process. The AIoT system dataset includes the essential parameters for optimizing Spirulina cultivation. The most common measures focused on:

- Transparency: The ideal water transparency should vary between 2 cm and 10 cm. If the transparency is 2 cm or less, 30% of the basin should be filtered. For transparency between 2 cm and 3 cm, 20% of the basin should be filtered. If the transparency is between 3 cm and 4 cm, 10% of the basin should be filtered. For transparency greater than 4 cm, filtering is not necessary. A darker appearance of the water, indicating a healthy density of phytoplankton, is desirable.
- pHValue: The ideal pH value is between 9 and 10. If the pH is less than 9, caustic soda (NaOH) should be added. If the pH exceeds 10.2, bicarbonate should be added at a rate of 1 g/l. If the pH exceeds 10.5, the rate of bicarbonate addition should be increased to 2 g/l.
- Water Temperature: The ideal water temperature is between 20 °C and 24 °C. Specific measures should be applied if the temperature drops below 4 °C or rises to 34 °C or higher. If the water remains stagnant for 3 days at temperatures above 20 °C, bicarbonate (1 g/l) and nitrates (0.2 g/l) should be added.
- Conductivity: The ideal salinity is between 15 g/l and 35 g/l. If the salinity is below 15 g/l, seawater should be added. If the salinity exceeds 35 g/l, 20% of the basin should be emptied and replaced with fresh water.

These parameters are critical to maintaining optimal growth conditions for Spirulina and ensuring the highest quality yield.

4.2. Dataset preparation

A comprehensive document was prepared to train the LLM to generate personalized outputs. This document constitutes the knowledge base that LLM accesses through RAG. A structured and well-organized table was created to serve as our knowledge base. As shown in Table 2, it specifies essential parameters, the corresponding recommendations, and commands based on different conditions. The purpose of this table is to ensure accurate interpretation and provide customized recommendations and commands.

The document is divided into three sections. The initial column covers the parameters associated with spirulina cultivation, including temperature, conductivity, transparency, and pH. The second column comprises the corresponding recommendations for each parameter, enabling the LLM model to deliver precise and context-aware responses. The final column details the specific actions to be taken when conditions fall outside the optimal range for each parameter and was designed for TinyML to recognize each condition through code.

Table 2. Operational parameters and corrective measures for Spirulina cultivation

Factor	Ideal Value/Range	Recommendation	Code
Transparency	2–10 cm	If ≤ 2 cm: filter 30% of the basin.	F
		If 2–3 cm: filter 20% of the basin.	G
		If 3–4 cm: filter 10% of the basin.	H
		If > 4 cm: no filtering required.	I
pH Value	9–10	If <9: add caustic soda (NaOH).	C
		If > 10.2: add bicarbonate at 1 g/L.	D
		If > 10.5: add bicarbonate at 2 g/L.	E
Water Temperature	20–24 °C	If < 4 °C: corrective action required.	K
		If ≥ 34 °C: corrective action required.	L
		If stagnant for 3 days at > 20 °C: add bicarbonate (1 g/L) and nitrates (0.2 g/L).	J
Salinity (Conductivity)	15–35 g/L	If < 15 g/L: add seawater.	A
		If > 35 g/L: empty 20% of the basin and replace with fresh water.	B

4.3. Data collection and acquisition

For data collection, various sensors have been integrated into the spirulina basins. The pH value is measured using the SEN0161 pH sensor, while the DFRobot Gravity analog electrical conductivity sensor is used to assess high electrical conductivity, such as seawater. Temperature readings are taken with the DS18B20 sensor. We used the DFROBOT Sen0205 FS-IR02 sensor to determine the water level in the basin. To measure light intensity, an endoscope camera is used to calculate darkness based on light intensity by detecting the time when a predefined point on a white disk turns dark within the water, thus providing an accurate distance measurement. To facilitate the descent and ascent of the measurement system underwater, an electronic actuator was installed.

Considering the acquisition unit, each sensor was connected to the Arduino UNO microcontroller, which plays a crucial role in converting the data from analog signals to digital values for processing. Figure 3 represents the Arduino UNO connection to the integrated sensors, including the pH sensor, the conductivity sensor, and the temperature sensor.

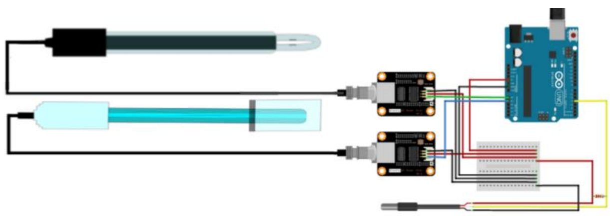


Figure 3. Sensor’s integration in the acquisition board

4.4. Data processing

In the next step, a Raspberry Pi 4 serves as the primary processing unit, collecting data from multiple sensors connected via the Arduino UNO, executing real-time AI/TinyML algorithms, and coordinating automated control actions in the Spirulina cultivation system. The endoscope camera and the water level sensor were connected directly to the Raspberry Pi, with the camera configured to capture the Secchi disk’s disappearance underwater. Specifically, the endoscope camera was attached to a box while the

Secchi disk was mounted on the piston rod of a linear actuator. As the rod moved underwater, the camera captured video frames, and image processing was applied to detect the white color of the disk, using the condition b, g, r = 255, 255, 255 and the iterative logic:

```
{
while b = 0 and g = 0 and r = 0 :
  ROI = frame[roi y:roi y+roi height, roi x:roi x+roi width]
  hsv ROI = cv2.cvtColor(ROI, cv2.COLOR BGR2HSV)
if b == 0 and g == 0 and r == 0:
  Disappearance_Height = time_ex * 0.4
}
```

The Raspberry Pi also converted the sensor data into a JavaScript Object Notation (JSON) format, chosen for its lightweight structure, efficient transmission in limited-bandwidth environments, and ability to represent hierarchical data. This JSON file was then immediately sent to the LLM for further analysis and generation of context-aware recommendations via the MQTT protocol. On the other hand, in scenarios where there is no internet connectivity, the Raspberry Pi relies on TinyML models to execute local decision-making processes. Figure 4 demonstrates the connection that links all components of the system.

4.5. Data transmission

The data collected by the sensors are transmitted via the MQTT protocol, which serves as a communication hub between the sensors and the AI model. As illustrated in Figure 5, the system is initiated by a Raspberry Pi that collects data from the indicated sensors. The data is then converted into a JSON file format to facilitate publication on a specific topic. Meanwhile, the AI model subscribes to the same topic to receive and analyze the data. In the Spirulina cultivation IoT control system, the MQTT protocol offers several advantages, including real-time data transmission from sensors to the LLM model server, enabling immediate analysis and rapid system adjustments. Its high transmission speed ensures minimal latency, facilitating prompt responses such as automated recommendations to clients. The protocol's lightweight design minimizes bandwidth consumption, making it particularly effective in low-connectivity environments like coastal areas.

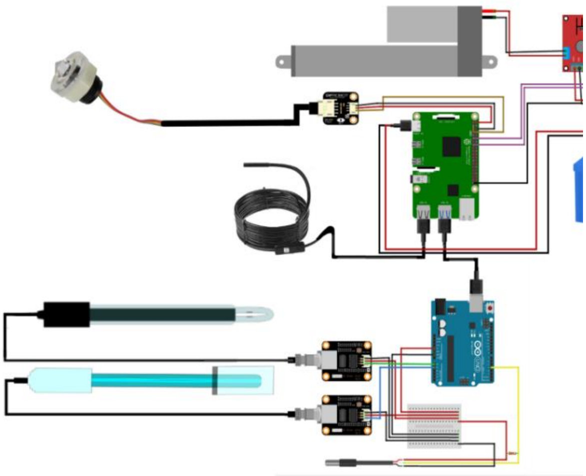


Figure 4. System circuit diagram

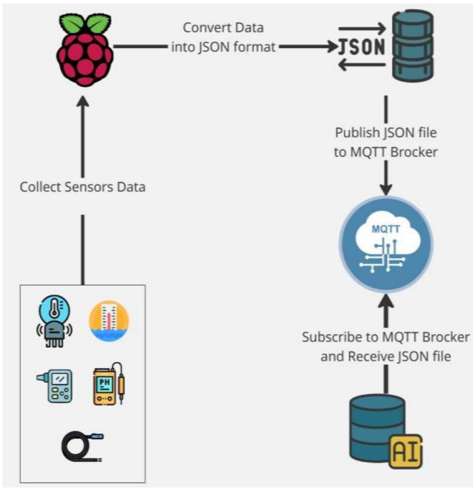


Figure 5. Data transmission through the MQTT broker

4.6. Data analyzation

4.6.1. Large language model (LLM)

In the case of online scenarios, a generative LLM was integrated to analyze sensor data and produce both recommendations and corrective commands. The system employs GPT-4, accessed through the LangChain framework, to process real-time inputs such as temperature, pH, water level, conductivity, and optical density collected from a Raspberry Pi. This enables automated decision-making that reduces manual intervention and generates precise, context-aware recommendations. The use of natural language output ensures that results are easily interpretable, even for non-expert farm managers, thereby facilitating practical adoption. The system is also highly scalable, allowing new sensors or parameters to be integrated with minimal reprogramming, strengthening its adaptability for future extensions. To provide domain knowledge, a FAISS vector database was constructed from a Spirulina cultivation handbook and supporting technical documentation. These documents were embedded with the SentenceTransformer (allmpnet-base-v2) model. Through LangChain's retrieval-augmented generation (RAG) architecture, GPT-4 retrieves the most relevant fragments from this knowledge base before generating outputs. This guarantees that recommendations are grounded in validated cultivation practices and remain situation-specific. The output of the LLM is structured in JSON format, providing both actionable commands and detailed recommendations for each monitored parameter. For example, given a scenario where the temperature is below optimal and pH is slightly low, the model generates the following output:

```
{
"commands: ["Increase temperature", "Add bicarbonate"],
"recommendations":[
  {"parameter": "temperature", "status": "below optimal", "action": "increase heating by 5∘C"},
  {"parameter": "pH", "status": "slightly low", "action": "add bicarbonate"}
 ]
}
```

This structure allows for precise, automated interventions while maintaining interpretability for the farm manager. Each recommendation object explicitly identifies the parameter, its current status, and the action to be taken, whereas the commands array summarizes the key interventions to execute, enabling both human operators and automated systems to respond efficiently.

4.6.2. TinyML integration

TinyML was integrated into the Spirulina cultivation system to ensure autonomous operation during periods of network failure. The choice of TinyML was motivated by its low power consumption, cost efficiency, resilience, and ability to support real-time decision-making. The primary goal was to classify sensor values accurately, allowing the system to maintain optimal growth conditions for Spirulina even in offline mode. For this purpose, datasets were created for four critical parameters: pH, conductivity, temperature, and optical density, as these directly influence the health and productivity of Spirulina.

The models deployed were neural networks designed and trained using TensorFlow. Each model follows the same general architecture: an input layer, three dense layers with rectified linear unit (ReLU) activation, and a SoftMax output layer. Each parameter dataset was generated individually, ensuring that the SoftMax layer contained unique classes specific to the parameter being analyzed. Once trained and validated, the models were converted into TensorFlow Lite format for deployment, enabling efficient inference on the Raspberry Pi 4.

The datasets contained over 9000 samples per parameter. Each dataset consisted of two columns: sensor value and sensor status. The simulated sensor readings were classified based on Spirulina's optimal growth conditions. For instance, water transparency between 2 cm and 10 cm was considered optimal, while deviations triggered corrective actions such as partial filtration. Similarly, temperature was maintained between 20 °C and 24 °C, pH between 9 and 11, and salinity between 15 g/l and 35 g/l. To improve model performance, the sensor values were standardized before training.

The training pipeline was executed on a PC, after which the optimized models were deployed to the Raspberry Pi 4. The workflow was designed such that, under normal operation, data from the sensors is processed by the Raspberry Pi and transmitted to the LLM server for high-level analysis. However, when the Internet connectivity is lost, the TinyML models are activated locally. In this mode, the Raspberry Pi executes inference directly on the standardized sensor values, classifying conditions and determining appropriate actions, such as adding nitrate or adjusting water salinity, to stabilize the environment.

4.7. System implementation

The system prototype has been successfully deployed in a Spirulina cultivation basin, where it autonomously monitors and adjusts environmental conditions in real time. It consists of a Raspberry Pi that serves as the central processing unit, connected to various sensors that measure critical parameters, including temperature, pH level, water level, conductivity, and optical density. The sensors are strategically placed within the basin to ensure accurate data collection, enabling on-site processing using embedded TinyML models for decision-making and edge computing. Once network connectivity is established, the system uses an LLM to generate detailed recommendations based on real-time sensor data.

Figure 6 provides a visual representation of the prototype setup, illustrating the functionality of the sensors. To protect the system from environmental hazards such as precipitation or dirt ingress, a waterproof enclosure is essential. Given the system's proximity to basins, exposure to water poses a risk to the electronic components. The NSF-grade PVC plastic housing offers excellent water resistance, similar to materials used in water pipelines.

Figure 6. Live system setup in the Spirulina cultivation basin

5. SYSTEM OVERVIEW
5.1. System workflow: data flow and processing

The workflow of the proposed Spirulina cultivation control system defines the dynamic process through which sensor data is collected, analyzed, and transformed into actionable recommendations. As illustrated in Figure 7, the process begins with the collection of environmental data from five sensors: pH sensor, conductivity sensor, temperature sensor, endoscope camera (for optical density), and water level sensor.

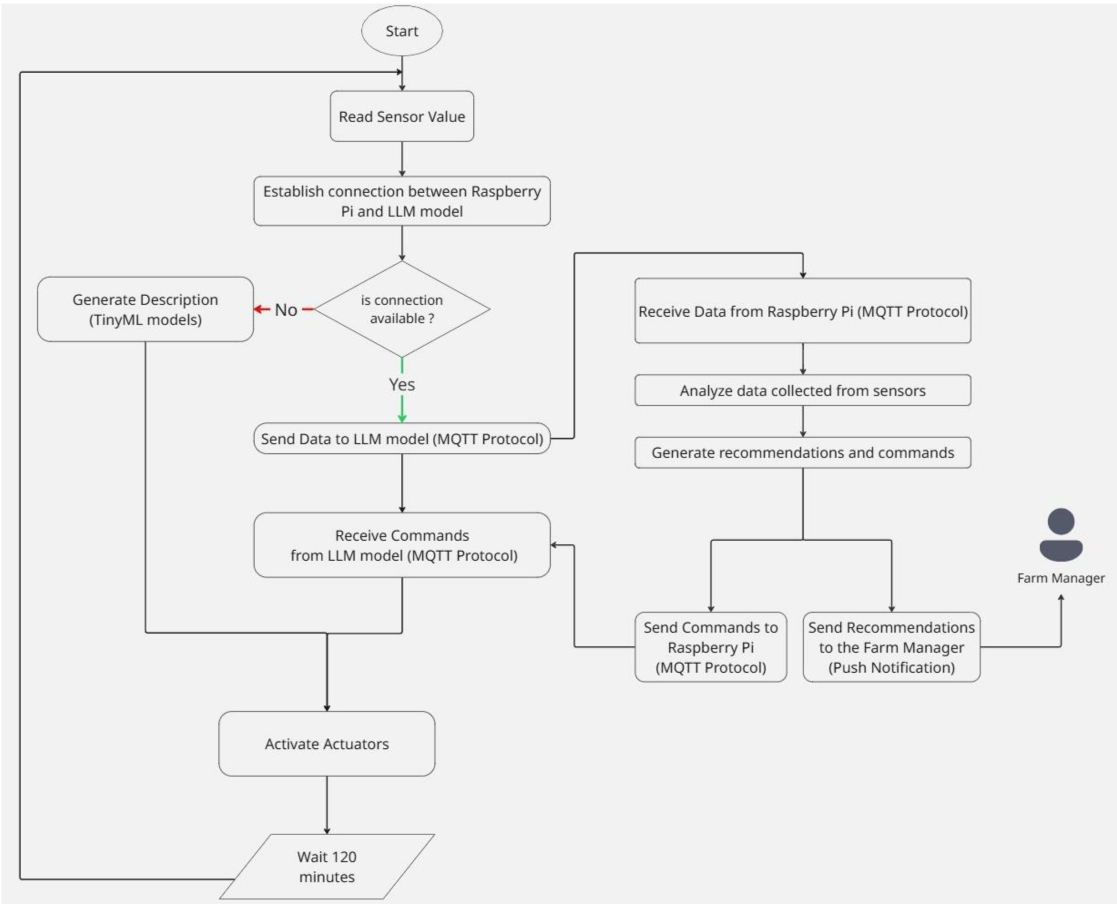


Figure 7. Workflow of the proposed AIoT solution for Spirulina cultivation control

Once data is acquired, the Raspberry Pi attempts to establish a connection with the LLM server. Two scenarios then arise:

- In case of connection availability, Sensor data is transmitted to the LLM server via the MQTT protocol. Within the LLM pipeline, the data is analyzed in conjunction with contextual knowledge, enabling the generation of precise recommendations and actuator commands. The commands are sent back to the Raspberry Pi (via MQTT) to activate actuators, while the recommendations are simultaneously forwarded to the farm manager as push notifications.
- In case of connection failure, the Raspberry Pi activates its embedded TinyML models, which analyze the sensor readings locally and generate system descriptions and commands. These commands are then used to drive the actuators directly, ensuring continuous system operation even in offline mode.

After actuator activation, the system enters a two-hour standby period before starting the data collection and processing loop. This workflow ensures responsive, reliable, and autonomous control of Spirulina cultivation under both connected and disconnected conditions.

5.2. System architecture: hardware–software integration

Figure 8 illustrates the overall architecture of the proposed Spirulina cultivation control system, integrating sensors, IoT communication, TinyML, and a retrieval-augmented generation (RAG) pipeline. On the hardware side, physical sensors (pH sensor, conductivity sensor, temperature sensor, endoscope camera, and water level sensor) are immersed in the Spirulina basin and connected to an Arduino Uno, which converts analog signals into digital values. These readings are transmitted to a Raspberry Pi that acts as the central processing unit. The Raspberry Pi processes sensor readings, runs TinyML models for offline autonomy, and communicates with the cloud-based LLM server using the MQTT protocol.

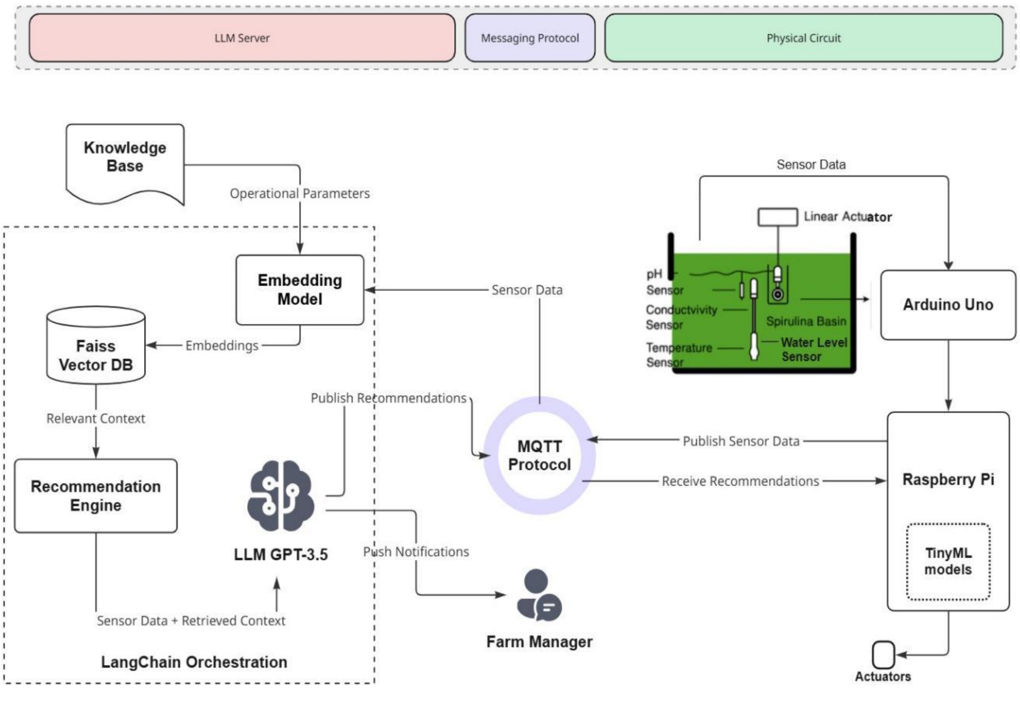


Figure 8. Architecture of the proposed AIoT solution for spirulina cultivation control

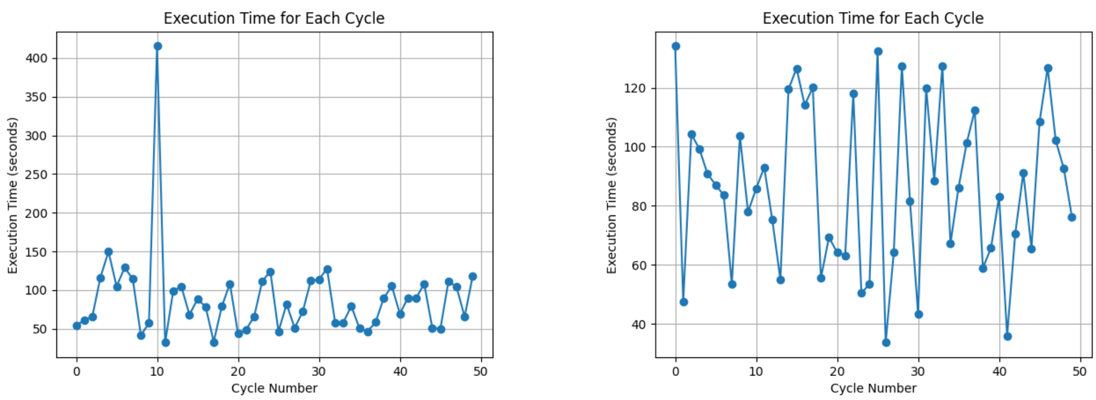
On the software side, the system employs a retrieval-augmented generation workflow coordinated by LangChain. Documents from the knowledge base are embedded using an embedding model and indexed in a FAISS vector database. When sensor data requires interpretation, LangChain orchestrates the retrieval of relevant context from FAISS and combines it with the raw sensor readings. A custom recommendation engine integrates this contextual information before passing it to the LLM (GPT-3.5), which generates precise and actionable recommendations. These recommendations are then transmitted back through the MQTT broker to the Raspberry Pi for actuator control and simultaneously delivered as push notifications to the farm manager.

6. RESULT

6.1. System responsiveness

The system's responsiveness to environmental changes was a critical factor in its performance. Figure 9 presents the results, illustrating the system's ability to maintain real-time data analysis capabilities under different operational conditions. For instance, as depicted in Figure 9(a), when a sudden drop in pH was detected, the system immediately responded to restore the pH level, leading to the spike observed in cycle 10. Additionally, Figure 9(b) shows that the execution time varies significantly between cycles due to network latency. However, it remains relatively efficient, with the execution time generally hovering around 80 seconds. In addition, when a sudden change in conditions is detected, the system promptly sends an alert notification to the farm manager, allowing them to take the necessary actions to restore the optimal range. This immediate response minimized stress on the Spirulina and prevented potential disruptions to its growth.

The LLMs in the system played a vital role in maintaining this responsiveness. These models continuously monitored sensor data and cross-referenced it with detailed documentation outlining optimal growth conditions for Spirulina. The Figure 10 presents a JSON-formatted output generated by the LLM, detailing system recommendations, associated actions, and command values. The commands section specifies predicted indices for pH, electrical conductivity (EC), brightness, and temperature parameters. The recommendations array provides condition-specific guidance, including the monitored parameter, its current status, and a corresponding operational action. For example, when pH is below 9, the system suggests adding NaOH; when conductivity is under 15, it recommends adding seawater; low brightness triggers a partial water filtration instruction; and an optimal temperature range is labeled as "Ideal."



(a) (b)

Figure 9. Comparison of system execution times (a) offline mode and (b) online mode

```
{
    "commands": {
        "ph_prediction": 4,
        "ec_prediction": 1,
        "brightness_prediction": 3,
        "temp_prediction": 1
    },
    "recommendations": [
        {
            "parameter": "pH",
            "status": "pH < 9",
            "action": "Add NaOH."
        },
        {
            "parameter": "Conductivity",
            "status": "Conductivity < 15",
            "action": "Add seawater."
        },
        {
            "parameter": "Brightness",
            "status": "Brightness ≤ 2",
            "action": "Filter 30% of basin."
        },
        {
            "parameter": "Temperature",
            "status": "20 ≤ Temperature ≤ 24",
            "action": "Ideal"
        }
    ]
}
```


Figure 10. LLM-generated recommendations, corresponding actions, and commands

6.2. Autonomy and reliability

The autonomy and reliability of the AIoT system were tested under various scenarios, including intentional network disruptions, to evaluate the performance of the TinyML models on the Raspberry Pi. During these disruptions, the TinyML models effectively maintained the necessary environmental conditions without any noticeable decrease in Spirulina growth or health. This demonstrated the system's robustness and ability to operate independently of constant internet connectivity. The performance of the classification system for the four key ecological parameters monitored by the TinyML models is summarized in the confusion matrices shown in Figure 11. These matrices include the following parameters: Figure 11(a) temperature, Figure 11(b) conductivity, Figure 11(c) transparency, and Figure 11(d) pH. Each matrix illustrates the distribution of correct and incorrect classifications by comparing predicted classes (x-axis) with actual classes (y-axis). As demonstrated by their confusion matrices, all models indicated a high degree of accuracy. The temperature model Figure 11(a) and the pH model Figure 11(d) demonstrate particularly high levels of accuracy, with minimal off-diagonal errors. In contrast, the transparency model Figure 11(c) shows the most concentrated correct predictions within fewer class categories, reflecting its narrower classification scope. Consequently, even during network interruptions, the performance of TinyML models was found to be reliable, thus ensuring the stability of system operation.

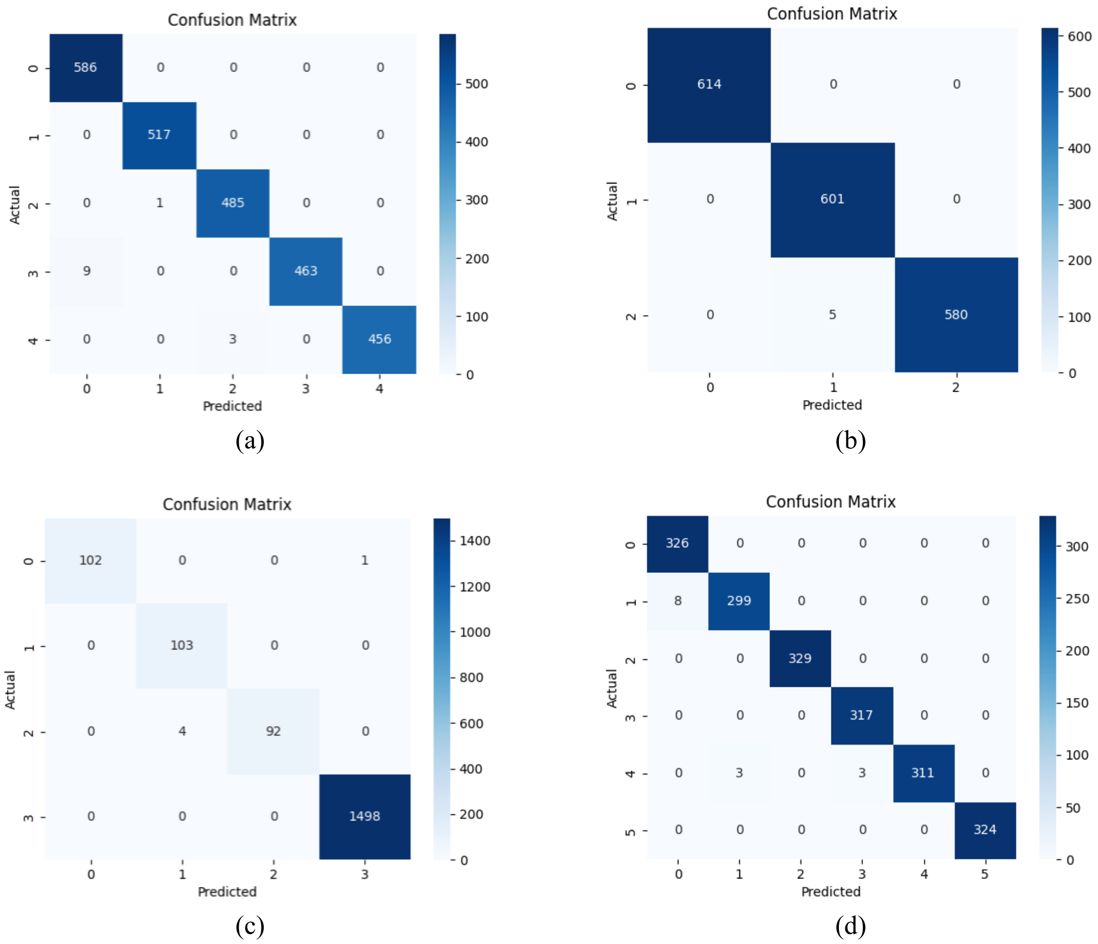


Figure 11. Confusion matrices for key environmental parameter models: (a) confusion matrix for the temperature model (b) confusion matrix for the conductivity model (c) confusion matrix for the transparency model and (d) confusion matrix for the pH model

According to this analysis, the LLMs generated specific recommendations, such as adding bicarbonate or nitrate, which were then transmitted to the farm manager via SMS. Figure 12 displays the transmitted SMS, conveying real-time system status updates and recommended actions for key environmental parameters. This process ensured that the manager was always informed and could take swift action to maintain the health of the Spirulina culture.

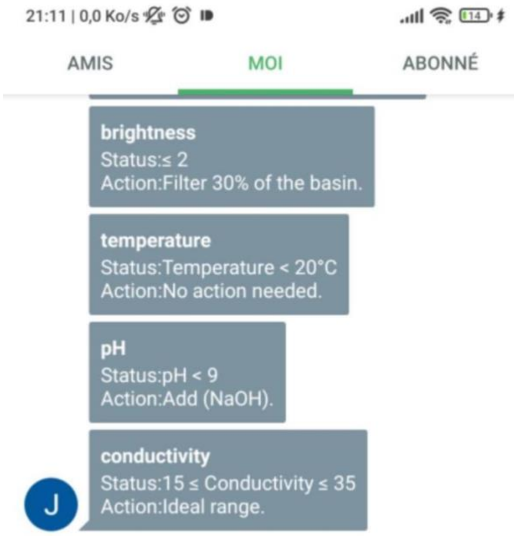


Figure 12. Notifications sent to the farm manager via SMS

6.3. Profitability

The AIoT system offers significant cost savings compared to traditional manual cultivation methods. Automating monitoring and control processes reduces the need for manual intervention, thereby lowering labor costs. The precision of the TinyML and LLM models also ensures efficient use of resources, such as nutrients and energy, further reducing operational expenses. These combined efficiencies reduce costs and save time, increasing profitability for the cultivation of Spirulina. Moreover, the system itself is not expensive to implement, as it relies on accessible and affordable hardware components. The total cost of these components is estimated at approximately $207 USD, which demonstrates that advanced AIoT-based monitoring and control can be achieved with relatively low investment compared to traditional large-scale cultivation infrastructures.

7. DISCUSSION

7.1. Main findings

Our study shows that the AIoT-based spirulina cultivation system was highly responsive and reliable in both online and offline scenarios, which is particularly valuable in coastal areas where Spirulina is commonly cultivated and internet connectivity is often slow or unstable. In an online setting, the system uses a LLM to generate adaptive, context-aware recommendations based on real-time sensor data. When internet connectivity was unavailable, the system switched to pre-trained TinyML models running locally on the Raspberry Pi to ensure continued monitoring and stable environmental control. This dual approach maintained all critical parameters, including temperature, conductivity, optical density, and pH, within their ideal ranges. The average execution time was approximately 80 seconds, which was fast enough to support timely interventions. In particular, the offline mode maintained optimal Spirulina growth while ensuring no reduction in yield or health. In addition, the system reduced labor costs, minimized human error, and improved efficiency compared to traditional manual cultivation methods. Furthermore, these findings align with previous research highlighting the benefits of integrating IoT and AI technologies in agriculture [35], [36]. For example, studies have shown that IoT-based systems can improve precision farming by providing real-time data and automated responses to environmental changes [37].

7.2. Implications and novelty

The novelty of this work lies in being the first to apply LLM-based reasoning to algae cultivation, combined with edge-based TinyML autonomy for reliable offline operation. While earlier systems primarily focused on data collection or small-scale automation, they lacked scalability, resilience to connectivity challenges, and integration of adaptive AI decision-making. Our system bridges this gap by connecting IoT sensing with advanced AI reasoning to maintain optimal growth conditions in real-world farming scenarios. This contribution paves the way for scalable AIoT solutions in aquaculture, offering a practical and cost-effective framework that can be extended to other crops and farming practices in the future.

8. CONCLUSION

This study demonstrates that traditional Spirulina cultivation methods—often constrained by inconsistent measurements, reliance on paper-based records, and outdated monitoring techniques—are insufficient for ensuring reliable productivity in dynamic laboratory environments. By contrast, the proposed AIoT system integrates cyber-physical systems with LLMs to deliver real-time monitoring, self-adaptive control, and secure data management. Experimental results confirm the system's ability to maintain optimal growth conditions while reducing human intervention, thereby outperforming conventional IoT-based approaches in accuracy, autonomy, and reliability. Beyond addressing current limitations, the framework paves the way for LLM–Edge integrated agricultural AI, where intelligent models operate locally to support resource-constrained farms. This enables self-adaptive Spirulina cultivation in rural and remote contexts, where continuous expert supervision is often unavailable. Furthermore, the architecture is extensible: future studies could expand its scope toward algae classification, contamination detection, and aquaculture optimization through advanced pattern recognition, underscoring its potential as a scalable solution for sustainable biotechnology applications.

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REFERENCES

[1] C. Bennouna, "Spirulina: its properties and cultivation methods," *Synoxis Algae*, 2020. https://www.synoxis-algae.com/spirulina-properties-and-cultivation-methods/ (accessed Jun. 12, 2020).
[2] I. S. Chronakis and M. Madsen, "Algal proteins," in *Handbook of Food Proteins*, G. Phillips and P. Williams, Eds. Woodhead Publishing, 2011, pp. 353–394. doi: 10.1533/9780857093639.353.
[3] B. Maddiboyina *et al.*, "Food and drug industry applications of microalgae Spirulina platensis: A review," *Journal of Basic Microbiology*, vol. 63, no. 6, pp. 573–583, 2023, doi: 10.1002/jobm.202200704.
[4] V. Henríquez, C. Escobar, J. Galarza, and J. Gimpel, "Carotenoids in microalgae," in *Sub-Cellular Biochemistry*, vol. 79, C. Stange, Ed. Cham: Springer, 2016, pp. 219–237. doi: 10.1007/978-3-319-39126-7_8.
[5] T. de C. D. Mendes-Silva *et al.*, "Biotechnological potential of carotenoids produced by extremophilic microorganisms and application prospects for the cosmetics industry," *Advances in Microbiology*, vol. 10, no. 08, pp. 397–410, 2020, doi: 10.4236/aim.2020.108029.
[6] E. D. Revellame, R. Aguda, A. Chistoserdov, D. L. Fortela, R. A. Hernandez, and M. E. Zappi, "Microalgae cultivation for space exploration: Assessing the potential for a new generation of waste to human life-support system for long duration space travel and planetary human habitation," *Algal Research*, vol. 55, p. 102258, 2021, doi: 10.1016/j.algal.2021.102258.
[7] E. D. Revellame *et al.*, "Microalgae in bioregenerative life support systems for space applications," *Algal Research*, vol. 77, p. 103332, 2024, doi: 10.1016/j.algal.2023.103332.
[8] R. Maddaly, "The beneficial effects of spirulina focusing on its immunomodulatory and antioxidant properties," *Nutrition and Dietary Supplements*, vol. 2, p. 73, 2010, doi: 10.2147/nds.s9838.
[9] M. A. Borowitzka and N. R. Moheimani, "Open pond culture systems," in *Algae for Biofuels and Energy*, Dordrecht: Springer, 2013, pp. 133–152. doi: 10.1007/978-94-007-5479-9_8.
[10] L. Manu *et al.*, "Photobioreactors are beneficial for mass cultivation of microalgae in terms of areal efficiency, climate implications, and metabolites content," *Journal of Agriculture and Food Research*, vol. 18, p. 101282, 2024, doi: 10.1016/j.jafr.2024.101282.
[11] A. U. Aquino, M. V. L. Bautista, C. H. Diaz, I. C. Valenzuela, and E. P. Dadios, "A vision-based closed spirulina (a. platensis) cultivation system with growth monitoring using artificial neural network," in *2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management, HNICEM 2018*, 2018, pp. 1–5. doi: 10.1109/HNICEM.2018.8666367.
[12] E. Ariawan and A. Stanley Makalew, "Smart micro farm: Sustainable algae spirulina growth monitoring system," in *Proceedings of 2018 10th International Conference on Information Technology and Electrical Engineering: Smart Technology for Better Society, ICITEE 2018*, 2018, pp. 587–591. doi: 10.1109/ICITEED.2018.8534904.
[13] I. Hermadi *et al.*, "Development of smart algae pond system for microalgae biomass production," *IOP Conference Series: Earth and Environmental Science*, vol. 749, no. 1, p. 12068, 2021.
[14] L. K. S. Tolentino *et al.*, "IoT-based closed algal cultivation system with vision system for cell count through ImageJ via Raspberry Pi," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 7, pp. 287–294, 2021, doi: 10.14569/IJACSA.2021.0120732.
[15] H. R. Lim *et al.*, "Evaluation of real-time monitoring on the growth of spirulina microalgae: Internet of things and microalgae technologies," *IEEE Internet of Things Journal*, vol. 11, no. 2, pp. 3274–3281, 2024, doi: 10.1109/JIOT.2023.3296525.
[16] M. B. Zrimec *et al.*, "Advances in Spirulina cultivation: Techniques, challenges, and applications," in *Insights Into Algae - Fundamentals, Culture Techniques and Biotechnological Uses of Microalgae and Cyanobacteria*, I. A. Severo, W. J. Martinez-Burgos, and J. Ordonez, Eds. Rijeka: IntechOpen, 2024. doi: 10.5772/intechopen.1005474.
[17] A. Vonshak and L. Tomaselli, "Arthrospira (Spirulina): systematics and ecophysiology," in *Ecology of Cyanobacteria.*, Dordrecht: Kluwer Academic Publishers, 2000, pp. 505–523.
[18] J. L. Farrar, *Les arbres du Canada*. Ottawa, Canada: Ressources naturelles Canada, 1995.
[19] N. K. Z. AlFadhly, N. Alhelfi, A. B. Altemimi, D. K. Verma, and F. Cacciola, "Tendencies affecting the growth and cultivation of genus spirulina: An investigative review on current trends," *Plants*, vol. 11, no. 22, p. 3063, 2022, doi: 10.3390/plants11223063.
[20] S. Farming, "Spirulina cultivation: Best practices and techniques," *Spirulina Farming*, 2024.

[21] J. Devanathan and N. Ramanathan, "Utilization of seawater as a medium for mass production of Spirulina platensis---A novel approach," *International Journal of Recent Scientific Research*, vol. 4, no. 5, pp. 597–602, 2013.
[22] K. A. Selvam, J. Devanathan, A. Selvam, and N. Ramanathan, "Optimization of biomass production of spirulina platensis in seawater medium," *Life Science Archives*, vol. 2, no. 2, pp. 708–716, 2016.
[23] S. J. Henrikson, *Principles of microbe and cell cultivation*, 2nd ed. Oxford, UK: Blackwell Scientific Publications, 1994.
[24] R. Chaiklahan, N. Chirasuwan, T. Srinorasing, S. Attasat, A. Nopharatana, and B. Bunnag, "Enhanced biomass and phycocyanin production of Arthrospira (Spirulina) platensis by a cultivation management strategy: Light intensity and cell concentration," *Bioresource Technology*, vol. 343, p. 126077, 2022, doi: 10.1016/j.biortech.2021.126077.
[25] C.-J. Kim, Y.-H. Jung, G.-G. Choi, Y.-H. Park, C.-Y. Ahn, and H.-M. Oh, "Optimization of outdoor cultivation of spirulina platensis and control of contaminant organisms," *Algae*, vol. 21, no. 1, pp. 133–139, 2006, doi: 10.4490/algae.2006.21.1.133.
[26] C. J. Kim, Y. H. Jung, S. R. Ko, H. I. Kim, Y. H. Park, and H. M. Oh, "Raceway cultivation of Spirulina platensis using underground water," *Journal of Microbiology and Biotechnology*, vol. 17, no. 5, pp. 853–857, 2007.
[27] F. Delrue *et al.*, "Optimization of Arthrospira platensis (Spirulina) growth: From laboratory scale to pilot scale," *Fermentation*, vol. 3, no. 4, 2017, doi: 10.3390/fermentation3040059.
[28] A. E.-K. El-sayed and M. El-sheekh, "Outdoor cultivation of spirulina platensis for mass production," *Notulae Scientia Biologicae*, vol. 10, no. 1, pp. 38–44, 2018, doi: 10.15835/nsb10110177.
[29] K. P. Sandeep *et al.*, "Utilization of inland saline water for Spirulina cultivation," *Journal of Water Reuse and Desalination*, vol. 3, no. 4, pp. 346–356, 2014, doi: 10.2166/wrd.2013.102.
[30] L. K. Ong, V. V. Lauw, S. Tang, Y. Arifin, and L. Riadi, "Application of solar photovoltaic for the cultivation of Arthospira platensis (Spirulina)," in *International Journal of Applied Science and Engineering*, 2023, vol. 20, no. 2. doi: 10.6703/IJASE.202306_20(2).008.
[31] T. Luis and N. Geovanni, "Application of IoT in agribusiness," in *Lecture Notes in Networks and Systems*, 2024, vol. 839, pp. 585–593. doi: 10.1007/978-981-99-8324-7_49.
[32] R. Jeyabharath *et al.*, "Smart aeroponic farms with IoT-enabled efficient automation and monitoring," in *2nd International Conference on Artificial Intelligence and Machine Learning Applications: Healthcare and Internet of Things, AIMLA 2024*, 2024, pp. 1–7. doi: 10.1109/AIMLA59606.2024.10531308.
[33] A. U. Mentsiev and F. F. Gatina, "Data analysis and digitalisation in the agricultural industry," *IOP Conference Series: Earth and Environmental Science*, vol. 677, no. 3, p. 32101, 2021, doi: 10.1088/1755-1315/677/3/032101.
[34] C. S. M. Babou, B. O. Sane, I. Diane, and I. Niang, "Home edge computing architecture for smart and sustainable agriculture and breeding," in *ACM International Conference Proceeding Series*, 2019, vol. Part F148154. doi: 10.1145/3320326.3320377.
[35] S. Nimmala, M. Ramchander, M. Mahendar, P. Manasa, M. A. Kiran, and B. Rambabu, "A recent survey on AI-enabled practices for smart agriculture," in *2024 International Conference on Intelligent Systems for Cybersecurity (ISCS)*, 2024, pp. 1–5.
[36] E. Elbasi *et al.*, "Artificial intelligence technology in the agricultural sector: A systematic literature review," *IEEE Access*, vol. 11, pp. 171–202, 2023, doi: 10.1109/ACCESS.2022.3232485.
[37] R. De-Luca, F. Bezzo, Q. Béchet, and O. Bernard, "Meteorological data-based optimal control strategy ´for microalgae cultivation in open pond systems," *Complexity*, vol. 2019, no. 1, p. 4363895, 2019, doi: 10.1155/2019/4363895.

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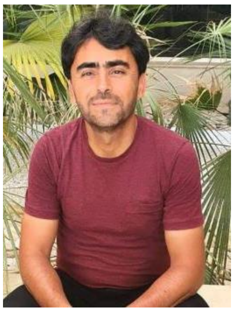

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