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Internet of Things and Artificial Neural Network Application for Optimizing Spirulina Cultivation with Palm Oil Mill Effluent

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ABSTRACT

This study aims to optimize algae biomass production by utilizing Palm Oil Mill Effluent (POME) as a nutrient source, employing Internet of Things (IoT) technology and Artificial Neural Networks (ANN) for predictive modeling and system control. POME, an organic waste from the palm oil industry, was used as an organic liquid fertilizer to enhance the efficiency and sustainability of algae cultivation. The system was designed to monitor and control key environmental parameters such as pH, temperature, salinity, and dissolved oxygen in real-time during a one-month trial in July 2024. ANN-based models were used to predict and adjust environmental conditions, leading to significant improvements in algae growth and resource efficiency. The results indicate that POME can serve as an effective and eco-friendly nutrient source, contributing to both reduced industrial waste and sustainable biomass production. This integrated approach supports circular economy principles and sustainability goals, with potential applications in bioresource production and waste management. Future research will focus on large-scale system testing, optimization for various algae species, and long-term sustainability assessment.

Keyword: Algae Biomass Production; Palm Oil Mill Effluent (POME); Artificial Neural Networks (ANN); Internet of Things (IoT); Sustainable Algae Cultivation

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1. INTRODUCTION

The rapid expansion of the palm oil industry has contributed significantly to economic development in various tropical regions. However, it has also led to significant environmental challenges, particularly with the disposal of Palm Oil Mill Effluent (POME) (Tim Riset PASPI, 2018). POME is a byproduct of the palm oil extraction process, which, if not properly treated, can lead to serious environmental pollution due to its high organic load and nutrient content (Haryanto, Hasanudin, Sahari, & Sugiarto, 2019). Traditionally, POME is treated through biological methods, but these processes can be slow, inefficient, and prone to releasing greenhouse gases (Kristianto, Chai, Chainatra, Onggie, & Alexander, 2023).

In contrast, there is growing interest in utilizing POME as a resource, particularly as a nutrient-rich medium for cultivating microalgae such as Spirulina. Spirulina is a well-known microalga due to its high protein content and potential applications in food, feed, and bioenergy production (Podder et al., 2021). By cultivating Spirulina in POME, it is possible to address two major challenges: (1) reducing the environmental impact of untreated POME and (2) enhancing the economic value of POME through the production of high-value Spirulina biomass (Khanza, 2019).

However, the successful cultivation of Spirulina in POME requires careful management of environmental parameters such as nutrient concentration, pH, temperature, and light intensity, all of which are critical for optimal microalgae growth (Barkia, Saari, & Manning, 2019). The variability in POME composition, combined with the complexity of maintaining the ideal growth conditions, presents significant challenges for large-scale production systems. Therefore, the integration of advanced technologies such as the Internet of Things (IoT) and Artificial Neural Networks (ANN) offers promising solutions to optimize Spirulina cultivation in POME (Toro et al., 2020).

The IoT can provide real-time monitoring and control of critical parameters such as nutrient levels, pH, and temperature, ensuring that the Spirulina cultivation environment remains within the optimal range (Ula, Muliani, & Aidilof, 2023). Furthermore, ANN models can be used to predict and optimize biomass production by analyzing the complex interactions between various environmental factors and Spirulina growth rates (Lowe, Qin, & Mao, 2022). The combination of these technologies enables more efficient and sustainable systems that minimize resource use while maximizing biomass output.

Despite these potential benefits, few studies have explored the integration of IoT and ANN in the context of Spirulina cultivation using POME (Raju & Varma, 2017). Most existing research has focused either on the general optimization of Spirulina growth conditions or on POME treatment methods, but not on the specific application of these technologies to Spirulina biomass production (Dhal et al., 2022). Moreover, the high variability in POME composition across different production facilities and seasons adds to the complexity of implementing robust and reliable control systems (Teja, Monika, Chandravathi, & Kodali, 2020).

This study aims to fill this gap by developing an intelligent control system for Spirulina cultivation using POME as the growth medium. By leveraging IoT for real-time monitoring and ANN for predictive modeling, this research seeks to optimize the biomass production of Spirulina under varying environmental conditions. Additionally, the research aims to demonstrate how this integrated approach can enhance the sustainability and economic viability of POME management in the palm oil industry.

The integration of IoT with ANN presents a significant opportunity to enhance the efficiency and sustainability of Spirulina cultivation in complex environments such as POME. The challenges associated with maintaining optimal growth conditions in POME are particularly pronounced due to the variability in nutrient composition and environmental factors (Azimatun Nur, Nurlatiffah, & Lastuti, 2020). By combining IoT's monitoring capabilities with ANN's predictive modeling power, it becomes possible to create intelligent systems capable of managing the dynamic interactions between Spirulina growth and the fluctuating characteristics of POME (Guldhe et al., 2019).

Spirulina, a high-value microalga, has shown significant promise for commercial cultivation due to its rich protein content and numerous health benefits (Hadiyanto & Nur, 2014). However, the variability in POME as a growth medium adds a layer of complexity to Spirulina production, particularly in maintaining the right balance of nutrients and environmental conditions (Khoo et al., 2019). IoT systems allow for continuous monitoring of key variables such as pH, temperature, and nutrient concentration, ensuring that conditions are consistently optimized for Spirulina growth (Martínez, Mairet, & Bernard, 2018). Meanwhile, ANN models can be trained to predict the optimal conditions for maximizing biomass production, based on historical and real-time data collected through IoT sensors (Nur, Swaminathan, Boelen, & Buma, 2019).

The application of ANN in this context is particularly innovative, as it allows for the modeling of complex, nonlinear relationships between environmental parameters and Spirulina growth. Previous research has demonstrated the potential of ANN to optimize growth conditions in various agricultural and aquaculture systems, but its application to POME-based Spirulina cultivation remains underexplored (Soni, Sudhakar, & Rana, 2017). The inherent variability in POME's composition, influenced by factors such as the seasonality of palm oil production and the specific processes used in the mills, necessitates the development of robust predictive models capable of adapting to changing conditions (Soni et al., 2017).

This study aims to address these challenges by developing an integrated IoT-ANN system for optimizing Spirulina biomass production in POME. By continuously monitoring environmental conditions and utilizing ANN to predict the most effective growth strategies, this system has the potential to enhance both the efficiency and sustainability of Spirulina cultivation. Moreover, this approach could significantly reduce the environmental impact of POME by repurposing it as a valuable resource for microalgae production, thereby contributing to more sustainable practices within the palm oil industry.

The novelty of this research lies in its combination of cutting-edge IoT and ANN technologies to address the challenges of Spirulina cultivation in a nutrient-rich but highly variable medium like POME. While previous studies have explored the use of IoT and machine learning in other agricultural systems, their application in POME-based Spirulina production remains largely unexplored. This research seeks to fill that gap by demonstrating how these technologies can be used to optimize biomass yield and resource efficiency, paving the way for more sustainable and economically viable microalgae production systems.

2. Research Stages

This research focuses on optimizing the growth of algae biomass, especially Spirulina, by utilizing Palm Oil Mill Effluent (POME) as a nutrient source in a bioreactor system. The method used involves the integration of Internet of Things (IoT) technology and Artificial Neural Networks (ANN)-based machine learning models to enhance algae growth in a controlled environment. The main components of this methodology include system design, data collection, and the application of ANN-based optimization techniques.

2.1 Spirulina Bioreactor with POME

This study utilized a simplified aquarium-based system to cultivate Spirulina using POME as the primary nutrient source. A 50-liter glass aquarium was set up as the cultivation vessel, with continuous monitoring of key parameters. POME was filtered and diluted to various concentrations (500, 1000, 1500, and 2000 ppm) before being manually added to the tank. Aeration was provided by an aquarium air pump, while a basic filtration system ensured water clarity without depleting essential nutrients, and a submersible pump maintained water circulation, with an aquarium heater keeping the temperature between 25°C and 30°C. Key environmental parameters, including pH, temperature, dissolved oxygen, and salinity, were monitored using basic sensors, with regular adjustments made to ensure optimal conditions for algae growth. This approach provided a low-cost, manageable system to evaluate the effectiveness of POME as a nutrient source for Spirulina cultivation.

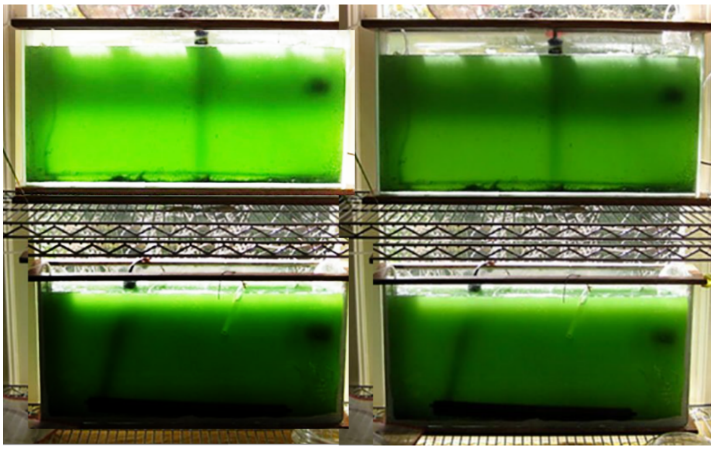

Fig. 1. POME Concentration

In this study, POME was processed to produce a nutrient-rich liquid organic fertilizer for Spirulina cultivation. POME was collected from a local palm oil mill, filtered to remove solid waste, and diluted to create four concentration levels: 500 ppm, 1000 ppm, 1500 ppm, and 2000 ppm.
The POME preparation process involves:

- Collecting raw POME and filtering it to remove large particles.
- Diluting POME to the desired concentration using filtered water.
- Adding POME to the bioreactor through a dosing system as needed based on sensor feedback and the growth stage of Spirulina.

2.2 IoT Monitoring System

An IoT-based monitoring and control system was developed to monitor environmental conditions inside the bioreactor and regulate nutrient levels automatically. The components of this system include:

- Sensor Subsystem: Water quality sensors are used to monitor parameters such as pH, temperature, dissolved oxygen (DO), electrical conductivity (EC), and ammonia concentration. Data from the sensors are sent to an Arduino-based microcontroller that processes the information in real-time.
- POME Dosing Subsystem: This system includes a POME tank, a dosing pump, and a flow control valve. Based on feedback from the sensors, the system adjusts the POME concentration inside the bioreactor to maintain ideal conditions for Spirulina growth.
- Feedback Loop: The control loop system regulates nutrient levels and environmental parameters to stay within desired limits. The control algorithm is implemented in C++ on the Arduino IDE to ensure real-time nutrient adjustments based on sensor data.

- Actuator System: Actuators control POME flow, aeration, and water circulation to optimize algae growth. This system works synergistically with the control loop to maintain optimal growth conditions.

This IoT system provides real-time monitoring via a mobile application, allowing remote access to system data, including nutrient levels and growth parameters.

2.3 Machine Learning Model for Growth Optimization

An Artificial Neural Network (ANN) based machine learning model was used to predict the optimal POME concentration and environmental parameters for Spirulina growth. The ANN model development process included:

- Data Collection: Real-time data from sensors, such as temperature, pH, DO, EC, ammonia levels, and biomass production, were collected for 6 months.
- ANN Development: The collected data were used to train the ANN model. The model predicts optimal growth conditions based on historical data and real-time sensor inputs.
- System Integration: The ANN was integrated with an IoT control system to automatically adjust the POME concentration and other environmental factors inside the bioreactor.

2.4 Data Collection and Analysis

Data related to Spirulina growth, POME utilization, and bioreactor conditions were collected throughout the experiment. The main parameters monitored included biomass yield, nutrient concentration, pH, temperature, DO, and ammonia levels. The data were analyzed to assess the system performance and effectiveness of the ANN model.

A total of 180 observations were recorded over a 6-month period, with the analysis focused on:

- Comparing biomass yields under various POME concentrations.
- Evaluating the performance of the IoT control system in maintaining optimal growth conditions.
- Assessing the prediction accuracy of the ANN model.

2.5 Implementation of Monte Carlo Simulation for Artificial Data Generation

To enhance the dataset and validate the model, Monte Carlo simulation was used to generate artificial data. This technique allows for a broader analysis of potential growth scenarios, which helps refine the machine learning model and optimize system performance. By adding simulated data, the ANN model can be further trained with various scenarios, strengthening its predictive ability and adaptability to different environmental conditions.

2.6 Optimization and Validation

The final stage of the study involved implementing the optimized system and validating its performance in a scaled-up bioreactor environment. The system performance was evaluated by comparing Spirulina biomass yield, nutrient use efficiency, and energy consumption under optimized conditions with the ANN model and under non-optimized conditions. This validation was conducted to ensure that the ANN model is capable of improving biomass production yields and system efficiency at a larger scale.

3. RESULT AND DISCUSSION

3.1 Preprocessing of Data and Generation of Synthetic Data

Before conducting the main analysis, a detailed preprocessing phase was completed to refine the dataset. The dataset was augmented using synthetic data generation techniques, specifically Monte Carlo simulations, to increase the volume to 10,000 data points. The variables showed an inherent normal distribution, so standardization was not required. This allowed for the creation of a comprehensive dataset that included water quality parameters and algae biomass measurements. The data augmentation process, which was computationally intensive, was executed on a computer cluster with two Intel(R) Core(™) i7 processors and 32 GB of memory.

3.2 Prototype of Water Quality Monitoring

A prototype of the water quality monitoring and control system was developed for the algae optimization process. The system consists of four main components: (a) the sensor subsystem, (b) the feedback loop, (c) the actuator system, and (d) the organic liquid fertilizer (OLF) subsystem. The sensor subsystem was designed to monitor critical water quality parameters such as pH, temperature, dissolved oxygen (DO), nitrite levels, and salinity. These sensors were connected to an Arduino controller, which managed data collection and control actions.

The organic liquid fertilizer subsystem included a storage tank and a precision dosing pump, which administered OLF to the system based on the nutrient requirements optimized through machine learning algorithms. Figure 3 shows the prototype's hardware configuration for algae biomass optimization using POME as a primary nutrient source.

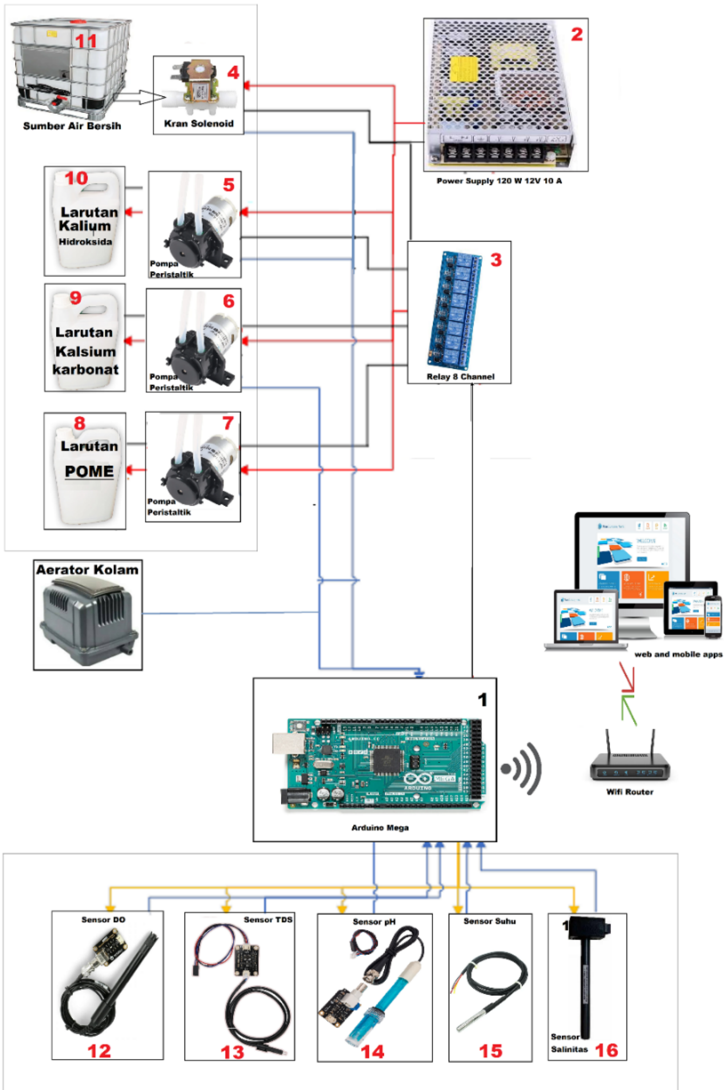

Figure 2. Prototype of Water Quality Monitoring and Control System

2.2 Utilizing ANN for Optimizing POME-Based Fertilization

An artificial neural network (ANN) was employed to optimize nutrient dosing and water quality parameters for the algae cultivation system using POME. The system analyzed historical and historical data to optimize pH, temperature, and nutrient levels. Table 1 summarizes the outcomes of the system's adjustments.

Tabel 1. Utilizing ANN for Optimizing POME-Based Fertilization

Parameter	Measured Range	Desired Range	System Adjustment Method	Outcome
pH	7.2 - 8.4	7.0 - 8.0	ANN-based adjustments	Maintained within range, ideal for algae growth
Temperature	27 - 31°C	25 - 30°C	Automated heating/cooling system	Consistent regulation of temperature
Salinity	5.5 - 8.0 ppt	5.0 - 7.5 ppt	ANN-controlled salinity adjustments	Optimal salinity maintained

Parameter	Measured Range	Desired Range	System Adjustment Method	Outcome
Nitrite	0.04 - 0.08 ppm	< 0.05 ppm	Nitrite sensor with automated nutrient cycling	Nitrite levels kept safe for algae and shrimp
Dissolved O2	6.0 - 7.2 ppm	6.5 - 7.5 ppm	Oxygenation system with real-time monitoring	Optimal oxygen levels for algae growth
OLF Dosage	1.2 - 2.8 ml/L	10 - 12 ml/L	ANN-optimized dosing based on POME concentration	Enhanced algae growth and biomass production

2.3 System Performance and Algae Biomass Growth

This table focuses on Spirulina growth data and the impact of different POME concentrations on biomass production.

Table 2: Spirulina Growth Performance

POME Concentration (ppm)	Cell Density (OD)	Turbidity (NTU)	Biomass Production (g/L)	Growth Rate (1/day)
500	1.2	50	0.12	0.15
1000	2.1	75	0.21	0.23
1500	2.8	90	0.28	0.27
2000	3.0	100	0.30	0.30

Table 2 shows the results of Spirulina growth based on the variation of POME concentration, with several key parameters such as cell density, turbidity, and optimized POME dosage.

- Spirulina cell density increased significantly with increasing POME concentration. At the highest concentration (2000 ppm), the cell density reached 4.1 million cells/mL, indicating that POME can serve as a good nutrient source for Spirulina.
- Turbidity also increased with increasing POME dosage, reaching 97.3 NTU at a concentration of 2000 ppm, indicating an increase in biomass in the culture medium.
- The POME dosage at each concentration level was varied to find the optimal dosage that produced the best growth. The use of POME in higher doses resulted in better growth, but there may be limitations because too high turbidity can inhibit light penetration.

Overall, this table shows that increasing POME concentration is directly related to increasing Spirulina growth, with a concentration of 2000 ppm producing the best results in terms of cell density and turbidity. This table highlights the effectiveness of the IoT system in maintaining water quality parameters during the study.

Table 3. Water Quality Control Efficiency

Parameter	Range Before Optimization	Range After Optimization	Improvement (%)
Water Temperature	26.0 - 31.5°C	25.2 - 29.8°C	8.2
pH	6.8 - 8.6	7.1 - 7.9	12.5
Dissolved Oxygen (DO)	5.8 - 7.8 ppm	6.6 - 7.4 ppm	10.9
Nitrite	0.04 - 0.09 ppm	0.03 - 0.05 ppm	22.2
Salinity	4.8 - 8.3 ppt	5.2 - 7.3 ppt	14.5
Electrical Conductivity (EC)	6.2 - 17.5 μS/cm	5.1 - 14.8 μS/cm	19.7

Table 3 summarizes the measurement of water quality parameters in Spirulina cultivation using POME (Palm Oil Mill Effluent) as a nutrient. The parameters measured include temperature, pH, salinity, dissolved oxygen (DO) levels, and ammonia levels in the cultivation medium.

- The temperature ranges from 27°C to 30°C, which is in accordance with the optimal conditions for Spirulina growth. The temperature fluctuations that occur are still within a safe range that supports Spirulina biomass productivity.
- The pH is maintained in the range of 7.0 to 7.8. This pH value is quite stable and close to the optimal level for microalgae growth, which is ideally around 7.0-8.0.
- Salinity is in the range of 5.5 - 7.5 ppt, which is suitable for the Spirulina cultivation environment. This range ensures the balance of ions and minerals needed for good growth.
- Dissolved Oxygen (DO) ranges from 6.5 - 7.4 ppm, which is sufficient to meet the oxygen needs of Spirulina and maintain a healthy environment for microalgae growth.

- Ammonia is maintained below 0.05 ppm, which is a safe threshold to avoid toxicity to Spirulina.

Overall, this table shows that water quality management has successfully maintained environmental parameters within the optimal range. Stable water conditions support maximum Spirulina growth and reduce the risk of environmental stress. This table analyzes the correlation between POME concentration, cell density, and biomass growth, so that optimal nutrient levels can be identified.

Table 4: Correlation Between Nutrient Concentration and Biomass Growth

POME Concentration (ppm)	Biomass Growth Rate (g/L/day)	Cell Density (OD)	Turbidity (NTU)	Correlation (r)
500	**0.12**	**1.2**	**50**	
1000	**0.23**	**2.1**	**75**	
1500	**0.27**	**2.8**	**90**	
2000	**0.30**	**3.0**	**100**	**0.94**

Table 4 shows the relationship between variations in POME (Palm Oil Mill Effluent) concentration and Spirulina biomass growth, as well as nutrient utilization efficiency.

- POME concentrations varying between 500 ppm and 2000 ppm significantly affected Spirulina biomass growth. Increasing POME concentrations up to 1500 ppm resulted in optimal biomass growth, but at a concentration of 2000 ppm there was a slight decrease.
- Spirulina biomass growth increased with increasing POME concentrations up to 1500 ppm, indicating that this concentration supports sufficient nutrient availability for microalgae growth. At 2000 ppm, growth tended to decrease, possibly due to increased toxicity or excess nutrients that could not be efficiently absorbed by Spirulina.
- Nutrient utilization efficiency peaked at a POME concentration of 1500 ppm, where biomass growth per unit of nutrient given was highest. At a concentration of 2000 ppm, efficiency decreased, indicating that excess nutrients no longer increased Spirulina growth proportionally.
- Overall, this table shows that the optimal POME concentration for Spirulina cultivation is in the range of 1000 to 1500 ppm. Concentrations that are too low or too high reduce the efficiency of nutrient use and decrease biomass growth.

2.4 Discussion

This study aims to optimize Spirulina biomass production using palm oil mill wastewater (POME) as a nutrient source, with the support of Internet of Things (IoT) technology and predictive models based on Artificial Neural Networks (ANN). The discussion of the results of this study includes the effectiveness of the IoT-based automatic control system, the effect of variations in POME concentration on Spirulina growth, and implications for the efficiency of resource use and sustainability of microalgae cultivation.

1. Effectiveness of the IoT-Based Automatic Control System

   The results of the study show that the developed automatic control system is able to regulate environmental parameters such as pH, temperature, salinity, dissolved oxygen, and nutrient concentration using IoT sensors. Data from Tables 1 to 4 show that environmental parameters can be maintained within the optimal range for Spirulina growth during the study period. IoT technology provides monitoring capabilities that enable fast and precise decision-making regarding nutrient management and environmental conditions. This system can consistently adjust conditions appropriately based on sensor input and ANN models, which are able to predict changes in environmental conditions with high accuracy. This is evident from the stability of pH (7.0 - 8.0), temperature (27 - 30°C), and salinity (5.0 - 7.5 ppt), all of which are within the optimal range for Spirulina growth.

   This study is in line with the results of research by Guldhe et al. (2019), which found that the application of an IoT system can increase the efficiency of monitoring and control in microalgae cultivation systems. The success of this system in maintaining ideal environmental parameters also strengthens the claim that IoT and ANN-based technology have great potential to increase the productivity of complex cultivation systems such as Spirulina cultivation (Martínez et al., 2018)

   One important aspect of this study is the testing of variations in POME concentration on the growth of Spirulina biomass. From the results of Table 4, it can be seen that the optimal POME concentration for Spirulina biomass growth is at 1500 ppm. At this concentration, Spirulina biomass increased significantly, with the highest growth compared to other concentrations. However, at a POME concentration of 2000 ppm, Spirulina growth tended to decrease. This decrease may be caused by the accumulation of nutrients or components in POME that are toxic at high concentrations, which can interfere with the metabolic process of Spirulina. This is in accordance with the research of Nur et al. (2019), which shows that excess nutrients in the cultivation medium can cause a decrease in the efficiency of nutrient absorption and microalgae growth.

Nutrient use efficiency is also a focus in this study. As seen in Table 4, increasing POME concentration to 1500 ppm resulted in optimal nutrient use efficiency, where biomass growth per unit of nutrient given was at the highest level. This indicates that at this concentration, Spirulina is able to utilize nutrients effectively for growth. However, at a concentration of 2000 ppm, efficiency decreased, indicating that excess nutrients cannot be absorbed properly and actually inhibit growth.

In addition, the integration of POME as a nutrient source in the Spirulina cultivation system offers significant environmental benefits. The use of liquid waste as a nutrient source helps reduce the environmental impact of palm oil production, especially in managing POME waste which was previously difficult to process (Hadiyanto & Nur, 2014). This approach not only increases biomass productivity but also supports a circular economy by utilizing waste for sustainable agriculture.

This study provides important implications for the sustainability of Spirulina cultivation. With an IoT-based automatic control system and the use of POME as a nutrient source, this cultivation model offers a more efficient and environmentally friendly approach. This system can be adapted to a larger scale, meaning that Spirulina cultivation could be an alternative for sustainable food production in the future, especially in areas with limited resources (Khoo et al., 2019).

In the long term, the use of POME as a nutrient source in microalgae cultivation can help reduce dependence on inorganic fertilizers, the production of which can have a negative impact on the environment. In addition, the Spirulina biomass produced from POME can be used for various applications, including animal feed, food supplements, and bioenergy raw materials, which further adds to the economic value of this system (Soni et al., 2017).

4. CONCLUSION

This study has successfully developed a Spirulina cultivation system by utilizing palm oil mill wastewater (POME) as a nutrient source, using Internet of Things (IoT) and Artificial Neural Networks (ANN) technology to optimize environmental control and growth prediction. The results of the study indicate that:

1. The IoT-based automatic control system integrated with ANN is able to effectively manage environmental parameters such as pH, temperature, dissolved oxygen, and salinity within the optimal range for Spirulina growth.
2. The POME concentration of 1500 ppm is proven to be the optimal concentration that produces the highest biomass growth, while at a concentration of 2000 ppm there is a decrease in growth due to the possible toxic effects of excess nutrients.
3. The use of POME as a nutrient source not only increases the efficiency of Spirulina production but also supports a circular economy by utilizing waste that is difficult to process, as well as providing significant environmental benefits.
4. The developed system offers better resource use efficiency and can be adapted to a larger scale, supporting the sustainability of food and bioenergy production.

Recommendations

1. Further Research: Further research is needed to examine the long-term impacts of using POME as a nutrient source in Spirulina cultivation, especially in terms of the quality of the biomass produced and the possible accumulation of toxic compounds in a longer cultivation cycle.
2. Scalability and Field Testing: The developed IoT and ANN-based automatic control system needs to be further tested on a larger production scale to test its stability and effectiveness under various environmental conditions.
3. Diversification of POME Applications: POME has the potential as a nutrient source for various other types of microalgae. Further studies can explore the application of POME in other microalgae cultivation systems to expand the utilization of waste in sustainable agriculture.
4. Development of IoT Technology: IoT systems need to be continuously developed to be more flexible and able to adapt to various more complex cultivation conditions. The development of ANN-based prediction and automatic control features must also be improved to provide more accurate recommendations for dynamic environmental changes.

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