



Algaboost: A Smart Cultivation Photobioreactor Combining UV-B Induction and ANN-Based Control for Enhanced Lipid Production in Microalgae *Botryococcus braunii*



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Abstract

The production of biodiesel from microalgae presents a sustainable solution to global energy challenges, particularly through the utilization of *Botryococcus braunii*, known for its high lipid yield. However, conventional cultivation methods remain constrained by manual monitoring and limited process optimization, resulting in suboptimal lipid productivity. This study introduces Algaboost, an intelligent photobioreactor that integrates UV-B induced stress with Artificial Neural Network (ANN)-based environmental control to enhance lipid accumulation in *B. braunii*. The system was designed with real-time sensor feedback, automated fluid control, and a graphical user interface (GUI) to facilitate dynamic cultivation management. The ANN model, trained on a dataset of 119 entries, successfully predicted optimal cultivation set points (pH 6.0; salinity 30.1 ppt) and demonstrated reliable performance as a software sensor. Under these conditions, a lipid yield of 41.49% was achieved, with 20.83% TAG content, suitable for biodiesel synthesis. The findings validate the feasibility of combining machine learning and photobiological stress in a semi-autonomous platform, offering a scalable approach to renewable fuel production. Algaboost not only improves operational efficiency but also marks a step toward adaptive, data-driven bioprocessing for sustainable energy systems.

Keywords: Artificial neural network; Biodiesel; Microalgae; Photobioreactor; UV-B mutation

1. Introduction

The global shift toward sustainable and renewable energy sources has intensified the search for alternative biofuels that do not compete with food supply chains or require fertile agricultural land [1]. Among the many candidates, microalgae have emerged as a highly promising source of biodiesel feedstock due to their fast growth rates and ability to accumulate high lipid content under specific environmental conditions [2].

Table 1. Lipid Content Comparison of Microalgae Species

Microalgae Species	Lipid Content (% Dry Weight)	Reference
<i>Botryococcus braunii</i>	25-75%	[3]
<i>Chlorella sp.</i>	28-32%	[4]
<i>Nannochloropsis sp.</i>	31-68%	[5]

Among these, *Botryococcus braunii* stands out as the most lipid-rich species, with lipid content reaching up to 75% of its dry biomass, far exceeding that of most other microalgae. This exceptional lipid-producing capability places *B. braunii* at the forefront of microalgal biodiesel research [6].

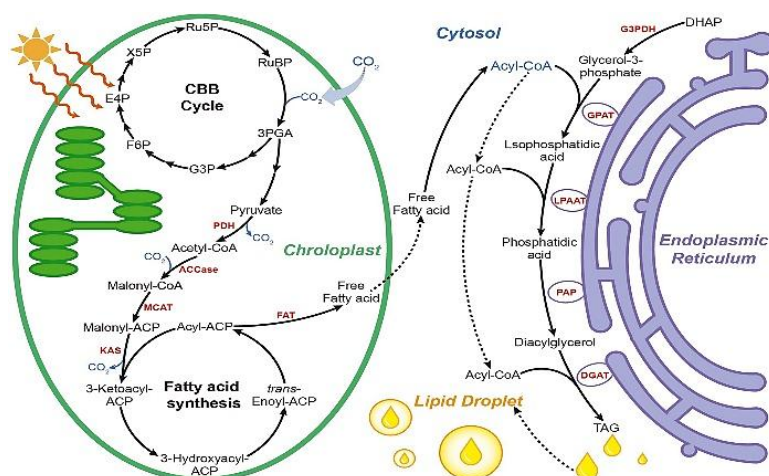


Figure 1. Overview of Metabolic Pathways Involved in Lipid Synthesis in Microalgae [7]

Lipids produced by microalgae have gained significant attention as a promising raw material for biofuel production, particularly biodiesel. These lipids, primarily in the form of triacylglycerols (TAG), can be efficiently converted into biodiesel through transesterification processes [7]. The advantages of microalgal lipids include high energy content, chemical similarity to petroleum-derived fuels, and suitability for existing diesel engines without major modifications. Recent studies have emphasized that microalgae can yield higher lipid productivity per hectare than most terrestrial crops, positioning them as a competitive and sustainable alternative in the biofuel sector. In contrast to conventional biodiesel sources such as crude palm oil (CPO), which are associated with deforestation, land-use conflicts, and food security issues, microalgae like *B. braunii* offer a far more sustainable alternative [8]. They can be cultivated in saline or wastewater environments, do not require arable land, and can yield significantly more oil per hectare than terrestrial oil crops [9].

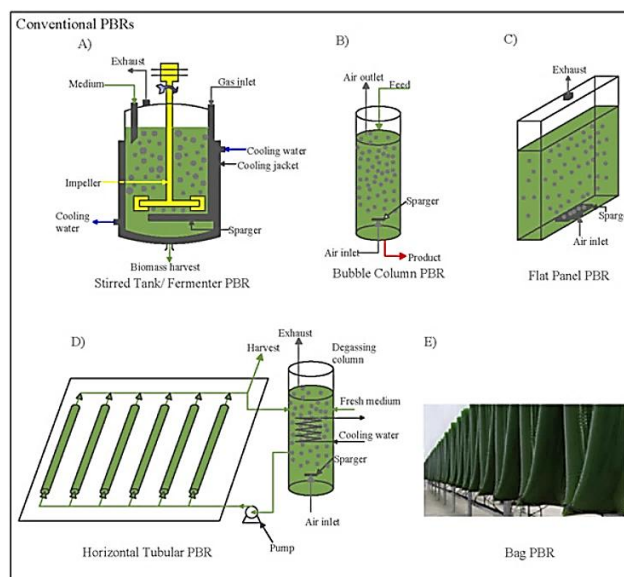


Figure 2. Example of Conventional Photobioreactor Systems Used for Microalgae Cultivation [10]

Despite their potential, the practical implementation of microalgae-based biodiesel remains constrained by suboptimal lipid yields during cultivation [10]. Achieving high lipid content requires precise control over environmental parameters such as pH, salinity, temperature, and light intensity [11]. In conventional systems, these parameters are often monitored manually, and lipid analysis relies on laboratory-based extraction methods that are time-consuming, labor intensive, and incompatible with continuous, large-scale production [12]. As a result, there is an urgent need for an intelligent, automated system that can monitor and optimize microalgae cultivation in real-time [13].

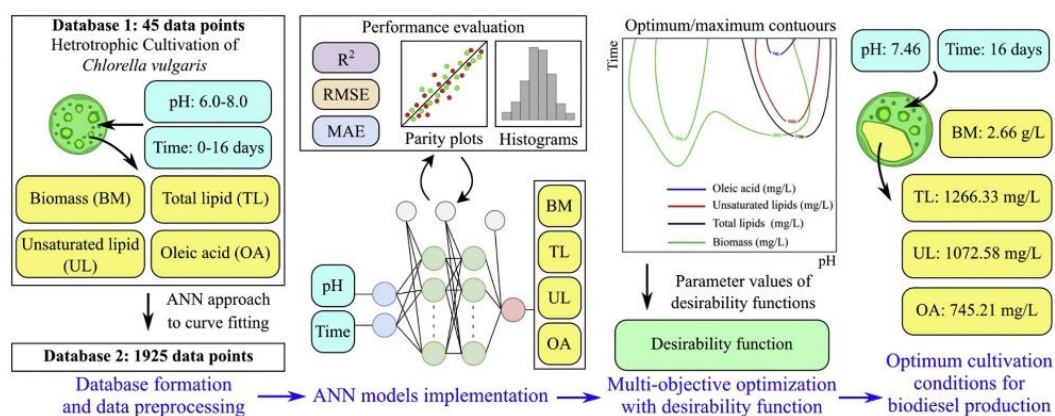


Figure 3. Example of Conventional Photobioreactor Systems Used for Microalgae Cultivation [14]

Recent advancements in Industry 4.0 technologies, particularly in artificial intelligence and automated control systems, have opened new opportunities for improving bioprocesses [15]. Among these, Artificial Neural Networks (ANNs) have emerged as a powerful tool capable of functioning as software sensors that predict biological outputs such as biomass and lipid content in real-time [16]. In the context of microalgae cultivation, ANNs can be trained on input variables such as pH, salinity, and cultivation time to estimate key parameters including total lipid content, unsaturated lipid composition, and oleic acid concentration [17]. These models not only predict outcomes but also assist in determining the optimal set points for cultivation, thereby enhancing productivity while minimizing the need for manual intervention.

This predictive capability is illustrated in Figure 3, which presents a multi-step ANN-based approach used to model and optimize the heterotrophic cultivation of *Chlorella vulgaris*. The ANN receives environmental input data (e.g., pH and time), processes them through multiple hidden layers, and outputs predictions for several biological responses. These predictions are then used in a desirability function to determine the optimum cultivation conditions for maximum lipid yield. Such models form the foundation for the development of real-time, intelligent control systems like the one implemented in this study.

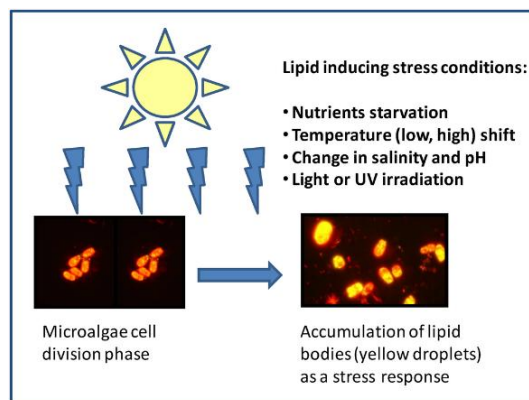


Figure 4. Illustration of lipid accumulation in microalgae under stress conditions [18]

In parallel, several studies have explored the use of UV-B radiation to induce lipid accumulation in microalgae. UV-B exposure creates controlled stress conditions that trigger defense responses at the cellular level, particularly the redirection of carbon flux toward neutral lipid synthesis such as triacylglycerols (TAG) [18]. As a result, microalgae exposed to UV-B often show an increase in intracellular lipid droplets, which are accumulated as an adaptive response to oxidative stress [19].

This mechanism is illustrated in Figure 4, where lipid-inducing stress conditions including nutrient deprivation, temperature shifts, salinity or pH changes, and light or UV irradiation led to a clear transition from the cell division phase to the accumulation of lipid bodies. The yellow droplets observed represent stored lipids, highlighting the physiological shift of microalgae under stress. Despite its proven effectiveness, UV-B mutation is rarely integrated with

intelligent automation systems, as most previous approaches have focused on isolated applications of either ANN or UV-B treatment. Few, if any, have successfully combined both methods into a unified, automated photobioreactor platform, which is the gap addressed in this study.

To address these challenges, this study presents “Algaboost”, an innovative smart photobioreactor designed to enhance lipid production in *Botryococcus braunii* through the integration of ANN-based real-time prediction, automated environmental control, and UV-B mutation. The system is supported by a user-friendly graphical interface (GUI) that enables real-time monitoring and control of all cultivation stages, including lipid prediction, media adjustment, stress induction, harvesting, and cleaning. This research aims to evaluate the performance of Algaboost in optimizing lipid content, demonstrate its potential as a scalable solution for biodiesel production, and contribute to the advancement of intelligent bioprocessing technologies.

2. Method

The development of Algaboost as a smart photobioreactor involved an integrated approach combining mechanical design, electronic systems, software programming, and bioprocess engineering. The system was physically constructed using lightweight materials and custom 3D-printed parts to form cultivation and mutation chambers capable of sustaining controlled environmental conditions. Real-time monitoring and automated control of parameters such as pH and salinity were essential for optimizing microalgae growth and lipid productivity. To further enhance lipid accumulation, a UV-B irradiation module was incorporated to induce stress responses in the cultured *Botryococcus braunii*.

To enable intelligent system behavior, an Artificial Neural Network (ANN) was developed and trained using experimental and literature-based datasets. The ANN was used both to predict lipid concentration from real-time inputs and to determine optimal cultivation set points. These predictions were embedded into the control logic of the system and accessed through a custom-built Graphical User Interface (GUI), allowing both manual and semi-autonomous operation.

2.1. Design & Fabrication of the Algaboost Photobioreactor

The Algaboost photobioreactor was designed as a modular, compact, and intelligent cultivation system tailored to optimize lipid content in *Botryococcus braunii*. The design process began with a 3D modeling phase using Autodesk Fusion 360 to define the system architecture, spatial layout, and interface between mechanical and electrical components. The frame of the photobioreactor was constructed using aluminum profile bars with a cross-section of 20 × 20 mm, chosen for their lightweight nature, corrosion resistance, and ease of assembly. The overall dimensions of the assembled frame are approximately 62 cm (height) × 54 cm (length) × 54 cm (width), optimized to house all functional modules including the cultivation chamber, mutation chamber, control electronics, and liquid handling components.

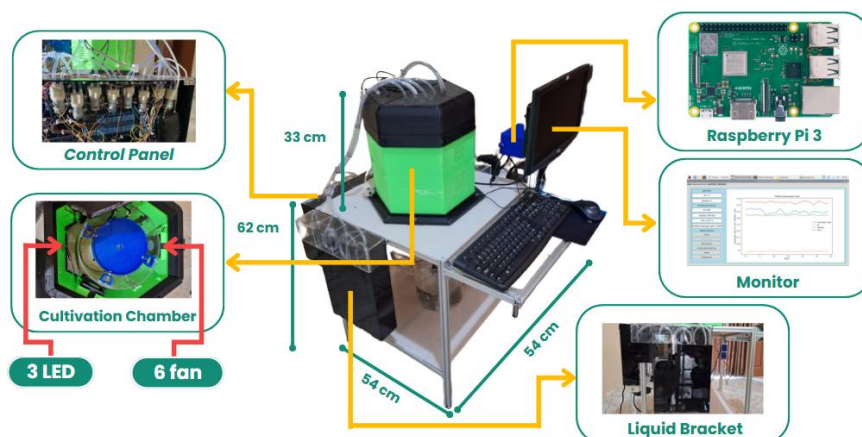


Figure 5. Prototype of Algaboost

The cultivation chamber was fabricated from cylindrical acrylic tubing with a total culture volume of approximately 2.3 liters. Acrylic was selected due to its high optical transparency, biocompatibility, and ease of sealing. The top and bottom plates of the chamber were laser-cut from 3 mm thick acrylic sheets, and all edges were bonded using two-part epoxy resin to ensure a watertight seal. Similar methods were applied to the harvesting chamber, which functions as a temporary reservoir for biomass separation during discharge. Supporting parts such as the bracket for UV-B lamps, control panel housing, sensor holders, and Raspberry Pi mount were produced using 3D printing technology. PLA+ filament was used as the printing material due to its higher thermal resistance and mechanical durability compared to standard PLA. Each component was designed with precise tolerances to ensure snap-fit or screw-fit assembly with the main frame, minimizing the use of adhesives or additional fasteners.

Liquid distribution within the system is handled by a series of inner diameter: 6 mm, connected via solenoid valves and mini water pumps to enable controlled flow between the cultivation tube, mutation chamber, and waste collection unit. A single inlet and outlet were installed on the cultivation chamber using PVC pipe fittings sealed with silicone gaskets and external clamping to prevent leakage during operation. The photobioreactor also features an enclosed compartment on the side of the frame designated for the electronic control system. This compartment is shielded by a 3 mm black acrylic panel, which is both aesthetically discrete and functional in reducing ambient light exposure to sensitive electronics. The final fabrication phase included functional tests for watertightness, component alignment, and mechanical stability.

2.2. Electrical System and Sensor Integration

The electrical system of Algaboost was designed to enable real-time environmental monitoring and automated control throughout each stage of microalgae cultivation, including UV-B-induced mutation, growth, harvesting, and system cleaning. This system integrates a combination of sensors, actuators, microcontrollers, and power management modules, forming a cohesive architecture capable of operating autonomously based on sensor feedback and neural network predictions. At the heart of the control system lies an Arduino Mega 2560 microcontroller, chosen for its high number of input and output pins, which is essential for managing multiple components simultaneously. Complementing the Arduino is a Raspberry Pi 3 Model B, which functions as the user interface host and local processing unit. The Raspberry Pi communicates with the Arduino via USB serial connection, facilitating real-time data exchange and control logic execution.

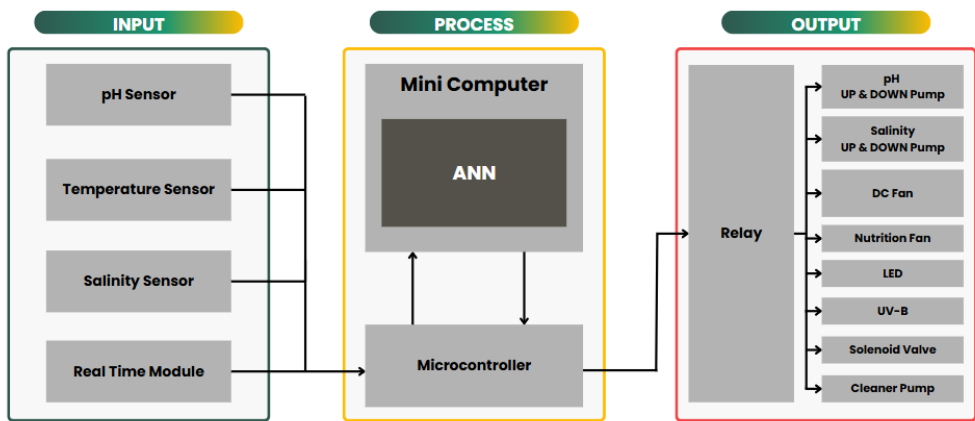


Figure 6. Electrical Diagram

The system employs three primary sensors to monitor critical environmental variables. A pH sensor equipped with a BNC interface and signal conditioning module is installed at the base of the cultivation chamber to measure acidity levels of the growth medium. A salinity sensor calibrated for marine conditions monitors the electrical conductivity of the medium, which directly correlates with salt concentration. Meanwhile, a waterproof DS18B20 temperature sensor continuously monitors the culture temperature to ensure that thermal conditions remain within

optimal limits. These sensor readings are acquired at regular intervals and transmitted to the Raspberry Pi for visualization and data logging.

In addition to sensors, several actuators are deployed throughout the system to regulate fluid flow and initiate environmental adjustments. The system includes two 12V mini water pumps responsible for circulating media and harvesting microalgae biomass, and two solenoid valves to control the direction of flow between the cultivation and mutation chambers. A UV-B lamp, positioned 3 centimeters above the mutation chamber, is programmed to activate during the pre-cultivation stress phase. For air circulation and heat dissipation, two axial DC fans are mounted near the cultivation chamber and run continuously during operation.

To manage power distribution, a regulated 12V power supply unit was installed to support all high-power components, while step-down buck converters were used to provide stable 5V power to logic-level electronics. The Arduino and Raspberry Pi operate on dedicated 5V adapters to prevent voltage fluctuations. Component switching is handled by a 16-channel 5V relay module, which interfaces with the Arduino's digital output pins, allowing precise control of pumps, valves, lamps, and fans.

All wiring was organized using insulated connectors and cable management systems, with additional protection provided by inline fuses and flyback diodes to prevent damage from inductive loads. The electrical components are housed within an acrylic-sealed compartment located at the base of the reactor frame, effectively isolated from the cultivation area to minimize moisture exposure and enhance electrical safety. Ventilation holes and passive heat sinks were also included to ensure thermal stability during continuous operation. With this integrated electrical system, Algaboost is capable of fully autonomous operation, adjusting cultivation conditions based on real-time data and commands from the neural network engine, while maintaining user oversight through the graphical user interface.

2.3. Graphical User Interface (GUI) and Control System

To provide a user-friendly and accessible interface for system operation, a graphical user interface (GUI) was developed and deployed on a Raspberry Pi 3 Model B, which serves as the control hub for the Algaboost photobioreactor. The GUI is displayed on a standard external monitor connected to the Raspberry Pi via HDMI and operated using a USB-connected keyboard and mouse. This setup allows for easier navigation and system control without the need for a touchscreen interface, while still maintaining a high level of usability. The GUI was developed using Python's Tkinter library and designed to offer a clear and organized display of all key system parameters and controls. It presents real-time sensor readings—pH, salinity, and temperature—updated at one-second intervals. These values are shown numerically and plotted graphically to allow users to monitor trends and fluctuations over time. In addition, the GUI displays predicted lipid content generated by the artificial neural network (ANN), which is updated based on current environmental conditions.

Operators interact with the system through clearly labeled buttons that control core processes, including UV-B mutation, cultivation start, harvesting, and cleaning. Upon initiating a process, the GUI communicates with the Arduino Mega 2560 via serial commands, triggering the appropriate sequence of actuator operations. For instance, when the "Mutation" button is pressed, the system activates the solenoid valve to route microalgae into the mutation chamber, powers the UV-B lamp for 90 seconds, and subsequently transfers the irradiated culture to the cultivation chamber. During cultivation, the system dynamically adjusts environmental conditions by controlling chemical dosing pumps and valves, following the set points recommended by the ANN model. The GUI also includes an internal logging function, which automatically records sensor data and system activity to local storage in CSV format. This feature enables post-cultivation analysis and helps identify correlations between environmental parameters and lipid yield.

By using a standard monitor and input peripherals, the GUI is made accessible for users in laboratory or field settings, eliminating dependencies on specialized hardware while preserving full functionality. The result is a reliable and efficient human-machine interface that ensures optimal system operability across various deployment environments.

2.4. Data Collection and ANN Model Training

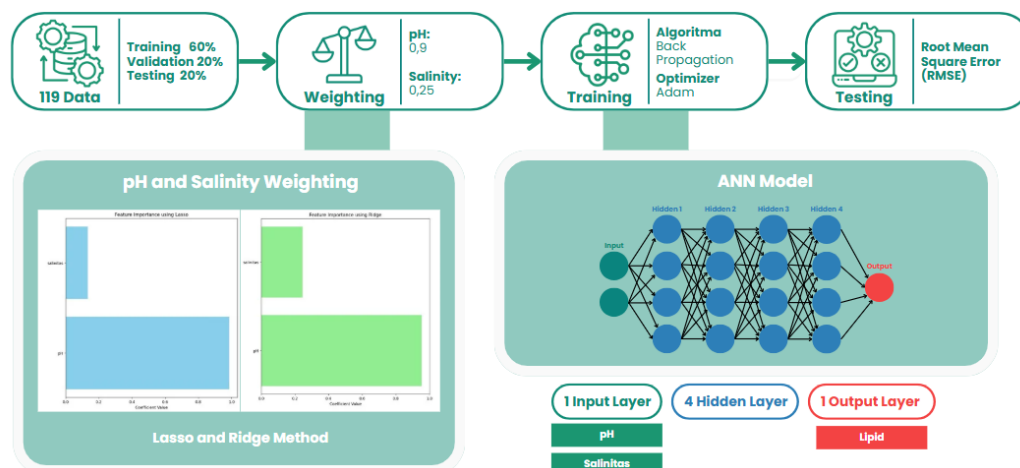


Figure 7. ANN Model Training

The artificial neural network (ANN) model embedded in Algaboost was designed to perform two main tasks: (1) to predict the lipid content of *Botryococcus braunii* based on real-time environmental input data, and (2) to recommend optimal set points for pH and salinity to maximize lipid productivity during cultivation. To develop and train this model, a total of 119 data entries were compiled, consisting of 18 primary datasets obtained through preliminary cultivation experiments using Algaboost, and 101 secondary datasets sourced from peer-reviewed scientific literature and databases relevant to *B. braunii* lipid optimization under varying environmental conditions.

Prior to training, a feature selection process was conducted using Lasso and Ridge regression techniques to identify the most influential input variables. The analysis revealed that pH and salinity had the highest predictive weights for lipid concentration, with normalized weight values of 0.9 and 0.25 respectively. Consequently, these two parameters were selected as the primary input features for the ANN model. Other potential variables such as temperature and light intensity were excluded at this stage due to data limitations and inconsistencies across sources.

The ANN architecture was designed with a single input layer consisting of two neurons (for pH and salinity), four hidden layers with a total of 243 neurons, and one output neuron representing the predicted lipid percentage. The model was implemented using Python's TensorFlow library and trained using the backpropagation algorithm with the Adam optimizer, selected for its fast convergence and ability to handle sparse gradients. The dataset was split into training (60%), validation (20%), and testing (20%) subsets to evaluate the model's generalizability and prevent overfitting.

Data preprocessing steps included normalization of input values to a [0,1] range, shuffling of the dataset to reduce bias, and mean squared error (MSE) minimization as the primary loss function. During training, early stopping criteria were implemented based on validation loss, and the model was tuned iteratively by adjusting the number of neurons and learning rate to achieve optimal performance.

The final trained model demonstrated consistent predictive capability, producing lipid content estimations with an acceptable margin of error when tested against unseen data. This model was then deployed on the Raspberry Pi and integrated with the control system, enabling real-time lipid prediction and automated decision-making for environmental parameter adjustments during the cultivation process.

2.5. Determination of Optimal Set Point and Cultivation Procedure

Following the training and validation of the ANN model, the system was employed to determine the optimal environmental conditions—specifically pH and salinity—for maximizing lipid accumulation in *Botryococcus braunii*. Based on the predictive model, 1,092 possible combinations of pH and salinity values within the biologically acceptable range were simulated. The model evaluated each combination by estimating the corresponding lipid yield. Among these, the combination of pH 6.0 and salinity 30.1 ppt was identified as the optimal set point, predicted to produce a lipid concentration of 37.32%.

These set points were then applied in the actual cultivation process. The cultivation phase began with the inoculation of *B. braunii* into the culture tube filled with a prepared medium, supplemented with Walne nutrients and seawater. The culture volume was maintained at approximately 2 liters, and the growth chamber was exposed to continuous white LED light, simulating natural daylight. Environmental conditions were actively maintained by the Algaboost control system, which monitored real-time pH and salinity levels and activated dosing pumps as needed to correct deviations from the target values. The control algorithm operated with a tolerance threshold of ± 0.2 pH units and ± 1.0 ppt for salinity, ensuring that the medium remained within the ANN-recommended conditions throughout the cultivation period.

The cultivation lasted for seven days, during which the microalgae biomass was allowed to accumulate under the influence of both optimized growth conditions and prior UV-B mutation-induced stress. The mutation process, which preceded cultivation, involved exposing the inoculum to UV-B light (365 nm, 9W) for 90 seconds at a distance of 3 cm to induce physiological stress known to promote lipid biosynthesis.

Upon completion of the cultivation cycle, the culture was harvested via gravity separation into the harvesting tube. The harvested biomass was then prepared for lipid extraction, with samples collected for chemical analysis and lipid quantification. Throughout the cultivation period, data logs were maintained automatically by the GUI system, capturing all sensor readings, ANN predictions, and actuator events, thereby providing a comprehensive dataset for performance evaluation and future model refinement.

2.6. Lipid Characterization and ANN Model Evaluation

To evaluate the effectiveness of the Algaboost system in enhancing lipid productivity, two stages of post-cultivation analysis were prepared: lipid characterization and ANN model performance evaluation. The lipid content of *Botryococcus braunii* biomass was quantified using a chemical extraction method known as Microwave Assisted Extraction (MAE). This method was selected due to its high efficiency and reduced solvent consumption compared to conventional Soxhlet extraction. In this approach, harvested microalgae biomass is mixed with a solvent combination of *n*-hexane and methanol in a predefined ratio. The mixture is then subjected to microwave irradiation at a controlled power level and duration, allowing the cell walls to rupture and release intracellular lipids into the solvent. After extraction, the mixture is filtered, and the lipid content is separated from the solvent phase for further analysis.

To identify and quantify the specific lipid components relevant to biodiesel applications, such as Free Fatty Acids (FFA), Monoacylglycerols (MAG), Diacylglycerols (DAG), and Triacylglycerols (TAG), a gas chromatography (GC) analysis was conducted. The extracted lipid samples were processed according to standardized GC protocols using a capillary column and temperature-controlled injection. This technique enables the separation and quantification of lipid classes based on their retention times and peak areas in the chromatogram.

In parallel, the performance of the Artificial Neural Network (ANN) model integrated in Algaboost was evaluated using multiple metrics. The first stage of evaluation was conducted during the model training phase using statistical performance indicators including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), calculated from the differences between predicted and actual lipid values in the test dataset. These metrics were used to assess the accuracy and generalization capability of the model.

For real-time application, the ANN was further assessed based on its predictive consistency using time-series input from pH and salinity sensors during the cultivation process. The model's behavior under dynamic environmental fluctuations was analyzed to determine its reliability as a software sensor during extended operation. Data logging mechanisms were employed to store predictions and corresponding environmental parameters for subsequent analysis and comparison with laboratory-validated lipid measurements.

3. Results and Discussion

3.1. System Integration and Functional Performance

Following the successful design and fabrication of the Algaboost prototype, all subsystems—mechanical, electrical, and software were integrated and tested for functionality. Each module responded accurately to operator input via the GUI, and environmental parameters such as pH and salinity were continuously monitored and logged.

The automated actuation system, consisting of solenoid valves and pumps, responded in real-time to ANN-generated commands and maintained stable cultivation conditions within the set tolerances.

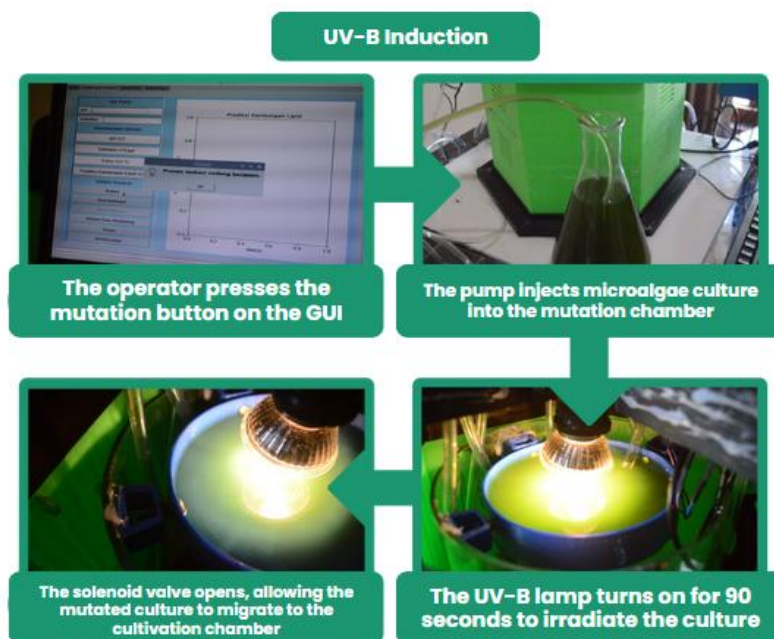


Figure 8. UV-B Induction Process

The UV-B mutation process was triggered through the control interface, activating the lamp for 90 seconds as programmed, and transferring the irradiated inoculum into the cultivation chamber without manual intervention. The UV-B induction process in the Algaboot system is fully automated and initiated through the graphical user interface (GUI). Once the mutation command is triggered by the operator, a peristaltic pump transfers the microalgae inoculum from the reservoir into the dedicated UV-B mutation chamber. Upon completion of the transfer, the system activates a UV-B lamp for precisely 90 seconds to expose the culture to controlled radiation, simulating stress conditions known to stimulate lipid accumulation. Simultaneously, the system ensures synchronization between the lamp activation and valve control. After irradiation, a solenoid valve opens automatically, allowing the mutated microalgae culture to flow into the cultivation chamber for further growth.

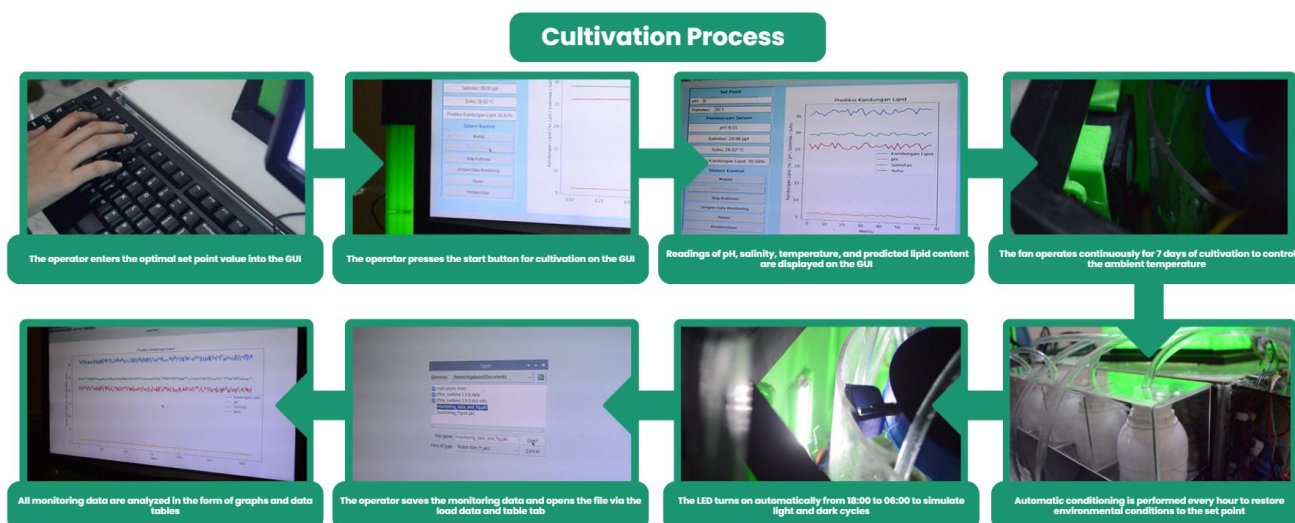


Figure 9. Cultivation Process

The cultivation phase of Algaboost commenced with the input of ANN-recommended set points (pH 6.0 and salinity 30.1 ppt) through the GUI, followed by the initiation of cultivation mode by the operator. The system autonomously monitored and recorded pH, salinity, and temperature values in real time, while simultaneously predicting lipid content using the trained ANN model. These data were visualized continuously on the GUI in both graphical and tabular formats, allowing for comprehensive system supervision. Environmental conditions were regulated through active cooling (fan operation) and automated dosing. The LED lighting system was programmed to simulate photoperiod conditions, turning on between 18:00 and 06:00 to alternate light and dark phases, supporting photosynthetic and lipid metabolic rhythms. In addition, the system performed conditioning every hour to restore parameters to the predefined set points, ensuring environmental stability.

All operational data were automatically saved and could be accessed via the load data tab for post-cultivation analysis. Throughout the 7-day cultivation, the system exhibited high functional reliability, with no observable hardware or software malfunctions. The consistent responsiveness of the dosing mechanism and accuracy of the ANN predictions validate the integrity of the closed-loop feedback control architecture.

These results confirmed the technical viability of Algaboost as a fully functional smart photobioreactor, capable of autonomous operation. The system's modular structure and ease of use further indicate its potential for scale-up and deployment in broader biofuel production settings.

In traditional photobioreactor systems, parameters such as pH, salinity, and temperature are often monitored and adjusted manually, requiring constant operator intervention to maintain optimal cultivation conditions [20]. This manual approach can lead to inconsistencies in data collection and increased labor demands. In contrast, the Algaboost system automates the cultivation process by integrating real-time sensor feedback and Artificial Neural Network (ANN) control, enabling precise and consistent environmental adjustments without continuous human oversight. This automation enhances operational efficiency and ensures reproducibility in microalgae cultivation.

3.2. Lipid Yield and GC Analysis

Lipid extraction from the harvested *Botryococcus braunii* biomass using the Microwave Assisted Extraction (MAE) method yielded a total lipid content of 41.49% of the dry biomass weight. This value reflects a significant improvement over typical yields obtained from conventional cultivation systems without optimization, indicating that the integration of UV-B stress and ANN-based environmental control in Algaboost contributed positively to lipid accumulation.

To evaluate the suitability of the extracted lipid for biodiesel applications, gas chromatography (GC) analysis was conducted. The chromatographic results identified and quantified four major lipid classes present in the sample: Free Fatty Acids (FFA), Monoacylglycerols (MAG), Diacylglycerols (DAG), and Triacylglycerols (TAG). The composition profile was as follows: 17.18% FFA, 58.64% MAG, 3.35% DAG, and 20.83% TAG.

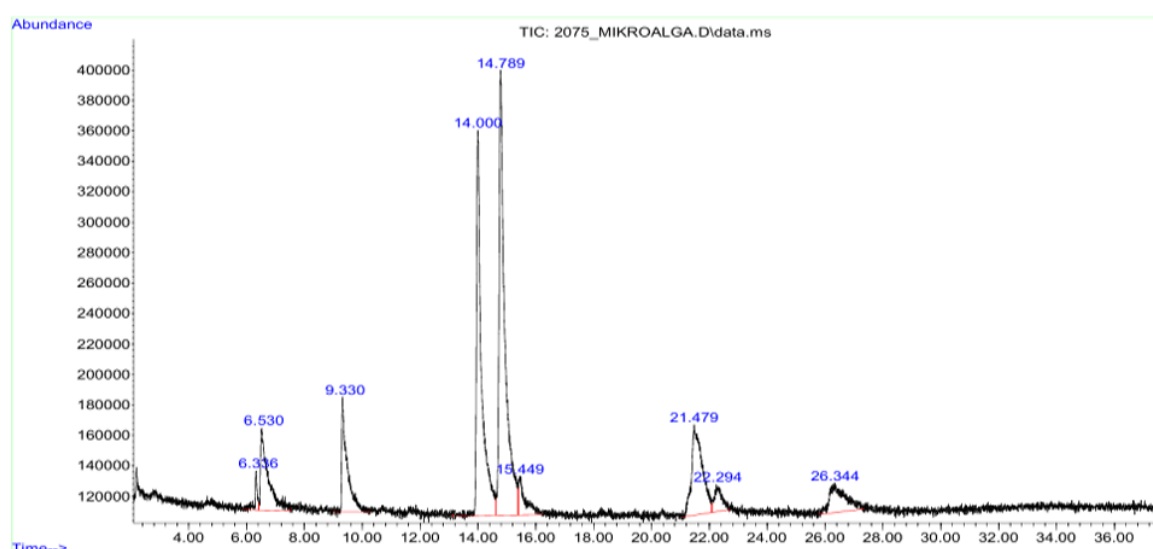


Figure 10. Chromatogram of Microalgae Lipid Gas Chromatography Test Results

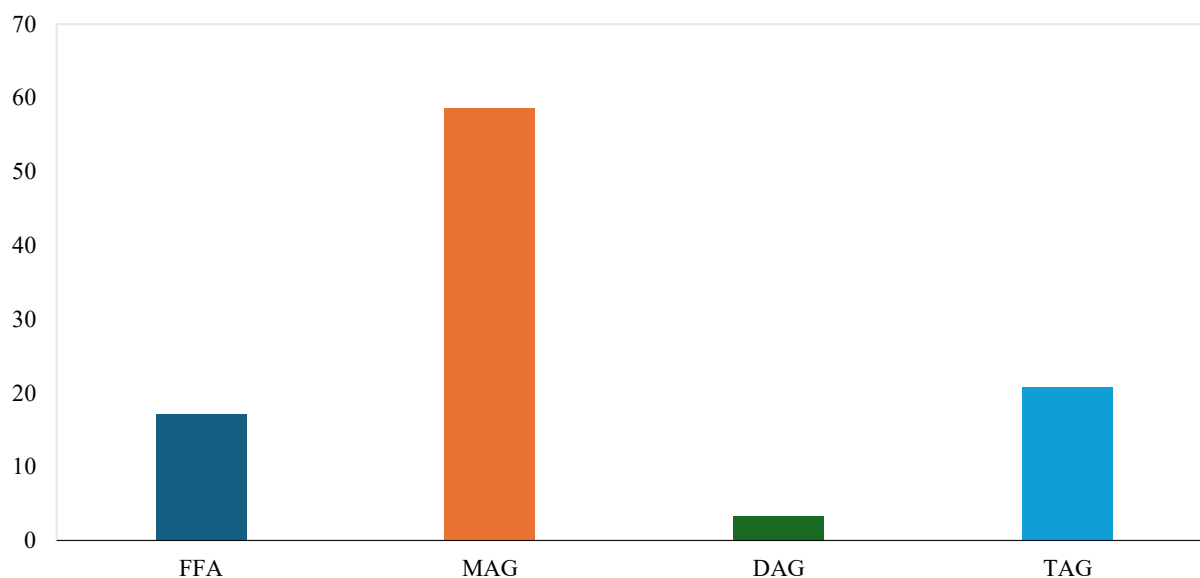


Figure 11. Percentage of Lipid Classes

Among these, TAG is the most desirable component for biodiesel synthesis through transesterification processes. The presence of over 20% TAG in the lipid profile confirms that the microalgae cultivated under Algaboost conditions produce lipid fractions suitable for direct conversion to biodiesel-grade fuel. While triacylglycerol (TAG) is the most desirable lipid class for biodiesel production via transesterification [21], the presence of other lipid fractions such as free fatty acids (FFA), monoacylglycerols (MAG), and diacylglycerols (DAG) must also be considered due to their potential impact on the efficiency of downstream processing. High concentrations of FFA, for instance, can lead to soap formation during base-catalyzed transesterification, thereby inhibiting the reaction and reducing biodiesel yield [22]. In this study, the FFA content was 17.18%, which is moderately high and may require pretreatment such as esterification to convert FFAs into esters before base transesterification. Meanwhile, MAG and DAG, which made up 58.64% and 3.35% of the lipid profile respectively, are partially converted intermediates and do not significantly inhibit the process but may reduce the overall yield unless completely converted. Their presence may also necessitate more refined separation techniques during biodiesel purification to achieve high fuel quality.

Compared to previous studies, such as Megarani, which reported lipid yields of 41.89% using UV-B mutation and manual cultivation, the performance of Algaboost is slightly lower [23]. However, the current study was conducted under semi-automated, non-laboratory conditions with limited environmental control variables, making the result promising. The ability to achieve comparable lipid yield with less human intervention and enhanced scalability further validates the potential of Algaboost as a practical bioprocessing solution.

3.3. ANN-Based Set Point Recommendation Evaluation

The primary function of the Artificial Neural Network (ANN) model in Algaboost was to recommend optimal cultivation conditions to maximize lipid production in *Botryococcus braunii*. After being trained on a dataset of 119 entries, the ANN identified pH 6.0 and salinity 30.1 ppt as the optimal set point combination. Under these conditions, the model predicted a lipid content of 37.32%, which was then used as the baseline for the actual cultivation experiment.

Upon completion of the 7-day cultivation period, the harvested biomass yielded a measured lipid content of 41.49%, resulting in an absolute prediction error of 4.17%. This deviation falls within an acceptable range, considering the limited training dataset and the biological variability of microalgal responses. The model's Root Mean Square Error (RMSE) on the static test dataset was calculated as 4.0, indicating that the ANN was able to generalize reasonably well within the defined parameter space.

Time	Lipid Predictions	pH Values	Salinity Values	Temperature Values
0.0004494190216064453	23.26859819272507	6.970728126565937	21.388309179365173	26.16331632305814
2.0288619995117188	23.79911183146253	7.065404951182089	20.95053924681083	26.154901934588946
3.724724292755127	23.260359699462306	7.110159095380206	21.319661200995206	26.18124571723909
5.4065821170806885	23.548578084239285	6.922362318612214	21.036644219329123	26.27150462537702
7.070621728897095	21.288933542119512	7.066241435596305	20.962738567114837	25.869225825756082
8.747506380081177	21.771993878295334	7.146275685149381	21.092693336699043	26.651161384307994
10.464930057525635	22.00371244666182	7.137945396105673	21.09183960110653	26.190888965368377
12.170113325119019	23.634499237489837	6.988258241742281	21.49061305050984	26.115327126329735
13.829551935195923	21.508614530642124	7.001077504177373	20.909227055554414	25.944874511753714
15.557059288024902	21.707125320523694	7.070707608639467	21.164481951534658	26.30896895989915
17.282711029052734	22.953692699194644	6.91519462686682	21.47604315459656	25.36755945824397
18.985156297683716	22.10340795837189	6.903627112354562	21.145154310473277	26.104624990614862
20.71232008934021	22.88175564978169	7.1752122963473335	20.992041467763222	26.68974608953602
22.37122678756714	21.493237416886142	7.00147840547205	21.08274439745585	26.375356848716883
24.027216911315918	22.594113815151495	7.18135953814338	21.277251622436935	25.080421161523617
25.70141100883484	22.34955904660942	6.989883290260957	21.00980489292216	26.752906583942096
27.374216079711914	21.85301975080131	7.115285901675248	21.10323980459629	25.89488071032469
29.118771076202393	22.75819972360139	7.132914605565038	20.955283305761643	25.36966088826684
30.804277658462524	21.637591536114165	6.9838317783379145	20.90562993034036	26.253133571895816
32.52630591392517	23.210467631245436	7.0781490961342675	20.98871245944023	25.405843822594093
34.213496685028076	23.185412411998108	7.006059469285871	21.404714769970422	26.186240455173774
35.89924955368042	23.688320836025497	7.150798020974249	21.261140529776203	25.95211000060356
37.59966588020325	22.885247980118997	6.909344337325613	21.18651617696716	25.58465733034143
39.464054107666016	21.3927276621364	7.027820689588134	21.31972472611211	26.677549497092752
41.171231508255005	23.764439838706796	7.003539077274823	20.98356723246877	26.60328114254444
42.837199449539185	21.555941053687448	7.075608766885496	21.024461151187452	26.31077166580338
44.48277401924133	21.88430552938436	7.012255989384316	21.199804014327476	25.64271624838299
46.1480815410614	22.152261949799033	6.958800974974231	21.28574819941076	26.862724685307672
47.81143808364868	23.312053494897523	7.128157988928331	21.349599208661445	25.073181218628743
49.47983980178833	21.736838604692682	7.169429541045064	21.442688963124137	26.508097900799378

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Figure 12. Real Time Data of Lipid Prediction, pH, salinity, and Temperature

As shown in Figure 13, the real-time graph of lipid prediction trends alongside pH, salinity, and temperature suggests that fluctuations in these parameters are visually associated with changes in predicted lipid levels. While this study did not isolate the specific effect of each variable experimentally, the data indicate that environmental stability plays a crucial role in supporting consistent lipid accumulation. Minor fluctuations in salinity, for example, appeared to coincide with dips in lipid prediction values, and similar trends were observed in relation to pH and temperature dynamics.

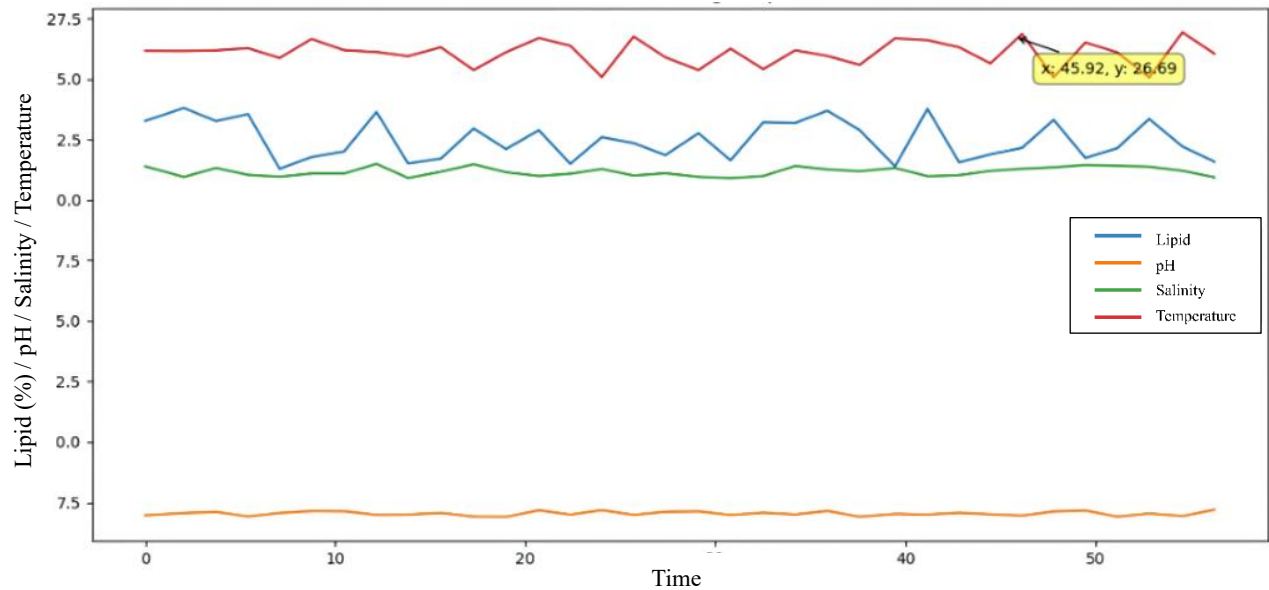


Figure 13. Graphical Visualization of Lipid Prediction vs pH, Salinity, and Temperature

Although the system was not designed to isolate the independent effect of each parameter in a controlled setting, the visual correlation between environmental deviations and lipid output captured in both the graph (Figure 13) and tabular data view (Figure 12) upports the notion that pH, salinity, and temperature are important inputs influencing lipid biosynthesis. These findings affirm the ANN’s capacity to operate under dynamic conditions and highlight the benefit of automated, real-time environmental control in optimizing microalgal cultivation outcomes.

3.4. ANN as a Real Time Software Sensor

In addition to pre-cultivation optimization, the ANN model was integrated into the control system as a real-time software sensor. This secondary function was designed to continuously predict lipid content based on live input from pH and salinity sensors during the cultivation phase. The goal was to provide dynamic insight into the physiological state of the culture without requiring manual sampling or destructive testing.

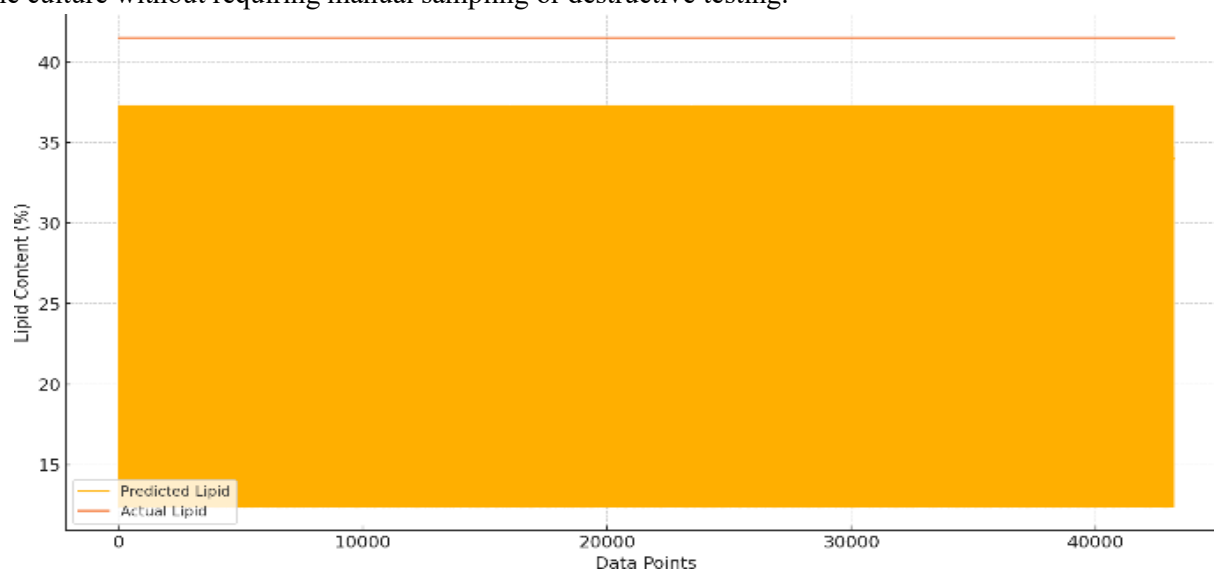


Figure 14. Comparison Between ANN-Based Real-Time Lipid Prediction and Actual Measured Lipid Content During Cultivation

During the 7th day of cultivation, a 12-hour observation session was conducted in which the ANN generated 43,200 lipid predictions, with one prediction generated every second. This high-frequency data stream was logged alongside real-time environmental readings. As shown in Figure 14, the predicted lipid content maintained a generally stable trend around 37.32%, which was close to the actual lipid content measured post-cultivation (41.49%). The actual value is represented as a constant reference line, while the predicted lipid values form the fluctuating area below. The deviation between the two remains relatively small across the entire observation period.

This performance reflects the ANN's capacity to approximate lipid trends in real time, despite the presence of minor noise and parameter variability. The Root Mean Square Error (RMSE) for the real-time observation was calculated as approximately 10.0, higher than the 4.0 RMSE obtained under static test conditions. This elevated error is likely due to momentary disturbances during early-phase conditioning and the absence of certain biological inputs such as light intensity or nutrient concentration, which were not included in the ANN model.

Traditionally, lipid monitoring in microalgae cultivation is conducted through discrete sampling, typically performed every 24 hours or only at the end of the cultivation cycle. This approach is described in standard references such as Richmond's *Manual of Microalgae Cultivation Techniques* [24], where destructive sampling methods—such as solvent extraction followed by gravimetric or chromatographic analysis are carried out at fixed intervals. Similarly, in biodiesel-oriented studies like that of Chisti [18], lipid content is generally assessed post-harvest through endpoint measurements. These methods, while reliable, are inherently time-consuming, labor-intensive, and incompatible with dynamic process control.

Moreover, conventional lipid analysis techniques such as Soxhlet extraction, thin-layer chromatography (TLC), and gas chromatography (GC) are performed offline in laboratory settings. This makes it difficult to respond in real time to environmental fluctuations or suboptimal conditions during cultivation. As a result, process optimization often relies on trial-and-error experiments with limited temporal resolution, which can delay feedback and reduce reproducibility.

In contrast, the real-time software sensor implemented in Algaboost provides continuous insight into lipid dynamics, enabling proactive system responses and eliminating the need for manual sampling. This advancement not only reduces operational workload but also opens the door to closed-loop automation and adaptive cultivation strategies features that are absent in most conventional systems.

4. Conclusions

This study confirms that integrating artificial neural networks (ANN) and automated control into a photobioreactor system can effectively support lipid production in *Botryococcus braunii*. The model's prediction error remained within an acceptable range, and its ability to operate as a software sensor shows that real-time, data-driven control is feasible even with limited training data. Importantly, the system functioned reliably under continuous operation, indicating that intelligent cultivation strategies can be implemented beyond conventional laboratory setups.

However, the system's performance is still constrained by the simplicity of the input parameters and limited biological variability in the training data. The ANN model did not incorporate other influential factors such as nutrient concentration or light intensity, which likely affected its generalization. Moreover, while the UV-B stress approach successfully induced lipid accumulation, its long-term effects on culture viability were not explored in this prototype.

These results open up new directions for future work: expanding the input feature set, increasing dataset diversity, and integrating adaptive learning that updates the model during cultivation. From a system design perspective, modular scalability and open-source architecture of Algaboost provide opportunities for further development in decentralized or educational settings. Overall, this research demonstrates a practical step forward in applying machine learning to real-time bioprocess control and sets a baseline for more complex, adaptive cultivation platforms in the future

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