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AI-Driven Strategies for Automated Microalgae Production Systems: Enhancing Yield, Efficiency, and Commercial Viability

Angela Paul Peter¹  | Wan Adibah Wan Mahari² | Sharoen Yu Ming Lim³  | Abdirahman Yasin Ibrahim⁴ | Revathy Sankaran⁴ | Kalaimani Markandan⁵  | Theeba Rajasegran⁶

¹School of Engineering, Faculty of Innovation & Technology, Taylor's University Lakeside Campus, Subang Jaya, Selangor, Malaysia | ²Pyrolysis Technology Research Group, Higher Institution Centre of Excellence (HICoE), Institute of Tropical Aquaculture and Fisheries, Universiti Malaysia Terengganu, Kuala Nerus, Terengganu, Malaysia | ³Department of Basic Medical Sciences, Faculty of Medicine and Health Sciences, Universiti Malaysia Sarawak, Kota Samarahan, Sarawak, Malaysia | ⁴UCSI Medical School, Faculty of Medicine and Health Sciences, UCSI University, Port Dickson, Negeri Sembilan, Malaysia | ⁵Department of Chemical & Petroleum Engineering, Faculty of Engineering, Technology and Built Environment, UCSI University, Kuala Lumpur, Malaysia | ⁶Independent Researcher, Kuala Lumpur, Malaysia

Correspondence: Angela Paul Peter (angelaipaulpeter@gmail.com) | Sharoen Yu Ming Lim (lymsharoen@unimas.my) | Theeba Rajasegran (theebarajasegran@gmail.com)

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ABSTRACT

Microalgal bioproducts hold significant promise for sustainable applications, but the high production costs associated with cultivation systems remain a major barrier to commercialization. The optimal growth of microalgae depends on a range of factors, including light, temperature, pH, nutrients, and mixing. Each strain of microalgae has unique cultivation requirements, necessitating tailored systems to maximize yield. Traditional cultivation systems, such as open ponds, photobioreactors, and fermentation tanks, each have distinct advantages and limitations. Open ponds rely on natural conditions but are difficult to control, while photobioreactors offer precise environmental control for maximum yield, albeit at higher costs. Fermentation tanks, which exploit heterotrophic growth, reduce operating expenses compared to photobioreactors. Machine learning-driven automation and smart technologies offer a promising strategy to reduce these costs by optimizing cultivation processes through electronic data logging, automated control, and minimal human intervention. This review explores the role of automation in the cultivation, harvesting, extraction, and post-processing of microalgae. It examines recent advancements in automated technologies and their potential to enhance the efficiency and scalability of microalgal bioproduct production. Key considerations for automation in microalgae production include system requirements, technological advancements, and integration across various stages of the production chain. The review emphasizes the mechanical aspects of automation, focusing on technologies that can be automated to improve yield and reduce operational costs, and highlights the need for further innovation in this field to facilitate the widespread commercialization of microalgae-based products.

1 | Introduction

Cultivation is one of the biggest contributors to the production cost of microalgal bioproducts. Different strains of microalgae require different growth conditions, meaning there is no universal cultivation solution. The challenges in microalgae cultivation,

including the need to balance several critical factors such as light source, temperature, humidity, pH value, carbon source, nutrient supply, and mixing, significantly affect yield and cost (Ali et al. 2021). Light is essential for autotrophic growth, with light intensity directly influencing the efficiency of microalgal production. In both natural sunlight and artificial illumination systems,

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optimizing light exposure is key to maximizing yield (Peter, Shiong, et al. 2021). Biological processes, such as cellular growth and metabolism, are highly dependent on environmental factors like temperature, humidity, and pH. Fine-tuning these parameters can significantly improve the overall production process (Perez-Garcia et al. 2011). Similarly, the availability of a suitable carbon source—whether from carbon dioxide, CO₂ for autotrophic growth, or renewable sugars for heterotrophic growth—affects growth rates and overall efficiency. Additionally, proper nutrient supply (e.g., nitrogen and phosphorus) and the method of nutrient introduction impact cultivation outcomes (Peter, Shiong, et al. 2021).

Mixing is essential to ensure even distribution of light and nutrients, but excessive shear stresses from mixing could damage the microalgae cells. Mixing is crucial to supply CO₂ and remove excess oxygen O₂ during autotrophic cultivation, while in heterotrophic cultivation, the mixing requirements are reversed. These numerous cultivation challenges underscore the need for optimized systems that can adapt to varying microalgal species and production needs. Automation plays a vital role in overcoming these challenges, as it allows for precise control over these factors, reducing manual intervention and ensuring more consistent and efficient production. The problem this study addresses is the high production cost of microalgal bioproducts, which remains a barrier to the commercial viability of microalgae-based products. Automation, by enabling real-time monitoring and precise control of cultivation parameters, can reduce these costs and improve production efficiency. The automation of microalgal cultivation is a promising strategy to optimize growth conditions, increase yield, and ultimately lower production costs. While photobioreactors and open pond systems offer different approaches to cultivation, automation can be applied to both to better control and optimize environmental factors, reducing variability and increasing productivity.

Automation is defined here as the minimization of human intervention through systems that autonomously monitor and adjust critical variables during cultivation. While the broader definition of automation is detailed, in the context of microalgae production, it specifically refers to the use of electronic data loggers, automatic correction systems, and centralized control stations to regulate parameters like light intensity, temperature, pH, and nutrient supply. Automation's role in microalgae cultivation is particularly important because it allows for real-time data collection, detection of deviations from ideal conditions, and immediate corrective action. The goal is to create a fully automated system where these factors are dynamically optimized to maximize yield and reduce the operational costs associated with manual control.

The sustainability of microalgae is well-established, with applications spanning biofuels, bioplastics, food supplements, and animal feed. However, the high cost of microalgae production compared to nonrenewable alternatives is a significant challenge. For example, the production cost of algal biofuels is approximately 10 times higher than traditional petroleum fuels (Madadi et al. 2021). One method to lower this cost is through automation, which can improve cultivation efficiency, reduce labor costs, and allow for the use of low-cost, high-throughput systems. To strengthen the relevance of this discussion, it would be beneficial to include quantitative data on the impact

of automation on the cost and yield of microalgal bioproducts. Case studies or experimental results showing reductions in operational costs or increases in yield through automation would add concrete evidence to the argument.

There are several levels of automation, each demanding a certain level of intelligence from the machine. Simpler, routine tasks are generally easier to automate than complex ones that require an individual decision to be made for each output. It follows then that the potential for automating the production chain of microalgal bioproducts depends a lot on the technologies and methods used in each part of the production chain. The production flow of manufacturing bioproducts from microalgae. This manuscript offers a novel perspective by focusing specifically on the automation of microalgae cultivation and bioproduction systems. While much research has focused on optimizing microalgal growth conditions manually or in semiautomated systems, this review brings attention to the potential for fully automated systems, offering a more practical and scalable solution to the challenges of microalgal bioproduction. The unique aspect of this study is its focus on mechanical automation technologies that address system requirements and their integration into existing cultivation and production infrastructures.

The scope of this study is clearly defined as it concentrates on the role of automation in microalgal cultivation, harvesting, extraction, and post-processing. Technologies that do not have direct implications for automation, such as those that enhance yield through nonmechanical means, are excluded. By focusing on automated solutions, the study aims to highlight the potential for cost reduction and scalability in the commercial production of microalgae-based products. Specifically, Section 2 examines automation and smart monitoring technologies in open pond and closed photobioreactor systems; Section 3 discusses machine learning (ML) applications in harvesting via flocculation, electrification, and nanoparticle-based methods; Section 4 addresses automation and AI integration in extraction and downstream bioproduct processing; and Section 5 synthesizes current barriers and future research directions.

2 | Digital Transformation in Algae Cultivation

2.1 | Automation and Smart Monitoring in Open Pond Systems

Open ponds, also known as raceway ponds, are large, shallow ponds for cultivating microalgae. Due to basic economics, large commercial systems employed today are mainly open-air systems (Romagnoli et al. 2020). The most common shape used is the raceway shape, but round configurations are sometimes also used (Hamed 2016). They are normally constructed of a closed-loop mixing duct that is around 0.3 m deep and is built of concrete, clay, and hard polymer. The paddle wheel runs continually to prevent biomass and nutrients from settling and promotes blending and flow throughout the cultivation process.

As of recent industry surveys, open ponds account for around 90% of commercial algal biomass production (Quiroz et al. 2021). This is due to their significantly lower capital and operating costs. With construction expenses ranging between costing 10

times less than the closed systems. For instance, building a 2000-gal open pond may cost the same as a 200-gal closed bioreactor (Wilcox 2026). Thus, open ponds offer a cost-effective solution for industries prioritizing bulk production. Additionally, their reliance on natural sunlight and simple paddlewheel mixing minimizes energy consumption, making them more economically viable for large-scale applications (Narala et al. 2016). Moreover, the ease of scalability for commercialization makes open pond system a particular favorite among biotechnology companies. It is probably for these reasons too, that most research done on open ponds are industry based.

However, the efficiency in open-air pond systems is considerably lower than it might be since it is difficult to manage growing conditions when the system is exposed to the surroundings. Temperature fluctuations can significantly impact algal growth and biomass productivity. Open ponds are exposed to seasonal and daily temperature variations that may push conditions outside the optimal range for algae cultivation. Research has shown that excessive heat can lead to thermal stress, while lower temperatures slow down metabolic processes, both of which can reduce yield and, in extreme cases, cause culture crashes. This challenge is particularly pronounced in regions with extreme climates, where summer heat and winter cold exacerbate instability (Nalley et al. 2018).

Automation and smart monitoring systems can help mitigate these effects. Automation in an open pond can be focused on a sensor mesh to monitor and measure changes in the entire pond medium (Das 2016). A study offers an aquatic pond smart water quality monitoring (SWQM) system that leverages a Wireless Sensor Network (WSN) at 900 MHz in an Internet of Things (IoT) platform (Boonsong et al. 2020). Temperature, dissolved oxygen in water, and potential hydrogen (pH) levels are the key factors investigated. Since the surrounding environment would be severe, this type of wireless sensor will be beneficial to place in an open pond cultivation as well. The data monitored by the SWQM device is transferred to a controller via a cloud Internet platform, where the captured information can be used by the technician to perform real-time monitoring. This can promote and enhance the productivity of microalgae cultivation ponds in a timely manner, especially for large scale.

Moreover, to demonstrate a technological advancement, Espinosa-Faller and Rendón-Rodríguez (2012) presented a WSN-based smart irrigation system that sends data and saves it in a database. Throughout the day, the system may additionally measure temperature, pressure, and dissolved oxygen. When an issue was found, an SMS or E-mail was sent to the person in charge of the facility. Next, the implementation of sensors in identifying the organic contamination would be very useful in increasing the yield efficiency of large-scaled open pond cultivation. Analytical sciences have made extensive use of nanoparticles and nanotechnologies. Surface-enhanced Raman spectroscopy (SERS) using metal nanoparticles is a promising approach for providing biometric data for trace compounds (Su et al. 2020). These sensors will promote the automation of open pond cultivation system and promote its biomass yield.

Besides, a pilot scale open pond automation system was created to improve CO₂ fed pH control-based performance. Researchers

were improving the usage of chemical carbon species at the pilot size by replacing them with gaseous CO₂, while also altering the required pH of the culture and the cultivation process was automated by inventing a controller for CO₂ feeding and online monitoring of culture parameters (Mehar et al. 2019). Although open pond cultivation systems are extensively embraced in the industry, the practicality of open ponds is confined to only a handful of microalgae species. This limitation stems from the difficulties associated with the limited control over cultivation conditions and the risk of biological contamination. Consequently, open system proves most suitable for cultivating “robust” microalgae strains, chiefly those belonging to the *Chlorophyta* group, characterized by rapid growth rates, or under highly selective conditions, such as specific microalgae strains like the cyanobacteria *Spirulina* (*Artrospira*) or the green microalga *Dubaliella* (Skifa et al. 2025). In terms of commercial scale microalgae cultivation, the growth variables must be controlled to improve microalgae culture productivity. Experiments were conducted over 14 consecutive days in a 12,000 L open pond, and a second parallel reactor operated in chemostat sensor mode under the same conditions. It was reported that the harvesting productivity increases from 9.52 to 23.20 g m⁻² day⁻¹ due to the ability of online biomass monitoring (González-Hernández et al. 2026). As a result, the automated system invented may be used to cultivate microalgae species efficiently in an open pond raceway. Although recent study has investigated process control strategies for open pond raceway ponds, including pH regulation, dissolve oxygen management, temperature control, and optimization of harvesting schedules (Rodríguez-Miranda et al. 2026), their implementation at large commercial scales remains limited, as most approaches are still in the experimental or pilot-development stage.

Critically, the WSN/IoT systems described above (Boonsong et al. 2020; Espinosa-Faller and Rendón-Rodríguez 2012) are monitoring-and-alert architectures rather than closed-loop control systems: they detect deviations and notify an operator (e.g., by SMS or email) but do not autonomously actuate a correction. This distinguishes them fundamentally from the PLC-based control used in photobioreactors (Section 2.2.1), where sensor input is used to directly drive an actuator without human intervention. The practical consequence is that open pond automation reduces labor and detection time but does not, by itself, remove the fundamental control limitation of open systems—namely that a 100-ha pond cannot be corrected as fast, or as uniformly, as a small, closed vessel once a deviation (e.g., a thermal or pH excursion) has been detected, because the actuation itself (mixing, dosing) is slow relative to the scale of the system.

2.2 | Smart Technologies for Closed Cultivation Systems

2.2.1 | Next-Gen Photobioreactors: Configurations and Automation Potential

Photobioreactors usually consist of tubes, a pump or airlift system to move the microalgae culture through the tubes, a light source, and a cooling system. Photobioreactors enable the cultivation of microalgae in colder climates and in four-season countries (Fuchs et al. 2021). It enables the installation of an artificial light source, custom mixing systems and more efficient harvesting

strategies. However, this advanced technological approach also means a higher operation and maintenance cost. Pumps, temperature regulating systems and light sources that are constantly running also significantly increase the energy and utility cost. Nevertheless, it also has a very high potential for automation and is being intensively researched by both industries and academia alike. There are several configurations of photobioreactors (Hamed 2016; Peter, Shiong, et al. 2021). These configurations were first inspired by the need to maximize light intensity for the microalgal culture inside the tubes for autotrophic growth, then by the need to facilitate scale-up of the photobioreactor systems. Table 1 demonstrates the potential automation on various photobioreactors configuration and the scale-up challenges.

As photobioreactors are designed specifically with the intention to optimize the growth of microalgae by providing as much light as possible, which is built as thin tubes or flat panels. Scaling up such a configuration girth-wise would automatically decrease light efficiency and light distribution within the culture. The center of the tube or panel effectively becomes a dark zone as the outer layer of culture spins around it reducing overall photosynthetic efficiency. This shading effect becomes more pronounced at larger scales, leading to uneven growth rates and lower biomass yields. Any vigorous mixing to pull the center layer of culture out risks damaging the fragile cultures. The helical shaped photobioreactor was designed with consideration to this. Photobioreactor has an impressive surface-to-volume ratio, its main drawbacks include the control of shear stress within the microalgal culture, since the culture has to be pumped upwards to the gas exchange unit (Parra et al. 2018). Light attenuation is influenced by many factors, such as algal concentration, light path, cell size and the types of intracellular pigments. Shading between cells exponentially decreases the light distribution from the illuminated side. With cultivation under constant high light intensity may lead to photo-inhibition at the initial culture stage due to the relatively low cell concentration. Whereas a low light intensity is insufficient for cell growth at the later stages of cultivation due to the mutual cell shading effect at relatively high cell densities (Wang et al. 2014). Therefore, a constant light intensity is not always suitable throughout the culture period but instead having a controlled adjustment of light intensity would strategically optimize the biomass growth.

Beyond light distribution, scaling up photobioreactors also brings challenges related to energy consumption. Larger systems require continuous mixing to prevent cell settling and ensure uniform exposure to light and nutrients. However, as the scale increases, so does the energy demand for pumping and agitation (Costa et al. 2019). Additionally, maintaining optimal temperatures, especially in regions with fluctuating climates, necessitates active heating or cooling, further driving up energy costs (Narala et al. 2016). Gas exchange is an additional, important factor to consider in closed systems. Not only should there be sufficient carbon dioxide gas within the culture for photosynthesis to occur, but the resulting oxygen gas produced from photosynthesis needs to be expelled as well. A buildup of oxygen gas within the photobioreactor tubes significantly reduces the biomass productivity of the culture (Kazbar et al. 2019). Hydrodynamics technique could identify the cell circulation between illuminated and dark zones, influencing photosynthetic efficiency, nutrient distribution, and CO₂ transfer. Poor mixing results in uneven

exposure to light and nutrient, reducing biomass productivity. In the last years, computational fluid dynamics (CFD) have been adopted to characterize the photobioreactor hydrodynamics (Olivieri et al. 2015). Hence, automated controlled strategies adopting CFD to optimize the mixing conditions will be useful. Moreover, CO₂ availability and oxygen accumulation are major limitations in closed PBR systems. The gas-liquid mass transfer coefficient (kLa), bubble size, gas velocity, and reactor geometry have influence carbon fixation efficiency (Ndiaye et al. 2018). Thus, automation of CO₂ injection, dissolved oxygen regulation, and gas flow rate adjustment is required to overcome mass transfer limitations.

Moreover, the Fraunhofer Institute for Interfacial Engineering and Biotechnology (Fraunhofer IGB) in Germany has designed and tested an automation concept for outdoor microalgae cultivation (Wolperdinger 2019). The concept used 30 L flat panel airlift reactors and a programmable logic controller (PLC) to monitor and control feeding cycles of *Chlorella vulgaris*. This enables process monitoring and control based on reactor temperature and pH value. Furthermore, a novel form of sterile operational flat panel gas-lift bioreactor with a remarkable asymmetrical U-shape was also presented (Fuchs et al. 2021). It employs automatable process control systems that correspond to technical specifications to improve data repeatability and help in commercial production. The innovative flat panel gas-lift photobioreactor bridges a technological gap at the laboratory scale with an autoclavable capacity of 7.2 L. Importantly, it is simple to construct, and it costs six times less than commercially available flat panel photobioreactors (Fuchs et al. 2021).

Under the “FutureProteins” project initiative, Fraunhofer IGB is also investigating using machine learning for algae cultivation (Schmid-Staiger 2022). This involves using Support Vector Machines (SVM) to model and predict algae growth, calibrating optical density sensors with cultivation data and developing a cultivation system using LEDs. Regarding automating photobioreactors, the closed system of photobioreactors makes it much easier to actuate an adjustment into the system. The main challenge then becomes the choice of measuring parameters to pick. Ideally, the measured parameters are easily detected, do not require frequent recalibration, and can be easily monitored. This means that, apart from advancing the technology of the photobioreactor systems themselves, research should also be done into testing and evaluation methods for microalgae. For example, a nonreactive additive could be added into the culture, which could begin to oxidize in the presence of excessive oxygen levels, which would then cause the significant change in the conductivity of the culture medium.

Table 2 compares the two automation paradigms reviewed above on operational performance, limitations, and scalability. The comparison shows that the choice of automation strategy is not independent of reactor configuration: sensor-mesh monitoring is well matched to the low-cost, large-footprint character of open ponds, while closed-loop PLC/actuator control is only economically justified in systems, such as photobioreactors, whose smaller volume and enclosed geometry make rapid, precise actuation both feasible and necessary. Consequently, scaling up automated PBR cultivation compounds two costs simultaneously: the reactor engineering cost of scale-up itself (Section 2.2.1) and the

TABLE 1 | Novel advanced photobioreactor configurations and the scale up challenges.

Photobioreactor type	Advantages	Scale-up challenges	Potential automation	References
Tubular (horizontal)	• Able to penetrate sunlight while protecting microalgal cultures from contamination. • 1.4-fold higher biomass productivity than the vertical column due to more solar radiation. • Mass transfer capacity of 2400–3200 W m⁻³.	• Horizontal configuration means more land area is required. • Might generate extra heat, hence, requires a cooling system. • Longer tubes increase friction losses and require high pumping energy. • Nutrient depletion can occur along tube length due to insufficient axial mixing. • At larger diameters, self-shading becomes severe. • The cost per gallon of production is at \$3.80 for a facility producing 100,000 kg biomass annually.	• Temperature control system. • Air bubble concept that reduces the need of horizontal configuration.	D'Agostin et al. (2017), Debelius et al. (2011), Huang et al. (2017), Richardson et al. (2014)
Column (vertical)	• Effective use of land area. • Lower power consumption. • Mass transfer capacity of 40 W m⁻³. • Low power consumption.	• Cell sedimentation if airlift not used. • Central dark zones appear as column diameter increases. • Gas sparging provides mixing, but larger diameters lead to heterogeneous circulation pattern. This leads to less efficient of oxygen stripping in large columns. • The investment cost for a vertical Leidos Hanging Bag type of vertical column will be \$5417/bag/acre/year, and it is known that each bag has a lifetime of only 6 years.	• Uniform LED light distribution. • Automation in cell culture stirring.	Huang et al. (2017), Saldarriaga et al. (2020), Clippinger and Davis (2019)
Flat-Plate	• High sunlight harvesting efficiency. • Uniform light distribution. • Biomass productivity by 2.5-fold in a flat-panel PBR. • Mass transfer capacity of 53 W m⁻³. • Low power consumption.	• Open gas transfer unit can make it more difficult to control contamination. • Mixing regime in large plates develop stagnant regions. • Light distribution requires increasing footprint rather than thickness. • Nutrient gradient is usually minimal because light path is short and circulation distances are small. • Oxygen can accumulate near illuminated surfaces if gas exchange is insufficient. • The green wall Panel-II (GWP-II) reported an OPEX of \$383,068/year, CAPEX of \$111,398/year, and a biomass production cost of \$13.76/kg.		Huang et al. (2017), Wang et al. (2021), Yan et al. (2016), Hashmi et al. (2025)
Helical	• High surface-to-volume ratio's. • Maximum photosynthetic efficiency of 6.84% PAR at 60° reactor. • 69.2% enhanced mass transfer coefficient with 40.8% biomass accumulation than non-helical tubular PBR.	• Excessively high towers will require more supports and stronger pumps. • Low efficiency in radial mixing as pressure drop increases substantially. • Oxygen buildup still occurs in long loops and requires degassing units. • Due to the spiral design, the OPEX and CAPEX, is estimated to be more than vertical column.	Installation of Proportional–Integral–Derivative, PID controller.	Borowiak et al. (2021), García et al. (2020), Morita et al. (2000), Xu, Cheng, et al. (2020)

(Continues)

TABLE 1 | (Continued)

Photobioreactor type	Advantages	Scale-up challenges	Potential automation	References
α -shaped	• High light harvesting efficiency due to 45°. • High flowrates can be achieved with comparatively lesser air input in the rising tubes. • Increased biomass productivity through enhanced mixing and mass transfer.	• Low surface-to-volume ratio (mutual shading between sections). • Lower dissolved oxygen accumulation. • Complex bends improve circulation but may generate uneven flow distribution at large scale. • Long flow paths may still cause nutrient heterogeneity. • Due to the unique cross design, the OPEX and CAPEX, is estimated to be more than tubular column.	Uniform LED light distribution.	Chandola et al. (2026)

TABLE 2 | Comparison of open-pond and photobioreactor automation approaches.

Automation approach	Operational performance	Key limitations	Scalability	References
Sensor-mesh/WSN-IoT monitoring (open ponds)	Continuous, low-cost tracking of temperature, DO, and pH over large areas; alerts reduce detection time from hours/days to minutes.	Monitoring only—no autonomous actuation; response still requires manual/operator intervention; sensor biofouling in outdoor exposed conditions; wireless range limits mesh density.	High—marginal automation cost is small relative to already-low pond capex ($\sim 0.37 \text{ M€ ha}^{-1}$); matches the $\sim 90\%$ share of commercial biomass already produced in ponds.	Boonsong et al. (2020), Espinosa-Faller and Rendón-Rodríguez (2012), Mehar et al. (2019)
PLC-based closed-loop control (photobioreactors)	Direct, autonomous actuation of pH/temperature/feeding with sub-vessel precision; enables the higher productivity and photosynthetic efficiency achievable in closed systems (Sections 2.2.1 and 2.2.2).	Control hardware adds cost on top of already higher reactor capex ($0.51\text{--}0.8 \text{ M€ ha}^{-1}$ vs. 0.37 M€ ha^{-1} for ponds); energy demand for pumping/mixing rises with scale; retrofitting legacy vessels is costly.	Constrained—scale-up is limited jointly by light attenuation/ O_2 buildup (reactor engineering) and by the cost of distributing sensors/actuators across a larger vessel network.	Wolperding (2019), Fuchs et al. (2021), Costa et al. (2019)

cost of the control hardware needed to actuate corrections across a larger, more distributed system—a compounding effect that is rarely quantified in the automation literature reviewed here and represents a specific gap this review identifies for future techno-economic work.

Automation in cultivation systems should also consider the role of advanced imaging technologies such as hyperspectral imaging, HSI. It provides a more detailed and comprehensive view of the algal behavior by analyzing the unique spectral signature of the cultivation, nutrient deficiencies, providing valuable information that can be used to optimize the cultivation yield and reduce input costs. It is reported that HSE provides a noninvasive method to detect molecular reflections and absorptions with the help of a wide range of wavelengths in the visible near-infrared, VNIR, and shortwave infrared (SWIR) regions of 400–2500 nm (Ram et al. 2024). To ensure the efficient processing of large amounts of HSI data, many researchers have explored the use of field programmable gate arrays, FPGAs, and GPUs in the implementation of ground hyperspectral sensors (Peng et al. 2025). This is very important in the automation of cultivation, as it helps in the decision-making related to the biomass growth and productivity. Moreover, the integration of machine vision systems is also essential in atomizing cultivation systems to overcome the traditional drawbacks such as time-consuming growth monitoring, expensive labor, and laboratory setups. In machine vision systems, lighting significantly impacts the quality of captured images and the effectiveness of visual algorithms. Hence, stable artificial light sources, designing appropriate lighting systems to ensure uniform light, or selecting cameras and sensors suitable for the lighting conditions is highly recommended to maintain consistent ambient light sources (Saberioon et al. 2017). In a recent study, it was discovered that an aggregated residual transformation algorithm, RES18-ART, significantly improves prediction performance, with grouped convolution reconstruction enhancing the model's generalization ability under varying light conditions, increasing the prediction accuracy from 0.83 to 0.93 (Peng et al. 2025). This superior generalization performance coupled with the simplified model architecture increases the feasibility and development potential of machine vision in online quantitative monitoring of microalgae.

2.2.2 | AI-Driven Optimization: Machine Learning in Photobioreactor Systems

Algal systems are extremely sensitive to environmental changes and face challenges related to numerous biotechnologies. As a result, legitimate continuous monitoring devices are extremely essential to maintain optimal conditions. Hence, the application of machine learning algorithms (MLAs) and dynamic models has shown remarkable outcomes for enhancing algal system efficiency, since it provides better knowledge of the fundamental methods of uncertainty than traditional kinetic or phenomenological approaches (Singh et al. 2023; Iratni and Chang 2019). Furthermore, using statistical formulas gives a thorough understanding of algal–bacterial interaction, where luminous intensity, humidity, N restriction, and dissolved inorganic carbon plays an important and distinct functions (Su 2021). Right now, numerous kinetic models have been used to forecast algal growth, biomass output, and the interaction between the

various process parameters (Lee, Jalalizadeh, and Zhang 2015). Yew et al. (2020) studied deep coloration features of molasses-cultivated microalgae, the k-Nearest Neighbor (k-NN) method was used to accomplish a unique photo-to-property prediction. A Red, Green, and Blue, RGB model pixel raster was utilized to rapidly transform the biomass content, nutrient content, and pH without the need of time-consuming analytical techniques. Moreover, linear regression analyses were employed to critically appraise its growth variance depending on the color gradient (Peter, Chew, et al. 2021). The study also discovered that the RGB color model delivers the most exact findings, with an R^2 value of 0.98, implying that the RGB color model is the best to use to monitor *Chlorella vulgaris* development for smart data microalgae growth surveillance.

Developing efficient photobioreactor setups and technical characteristics is crucial for industrialization of microalgae-derived bio-renewables. Traditionally, this was handled by evaluating a variety of design scenarios using integrated physical models that included computational fluid dynamics and kinetic modeling. However, when modeling large-scale systems, this technique exhibits computational aspects and numerical disturbances, resulting in time-consuming computing efforts and mathematical programming infeasibility. As a result, a unique data-driven surrogate modeling framework was developed, which significantly decreases computation time from months to days by utilizing cutting-edge deep learning architectures (del Rio-Chanona et al. 2019). The approach is based on a few simulation data from the working prototype to discover the complicated hydrodynamic and biochemical kinetic mechanisms, and it then uses a hybrid stochastic optimization technique to explore unproven processes to identify optimal path. Moreover, radial basis neural networks (RBNN), recurrent neural networks (RNN), and generalized processing regression (GPR) were built independently to estimate contact area focusing on environmental variables and color characteristics (Concepcion et al. 2020). The respective study found that RBNN exhibited the greatest estimation selectivity and reliability with the lowest root mean standard error (RMSE) score, and that the optimal photobioreactor condition in producing *Chlorella vulgaris* is a water temperature of 27°C. Nonetheless, by combining color sensing with artificial intelligence (AI), the surveillance of microalgae production in PBR may be automated. Artificial neural networks (ANN) and back-propagation ANN Optimized by Genetic Algorithms have been used to specifically detect algal concentration using a single luminescence spectrum and back-propagation ANN Optimized by Genetic Algorithms (GA-BP model) (Liu et al. 2020).

Besides, the functioning of the continuous data tracking via PID (proportional–integral–derivative) regulator necessitates the use of power. The usage of Simple JAVA Simulations to begin learning about manipulating an important variable to improve a PBR configuration for effective microalgae cultivation (Peter et al. 2022). This strategy will be beneficial for avoiding energy waste in a large-scale PBR design facility. The continuous development of traditional cultivation approach with advanced devices attracts the interest of pilot scale microalgae operation stakeholders. In this context, an aggregation-based sedimentation (ABS) technique was developed to enable low-cost biomass extraction and cost-effective semicontinuous algal production (Long et al. 2022). This work demonstrates machine learning as

an excellent light distribution pattern prediction method for assessing light penetration inside algal cultures, and subsequently light availability is applied to forecast cyanobacterial growth rates using a machine learning model, GRM (growth rate prediction model) with ABS approach. Furthermore, the Internet of Things (IoT) sensor network also allows technicians to evaluate microalgae growth and yield in a timely manner. Roxby et al. (2020) developed a unique method for detecting metal ions in aqueous solution using copper nanocavities: a live algae probe. The study reveals that the identification of chromium at each concentration took only seconds, which is 30 min quicker than conventional metal ion testing (Roxby et al. 2020).

Table 3 draws together the predictive accuracy, robustness, and practical implementation characteristics of the ML algorithms discussed above. Comparing the reported metrics highlights that tree-based ensemble methods (e.g., random forest) tend to offer the best accuracy-to-computational-cost ratio for classification tasks such as species/growth-phase identification (up to 98.1% accuracy: Xu, Cheng, et al. 2020), while ANN- and hybrid-optimized models (e.g., GA-ANFIS, BOA-BRT/SVR) achieve the highest accuracy for continuous prediction tasks such as biomass or CO₂-biofixation forecasting (R^2 up to 0.98–0.99), at the cost of larger training datasets, longer tuning times, and reduced interpretability. Importantly, because these comparisons are drawn from studies using different microalgal species, sensors, and operating conditions, a single algorithm cannot be declared universally superior; the more actionable comparison for industrial deployment is therefore accuracy against data requirements and computational cost, which is summarized in Table 3.

Because the algorithms summarized in Table 3 have been benchmarked on different microalgal species, sensor configurations, and operating conditions, reported accuracy values are not directly transferable between studies; standardized, multispecies benchmarking datasets are needed before industrial operators can select an algorithm on accuracy grounds alone.

2.2.3 | AI-Powered Genetic Optimization for Enhanced Microalgae Cultivation

Apart from photobioreactor designs, enhancing microalgae cultivation for optimal growth is essential. With latest innovations in innovative gene-editing technologies including RNA interference (RNAi), zinc finger nucleases (ZFNs), transcription activator-like effector nucleases (TALENs), and clustered regularly interspaced short palindromic repeats and CRISPR-associated protein 9 (CRISPR-Cas9), the prospect of modifying microalgae to achieve desired traits for numerous applications is possible (Zhang et al. 2020). Since microalgae generation sequencing is extensive and complicated, the present degree of understanding the useful details of diverse microalgae gene sequences is still a challenge. As a result, artificial intelligence (AI) can bridge the performance gaps connecting microalgae genetic data and optimal biomaterials. Modern machine-learning techniques have enabled precise strain species identification and categorization, resulting in high-quality microalgae pictures in a few approaches (Teng et al. 2020). Firstly, AI can be combined with microscope photo recognition, resulting in a quick species identification approach, which was then followed by the integration

TABLE 3 | Comparison of ML algorithms for microalgae cultivation prediction.

Algorithm	Reported predictive performance	Robustness/data and compute requirements	Industrial applicability
k-Nearest Neighbor (k-NN) + RGB color model	$R^2 = 0.98$ for biomass/nutrient/pH prediction from image color gradient (Peter, Chew, et al. 2021; Yew et al. 2020).	Low compute cost; sensitive to lighting/camera calibration drift; needs periodic recalibration.	High—low-cost camera-based sensing, suitable for on-site deployment.
Random Forest (RF)	Classification accuracy up to 98.1% for growth-stage prediction from spectral imaging (Xu, Cheng, et al. 2020).	Robust to noisy sensor data; faster training/inference than deep nets; lower hyperparameter sensitivity.	High—favored where computational resources are limited (edge devices, pilot plants).
Radial Basis Neural Network (RBNN)/RNN/Gaussian Process Regression (GPR)	RBNN gave lowest RMSE among the three for photobioreactor contact area/condition estimation (Concepcion et al. 2020).	Requires moderate-to-large training sets; RNN/GPR more sensitive to hyperparameter tuning than RF.	Moderate—mainly demonstrated at lab/pilot scale.
Artificial Neural Network (ANN)/Back-propagation ANN + Genetic Algorithm (GA-BP)	Outperformed response-surface methodology in growth prediction ($R^2 = 0.99$ vs. 0.96); GA-ANFIS $R^2 = 0.9846$ vs. standard ANFIS.	Data-hungry; prone to overfitting on small datasets; largely a “black box,” limiting interpretability for process operators.	Moderate—strong accuracy but explainability and validation-data needs slow industrial adoption (Imamoglu 2024).
Support Vector Regression (SVR)/Bayesian-optimized hybrid models (BOA-BRT-ANN-SVR)	Predicted biomass yield and CO ₂ biofixation within < 5% deviation from experimental values (Hossain et al. 2022); SVR $R^2 = 0.991$ for biodiesel yield prediction.	Performs well on comparatively small datasets; Bayesian tuning adds computational overhead but improves generalization.	Moderate-high—good candidate where labeled data is scarce, a common industrial constraint.

of AI tools based on fluorescence detection aimed at quantifying cells (Liu et al. 2020). Subsequently, AI was combined with a spectrophotometer based on matrix-assisted laser desorption/ionization (MALDI) to analyze microalgae based on their mass spectral data (Barbano et al. 2015). Table 4 summarizes the possible uses of AI algorithms in microalgae development.

Razzak et al. (2015) revealed that temperature, light distribution, luminous cycle, pH of culture medium, vitamins content, nitrogen-phosphorus ratio, and CO₂ biofixation should be continuously improvised. Among all the parameters, findings on the CO₂ biofixation demands multiple experimental studies, which take a tremendous amount of time, skilled hands, and other facilities. Hence, predictive estimate is a comprehensive and

successful method for solving these challenges when researching complicated systems with multiple response factors (Gillard and Kvasov 2017). Another study utilized three hybrid intelligence techniques, in Bayesian optimization algorithm (BOA) combine with Boosted Regression Tree (BRT), Artificial Neural Network (ANN), and Support Vector Regression (SVR), to create innovative prediction models for microalgae biomass output and CO₂ biofixation (Hossain et al. 2022). The investigation revealed that the projected best values for both outputs were validated by correlating them with experimental evidence with less than a 5% variance. Ultimately, AI aids in the discovery of ideal operating parameters for developing algae in many bioreactors scattered over a network, hence enhancing the productivity of microalgae production.

TABLE 4 | Possible uses of AI algorithms in microalgae development (Teng et al. 2020).

Research task	AI algorithms	Description
Microalgae gene editing	- Logistic regression - Random forest - Random subspace	- Primer selection - Detection of gene expression - Genome feature extraction - Feature ranking
Genome sequencing	- Logistic regression - Random forest - Random subspace	- Primer selection - Detection of gene expression - Genome feature extraction feature ranking
Algae strain identification	- Mask Region-Based Convolutional Neural Network, R-CNN - Artificial Neural Network, ANN - Support Vector Machine, SVM - System Operational Manager, SOM	- Image classification - Property classification - Featurization of microalgae signature
Biomass cultivation	- Radial basis function ANN - Hyperbolic tangent ANN - Evolving neural network	- Optimal condition prediction, experiment design under uncertainty, parameter tuning - Multi-criteria analysis for optimization
Photobioreactor design and control	- ANN - Gaussian process - Differential evolution	- System dynamics prediction - Predictive control system - Optimal design systems and control

While AI and machine learning have significantly improved algae growth monitoring and optimization, several limitations must be addressed for broader adoption. One key challenge is the availability and quality of data, as AI models require large, high-quality datasets, yet environmental variations and inconsistencies can introduce noise. Additionally, AI models, particularly deep learning algorithms, are prone to overfitting and lack transparency, making their decision-making processes difficult to interpret. Scalability poses another issue, as AI systems must handle increasingly complex datasets while maintaining efficiency. Moreover, cybersecurity threats may compromise data integrity and system control in connected AI-driven monitoring platforms. Regulatory challenges also arise, requiring compliance with environmental and safety standards (Imamoglu 2024). Furthermore, the accuracy of AI-driven predictions depends on sensor reliability, and sensor malfunctions could lead to incorrect assessments (Tummawai et al. 2024). A further limitation, closely related to data quality and sensor reliability, is the propagation of uncertainty through AI-driven cultivation control pipelines. In a typical closed-loop system, sensor measurements (e.g., turbidity, pH, dissolved oxygen) carry inherent measurement error, which enters the ML model as input noise; the model then adds its own predictive uncertainty, particularly when operating outside the range of conditions represented in its training data. When the model's output is used directly to drive an actuator—for example, adjusting nutrient dosing or light intensity—these compounded uncertainties can result in control actions based on point estimates that do not reflect the true confidence bounds of the prediction, increasing the risk of over- or under-correction (Iratni and Chang 2019). Few of the frameworks reviewed here report calibrated uncertainty estimates, such as prediction intervals or Bayesian posterior distributions, alongside their point predictions, meaning the reliability of automated decisions under compounded error is rarely quantified. Incorporating probabilistic or Bayesian ML approaches, which propagate uncertainty explicitly through each stage of the pipeline rather than collapsing it into a single output value, would allow operators to distinguish confident predictions from those requiring human review, and represents an important direction for improving the trustworthiness of closed-loop AI control in microalgae cultivation.

To address these challenges, future research should focus on collaborative data-sharing efforts, standardized data collection protocols, and the development of explainable AI (XAI) models for enhanced transparency (Yuan et al. 2023). Implementing regularization techniques can mitigate overfitting, while

leveraging cloud computing can improve scalability (Tummawai et al. 2024). Additionally, secure data transmission and encryption are essential to counter cybersecurity risks. Advances in sensor technology, including more reliable and redundant systems, will further enhance AI's effectiveness in algae cultivation (Yuan et al. 2023).

3 | Machine Learning in Harvesting Process

Microalgae harvesting is a critical step in producing biofuels, food supplements, and pharmaceuticals, yet traditional methods face challenges such as high energy consumption, contamination risks, and economic inefficiencies (Imamoglu 2024). Machine learning is transforming these processes by optimizing key variables in auto-flocculation and electro-flocculation, improving efficiency and reducing costs. In auto-flocculation, ML can help regulate parameters like pH and cell density, making large-scale implementation more feasible. Similarly, ML-driven optimization in electro-flocculation aids in electrode selection and current density control, minimizing energy use (Li et al. 2020). This section explores ML's role in enhancing these harvesting techniques, offering a roadmap for its application and future advancements in the field.

3.1 | Auto and Bio-Flocculation Processes

Flocculation is a significant mechanism of microalgae extraction; however, electrolyte supplements are required to destabilize microalgae suspensions and enable them to flocculate. Electrolytes pollute cell biomass and impede separation process, such as lipid extraction and transesterification (Kim et al. 2017). Furthermore, the excessive flocculant dose required renders this procedure financially unfeasible, particularly on a big scale (Lopez-Exposito et al. 2019). Bio-flocculants have mostly been actively explored in recent years; nonetheless, they have still not been used on a commercial basis (Kim et al. 2017). Auto-flocculation is a customized variant of traditional flocculation that removes microalgae without the need for a flocculant. Several investigations have been done to demonstrate the involvement of auto-flocculation, that includes pulsed electric fields, ultrasonic, and electro-flocculation, which have yet to be applied on an industrial scale (T Lam et al. 2018). However, with the integration of machine learning, the system of auto-flocculation may be simplified for commercial scale.

A first-principles modeling technique is commonly applied to facilitate the auto-flocculation process states (Nazemzadeh et al. 2021). When a first-principles model is inaccessible for analyzing the system, machine learning algorithms play their role. In other words, these models are utilized when there is an uncertain or complicated link between processes in the system that is complex to define using basic principles via a hybrid model. One such approach involves kinetic formulations, which are mathematical models used to describe microalgae growth rates, nutrient uptake, and product synthesis under varying environmental conditions. These models include logistic equations to predict biomass growth under resource limitations, Luedeking–Piret models that describe lipid biosynthesis under stress conditions, and light-dependent kinetics that link photon absorption

to growth rates. For example, studies on *Chlorella salina* and *Nannochloropsis oculata* have shown that nitrogen limitation leads to metabolic shifts that increase lipid production, which kinetic models can accurately predict (Surendhiran et al. 2015). Integrating ML into these kinetic formulations allows for real-time process optimization, improving auto-flocculation by adjusting environmental conditions dynamically. For example, ML could utilize an inhibition kinetic formula based on the surrounding biomass to describe the average growth rate of culture (Jung et al. 2021). The calibration of the parameters and the regression functions are based on the numerical solutions of the growth rate computed with a classical Type II model. It was reported that the resulting formula fits the numerical data with $R^2 > 0.8$ for reactor radii in the range of $r = 0.01$ to $r = 0.2$ m and light intensities up to $I_0 = 10^4 \mu\text{mol m}^{-2} \text{s}^{-1}$ (Jung et al. 2021).

While implementing a hybrid method to simulate flocculation, it is critical to be able to monitor the process and have access to appropriate and accurate process datasets. Light diffraction approaches and turbidity techniques, particle measuring and size, electro-optical impacts, ultrasonic strategies, precipitation, and given multiple have all been used to evaluate the flocculation operations (Gregory 2009). Light diffraction approaches involve strategies to optimize light distribution within microalgal cultures to reduce self-shading and spectral inefficiencies. Computational techniques such as ray tracing and 3D modeling are used to analyze how light propagates through dense microalgal suspensions (Wang et al. 2015). Additionally, spectral optimization methods, including the incorporation of carbon quantum dots or plasmonic nanoparticles, shift light spectra toward wavelengths that enhance photosynthetic efficiency. For instance, green light (500–600 nm) enhances penetration in dense *Synechococcus* cultures, improving yields by up to four times compared to red light (Ievina and Romagnoli 2025). By integrating ML into these diffraction techniques, reactors can automatically adjust light exposure based on real-time biomass density, improving auto-flocculation efficiency and reducing energy consumption. Recently a study has been conducted using commercial scalable system that compares the performance, energy consumption, and operating costs of flocculation-based harvesting system and the traditional filtration-based harvesting system. It was reported that the average energy consumption of the flocculation-based method was 0.389 kWh/m^3 , while that for the filtration-based method was 4.343 kWh/m^3 . The average harvesting cost of the filtration-based method was $5.35 \text{ \$/m}^3$, while for the flocculation-based method it was $4.52 \text{ \$/m}^3$ (Lu et al. 2022). The concentration factor of filtration-based and flocculation-based method were 770–1086 and 407–448, respectively (Lu et al. 2022). Hence further system automation is a potential method to lower harvesting cost.

It was concluded that kinetic formulations of the flocculation process, as a new first-principles model, accurately predicted the particle size distributions. By leveraging ML-driven predictive models, researchers can simplify the auto-flocculation process by automating key operational parameters in real-time, eliminating the need for manual adjustments. Traditional auto-flocculation methods require continuous monitoring of environmental variables such as pH, ionic strength, and nutrient depletion, which can be time-consuming and inefficient in large-scale operations (Alzahmi et al. 2024). ML simplifies this by analyzing vast

datasets collected from sensors and historical process data, allowing predictive algorithms to adjust parameters dynamically. This ensures optimal microalgal aggregation while minimizing resource consumption, making the process more energy-efficient and cost-effective. Additionally, ML-powered image recognition systems can continuously track particle size distribution and floc structure, providing immediate feedback for process optimization (Ning et al. 2022). In specific, vector machine algorithm and random forest algorithm were used to measure microalgae concentration. The laser irradiated the suspended particles of microalgae to get reflectance spectra, which could be analyze algal concentrations, floc length, and geometric shape during the growth of microalgae in a random forest regression model to reduce cost of microalgae harvesting (Ning et al. 2022). It was also reported that the trained and optimized model achieved very high accuracy and could be quickly adapted to the floc structure according to the actual requirements. This automation reduces human intervention, improves consistency in biomass recovery, and enables large-scale implementation of auto-flocculation in industrial microalgae production facilities (Kavitha et al. 2024).

3.2 | Electrification

Microalgae are being explored as a potential source of energy and the dewatering of algae is a challenge in terms of costing and scaling up. This is because a secondary dewatering technique needs more energy than initial thickening procedures. Microalgal cells are now extracted via physical, chemical, or biological approaches, and it has been revealed that electrical-based methods are a unique approach. Electro-flocculation is a physicochemical process in which an anode, such as iron or aluminium, emits metallic ions that cause coagulation (Holt et al. 2002). Electro-flocculation does not require coagulant, and the only requirement is electrical power. The electrodes are positioned vertically in the media throughout this process, and the negatively charged microalgae travel toward the positively charged anode, resulting in charge neutralization and the formation of clumps as shown in Figure 1 (Patel et al. 2013). Electro-flotation works on the same concept as electro-flocculation, except that the anode is made of an active metal. The electrocoagulation-flotation (ECF) process, which combines the hydrogen bubbles created by water

electrolysis at the anode with the electrocoagulation process at the cathode, has increasingly taken center stage as an alternative to coagulation (Gao et al. 2010). Recent advancements suggest that machine learning (ML) can enhance these processes by optimizing electrode selection, predicting the ideal current density, and reducing energy consumption through adaptive control mechanisms. ML-driven algorithms analyze large datasets to determine the most efficient harvesting conditions, minimizing operational costs and improving system performance (Li et al. 2020).

Electric extracting techniques use two types of electrodes: sacrificial and non-sacrificial electrodes (Hansen et al. 2020). In the context of sacrificial electrodes, metal ions are removed from the active anode into the culture broth dependent on the electrolytic solution's conductivity. The cationic metal ions that are produced then destabilize and combine with the anionic microalgal cells. When compared to chemical coagulants, the cationic ions generated by the anode are not harmful (Zenouzi et al. 2013). However, in the context of a non-sacrificial electrode, the negatively charged microalgal cells move toward the anode and the microalgae cells collapse and agglomerate once they reach the anode. It is also observed that fouling occurs when non-sacrificial electrodes are used (Roy and Mohanty 2019). ML can aid in selecting the optimal electrode type by analyzing historical performance data and predicting material wear rates, thereby reducing downtime due to electrode degradation. Additionally, *k*-means algorithm was used to identify clusters using data obtained from sensors of the platform temperature, oxygen percentage in the process chamber through a selective laser melting machine tool (Carvalho et al. 2019). The *k*-algorithm was reported to be able to identify the clusters such as operation conditions, faulty conditions of the protection gas system, faulty conditions of the pressure system, and faulty conditions that keep the machine tool in a standby mode from the sensors beforehand. Hence, it is known that the implementation of sensor into machine learning could predict the failures before they occur.

The quality of the electrodes has an impact on the efficiency of the electrically based harvesting process. Electrodes used in this technique are typically comprised of aluminium and iron. Iron electrodes have lower current efficiency than aluminium electrodes, which causes them to dissolve to a lower percentage, resulting in reduced harvesting efficiency (Barros et al. 2015). Furthermore, the ferric electrode requires more energy, and the production of ferric oxide results in browning of the sludge. As a result, aluminium electrodes have attracted more attention than iron electrodes. By leveraging ML, researchers can develop predictive models that assess the performance of different electrode materials under varying conditions. ML algorithms such as artificial neural networks (ANN) and support vector machines (SVM) can help optimize energy input while maximizing microalgae separation efficiency (Imamoglu 2024).

The transformation of algal cells is influenced by factors such as pH, initial cell concentration, and medium ionic strength (Roy and Mohanty 2019). The type of metal ions generated during the electrolytic process is determined by the medium's pH. It has been discovered that a high starting cell density affects harvesting efficiency because the initial cationic metal ions are insufficient for collecting surplus microalgal cells (Gao et al. 2010).

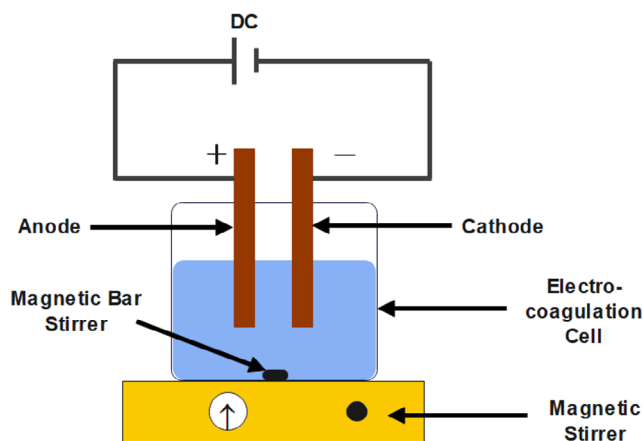


FIGURE 1 | Schematic diagram of the electro-flocculation process using an electrocoagulation cell with an anode, cathode, DC power supply, and magnetic stirrer.

Harvesting cells at an initial cell density of 0.55×10^9 cells/L took just 25 min, while harvesting cells at an initial cell density of 2.10×10^9 cells/L took 75 min. The high electron strength of marine microalgae allows for easy harvesting, whereas freshwater microalgae require double the energy and settling time due to their low ionic strength. ML-driven predictive models can address these challenges by analyzing process parameters in real time and adjusting them dynamically to maintain optimal efficiency. For instance, ML can help determine the best current density and harvesting duration for different microalgae species, ensuring energy-efficient and scalable operations. By integrating ML with real-time monitoring systems, the electrification process can become more adaptive and autonomous, significantly improving its commercial viability (Imamoglu 2024). Recently, a study was developed to validate the innovation of electro-flocculation with high-surface-area aluminium mesh electrodes, aimed at minimizing operational constraints, reducing harvesting time, and enhancing overall process efficiency. The study reported a harvesting efficiency of 93% was achieved in 30 min with a very low energy input of 0.0049 kWh/kg for a 7 L microalgae culture. The electrical energy cost is estimated to be 0.0004 USD/kg of the microalgal biomass which is lower than polymer-based flocculation at 2.94 USD/kg and centrifugation method at 1.28 USD/kg (Kumar et al. 2025).

3.3 | Nanoparticles

Metal nanoparticles are used in a wide range of medicinal and nonmedical industries. One of the most recent developments is the use of biologically active chemical nanoencapsulation as a health-promoting element in functional food and nutraceutical products. On the other hand, microalgae metabolites are biologically active molecules having anticancer, antioxidant, anti-inflammatory, and antibacterial properties (Tang et al. 2020). Hence, it will be an excellent resource for fulfilling today's need for natural and nutritious food components. Moreover, nanomaterials can also be ingested into human blood and can enter the skin directly, and nano-capsules not only preserve the technological benefits of microcapsules but also adapt to their limitations (Martínez-Álvarez et al. 2020). ML has emerged as a crucial tool in optimizing nanoparticle-based encapsulation, particularly in predicting and controlling nanoparticle formation, stability, and interaction with bioactive compounds. ML models, trained on large datasets, can help fine-tune process parameters such as solvent ratios, pH, and encapsulation efficiency, ultimately enhancing the stability and bioavailability of microalgae-derived bioactives (Ortiz-Perez et al. 2024).

Nanoencapsulation also favors protein-based materials as coatings due to their outstanding capabilities of film formation, gelation, foaming emulsification, and moisture retention, which provide the encapsulation system with a high efficiency (Ha et al. 2019). Encapsulation may successfully preserve bioactive substances against a variety of circumstances, hence preserving the proteins and extending the probable shelf-life and storage period of functional foods (McClements 2018). Higuera-Ciupara et al. (2004) were the first to encapsulate astaxanthin in a chitosan matrix, and the results suggest that this pigment is more stable in the encapsulated form. In this regard, ML-driven predictive modeling can analyze various formulation parameters

and real-time environmental conditions to optimize the encapsulation process. By leveraging deep learning algorithms, researchers can predict the degradation kinetics of encapsulated bioactives, allowing for better storage and processing techniques that maximize product stability (Ortiz-Perez et al. 2024).

Further research was carried out on the stability of astaxanthin-enriched microalgae oil in sodium alginate and low-methoxyl pectin using oscillating nozzle extruders encapsulation innovation, and it was discovered that the microcapsule retains a high amount of total-astaxanthin under varying conditions (Vakarelova et al. 2017). Moreover, Zhou et al. (2018) discover evidence of improved esterified astaxanthin absorption from microalgae resources following complicated coprecipitation with whey protein and Arabic gum. A few investigators have also come up with some intriguing ideas for using polysaccharides derived from waste wastes for encapsulation (Bezerra et al. 2019). ML algorithms can play a vital role in identifying the best encapsulation matrices by analyzing large datasets of biopolymer interactions, ensuring compatibility with bioactive compounds while minimizing degradation risks. Additionally, ML-driven simulations can help optimize the conditions for scaling up encapsulation technologies, making the process more energy-efficient and cost-effective (Ortiz-Perez et al. 2024).

Biopolymer-based encapsulation systems and nano-emulsion-based systems are the most often used encapsulation systems. Another important feedstock for microalgae bioactive encapsulation is lipid-based coating. Another study found that astaxanthin-contained lecithin nano-emulsion had greater astaxanthin bioavailability in the lipid-based nanoparticles system than astaxanthin-contained sodium caseinate nano-emulsion (Khalid et al. 2017). Rodriguez-Ruiz et al. (2018) also developed an astaxanthin-loaded nanostructured lipid transporter using sunflower oil as a liquid lipid, which adds to enhanced storage stability since sunflower oil is also an excellent source of antioxidants. Salatti-Dorado et al. (2019) also developed an innovative nano-systems by extracting microalgae lipid fractions using supramolecular solvents and then homogenizing them with SUPRAS (oleoresin)-NLCs. This system is highly stable at 4°C for at least 180 days. This is a novel, cost-effective, and long-term approach, but it is time-consuming and requires certain process parameters. On top this, a researcher developed a continuous magnetic separation system for *C. ellipsoidea* that entails capture of CPAM-coated Fe_3O_4 nanoparticle with 120 mg/L of loading capacity and able to generate harvesting efficiency of 96% in processing time of < 10 min (Lee, Lee, and Oh 2015). It is estimated that the overall cost of CPAM-coated Fe_3O_4 is at USD 0.73/kg algal cell which is still lower than the magnetic harvesting system at USD 2.1/kg of algal cell (Lee, Lee, and Oh 2015). To further enhance efficiency, ML can be applied to automate process control, adjusting critical parameters such as nanoparticle size, encapsulation efficiency, and lipid composition in real-time. This integration enables more precise formulation strategies while reducing material wastage and processing costs (Ortiz-Perez et al. 2024).

Overall, the nanoencapsulation technique improves the stability and bioactive components of nutraceuticals generated from microalgae. When combined with ML, these advancements allow for more precise, scalable, and cost-effective nanoparticle

production, ensuring consistent quality while reducing reliance on trial-and-error experimental approaches. Furthermore, ML-driven models can integrate data from microalgae harvesting processes to optimize downstream nanoencapsulation, creating a seamless and highly efficient workflow from biomass extraction to functional product formulation (Ortiz-Perez et al. 2024).

In summary, advancements in auto-flocculation, electrification, and nanoparticle-based techniques could significantly improve the efficiency of microalgae harvesting and utilization. The integration of machine learning may further enhance these processes by enabling real-time monitoring, predictive optimization, and adaptive control, potentially ensuring scalability for industrial applications. By leveraging data-driven insights, ML could refine flocculation precision, reduce energy consumption in electro-based methods, and optimize encapsulation efficiency in nanoparticle systems. As these technologies continue to evolve, the fusion of AI-driven automation with innovative harvesting techniques may offer promising solutions for making microalgae-based bioresources more viable and sustainable on a global scale.

4 | Advancement in Extractions of Bioproducts

4.1 | Technologies of Bioproducts

The development of downstream processing of microalgae is important to extract different kind of bioproducts from microalgae. Different species of microalgae possess various composition that influence the production of final bioproducts. Table 5 summarizes the emerging downstream processing technology to produce bioproducts. Li et al. (2019) extracted lipid from microalgae (*Schizochytrium* sp.) using subcritical CO₂-expanded ethanol. It was found that CO₂-expanded ethanol approach has increased solubility of lipid which resulted to higher extraction of lipid (75.6%–92.4%) compared to that obtained via supercritical CO₂ approach (66.2%). The subcritical CO₂-expanded ethanol also extracted higher concentration of docosahexaenoic acid or DHA (41.92%) from phospholipid and triglycerides in microalgae as compared to supercritical CO₂ (37.09%). In addition, subcritical CO₂-expanded ethanol approach consumed lower operating pressure (lower than 9.05 MPa) compared to supercritical CO₂ extraction (25–45 MPa), thereby reducing energy consumption and operating cost. Nevertheless, both subcritical CO₂-expanded ethanol and supercritical CO₂ are considered as excellent extraction techniques due to higher amount of lipid extraction. This high content of DHA in the lipid also implies its potential to be used as dietary supplement. However, those techniques are not economical for low-value product, thus further studies are needed to reduce the operating cost of lipid extraction.

Owing to the problem, Chua et al. (2019) investigated the potential of several ionic liquids, that is, cholinium-based ionic liquids to extract lipid from microalgae (*Nannochloropsis* sp.). Ionic liquids have been reported as highly polar solvents that can dissolve inorganic and organic compounds, low toxicity and biodegradable (Ai et al. 2021; Chua et al. 2019). Among the ionic liquids, cholinium arginate ([Ch][Arg]) has multiple H-bonding sites that developed the strongest hydrogen bonds with the microalgae cell wall which led to the highest lipid extraction

efficiency (94%). The extracted lipid can be further used as supplement or biofuel.

In another recent study, Huang et al. (2022) extracted lipid from *Desmodemus* sp. using a mixture of solvent containing water, methanol, and chloroform, followed by pyrolysis to remove the defatted residues and convert it into biofuel. Pyrolysis is an emerging thermochemical conversion technology that usually operated at a temperature range of 300°C–800°C under an oxygen-free condition to convert biomass or waste materials into value-added products such as biofuel (Wan Mahari et al. 2021; Wan Mahari, Kee, et al. 2022). It was revealed that pyrolysis of *Desmodemus* sp. produced bio-oil with high composition of hydrocarbons that can be upgraded into biofuel (Huang et al. 2022). Pyrolysis also reduced the composition of fatty acids in the microalgal lipid during pyrolysis reactions such as cracking, decarboxylation and deoxygenation by converting fatty acids into alkenes, aldehydes and ketones. Some proteins from the microalgae were converted into aromatics hydrocarbons (e.g., benzenes) and nitrogen containing compounds (e.g., pyrroles, pyridines) via deamination and cyclization reactions. Nonetheless, the yield of bio-oil is not reported in this study and the composition of aliphatic hydrocarbons of the bio-oil obtained in this study is low (<10%) compared to other studies that use different feedstocks (>80%) (Wan Mahari, Awang, et al. 2022).

Owing to the limitation of conventional pyrolysis to produce high yield of biofuel, Xu, Cheng, et al. (2020) have performed catalytic pyrolysis and liquefaction of *Spirulina platensis* in order to improve the yield of bio-oil. The combination of catalytic pyrolysis and liquefaction has successfully increased the yield of bio-oil up to 49.71 wt%. This work also reveals that the combustion performance of *Spirulina* bio-oil is greater than rice husk bio-oil, but poor compared to diesel fuel. This could be due to the lower composition of aliphatic hydrocarbons in the *Spirulina* bio-oil compared to diesel fuel. Therefore, co-pyrolysis of microalgae and plastic materials has been performed to increase the composition of aliphatic hydrocarbon of the bio-oil (Xu, Hu, et al. 2020). Jiang et al. (2022) reported that co-pyrolysis of *Chlorella vulgaris* (CV) and polypropylene (PP) has produced a positive synergistic effect that stimulates the interaction between hydrocarbon radicals from PP and protein, carbohydrates and oxygenates from CV. The interaction has led to the formation of aliphatic hydrocarbons and reduced the production of nitrogen containing compounds, aromatic hydrocarbons, and oxygenated compounds, thus implying the potential of the bio-oil to be upgraded into biofuel. Other than pyrolysis technology, hydrothermal liquefaction can be used to convert microalgae into a high-quality biofuel. Masoumi and Dalai (2021) investigated hydrothermal liquefaction of microalgae in the methanol–water system for biofuel production. Hydrothermal liquefaction performed at pressure of 11.5 MPa, 75 wt% of methanol in water, temperature of 275°C and a reaction time of 35 min were chosen as the optimum reaction conditions, which produced the highest yield of biocrude oil (57.8 wt%). The use of methanol–water as a cosolvent offers several benefits over pure water or other solvents. Methanol acts as a hydrogen donor and helps stabilize the intermediate radicals formed during thermal degradation, thereby improving biocrude yield and quality (Aboo et al. 2018). Additionally, methanol reduces the viscosity and polarity of the solvent system, which enhances solubility of organic compounds and facilitates their extraction into the oil phase.

TABLE 5 | Emerging downstream technologies for microalgae extraction and conversion into bioproducts.

Technologies	Microalgae types	Bioproducts	Remarks	References
Subcritical CO ₂ -expanded ethanol	<i>Schizochytrium</i> sp.	Bio-supplement	- Yield of lipid: 75.6%–92.4%. - CO₂-expanded ethanol extracted higher amount of lipid and DHA, reduce operating pressure and energy consumption compared to supercritical CO₂ extraction method.	Li et al. (2019)
Pyrolysis	<i>Desmodesmus</i> sp.	Biofuel—bio-oil	Bio-oil contain low composition of aliphatic hydrocarbon but high composition of aromatics.	Huang et al. (2022)
Catalytic pyrolysis and liquefaction	<i>Spirulina platensis</i>	Biofuel—bio-oil	- Yield of bio-oil: 49.71 wt%. - Combustion performance of <i>Spirulina</i> bio-oil is greater than rice husk bio-oil, but poor compared to diesel fuel.	Kozlova et al. (2017)
Co-pyrolysis	<i>Chlorella vulgaris</i> and propylene	Biofuel—bio-oil	Synergistic effect between <i>Chlorella vulgaris</i> and polypropylene increased the formation of aliphatic hydrocarbons and lowering the composition of nitrogen containing compounds, oxygenates and aromatic hydrocarbons in the bio-oil.	Xu, Hu, et al. (2020)
Hydrothermal liquefaction	Microalgae	Biofuel—bio-oil	- Yield of bio-oil: 57.8 wt%. - The algae biocrude oil treated with catalytic hydrodeoxygenation higher calorific value (42 MJ/kg) compared to untreated oil (33.4 MJ/kg).	Saadatfar et al. (2021)
Dark fermentation and bioremediation	<i>Scenedesmus obliquus</i>	Biofuel—biohydrogen	Dark fermentation and bioremediation, approach enhanced the production of biohydrogen 10 times higher than untreated lipid/oil.	Jiang et al. (2022)
Dark and photofermentation	<i>Spirulina platensis</i>	Biohydrogen Methane	Sequential dark and photofermentation approach increased the production of hydrogen up to 1510 mL/L, whilst methane production is increased up to 1060 mL/L.	Mohammadpour et al. (2014)
Fermentation	<i>Chlorella minutissima</i> and <i>Synechococcus subsalsus</i> , <i>Spirulina</i> sp. LEB-18	Bioplastics	- Low amount of nitrogen in microalgae culture medium had increased the accumulation of PHA by <i>Spirulina</i> sp. and <i>Synechococcus subsalsus</i>. <i>Chlorella minutissima</i> do not accumulate PHA, hence requires other growth conditions or substrate during cultivation to stimulate the synthesis of PHA.	Moaveni et al. (2022)
Dye-sensitized solar cells	<i>Chlorella vulgaris</i>	Photosynthetic pigments	Photosynthetic pigments extracted from microalgae shows potential as sensitizer and the performance is better than fabricated sensitizer using natural dyes.	Van Ginkel et al. (2001)
Enzymatic hydrolysis	<i>Schizochytrium limacinum</i>	High protein food ingredient	Enzymatic hydrolysis of <i>Schizochytrium limacinum</i> produced protein hydrolysates with desirable properties to be used as antioxidants in foods or supplements.	Singh et al. (2022)
Extraction and Waters Acquity UPLC system	<i>Chlorella</i> sp., <i>Spirulina</i> (<i>Arthrospira</i> sp.)	Vitamin	Each microalgal possesses different composition of vitamins that can be used in many applications.	Costa et al. (2018)
Gasification	<i>Porphyra</i>	Syngas	Adjusting the biochar fraction enhances hydrogen concentration in syngas and electric power generation, despite the moisture content adversely affecting overall energy and exergy efficiencies but positively impacting hydrogen concentration.	Adnan et al. (2020)
Transesterification	Dry/wet (<i>Chlorella vulgaris</i>)	Biodiesel	Biodiesel yields exceeding 90% were achieved in only 25–35 min at 60°C.	Nguyen et al. (2021)

This cosolvent system also promotes hydrolysis and depolymerization reactions while minimizing the formation of char and solid residues (Yerrayya et al. 2020). The biocrude oil produced from this technology was further treated with hydrodeoxygenation at hydrogen pressure of 3 MPa and a temperature ranging from 350°C to 450°C. The hydrodeoxygenation process increased the calorific value of the oil from 33.4 to 42 MJ/kg, further improving the combustion performance of the oil.

Other than bio-oil, microalgae can be converted into biohydrogen as cleaner biofuel via biotechnological approach. Pandey et al. (2021) performed dark fermentation of *Spirulina platensis* using *Bacillus firmus* NMBL-03 as substrate, followed by photofermentation using coculture of *Rhodobacter sphaeroides* NMBL-01 and *Bacillus firmus* NMBL-03. During dark fermentation, 23.06 ± 3.63 mmol of biohydrogen was produced. Interestingly, the production of biohydrogen was increased up to 1510 mL/L, showing the positive impact of sequential dark and photofermentation approach in improving biohydrogen production. This finding is also supported by Singh et al. (2022) who extracted lipid/oil from *Scenedesmus obliquus*, followed by treatment via dark fermentation and biomethanation, which resulted in production of biohydrogen 10 times higher than untreated lipid/oil (Jiang et al. 2022).

Costa et al. (2018) investigated the influence of nitrogen availability on the growth and composition of bioplastics named polyhydroxyalkanoates (PHA) during cultivation of several microalgae species, namely *Spirulina* sp. LEB-18, *Synechococcus subsalsus*, and *Chlorella minutissima*. It was found that low amount of nitrogen in microalgae culture medium had increased the accumulation of PHA by *Spirulina* sp. LEB-18 (12%, dry cell weight) and *Synechococcus subsalsus* (16%, dry cell weight). Each microalgae synthesized PHA with different length of carbon chain, in which PHA obtained from *Synechococcus subsalsus* showed longer carbon chains (C16, 51.78% and C18, 34.10%), whilst PHA obtained from *Spirulina* sp. LEB-18 had 16.49% of C14 and 72.58% of C16. However, no PHA accumulation was observed in *Chlorella minutissima* even under nitrogen deficient condition. This implies that *Chlorella minutissima* requires other growth conditions or substrate during cultivation to stimulate the synthesis of PHA.

High-value compounds such as vitamins, antioxidants, fatty acids, and pigments can also be extracted from microalgae. Nevertheless, the production of high-value compounds in the microalgae is influenced by several factors such as types of phytohormones, nutrient composition, and lighting condition. For instance, Kozlova et al. (2017) investigated the influence of phytohormones such as brassinolide (BL), 3-indoleacetic acid (IAA), 24-epibrassinolide (EBL), and abscisic acid (ABA) on the accumulation of fatty acids and pigments in the *Scenedesmus quadricauda*. IAA and ABA significantly influence the biosynthesis of fatty acids, whilst EBL and IAA greatly stimulated the accumulation of pigments such as chlorophyll and carotenoids. In another study, BL increased the cell growth of *Chlorella vulgaris*, as well as production of chlorophyll and monosaccharides (Masoumi and Dalai 2021). Hence, hormones greatly influence the growth of microalgae and production of high-value compounds, especially pigments that can be used in many applications.

Mohammadpour et al. (2014) used microalgae pigments as a sensitizer of nanostructured photovoltaic cell to produce electricity

from visual light (Van Ginkel et al. 2001). Photosynthetic pigments derived from *Chlorella vulgaris* grown in wastewater were extracted and loaded on nanostructured electrodes. The performance of photovoltaic cells was measured based on the current–voltage curves under AM 1.5 illuminations (100 mW cm²) condition. It was found that the maximum power conversion efficiency is comparable to that of other green plants; thereby, showing the potential to further investigate the environmental and economic feasibility of using microalgae pigments as sensitizers of photovoltaic cells.

Moaveni et al. (2022) produced antioxidant bioactive peptides as ingredients for high protein food from *Schizochytrium limacinum* via enzymatic hydrolysis (Singh et al. 2022). The use of digestive enzymes completely hydrolyzed the microalgae proteins, while the enzymatic hydrolysis of proteins enhanced the antioxidant activity, especially the peptide fraction F₃ (MWCO = 5–10 kDa). The protein hydrolysates also exhibited high capacity for radical scavenging, reducing power, and ability to inhibit oxidation of low-density lipoprotein (bad cholesterol), thus implying the potential of protein hydrolysate derived from *S. limacinum* to be used as antioxidants in foods or supplements.

Other than nutritional food, microalgae contain niacin, riboflavin, and folate that can be used as vitamins (Costa et al. 2018). UPHLC method was applied to quantify the composition of vitamins in *Spirulina* (*Arthrospira* sp.), *Chlorella* sp., and *Nannochloropsis gaditana* powder. It was revealed that *Spirulina* (*Arthrospira* sp.) contains a higher concentration of riboflavin (36.3 µg/g) compared to *Chlorella* sp. (28 µg/g) and *Nannochloropsis gaditana* (22.1 µg/g). *Spirulina* powders contain a lower concentration of folate (3.5 µg/g) and niacin (0.16 mg/g) compared to *Chlorella* sp. (folate: 19.7 µg/g; niacin: 0.24 mg/g). Nevertheless, *Nannochloropsis gaditana* showed lower concentration of niacin (0.11 mg/g) but a higher concentration of folate (20.8 µg/g) compared to the other microalgae. Hence, different species of microalgae composed different compositions of vitamins that can be used for many applications, especially in pharmaceuticals sector.

4.2 | Impact of Artificial Intelligence in Microalgae-Based Refinery

In the past few years, the implementation of artificial intelligence (IoT) and sensors in microalgae-based refineries have been discovered for improving the water quality monitoring and detection of biochemicals (i.e., toxic compounds). IoT relies on wireless sensor networks that collect certain information, transfer and develop the technologies to rectify limitation and control the interaction of the equipment involved. For example, Tham et al. (2022) developed a smart photobioreactor for continuous cultivation of microalgae by incorporating sensors such as temperature, ultrasonic level and pH sensors into cultivation and extraction systems. The findings revealed that incorporation of IoT into the cultivation and extraction of microalgae system greatly assists the monitoring of microalgae growth and productivity. Nevertheless, several improvements are needed to optimize the microalgae growth and productivity for the application in microalgae biorefinery industry. For instance, installing optical camera communication device and light intensity sensor could improve the microalgae growth and biomass concentration.

Microbial-based sensors have been used as biological-friendly materials to replace artificially fabricated materials and devices. For example, microbial-based sensors can detect metal ions by using electrochemical fuel cells and fluorescence emissions (Shing et al. 2013; Tham et al. 2022). However, those sensors lack rapid detection and sensitivity, and require long measurement times, thus more efforts are needed to rectify the limitations. In recent years, Roxby et al. (2020) investigated energy coupling between *Chlorella* sp. and copper (Cu) nanoparticles to improve the sensitivity of microalgae sensors for detecting metal ions and toxic chemicals in water resources (Chouler et al. 2019). It was found that the addition of copper (Cu) nanoparticles to the microalgae increased the nanocavities, resulting in increased photocurrent and detection of metal ions. The increased sensitivity of microalgae sensors led to shorter measurement times in detecting the toxic chemicals, therefore showing the potential of using microalgae sensors incorporated with copper (Cu) nanoparticles to detect biochemicals and monitor water quality.

4.3 | Current Barriers to Implementing Automation

Despite significant advancements in extraction technologies and the growing role of AI in microalgae-based biorefineries, several barriers still hinder the widespread adoption of automation. One of the major challenges is the high capital cost associated with these technologies (Koyande et al. 2019). Additionally, AI systems require substantial energy for model training and operation, with some models consuming up to 1000 kWh. This not only makes the initial investment steep but also leads to higher ongoing operational costs. The integration of these new systems with existing infrastructure is also a significant challenge. Many legacy systems in biorefineries lack compatibility with modern AI technologies, and retrofitting them can be time-consuming and expensive (Imamoglu 2024).

Moreover, data scarcity is another major barrier. AI models depend heavily on large, high-quality datasets, and the lack of labeled data for rare species or specific biomass types limits the effectiveness of these technologies. For instance, training models for species like *Vicicitus* requires over 10,000 images to achieve a reliable prediction. Regulatory gaps further complicate the process, as there are no standardized guidelines for AI-driven biorefineries and approval for certain technologies (Koyande et al. 2019). On top of that, cybersecurity risks associated with cloud-based platforms can delay the adoption of automation technologies, as proprietary research data might be vulnerable to breaches. For AI and automation to be implemented successfully at an industrial scale in microalgae biorefineries, overcoming these financial, technical, and regulatory hurdles will be essential. This would enable the development of more cost-effective, scalable, and secure solutions for extracting bioproducts and improving sustainability in the sector.

5 | Conclusion and Future Perspectives

In conclusion, this review demonstrates that automation and machine learning offer substantial potential to address the persistent cost and efficiency barriers limiting the commercialization

of microalgal bioproducts. Across the cultivation stage, sensor-based monitoring and IoT-enabled control systems improve the management of open pond and photobioreactor environments, while machine learning algorithms enhance predictive modeling of growth parameters and enable more precise control of light, temperature, pH, and nutrient supply than manual operation allows. In harvesting, ML-driven optimization of auto-flocculation, electro-flocculation, and related separation processes reduces energy consumption and improves consistency in biomass recovery, while in downstream extraction and refining, AI-assisted process control and IoT-integrated sensing support more efficient and better-monitored bioproduct recovery. Collectively, these advances confirm that automation is not merely a supporting technology but a central strategy for improving the productivity, consistency, and scalability of microalgae-based production systems. However, this review also highlights that most of these technologies remain at laboratory or pilot scale, and that realizing their full commercial potential will require overcoming significant technical, economic, and regulatory barriers, including data scarcity, model transferability across cultivation systems, high capital and energy costs, and the absence of standardized industrial protocols. This transferability challenge is particularly acute given the fundamental differences between cultivation platforms: models trained on sensor and growth data from a fully enclosed, low-noise photobioreactor rarely generalize to the more variable, less-controlled conditions of an open pond, and vice versa, since the underlying feature distributions, for example, light penetration, mixing dynamics, contamination risk, temperature fluctuation, differ substantially between the two. A model validated on one reactor configuration therefore cannot be assumed to perform reliably if deployed on another without retraining or domain adaptation, which itself requires additional labeled data that is often unavailable at the point of transfer.

Future research should move beyond isolated automation of individual process steps toward several specific, interconnected research directions. *Digital twin-assisted cultivation* is a key priority: real-time virtual replicas of cultivation and processing systems, continuously updated from streaming sensor data, would enable predictive fault detection and scenario testing without disrupting live production. Closely coupled to this is *adaptive process control*, in which the digital twin or an equivalent online model recommends or executes real-time adjustments to light, temperature, pH, or nutrient dosing in response to deviations from optimal growth trajectories, rather than relying on fixed setpoints. A related but distinct direction is the development of *self-learning photobioreactors*, which continuously refine their own operating parameters from streaming sensor data over successive cultivation cycles, reducing reliance on static, preprogrammed control logic and allowing systems to adapt to drift in culture behavior or equipment performance. Extending these capabilities across the full production chain points toward *integrated AI-driven production platforms*, in which cultivation, harvesting, extraction, and post-processing modules share data and coordinate decisions through a common control architecture rather than operating as isolated automated units. The long-term convergence of these four directions is the *autonomous biorefinery*, in which digital twins, adaptive control, self-learning reactors, and platform-level integration operate together with minimal human intervention across the entire production chain. Achieving this will require parallel progress in

explainable and transferable machine learning models capable of generalizing not only across microalgal strains but also across fundamentally different cultivation platforms—open ponds, closed photobioreactors, and hybrid systems—whose differing sensor architectures, noise profiles, and environmental variability currently limit direct model transfer. Approaches such as transfer learning, domain adaptation, and cross-platform benchmarking datasets represent promising routes to closing this gap, together with more robust and lower-cost sensor networks capable of reliable long-term operation under industrial conditions, and standardized data-sharing frameworks to overcome current data scarcity limitations. Equally important is a clear-eyed accounting of the sustainability trade-offs of automation itself: the energy, computational, and infrastructure demands of AI-driven control systems must be weighed against the productivity and resource savings they deliver, and future techno-economic assessments should quantify this balance explicitly rather than assuming automation is unconditionally beneficial. Addressing these interconnected technical, economic, and sustainability challenges will be essential to translating the automation strategies reviewed here from promising research demonstrations into commercially viable, industrial-scale microalgae production systems.

Author Contributions

Angela Paul Peter: visualization, conceptualization, writing – original draft. **Wan Adibah Wan Mahari:** writing – original draft. **Sharoen Yu Ming Lim:** funding acquisition, writing – review and editing. **Abdirahman Yasin Ibrahim:** conceptualization, writing – original draft. **Revathy Sankaran:** funding acquisition, writing – review and editing. **Kalaimani Markandan:** conceptualization, writing – original draft. **Theeba Rajasegran:** conceptualization, writing – original draft.

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Ethics Statement

The authors have nothing to report.

Consent

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing is not applicable to this article as no datasets were generated or analyzed during this study.

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