ZIBELINE INTERNATIONAL™ PUBLISHING
ISSN: 2521-294X (Online)
ISSN: 2521-2931 (Print)
CODEN: MJSAEJ

Malaysian Journal of Sustainable Agriculture (MJSA)

DOI: http://doi.org/10.26480/mjsa.01.2026.80.83

RESEARCH ARTICLE

AI-DRIVEN MICROALGAL BIOETHANOL PRODUCTION: OPTIMIZING CULTIVATION, STRAIN ENGINEERING AND CONVERSION PROCESSES

Mudasir Hussain[ab*], Inayat Ali[b], Bisma Jabbar[b], Sara Ikram[b]

[a] Department of Biology, Soonchunhyang University, Asan 31538, Chungcheongnam-do, Republic of Korea
[b] Department of Biotechnology, Federal Urdu University of Arts, Science and Technology, Karachi, Pakistan
**Corresponding Author Email: khaylihussain0311@gmail.com*

ARTICLE DETAILS

Article History:

Received 17 March 2026
Revised 20 April 2026
Accepted 25 May 2026
Available online 03 June 2026

ABSTRACT

Microalgae are a promising third-generation feedstock for bioethanol production due to their rapid growth and high-carbohydrate content, although current ethanol yields remain modest. This review article analyzes how artificial intelligence can substantially enhance microalgal bioethanol production across all stages, from cultivation to bioconversion. We structured AI applications to enhance cultivation parameters such as light, CO_2, and nutrients through real-time sensor monitoring and machine-learning control, which have increased algal biomass productivity by approximately 15–50% in preliminary trials. Discuss AI-guided strain selection and metabolic engineering strategies that leverage omics data and predictive modeling to identify high-carbohydrate phenotypes, with recent work proposing up to 30–40% improvements in product yield via AI-optimized strain design. Downstream, AI-driven process enhancement in pretreatment and fermentation can improve sugar release and fermentation effectiveness, for instance, by forecasting optimal pretreatment conditions and dynamically maintaining fermentation parameters to maximize ethanol titer. A unified digital twin framework is proposed as a future paradigm in which the digital counterpart of the algal biorefinery continuously learns and optimizes the entire process, from photobioreactor to fermentation, in silico. While AI offers significant gains in efficiency and product yield, we note that data insufficiency, model generalizability and scaling issues remain challenges. Tackling these issues through interdisciplinary partnership and data-sharing will be important. Overall, AI integration can accelerate micro-algal bioethanol development, making production more versatile, productive and eco-friendly.

KEYWORDS

Microalgae, Bioethanol production, artificial intelligence, Strain engineering, Digital twin biorefinery

1. INTRODUCTION

Artificial intelligence (AI) refers to the capability of machines to mimic human intelligence, allowing them to perform complex tasks such as the identification of objects, decision-making, and solving problems (Rayamajhi et al., 2025). According to recent research works, microalgae like planktons are mainly responsible for approximately 40–50% of the Earth's oxygen, and are growing as a favorable third-generation bioethanol feedstock because of their rapid growth and maximum carbohydrate amount (almost 40–70% of dry biomass (Yang et al., 2024; Phwan et al., 2019). Unlike terrestrial crops, microalgae need no cultivable land or freshwater and contain no lignin, making them easier to hydrolyze (Phwan et al., 2019). For example, a *Chlorella* strain attains approximately 12% sugar (w/v) and 0.47 g ethanol per g sugar. However, reported ethanol yields from microalgal biomass last for modest (typically <0.30 g/g due to partial conversion and process incompetence (Phwan et al., 2019).

AI offers life-changing tools to address these challenges by optimizing each stage of the bioethanol pipeline. AI-based models can increase cultivation (boosting biomass productivity), inform strain and metabolic plan and fine-tune conversion processes (Syed et al., 2024; Wu et al., 2025). The use of fossil fuels in the energy sector has been a significant contributor to global warming. As a potential solution, microalgae have gained recognition as an alternative energy source for many biofuel production processes, such as biodiesel and biohydrogen. Thus, the carbon-neutral and carbon-level nature addresses different challenges caused by global warming. In this review, we critically analyze current advancements where AI techniques (machine learning, deep learning, digital twins, etc.) are applied to microalgal cultivation and bioethanol production, highlighting novel strategies, key successes and remaining hurdles (Chisti, 2013; Richardson et al., 2012; Usher et al., 2014).

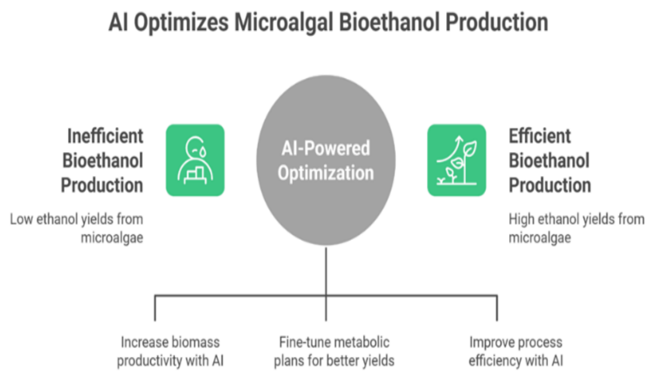

Figure 1: Conceptual overview of AI-assisted optimization in microalgal bioethanol production. AI integrates cultivation control, metabolic engineering, and process optimization to improve biomass productivity and ethanol yield.

Quick Response Code	Access this article online	
	Website: www.mjsa.com.my	**DOI:** 10.26480/mjsa.01.2026.80.83

Cite The Article: Mudasir Hussain, Inayat Ali, Bisma Jabbar, Sara Ikram (2026). Ai-Driven Microalgal Bioethanol Production: Optimizing Cultivation, Strain Engineering And Conversion Processes. *Malaysian Journal of Sustainable Agriculture (MJSA)*, 10(1): 80-83.

2. Artificial Intelligence Techniques In Microalgal Processes

2.1 Modern AI encompasses a variety of data-driven methods

Machine Learning (ML) is a method that encompasses a range of techniques, including support vector machines, random forests, neural networks and genetic algorithms. It has been broadly used to model and redict sophisticated bioprocess results (Imamoglu, 2024). Deep learning extracts characteristics from imaging data, such as cell morphology or fluorescence and time-series sensor data to monitor algal health. Reinforcement learning and evolutionary algorithms maximize multivariate processes (e.g., nutrient dosing schedules). Internet-of-Things (IoT) integration networks of probes and actuators give the real-time continuous March's data flow like pH, CO_2, light and biomass density, etc. that feed into AI models for closed-loop control (Imamoglu, 2024).

Fundamentally, AI activates predictive analytics and auto control systems that can consistently modulate cultivation and processing specifications. Supervised ML (SVM, decision trees, neural nets) is used for growth and yield prediction and classification of algal strains, while Unsupervised ML (clustering, principal component analysis) is used to identify patterns in multispectral or omics data, as the AI amplifies the precision and economic feasibility of microalgal productions (Alzahmi et al., 2024; Peter et al., 2023). In Optimization, genetic algorithms and reinforcement learning are functional to tune culture conditions such as light/dark cycles and nutrient pulses for maximal productivity. While in digitalization, digital twin frameworks construct virtual clones of photobioreactors that replicate environmental dynamics; these incorporate AI models with real sensors to forecast culture behavior and enhance control strategies (Sheik et al., 2024; Imamoglu, 2024).

2.2 AI-Driven Cultivation Optimization

One of the predominant mature applications of AI is in enhancing microalgal culture parameters. In controlled photobioreactors, AI evaluates sensor data (light intensity, CO_2, pH, biomass concentration) and aligns inputs in real-time. For example, Fraunhofer researchers used an SVM model to predict *Phaeodactylum tricornutum* growth; the SVM attained a correlation coefficient of approximately 88% versus 82% for a traditional Monod-kinetics model (Yang et al., 2024). These types of predictive models can feed a model-predictive control system that calibrates variables (e.g., nutrient feed rate, mixing speed) to stabilize maximum growth. AI also helps in observing cultural health through imaging. High-throughput cameras or flow cytometers capture cell morphology or fluorescence, as convolutional neural networks can categorize algal strains or detect stress responses (e.g., chlorosis) that precede productivity loss.

Drone-based or satellite imaging combined with machine learning has even been presented for monitoring open-pond systems at scale (Imamoglu, 2024). Significantly, the digital twin concept has introduced microalgae cultivation. A recent review describes algal digital twins (ADT) that incorporate many variables (nutrients, dissolved gases, optical density) into a virtual management system (Sheik et al., 2024). In theory, an ADT consistently simulates a channel pond or photobioreactor and specifies control actions (e.g., CO_2 injection, harvest timing) to enhance biomass. By closing the loop, these systems intend to cut energy use and increase yield.

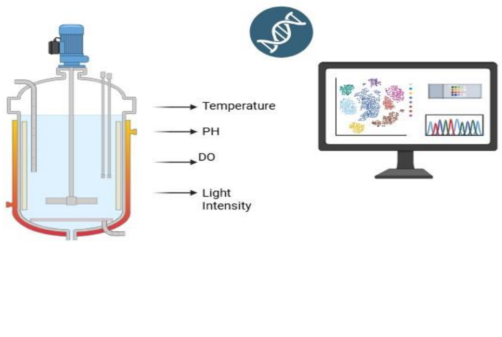

Figure 2: Illustrates a conceptual framework for AI-assisted microalgal cultivation integrating real-time sensing, machine-learning prediction and digital twin–based control.

In practice, pilot studies have validated that AI-driven control can considerably enhance productivity and adaptability. One case study analyzed that incorporating advanced controls enhanced daily biomass productivity by approximately 15–30% over traditional methods (Wu et al., 2025). Likewise, applying machine learning to photobioreactor tuning (light cycles, CO_2 dosing) has led to *30–50% higher yields* in some simulations. Exceeding productivity, AI refines viability, specifically by dynamically lowering nutrient or energy inputs once growth targets are achieved (Wu et al., 2025).

2.3 AI in Strain Selection and Metabolic Engineering

Another limit is using artificial intelligence to frame or select algal strains optimal for ethanol production. Microalgal genomics and biology systems yield vast datasets but coupling these datasets to intended traits is more challenging. Here, machine learning helps in identifying genetic markers associated with high fermentable-carbohydrate flux. For example, supervised ML has been used to identify genetic markers bound to high lipid production (Imamoglu, 2024). Equivalent approaches can be used to search for markers of carbohydrate abundance or ethanol tolerance. While still largely theoretical for microalgae, evolving AI-assisted metabolic design frameworks are evidenced in bacterial and yeast systems suggest future validation. In synthetic biology, AI techniques such as reinforcement learning have been used in other organisms to maximize metabolic pathways.

In microalgae, this shows that combining genome-scale metabolic modeling with machine learning is one could reproduce thousands of gene-transformed networks and use an AI agent to determine those yielding maximal ethanol output. Although still in early stages, such in silico design tools promise to lower the trial-and-error of genetic engineering. Real examples of emerging hybrid strategies using AI-guided mutagenesis have been shown to enhance lipid titers in algae by extension, similar pipelines could raise starch aggregation (Wang et al., 2024). Finally, incorporating artificial intelligence with omics and CRISPR techniques could yield super strains that aggregate carbohydrates rapidly. Any success here would be novel as few studies have yet aimed at ethanol-specific pathways in microalgae with AI. In the last decade, genetic engineering and especially now, AI-guided strain selection have increased the lipid production by almost 40%, optimizing the biomass while reducing the costs (Kanwal et al., 2025).

2.4 AI-Optimized Conversion to Ethanol

After cultivation, microalgal biomass must be treated into ethanol, generally through cell disruption, saccharification and fermentation. Each of these steps can benefit from AI-driven optimization. For example, pretreatment, such as chemical or enzymatic processes. Conditions greatly affect sugar production. A study reported that 5% sulphuric acid pretreatment gave approximately 0.28 g ethanol/g biomass, versus 0.23 g/g with acetic acid (Phwan et al., 2019). AI could use these types of data in a predictive model to propose the maximum acid type and amount based on biomass composition, e.g., starch vs cellulose content. Even without algal-specific AI studies, comparable work in lignocellulosic ethanol has used ML to predict maximum severities and enzyme mixes for maximal sugar release. In fermentation, AI tunes yeast or bacterial cultures that convert algal sugars. AI models can maximize fermentation variables (pH, light intensity, temperature, nutrient and CO2 concentrations) to advance higher microalgal biomass growth (Wu et al., 2025).

Machine learning models link fermentation inputs with outputs (ethanol titer, productivity) using laboratory data. Once trained, they guide real-time control, e.g., adjusting pH or nutrient feed if the model predicts stalled fermentation. Such approaches are general in industrial fermentation and could be transferred to micro-algal hydrolysates. Integration of AI extends to process surveillance and quality control. Vision systems and spectral sensors, analyzed by AI, track cell feasibility and detect contaminants or byproduct aggregation during fermentation. Fault-detection algorithms could quickly flag off-spec batches or suggest interventions. Overall, while specific case studies on AI for microalgae-to-ethanol conversion are scarce, the general principle is established. AI-driven process optimization can progressively increase ethanol production and reduce downtime (Wu et al., 2025; Guo et al., 2025) .

3. Integrated Biorefinery And Digital Infrastructure

Looking beyond each step, a key novel idea is utilizing the entire micro-algal bioethanol system as a cyber-physical system. Under this framework, artificial intelligence and data connectivity are integrating cultivation, harvesting, conversion and even logistics. For example, production plans could be maintained weekly by an AI scheduling agent that forecasts biomass accessibility and matches it to fermentation production rate and market demand. Real-time energy and resource maximization could be attained by co-optimizing electricity use with ethanol output using reinforcement learning. One feasible structure is the industry 5.0 digital twin, a virtual model of the whole plant that learns and adapts over-time.

A recent review argues that such algal digital twins (ADT) could transform channel ponds and bioreactors into a smart and sustainable fundamental system (Sheik et al., 2024). The ADT would simulate nutrient cycling, gas exchange, light penetration and biomass growth, enabling predictive modification, for example, lowering light intensity late in the day to save energy once carbon fixation decreases.

Case studies of ADTs have evidence of potential for up to 10–20% savings in energy and nutrients by dynamic control of multi-variable processes. Incorporating AI of Things (AIoT), where edge devices (sensors/actuators) and cloud AI coordinate, could further increase scalability and resilience (Sheik et al., 2024; Imamoglu, 2024; Kim et al., 2026).

Table 1: Comparisons of AI applications in microalgal cultivation across species

Observation	AI Technique Used	Species Involved	Key Insights and Results	References
Due to physiological variance, AI models developed for specific species mostly perform poorly when applied to another (light response, food uptake, and stress tolerance).	ANN	*Synechocystis vs. Chlorella*	Each strain requires correction to maintain its accuracy	(Wu et al., 2025)
Mixed datasets from different studies to produce forecasts which are widely used	Decision Tree	Mixed species (>100 studies)	Revealed wide trends in biomass and lipid optimization	(Wu et al., 2025, Mayol et al., 2018)
Combines mechanistic and data-driven models for adaptability	Hybrid ML–mechanistic	General application	Improved generalization and readability	(Syed et al., 2024)

4. Challenges And Outlook

Despite the promise, AI-driven microalgal bioethanol exposes considerable challenges. Data deficiency remains paramount most lab studies lack the capacity and diversity of data needed for resilient AI models. Building shared databases of algal growth and fermentation results would accelerate progress. Universality is also an issue, as models trained on one specific strain or reactor may not transfer to another. Hybrid models (combining first-principles and AI) and transfer learning techniques may help. Regardless of their promise, current AI applications are restricted by data confinement and variance. Previously published reviews record that few large-scale datasets exist for microalgae and species-specific differences restrict model generalization (Wu et al., 2025). Furthermore, many AI studies use small lab-scale data. High variance and lack of transparency in complex models (e.g., deep nets) remain concerns.

Careful model validation and cross-system transfer will be needed as AI moves from research to industrial microalgae biorefineries. On the engineering side, integrating AI requires consistent sensors and automation hardware, which can be costly in bioreactors. Fouling, biofilm formation and sensor drift are practical hurdles. Cybersecurity of IoT networks and the transparency of AI decisions are additional concerns, especially for regulatory approval of biotech processes. Analytically, many studies to date show progressive gains (10–50% productivity) but not yet transformative advancement. True novelty may come from cross-disciplinary integration, e.g., AI-guided synthetic ecology, where a pool of microalgae and fermentative microbes is co-designed for symbiosis. Or real-time adaptive evolution, where AI leads microbial evolution in situ to improve ethanol tolerance, these ideas hint at future research directions.

5. Ethical Perspectives Of Using AI

Table 2: Summary of ethical principles of AI regulations

Principle (Reference)	Explanation
Privacy	Safeguarding personal data against misuse, emphasizing informed consent and controlled data access.
Justice and Fairness	Ensuring equality by preventing biases and inequitable impacts of AI algorithms, considering fairness parameters and balancing fairness with accuracy.
Transparency	Making AI decisions clear and understandable, focusing on understandability, explainability and documentation.
Responsibility	Holding developers and users accountable, emphasizing integrity, clear attribution of legal liability and promoting a culture of ethical behavior.
Non-maleficence	Ensuring AI systems do no harm, prioritizing safety, security, and protection from misuse or harmful impacts.
Beneficence	Promoting positive impacts and societal well-being, encouraging beneficial AI applications while closely supervising those with negative impacts.
Freedom and Autonomy	Respecting and supporting individual autonomy in decision-making and data control, requiring clear consent and transparency.

6. Conclusion

In summary, AI offers a powerful new conceptual model for increasing microalgal bioethanol productivity by increasing both biology and process engineering. From smart photobioreactors that learn to maximize growth to AI-derived gene targets for high ethanol production and to digital twin control of entire biorefineries, the range of applications is broad. Early case studies suggest double-digit improvements in productivity and process indicate potential yield increases of approximately 30–50% under integrated AI control. To fully realize this potential, the community must address data and infrastructure limitations, build interdisciplinary teams and validate artificial intelligence methods at trial and demonstration scales. If successful, the fusion of AI and microalgal biotechnology could overcome key barriers to sustainable bioethanol and set a new standard for intelligent biorefineries.

Competing Interests

During the preparation of this manuscript, the authors used ChatGPT and Napkin to assist with improving language clarity, readability, and figure preparation. All outputs generated with these tools were carefully reviewed, revised, and validated by the authors. The authors take full responsibility for the accuracy, interpretation, and integrity of the content presented in this publication.

References

Alzahmi, A. S., Daakour, S., Nelson, D., Al-Khairy, D., Twizere, J.C., and Salehi-Ashtiani, K. 2024. Enhancing Algal Production Strategies: Strain Selection, AI-Informed Cultivation, And Mutagenesis. Frontiers In Sustainable Food Systems, 8, 1331251.

Chisti, Y. 2013. Raceways-Based Production Of Algal Crude Oil. Green, 3, 195.

Guo, B., Lu, X., Jiang, X., Shen, X. L., Wei, Z. and Zhang, Y. 2025. Artificial Intelligence in Advancing Algal Bioactive Ingredients: Production, Characterization, And Application. Foods, 14.

Hoffmann-Riem, W. 2019. Artificial Intelligence As A Challenge For Law And Regulation. Regulating Artificial Intelligence. Springer.

Imamoglu, E. 2024. Artificial Intelligence And/Or Machine Learning Algorithms In Microalgae Bioprocesses. Bioengineering, 11, 1143.

Jobin, A., Ienca, M. and Vayena, E. 2019. The Global Landscape Of Ai Ethics Guidelines. Nature Machine Intelligence, 1, 389–399.

Kanwal, F., Aslam, A. and Torriero, A. A. J. 2025. Microalgae-Based Biodiesel: Integrating Ai, Crispr And Nanotechnology For Sustainable Biofuel Development. Emerg Top Life Sci, 8, 131–143.

Kim, M., Ghobadi, F., Tayerani Charmchi, A. S., Lee, M. and Lee, J. 2026. Digital Twins For Clean Energy Systems: A State-Of-The-Art Review Of Applications, Integrated Technologies, And Key Challenges. Sustainability, 18, 43.

Mayol, A. P., Maningo, J. M. Z., Chua-Unsu, A. G. A. Y., Felix, C. B., Rico, P. I., Chua, G. S., Manalili, E. V., Fernandez, D. D., Cuello, J. L. and Bandala, A. A. Application Of Artificial Neural Networks In Prediction Of Pyrolysis Behavior For Algal Mat (Lablab) Biomass. 2018 Ieee 10th International Conference On Humanoid, Nanotechnology, Information Technology, Communication And Control, Environment And Management (Hnicem), 2018. Ieee, 1–5.

Peter, A. P., Chew, K. W., Pandey, A., Lau, S. Y., Rajendran, S., Ting, H. Y., Munawaroh, H. S. H., Van Phuong, N. and Show, P. L. 2023. Artificial Intelligence Model For Monitoring Biomass Growth In Semi-Batch Chlorella Vulgaris Cultivation. Fuel, 333, 126438.

Phwan, C. K., Chew, K. W., Sebayang, A. H., Ong, H. C., Ling, T. C., Malek, M. A., Ho, Y.-C. and Show, P. L. 2019. Effects Of Acids Pre-Treatment On The Microbial Fermentation Process For Bioethanol Production From Microalgae. Biotechnology For Biofuels, 12, 191.

Rayamajhi, V., Hussain, M., Shin, H. and Jung, S. 2025. Recent Advances In The Application Of Artificial Intelligence In Microalgal Cultivation. Processes, 13, 3764.

Richardson, J. W., Johnson, M. D. and Outlaw, J. L. 2012. Economic Comparison Of Open Pond Raceways To Photo Bio-Reactors For Profitable Production Of Algae For Transportation Fuels In The Southwest. Algal Research, 1, 93–100.

Sheik, A. G., Kumar, A., Ansari, F. A., Raj, V., Peleato, N. M., Patan, A. K., Kumari, S. and Bux, F. 2024. Reinvigorating Algal Cultivation For Biomass Production With Digital Twin Technology - A Smart Sustainable Infrastructure. Algal Research, 84, 103779.

Syed, T., Krujatz, F., Ihadjadene, Y., Mühlstädt, G., Hamedi, H., Mädler, J. and Urbas, L. 2024. A Review On Machine Learning Approaches For Microalgae Cultivation Systems. Computers In Biology And Medicine, 172, 108248.

Usher, P. K., Ross, A. B., Camargo-Valero, M. A., Tomlin, A. S. and Gale, W. F. 2014. An Overview Of The Potential Environmental Impacts Of Large-Scale Microalgae Cultivation. Biofuels, 5, 331–349.

Wang, M., Ye, X., Bi, H. and Shen, Z. 2024. Microalgae Biofuels: Illuminating The Path To A Sustainable Future Amidst Challenges And Opportunities. Biotechnology For Biofuels And Bioproducts, 17, 10.

Wu, Y., Shan, L., Zhao, W. and Lu, X. 2025. Harnessing Artificial Intelligence To Revolutionize Microalgae Biotechnology: Unlocking Sustainable Solutions For High-Value Compounds And Carbon Neutrality. Marine Drugs, 23, 184.

Yang, C.T., Kristiani, E., Leong, Y. K. and Chang, J.-S. 2024. Machine Learning In Microalgae Biotechnology For Sustainable Biofuel Production: Advancements, Applications, And Prospects. Bioresource Technology, 413, 131549.