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A Comprehensive Review on AI, Digitalization and Industry 4.0 in Biofuel Production Processes

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A B S T R A C T :

Rising energy demands and climate concerns have accelerated research into renewable biofuels. However, conventional production processes face challenges like feedstock variability, high energy use, and operational instability. Integrating Artificial Intelligence (AI), digitalization, and Industry 4.0 offers transformative solutions to convert traditional plants into intelligent biorefineries. This comprehensive review critically assesses these advanced technologies—including machine learning, digital twins, IoT, and cyber-physical systems—across major biofuel pathways such as bioethanol, biodiesel, biogas, and algal fuels. It examines their impact on yield prediction, process optimization, energy efficiency, and techno-economic performance. Furthermore, key implementation barriers—such as data limitations, cybersecurity, and industrial-scale validation—are addressed. Finally, an integrated framework connecting AI, digitalization, and Industry 4.0 across the biofuel value chain is proposed to guide future research toward scalable, environmentally sustainable, and intelligent bioenergy systems.

Keywords: Artificial intelligence; Biofuel production; Digitalization; Industry 4.0; Smart biorefineries; Digital twins; Machine learning; Sustainable bioenergy

1. INTRODUCTION

The increasing global demand for energy, combined with concerns over fossil fuel depletion, climate change, and environmental pollution, has accelerated the search for sustainable and renewable alternatives. Conventional fossil fuels remain central to meeting global energy needs, but their extensive use leads to high amount of greenhouse gas emissions and environmental degradation. As a result, biofuels have emerged as promising renewable energy carriers derived from biological resources, offering possible pathways to reduce the dependencies on fossil-based systems across transportation, electricity generation, heating, including other industrial applications. Despite their potential, traditional biofuel production processes face persistent challenges, including feedstock variability, high energy consumption, process inefficiencies, operational instability, and economic hurdles. To address these limitations, recent advancements in Artificial Intelligence (AI) have introduced powerful tools for data driven decision making. Computational techniques such as machine learning, artificial neural networks, deep learning, and genetic algorithms are increasingly investigated for feedstock characterization, biomass composition prediction, microbial and algal growth modelling, fermentation optimization, biodiesel yield prediction, anaerobic digestion monitoring, and process parameter optimization. These methods excel at analyzing complex, nonlinear relationships among operating variables that often challenge conventional empirical or mathematical models. Further, predictive analytics enable the early detection of process deviations, equipment faults, and performance fluctuations. However, the effectiveness of these AI driven approaches depends heavily on the availability, quality, and representativeness of the data, alongside the capacity of these models to generalize across diverse feedstocks, varying operating conditions, and distinct production scales. Along with these AI models, the broader digital transformation including Internet of Things (IoT), Industrial IoT, digital twins, big data analytics, and Industry 4.0 offers various opportunities to convert conventional facilities into intelligent, interconnected biorefineries. This review critically assesses these technologies across major biofuel pathways, including bioethanol, biodiesel, biogas, biohydrogen, bio-oil, and algal biofuels. This review examines the results of AI enabled digital transformation for process efficiency, energy consumption, resource utilization, environmental sustainability, and techno-economic performance, ultimately proposing an integrated framework to guide future research toward scalable, smart biorefineries.

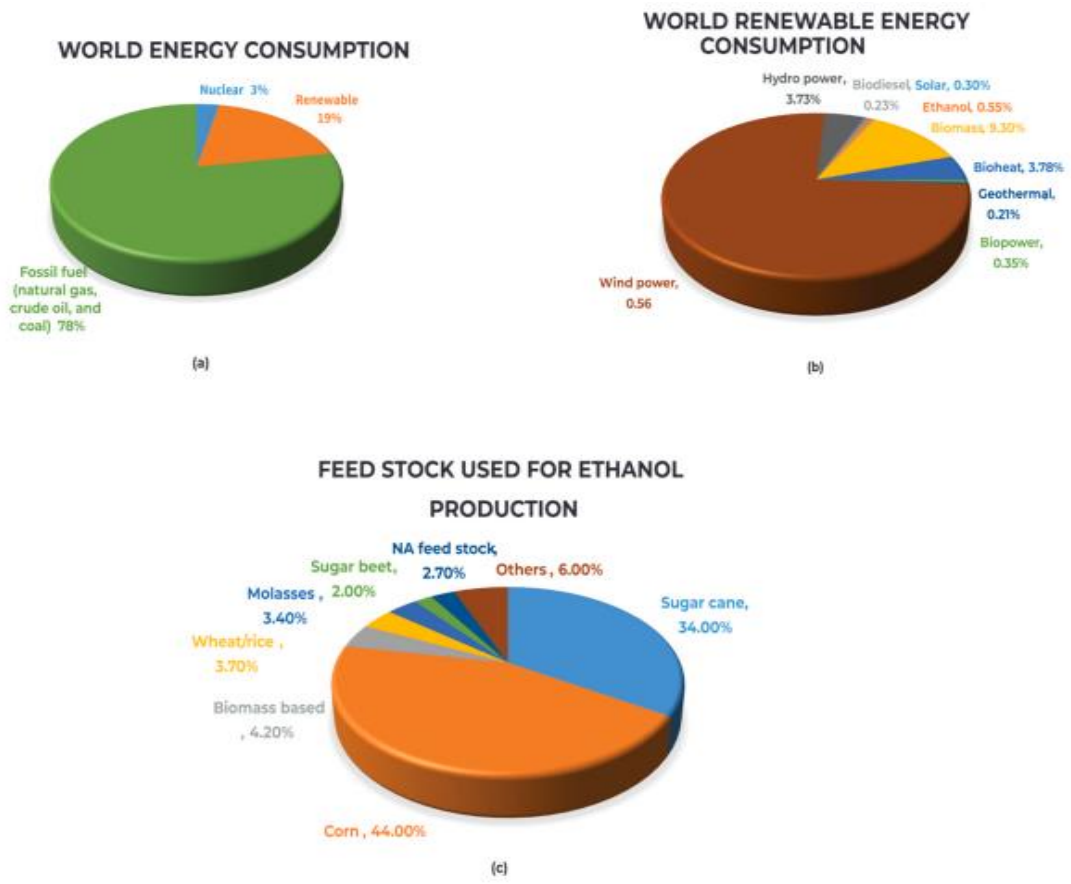


Fig 1. Global energy consumption and bioenergy sources breakdown, including renewable energy and feedstock for biomass production.

2. CLASSIFICATION OF BIOFUELS

Biofuels are termed as most important renewable as well as sustainable energy sources which are considered as the alternatives to traditional or fossil fuels. The use of biofuels as sustainable energy resources depends heavily on the type and nature of the biomass feedstock, the chosen production technology, and the specific process conditions—such as temperature, pH, reaction time, and reagents. Additionally, selecting the right catalyst is critical to ensuring the production process remains efficient, eco-friendly, and economically viable.

Biofuels are classified according to the following categories:

1. Classification based on Generation of Feedstock
2. Classification based on the Physical State
3. Classification based on Conversion Process for Biofuel Production

2.1. Classification based on Generation of Feedstock

Biofuels can be classified into different generations based on the type of feedstock used and the product obtained from them. This classification provides a clear view of understanding the evolution of biofuel production, from conventional food-based feedstocks to advanced non-food biomass, algae and genetically engineered biological resources.

The classification of biofuels based on generation of feedstocks is as follows:

Table 1. Classifications, product and feedstocks of different generations of biofuels.

Classification	**Product**	**Feedstocks**
First generation (food feedstocks)	Ethanol Biodiesel	Corn, sugar beet, sugarcane, cereals, sorghum, grains etc. Rapeseed, palm oil, soybean, waste oils, animal fats.
Second generation (biomass)	Cellulosic Ethanol	Switch grass, wheat straw. Jatropha, miscanthus, corn stover, stalks, stubbles, leaves, speed pods, rice and wheat straw, sugarcane bagasse, fruit and vegetable wastes.
Third generation	Bioethanol/ ethanol	Algae
Fourth generation	Biodiesel/ bioethanol	"Drop in" biofuels, genetically modified crops for biofuels, renewable solar fuel.

2.2. Classification based on Physical state

Biofuels can also be classified according to their physical state at the atmospheric conditions. Based on this criterion, biofuels are widely divided as:

Table 2. Classifications, examples and applications of different states of biofuels.

Physical State	Examples	Major Applications
Solid biofuels	wood, wood pellets, briquettes, agricultural residues, charcoal.	Heating, cooking, electricity generation.
Liquid biofuels	Bioethanol, Biodiesel, Biobutanol, Bio-oil.	Transportations and power generation.
Gaseous Biofuels	Biogas, Biomethane, Biohydrogen, Syngas.	Heating, electricity generation, transportation.

2.3. Classification based on Conversion Process for Biofuel Production

There exist several developing methods for converting biomass and other feedstocks and raw materials into different products.

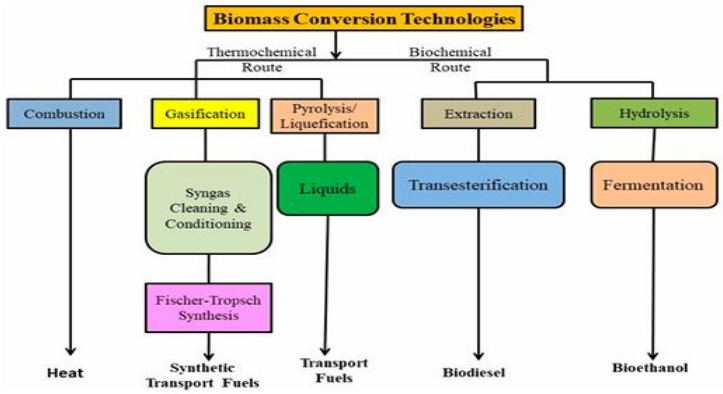


Fig 2. Biomass conversion technology for biofuels production.

3. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN BIOFUEL PRODUCTION

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly being researched as tools for improving the efficiency, productivity, and sustainability of biofuel production. Biofuel processes involve several interacting variables, including temperature, pH, pressure, reaction time, substrate concentration, catalyst loading, and feedstock composition. These variables influence conversion efficiency, product yield, and fuel quality. Conventional experimental approaches can require number of trials to identify suitable operating conditions, particularly when the process exhibits complex and nonuniform behaviour. AI based approaches provide data driven methods for learning relationships between process parameters and production outcomes.

Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Random Forests (RFs), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Genetic Algorithms (GAs) are one of the techniques used in modelling and optimization of biofuels. ANNs can analyse nonlinear relationships between multiple input variables and process outputs, enabling the prediction of biofuel yield, product concentration, and process performance. These techniques have been investigated for biodiesel, bioethanol, biogas, and biohydrogen production. Response Surface Methodology (RSM) is also used to study the effects of operating variables and their interactions. Combining predictive models with optimization methods can reduce experimental effort and help in finding suitable production conditions [1].

Machine learning can also be applied not only for the conversion stage. It can support biomass availability assessment, feedstock-yield estimation, prediction of feedstock properties, fuel quality evaluation, and analysis of engine performance and emissions.ML applications across soil, feedstock, production, consumption, and emissions, illustrating that data-driven methods can contribute throughout the biofuel life cycle rather than at a single production step [2].

Table 3. Qualitative and Quantitative Analysis of the Five Generations of Biomass.

Generation	Qualitative Improvements	Quantitative Improvements
1st Generation	High fermentable sugar content, simplified processing, and proven fermentation techniques.	High yield: 400–500 L ethanol/tonne of biomass.
2nd Generation	Sustainable waste utilization reduces competition with food resources; requires pretreatment and detoxification.	Yield: approximately 250–400 L/tonne; decreased effectiveness due to recalcitrance and inhibitors.
3rd Generation	Significant growth, no competition for land or food, usage of CO_2 and wastewater, and high levels of fats and carbohydrates.	Extremely high potential productivity: more than 5,000–20,000 L/ha/year; cost constraints are considerable in large-scale yields.

Generation	Qualitative Improvements	Quantitative Improvements
4th Generation	Reduced inhibitors, modified bacteria that digest hexose and pentose sugars, and feedstocks having high cellulose content and small amounts of lignin.	Improvement in yield: 20–40% greater than usual; quicker rates of fermentation.
5th Generation	Multiple commodity blending, net-zero carbon methodology, integration of machine learning (ANN, RSM), and the circular bioeconomy model.	Increased yield and efficiency; scalable, energy-efficient systems are expected to produce more than 600–700 L/ton.

4. DIGITALIZATION AND REAL-TIME PROCESS MONITORING

Digitalization involves collecting, processing, integrating, and analysing data generated all throughout the entire biofuel production. The Internet of Things (IoT), smart sensors, automated measurement systems, and industrial communication networks allow operating conditions to be monitored continuously. Depending on the process, parameters such as temperature, pressure, pH, dissolved carbon dioxide concentration, electrical conductivity, and equipment performance can be recorded and analysed to understand process behaviour.

When sensor networks are integrated with AI and ML models, collected data can be used to identify changes, predict process behaviour, and support the operational decisions with respect to time. For example, change in temperature or pH during fermentation may indicate a change from suitable operating conditions. Monitoring systems can help operators identify such changes and adjust process parameters before they affect production. Digital monitoring can also support equipment condition assessment, predictive maintenance, and the reduction of unnecessary energy and material consumption [3].

An example of data driven process monitoring was reported for microbial electrosynthesis, a bio-electrochemical process that can convert carbon dioxide into products including ethanol. Integration of Automated experimental platform controls dissolved CO_2 concentration, pH, and pressure while monitoring other operating variables. A study reported that 35% improvement in the ethanol production rate under the investigated operating conditions. This result shows the potential of real-time monitoring, automated control, and data analysis to improve process understanding and reduce reliability on trial and error method [4].

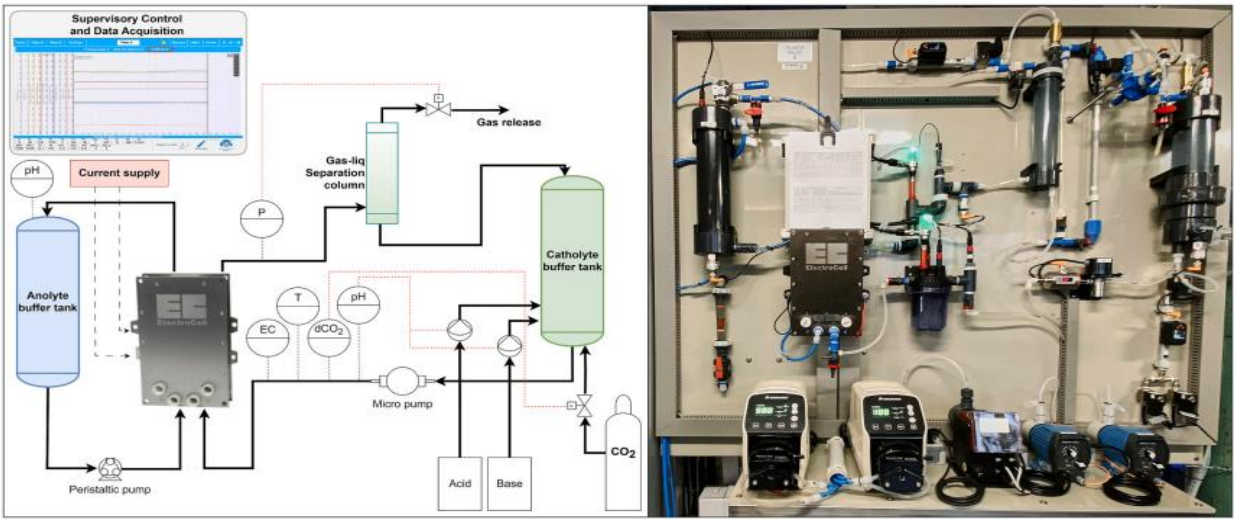


Fig 3. Schematic overview and picture of the bench scale MES platform.

5. INDUSTRY 4.0 AND SMART BIOREFINERIES

Industry 4.0 refers to the integration of connected digital technologies, data analytics, automation, and intelligent control into industrial operations. In biofuel production, these technologies can support smart biorefineries in which feedstock handling, conversion, separation, equipment monitoring, and quality assessment are coordinated through integrated digital systems.

A digital twin is a virtual representation of physical process, item of equipment, or production facility. By combining process simulations with historical and real time operational data, digital twins can help analyse plant behaviour, detect abnormal operating conditions, evaluate alternative operating strategies and support process optimization. When integrated with machine learning models, they may also assist predictive maintenance and coordination between production stages. It is a developing tool for real time monitoring, predictive analytics, and optimization in large-scale biofuel plants [3].

Blockchain technology can complement digital production systems by supporting the traceability of biomass feedstocks and documenting their origin and transportation. This can improve transparency across supply chains and support the verification of sustainability-related information. Geographic Information Systems (GIS), remote sensing, and digital logistics platforms can also help estimate biomass availability, assess feedstock characteristics, and plan transportation and collection. The practical benefits of these technologies depend on reliable data, compatible systems, suitable infrastructure, and effective cybersecurity.

6. APPLICATIONS ACROSS DIFFERENT BIOFUEL PRODUCTION PATHWAYS

6.1 Biodiesel Production

Biodiesel production through esterification and transesterification involves interacting reaction parameters that influence conversion, yield, and fuel properties. AI and ML models can predict biodiesel yield and properties using information such as feedstock characteristics, reaction temperature and time, catalyst concentration, and other operating variables. Optimization algorithms can then help identify combinations of conditions that meet production objectives.

The use of waste cooking oil and other low cost feedstocks make process optimization particularly relevant because feedstock composition can vary. After analysing energy efficient machine learning approaches for biodiesel production and process optimization should be considered alongside the computational energy requirements of AI systems. Energy efficient modelling, reliable process control, and economic feasibility are therefore important considerations when moving from research studies to industrial implementation [5].

6.2 Bioethanol Production

Bioethanol production from lignocellulosic biomass generally involves pretreatment, enzymatic hydrolysis, fermentation, and separation. Variations in biomass composition and pretreatment conditions can affect enzyme accessibility, fermentable-sugar release, inhibitor formation, and final ethanol yield.

ANNs and RSM can be used to model and optimize these interconnected stages. Predictive models can evaluate the influence of pretreatment conditions, enzyme loading, temperature, pH, and fermentation parameters on process performance. Their application can reduce the number of experimental trials required to identify promising conditions and support improvements in conversion efficiency. Recent developments in lignocellulosic bioethanol production, including the use of ANN and RSM for process modelling and optimization. Integrating such models with real-time monitoring may further support more adaptive production systems [6].

6.3 Biogas and Biohydrogen Production

Biogas and biohydrogen production depend on biological processes influenced by operating parameters such as substrate composition, pH, temperature, substrate concentration, and hydraulic retention time. Machine-learning models can help predict gas production and identify operating conditions associated with improved process performance.

ANN-based modelling has been investigated for biogas and biohydrogen because these processes involve complex biological interactions that may be difficult to describe using simple linear relationships. Combining predictive models with process monitoring and optimization can help identify deviations and improve the consistency of biological conversion systems. However, the reliability of predictions depends on representative experimental data and suitable model validation [1].

6.4 Microalgae-Based Biodiesel

Microalgae are a potential feedstock for biodiesel because of their capacity to accumulate lipids and their potential to be cultivated using resources such as wastewater or non-arable land. AI can assist in selecting suitable strains and optimizing cultivation variables, including light intensity, temperature, pH, nutrient availability, and CO_2 concentration.

Advances in AI-guided strain optimization alongside genetic engineering and nanotechnology-assisted processing. These approaches may improve biomass and lipid productivity and support more efficient harvesting and extraction. Nevertheless, the overall feasibility of microalgal biodiesel depends on cultivation requirements, energy consumption, processing costs, and life-cycle environmental impacts. These factors should be evaluated together when considering the potential for large-scale production [7].

7. SUSTAINABILITY, CHALLENGES, AND FUTURE RESEARCH DIRECTIONS

AI and Industry 4.0 technologies offer opportunities to improve biofuel production through resource optimization, reduced production losses, better operational reliability, and improved process control. Digital monitoring can also generate data for techno-economic analysis (TEA) and life-cycle assessment (LCA), enabling technical performance to be evaluated alongside production costs and environmental impacts.

Several challenges remain. The accuracy of machine-learning models depends on the availability, quality, and representativeness of training and validation data. Variations in feedstock composition and operating conditions can limit the transferability of models between plants or production scales. Installing sensors, communication networks, digital platforms, and automated control systems may require substantial investment. Data interoperability, cybersecurity, technical expertise, and integration with existing equipment also need attention [3].

The energy consumption associated with training and operating AI models is an additional consideration. Environmental benefits from process optimization should therefore be assessed against the energy and computational resources required by the digital system. Song et al. [5] highlighted the importance of energy-efficient AI, scalable architectures, real-time optimization, and human-assisted decision-making in the development of sustainable biodiesel production systems.

Future research should focus on combining physics-based process models with machine learning, developing reliable digital twins, improving the transferability of predictive models, and validating AI-assisted control under industrial operating conditions. Greater integration of process monitoring, optimization, TEA, and LCA could help determine whether improvements in yield and productivity translate into lower production costs and reduced environmental impacts. Overall, AI, digitalization, and Industry 4.0 offer promising approaches for developing intelligent and resource-efficient biofuel production systems, but their long-term benefits depend on reliable data, practical scalability, and demonstrable economic and environmental performance.

8. CONCLUSION

The integration of Artificial Intelligence (AI), digitalization, and Industry 4.0 technologies has the potential to significantly transform conventional biofuel production systems into intelligent, efficient, and sustainable biorefineries. These technologies enable advanced process monitoring, predictive modeling, optimization, automation, and real-time decision-making, thereby addressing many of the challenges associated with traditional biofuel production, such

as feedstock variability, high energy consumption, process inefficiencies, and operational instability. A Comprehensive Review on AI, Digitalization and Industry 4.0 in Biofuel Production Processes highlights that AI driven techniques including machine learning, artificial neural networks, digital twins, IoT enabled monitoring systems, and cyber physical infrastructures can improve biofuel yield, enhance resource utilization, reduce operational costs, and support environmentally sustainable production practices. Furthermore, these technologies have demonstrated promising applications across diverse biofuel pathways, including biodiesel, bioethanol, biogas, biohydrogen, and microalgae-based fuels, while enabling integrated assessment through techno-economic analysis and life-cycle evaluation. However, successful industrial implementation still faces challenges related to data quality, model transferability, cybersecurity, infrastructure costs, interoperability, and large-scale validation. Future advancements should focus on developing robust digital twins, integrating physics based and data driven models, improving the scalability of AI assisted systems, and validating these technologies under real industrial conditions. Ultimately, the convergence of AI, digitalization, and Industry 4.0 provides a strategic pathway toward the development of smart, resilient, economically viable, and environmentally sustainable biofuel production systems capable of supporting the global transition toward clean energy

REFERENCES

[1] Y. Sewsynker-Sukai, F. Faloye, and E. B. Gueguim Kana, "Artificial neural networks: An efficient tool for modelling and optimization of biofuel production (a mini review)," Biotechnology & Biotechnological Equipment, vol. 31, no. 2, pp. 221–235, 2017. https://doi.org/10.1080/13102818.2016.1269616

[2] I. Ahmad, A. Sana, M. Kano, I. I. Cheema, B. C. Menezes, J. Shahzad, Z. Ullah, M. Khan, and A. Habib, "Machine learning applications in biofuels' life cycle: Soil, feedstock, production, consumption, and emissions," Energies, vol. 14, no. 16, p. 5072, 2021. https://doi.org/10.3390/en14165072

[3] R. Yeassin, M. M. R. Adnan, M. M. A. Chowdhury, A. Mia, M. A. J. Chowdhury Enan, and M. H. Fuad, "A comprehensive review of biomass and biofuels and their progress using digital technologies," Energy Conversion and Management: X, vol. 28, p. 101254, 2025. https://doi.org/10.1016/j.ecmx.2025.101254

[4] J. A. Albarracin-Arias, M. Romans-Casas, P. Dessì, M. D. Balaguer, and S. Puig, "Digitalization of microbial electrosynthesis: Understanding operational variables for ethanol production optimization," Chemical Engineering Journal, vol. 534, p. 174960, 2026. https://doi.org/10.1016/j.cej.2026.174960

[5] M.-K. Song, D.-W. Kim, S. Mohanty, M. Son, S. S. Lee, E.-S. Salama, X. Li, R. Kumar, and B.-H. Jeon, "Energy-efficient machine learning approaches for enhanced biofuel (biodiesel) production: A review," Energy and AI, vol. 24, p. 100696, 2026. https://doi.org/10.1016/j.egyai.2026.100696

[6] V. H. Farheen, M. A. Abdullah, and I. G. Moorthy, "Lignocellulosic bioethanol production: A review on pretreatment strategies, biofuel separation, and artificial intelligence/machine learning-based sustainable optimization," Current Research in Biotechnology, vol. 11, p. 100355, 2026. https://doi.org/10.1016/j.crbiot.2025.100355

[7] F. Kanwal, A. Aslam, and A. A. J. Torriero, "Microalgae-based biodiesel: Integrating AI, CRISPR and nanotechnology for sustainable biofuel development," Emerging Topics in Life Sciences, 2025. https://doi.org/10.1042/ETLS20240004