BORNEO JOURNAL OF SCIENCES AND TECHNOLOGY (BJoST)
VOL. : 6, ISSUE: 1 , 96-104
DOI: http://doi.org/10.35370/bjost.2024.6.1-10
e-ISSN: 2672-7439 © 2018, UTS Publisher.

University of Technology Sarawak

ORIGINAL ARTICLE

Application of Supervised Machine Learning Models in Biodiesel Production Research - A Short Review

*[1]Amaranadha Reddy Manchuri, [2]Akhila Kakera, [3]Abu Saleh Ahmed and [4]Siva Raja Sindiramutty

[1]ESEL, Department of Environmental Engineering, Kyungpook National University, Daegu, Republic of Korea
[2]School of Engineering, Malla Reddy University, Hyderabad, India
[3]School of Engineering and Technology, University of Technology Sarawak, 96000 Sibu, Sarawak, Malaysia
[4]School of Computer Science, Taylor's University, Malaysia

ABSTRACT - Since industrialization, commercialization, and globalization of the supply chains in the world, non-renewable fossil fuels continue to be a primary source of energy for most of the segments. On the contrary, excessive consumption of these fuels has a significant impact on the environment and global ecosystem. Owing to several promising advantageous characteristics biodiesel fuels have attracted researchers and policy makers' attention as a replacement for non-renewable fossil diesels. There have been established biodiesel production experimental techniques focused on improving its yield and fuel characteristics. This short review focuses on covering supervised machine learning (SML) approaches in biodiesel production research. The SML methods powered predictions for biodiesel research not only optimizes the overall production process and fuel quality but also minimizes operational costs. The proposed analysis and directions will help prospective researchers in adopting machine learning to biodiesel research.

ARTICLE HISTORY
Received: 26 Nov 2023
Revised: 28 Dec 2023
Accepted: 11 Jan 2024

KEYWORDS
Biodiesel production, Mathematical modeling, Machine learning, Supervised learning, Optimization.

INTRODUCTION

Over 80% of global energy needs are primarily provided by fossil sources including coal, petroleum, and natural gas indicates their essential part in development and heavy dependency on non-renewable sources [1]. Essentially the depleting fossil fuel reserves and increased utilization in industrial and transport sectors emitting greenhouse gases (GHG), causing climate change, global warming, air pollution, health problems [2]. In addition, Organization of the Petroleum Exporting Countries (OPEC) statistical reports projected world's demand for diesel and gas fuels in 2040 as 1834 billion liters which is about 10% more compared to 2017 usages [3; 4]. These critical developments directly pose significant challenges to the environment, ecological imbalance, and humanity. Owing to the energy crisis, the researchers, and policymakers' interests moved contributions towards clean and renewable alternative fuels such as biodiesel. With the growing trends by 2030 renewable fuel generated energy is expected to have a share of 23%. Compared to 2021, in 2022 it is expected that globally biofuel demand is anticipated as 6% or 9 100 million liters [5].

Biodiesel has been received as a sustainable choice due to advantageous physicochemical fuel properties and lower exhaust gas emissions, except nitrogen oxides. Although biodiesel has many benefits, the fuel suffers from stumbling limitations such as lower calorific values, higher viscosity, pour and cloud points, corrosion for large scale commercialization [6]. Biodiesel can be used in diesel-powered engines without significant changes [7]. Nevertheless, production and use of biodiesel and petro diesel blends are growing in both developed and developing countries including the USA, Germany, France, Malaysia, India, Brazil, Argentina, and Indonesia [5].

In addition to numerous experimental explorations, mathematical or statistical modeling techniques are widely used in biodiesel production and quality metric optimization. Traditional statistical data

*Corresponding Author: Amaranadha Reddy Manchuri. Kyungpook National University,
email: dranreddy@gmail.com

models are widely used in biodiesel production optimization research. Nonetheless, these approaches are constrained to capture intricate non-linear correlations of the biodiesel production as well as inadequate databases. Also, the predictive capabilities of these models are constrained in processing large datasets. Hence, it is essential to develop efficient, robust, and accurate mathematical modelling procedures for analyzing the correlations among various operating parameters and to optimize the desired outputs [8]. Further, a robust system estimation minimizes experiments within the set boundary conditions. In recent years there has been an efficient use of data-driven machine learning (ML) models in biodiesel production [9-11]. This short review paper presents basics of biodiesel production parametric studies, followed by state of use of machine learning algorithms in biodiesel research. Lastly concludes with applications of supervised machine learning (SML) algorithms, emphasizing on future perspective for adapting to the field of biodiesel production research.

BIODIESEL FEEDSTOCK, PRODUCTION, AND QUALITY METRICS

Mathematically biodiesel production optimization is a multi-objective optimization problem (MOOP) [12; 13]. The objective functions concerned are complex and mutually depend on the competing constraints and parameters. The general form of MOOP is presented in Eq.1.

$$\begin{array}{lll} min/max\ f_m(x), & & m = 1,2,\dots,M \\ \text{Subject to} & g_j(x) \geq 0, & j = 1,2,\dots,J \\ & h_k(x) = 0, & k = 1,2,\dots,K \\ & x_i^{(L)} \leq x_i \leq x_i^{(U)} & i = 1,2,\dots,n \\ & L: Lower\ bound, U: Upper\ bound & \end{array} \quad (1)$$

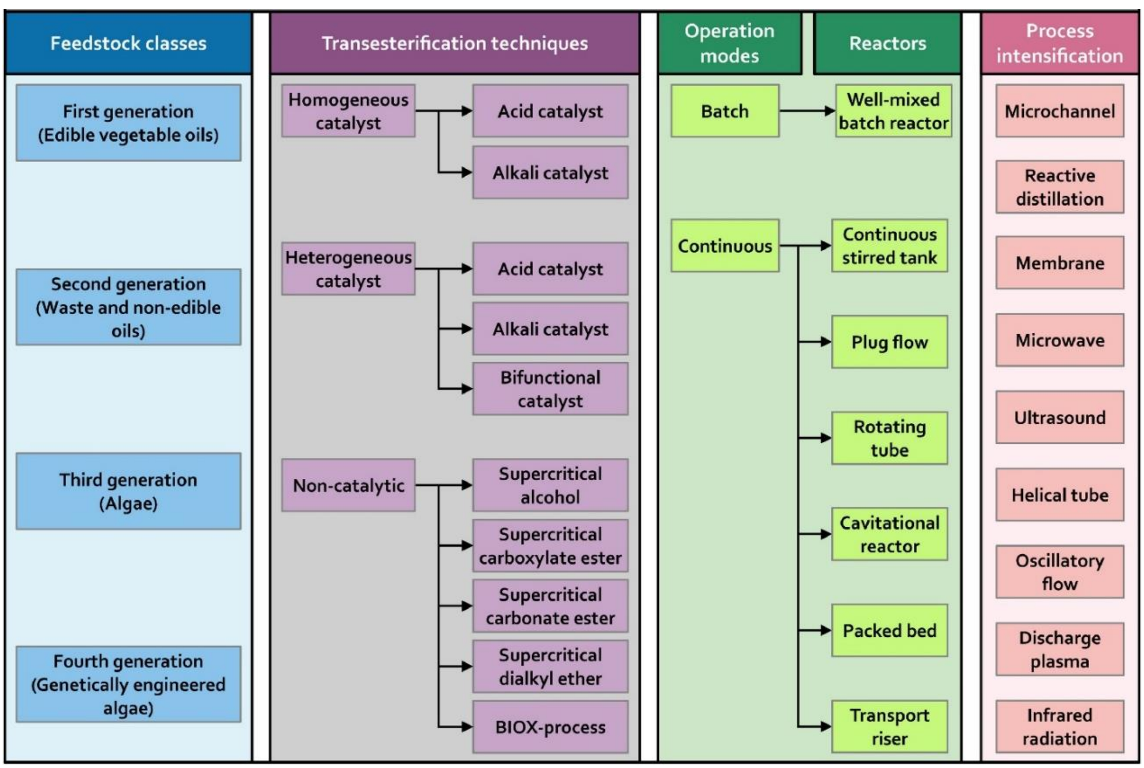

Figure 1. Classification of feedstock, techniques, reactors, and process intensification processes in biodiesel production [14; 15].

Classification and biodiesel production process influencing parameters are briefly presented in Figure 1. A wide range of promising feedstocks including edible non-edible vegetable oils, animal fat oils, waste oils and microalgae can be used for producing biodiesels. The feedstock source characteristics such as geographical regions, seed genetic conditions, harvest season have significant effects on oil refining and purification processes [16]. However, use of edible oils has been strategically critiqued because of its estimated impact on oil prices. The feedstocks contain long-chain fatty acids that remarkably influence biodiesel process kinetics. Biodiesel is produced by esterification of free fatty acids (FFAs) or transesterification of triglycerides (TG) in the presence of a catalyst.

Researchers explored non-catalyst pathways of biodiesel production such as supercritical conditions [6]. Besides, biodiesel production involves a critical chemical procedure controlled by many parameters involving feedstock physicochemical properties, (trans)esterification process, alcohol type and quantity, catalyst type and concentration, reaction time, reaction and ambient temperatures, reactor geometry [17]. Consequent to the complexities in the biodiesel production mechanism substantially undertook sophisticated design and modeling methodologies. Numerical modeling of (trans)esterification reaction kinetics considering heat and mass transfer boundary conditions and subsequent simulations enhances biodiesel production processes [18]. Optimization of controlling and operating conditions results in produced biodiesel quality and quantity along with minimizing production cost, time, and flexibility in feedstock resources [8].

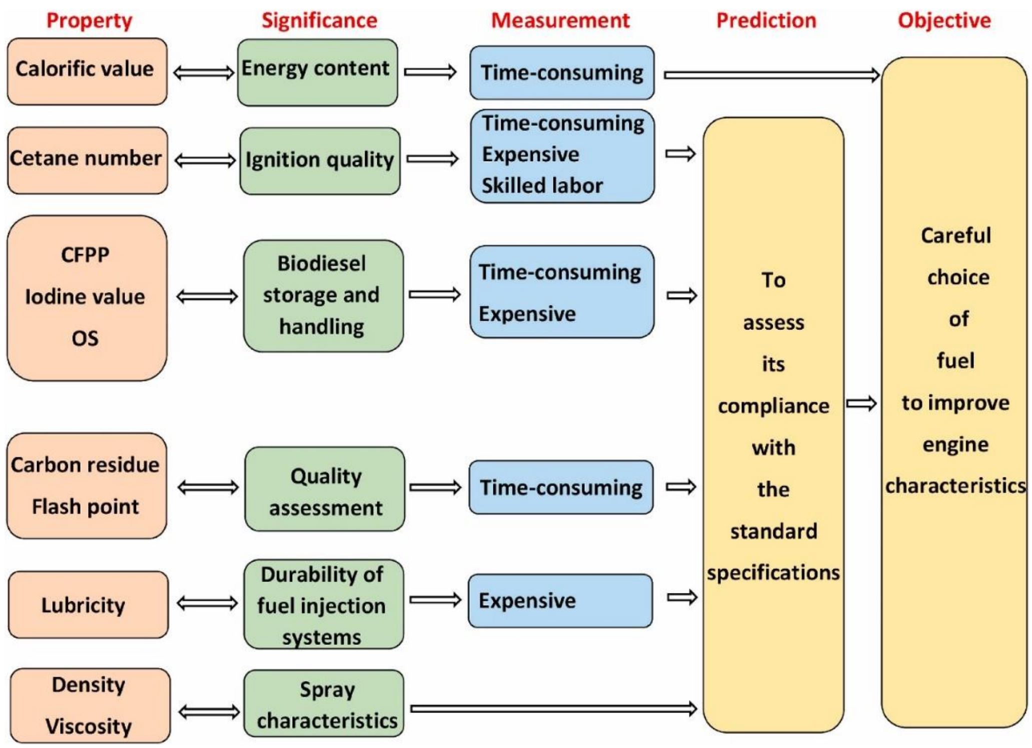

Figure 2. Importance of employing modeling techniques for predicting biodiesel fuel properties [19].

The biodiesel fuel properties determine its suitability for commercial application. European Norms (EN) and American Society for Testing and Materials (ASTM) standards determine fuel compliance. The important physicochemical property of a fuel includes density, viscosity, cetane number (CN), pour point (PP), cold point (CP), flash point (FP), cold filter plugging point (CFPP), oxidation stability (OS), iodine value (IV), acid value (AV) [16]. Many of these properties are potentially influenced by biodiesel feedstock, production process, storage, and transportation. Calibration, evaluation and optimization of the reaction kinetics of biodiesel production and its physicochemical properties require a comprehensive experimental data-driven analysis [19]. Importance of employing modeling techniques for predicting biodiesel fuel properties briefly resented in Figure 2. Statistical and mathematical models such as response surface methodologies are widely reported in optimizing including optimizing biodiesel production with limited datasets.

MACHINE LEARNING TECHNOLOGIES IN BIODIESEL PRODUCTION RESEARCH

Machine learning model analytics in biodiesel production research can be applied considering numerous process domains including feedstock classification and supply chain, catalyst, production mode, controlling and operating parameters, and physicochemical fuel properties. Figure 3 shows recent data of research publications and citation details that employed ML models in biodiesel production.

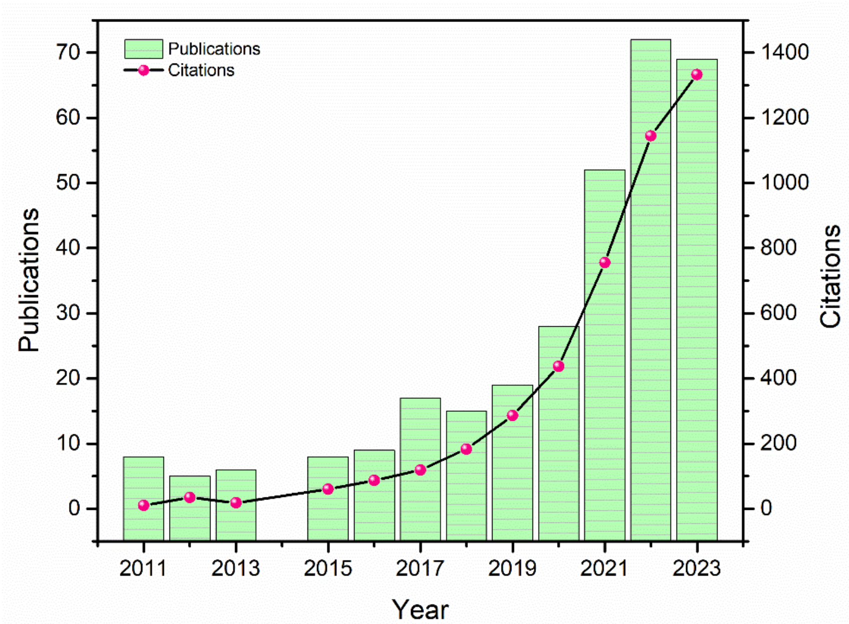

Figure 3. Number of research publications that dealt with employing machine learning in biodiesel production research.

The ML programs are proven as a predictive analytics approach, that uses computational methods structured on algorithms for learning from input data sets and training to generate desired responses as output. The input parameters for a typical biodiesel production include catalyst concentration, methanol to oil ratio, reaction temperature, reaction time and agitation speed [20; 21]. While the output responses include biodiesel yield and fuel quality. Implementation of ML model workflow is presented in Figure 4. The Major steps include dataset collection, data curation, ML model training, Predicting the responses, evaluation, and testing of the ML model. Selection and adoption of a ML model broadly evolves on both the responses and tradeoffs of data sets and their complexity.

Figure 4: Machine learning model workflow for biodiesel data processing.

The comprehensive efforts made to review on ML models employed in biodiesel research reveals their potential applications in classification of biodiesel feedstock, biodiesel production, fuel property analysis, and biodiesel fueled diesel engine analytics [15; 20; 21; 22]. Among all ML models, supervised learning algorithms are being potentially devoted in various biodiesel production applications and there is a much scope for development.

SUPERVISED MACHINE LEARNING MODELS IN BIODIESEL PRODUCTION RESEARCH.

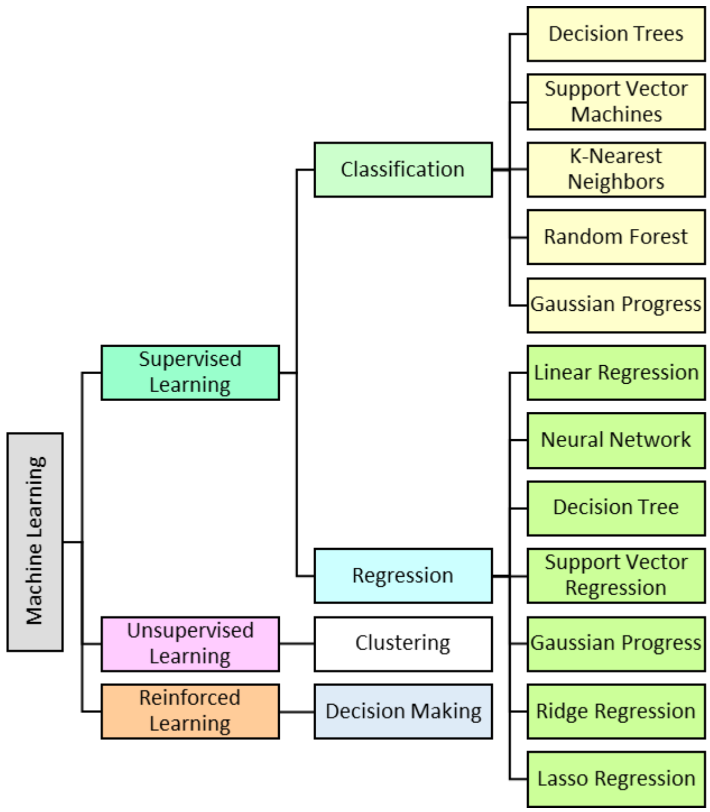

Figure 5. Broad categorization of supervised machine learning models.

A wide range of tailormade ML models are employed for multiple discoveries and optimization. Classification of ML algorithms shown in Figure 5. Broadly supervised learning, unsupervised learning, and reinforced learning. Supervised machine learning (SML) is a subcategory of ML, where a model is trained on a labeled dataset to yield the required output. While the results of these predictive analysis are used to build applications such as feedstock studies, fuel quality prediction, yield estimation, production optimization, and process parameters. In biodiesel research, for classification and regression analysis ML models are widely used. The built SML model's performance is being continuously evaluated to achieve desirable accuracy. Evaluation metrics that uses for cross validation of SML models include RMSE, R^2 and MAPE Eq. (2-4). However, based on ML models, other metrics such as F1 score, kolomogorov Smirnov chart, Gini coefficient, confusion matrix and log loss are also used [23-25].

$$\text{Root mean squared error } (RMSE) = \sqrt{\frac{\sum_{i=1}^{N}(Predivted_i - Actual_i)^2}{N}} \tag{2}$$

Where: *N is the total number of observations.*

$$\text{R} - \text{squared } (R^2) = 1 - \frac{Mean\ squared\ error\ (model)}{Mean\ squared\ error\ (baseline)} \tag{3}$$

$$\text{Mean absolute percent error } (MAPE) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Actual\ value_i - Forecast\ value_i}{Actual\ value_i}\right| \tag{4}$$

Table 1 describes biodiesel yield optimization employing various SML models considering input parameters including catalyst quantity (CQ), agitation speed (AS), methanol to oil ratio (MOR), reaction temperature, reaction time and agitation speed. Jin et al., employed three ML models kNN, SVM and RF to predict biodiesel production considering input features such as biodiesel feedstock type, catalyst, reaction temperature, and reaction time with a total of 381 experimental data collected from 13 cases [26]. Bukkarapu et al., [27] applied ANN and SVM based Multilinear regression models to predict biodiesel properties. Gradient boosting ML model combined with Genetic algorithm (GA) were utilized to predict and optimize biodiesel production yield from waste cooking oil feedstock [28]. AdaBoost regression ML models were utilized to predict fuel properties including flash point, oxidation stability, density, and viscosity for biodiesel fuel application public vehicles considering various reaction operating parameters including agitation speed, fuel blend composition, reaction duration and temperature [29]. Hoang et al. conducted experimental analysis of pyrolysis oil and biodiesel oil blends for an application of natural gas enriched homogeneous charge compression-ignition engine [30]. Data modeling and analysis was carried out employing RF and SVR ML models. A combination of Gradient boosting ML, RSM and GA were effectively employed for predicting WCO biodiesel yield and fuel characteristics and their applications in CI engines [31]. DNN, LR, PR and kNN ML algorithm models are adopted to prediction and analysis of Jatropha biodiesel production via transesterification process [32]. Silitonga et al. studied microwave assisted *Ceiba pentandra* oil biodiesel synthesis employing extreme ML algorithm models and RSM for optimizing process conditions considering methanol/ oil ratio, catalyst concentration, reaction time and stirring speed [33]. Long et al. applied ML model techniques on semi-continuous algal cultivation for biodiesel production [34]. Therefor the research works concluded that employing SML model predictions gives accurate results.

Table 1. Supervised machine learning models applied for biodiesel production research.

Feedstock(s)	Model input parameters					Dataset size	ML Model	Reference
	CQ	MOR	Temp	Time	AS			
Castor oil	✓	✓	✓	✓		156	ANN	[35]
Castor oil	✓	✓	✓	✓	✓	156	Least square SVM	[36]
Castor oil	✓	✓	✓	✓		156	SVM, GA	[37]
Degummed waste cooking oil	✓	✓		✓	✓	27	ANN and RSM	[38]
Esterified soybean oil	✓	✓		✓		17	LR and ANN	[39]
Esterified *Ceiba pentandra* oil	✓	✓	✓	✓	✓	46	kernel- ELM and ANN	[40]
Jatropha-algae oil blend	✓	✓	✓	✓		29	ANN	[41]
Polanga oil	✓	✓	✓	✓	✓	26	ANN, GA	[42]
Sunflower oil	✓	✓	✓	✓		456	ANN and RSM	[43]
waste cooking oil	✓	✓	✓	✓	✓	29	ELM SVM and RSM	[44]
waste cooking oil#	✓	✓	✓	✓	✓	56	SVM	[45]
Waste olive oil	✓	✓	✓	✓		45	ANN	[46]

#water content and impurity also considered for modeling

FUTURE PERSPECTIVES AND RECOMMENDATIONS

Biodiesel fuel production and physicochemical properties assessment relies on higher accuracy and predictability of a model. As discussed previously, biodiesel production is a complex process. There are numerous factors influencing the fuel yield and its characteristics. The traditional and other linear mathematical models are constrained with dataset processing approaches. Hence, there is a need for developing reliable and sophisticated models that accommodate non-linear relationships between empirical research results and production operating parameters. Owing to their simplicity the SML models are preferred to overcome the poor predictability of traditional linear models. Developing generic ML integrated models for datasets from laboratory experiments, industry and synthetic sources would enhance the model accuracy driven analytics. The analytics will help to breakthrough many limitations in this domain as well as commercialize the research.

CONCLUSION

Several supervised machine learning models are presented in literature to improve biodiesel production research specific to fuel quality and transesterification process are discussed. Major factors are given to standardize and perspectives for formulations based on multi objective optimization nature of biodiesel research. Credibility of data-driven models depends on size of the dataset as well as statistical validation approaches. The most important methodology for enhanced efficiency of predicted models in biodiesel research could be evolved from industrial scale research. Among reported literature limited efforts are devoted to building integrated models for biodiesel experimental research and industrial process results. Supervised machine learning powered empirical biodiesel processes will surely contribute to establish the most effective, inexpensive, and sustainable biodiesel supply chain as compared to the present.

REFERENCES

[1] P. Sharma, V. K. Gaur, R. Sirohi, S. Varjani, S. Hyoun Kim, and J. W. C. Wong, "Sustainable processing of food waste for production of bio-based products for circular bioeconomy," *Bioresour. Technol.*, vol. 325, p. 124684, Apr. 2021, doi: 10.1016/j.biortech.2021.124684.

[2] M. S. Habib, M. Omair, M. B. Ramzan, T. N. Chaudhary, M. Farooq, and B. Sarkar, "A robust possibilistic flexible programming approach toward a resilient and cost-efficient biodiesel supply chain network," *J. Clean. Prod.*, vol. 366, p. 132752, Sep. 2022, doi: 10.1016/j.jclepro.2022.132752.

[3] M. Aghbashlo *et al.*, "Exergoenvironmental analysis of bioenergy systems: A comprehensive review," *Renew. Sustain. Energy Rev.*, vol. 149, p. 111399, Oct. 2021, doi: 10.1016/j.rser.2021.111399.

[4] O. Bahadorizadeh, M. A. Sobati, and S. Shahnazari, "Emission characteristics of a semi-industrial boiler fueled by waste cooking oil biodiesel containing different metal oxide nanoparticles," *Process Saf. Environ. Prot.*, vol. 158, pp. 199–209, Feb. 2022, doi: 10.1016/j.psep.2021.11.050.

[5] IEA, "Biofuel use expands in 2022 despite rising costs," Renewables 2022. Accessed: Dec. 27, 2023. [Online]. Available: https://www.iea.org/reports/renewables-2022/transport-biofuels

[6] A. A. Babadi *et al.*, "Emerging technologies for biodiesel production: Processes, challenges, and opportunities," *Biomass and Bioenergy*, vol. 163, p. 106521, Aug. 2022, doi: 10.1016/j.biombioe.2022.106521.

[7] S. N. Gebremariam, "Biodiesel as a transport fuel, advantages and disadvantages: review," *Biofuels, Bioprod. Biorefining*, vol. 17, no. 5, pp. 1445–1456, Sep. 2023, doi: 10.1002/bbb.2503.

[8] S. N. Gebremariam and J. M. Marchetti, "Economics of biodiesel production: Review," *Energy Convers. Manag.*, vol. 168, pp. 74–84, Jul. 2018, doi: 10.1016/j.enconman.2018.05.002.

[9] S. D. Shelare *et al.*, "Biofuels for a sustainable future: Examining the role of nano-additives, economics, policy, internet of things, artificial intelligence and machine learning technology in biodiesel production," *Energy*, vol. 282, p. 128874, Nov. 2023, doi: 10.1016/j.energy.2023.128874.

[10] S. Sukpancharoen, T. Katongtung, N. Rattanachoung, and N. Tippayawong, "Unlocking the potential of transesterification catalysts for biodiesel production through machine learning approach," *Bioresour. Technol.*, vol. 378, p. 128961, Jun. 2023, doi: 10.1016/j.biortech.2023.128961.

[11] J. Ahmad, M. Awais, U. Rashid, C. Ngamcharussrivichai, S. Raza Naqvi, and I. Ali, "A systematic and critical review on effective utilization of artificial intelligence for bio-diesel production techniques," *Fuel*, vol. 338, p. 127379, Apr. 2023, doi: 10.1016/j.fuel.2022.127379.

[12] Kalyanmoy Deb, *Multi-Objective Optimization using Evolutionary Algorithms*. John Wiley and Sons Inc, 2001. [Online]. Available: https://www.wiley.com/en-kr/Multi+Objective+Optimization+using+Evolutionary+Algorithms-p-9780471873396

[13] N. Gunantara, "A review of multi-objective optimization: Methods and its applications," *Cogent Eng.*, vol. 5, no. 1, p. 1502242, Jan. 2018, doi: 10.1080/23311916.2018.1502242.

[14] E. López-Guajardo, E. Ortiz-Nadal, A. Montesinos-Castellanos, and K. D. P. Nigam, "Process Intensification

of Biodiesel Production Using a Tubular Micro-Reactor (TMR): Experimental and Numerical Assessment," *Chem. Eng. Commun.*, vol. 204, no. 4, pp. 467–475, Apr. 2017, doi: 10.1080/00986445.2016.1277521.

[15] M. Aghbashlo *et al.*, "Machine learning technology in biodiesel research: A review," *Prog. Energy Combust. Sci.*, vol. 85, p. 100904, 2021, doi: 10.1016/j.pecs.2021.100904.

[16] A. N. R. Reddy, A. A. Saleh, M. S. Islam, S. Hamdan, M. R. Rahman, and H. H. Masjuki, "Experimental evaluation of fatty acid composition influence on Jatropha biodiesel physicochemical properties," *J. Renew. Sustain. Energy*, vol. 10, no. 1, Jan. 2018, doi: 10.1063/1.5018743.

[17] A. N. R. Reddy, A. A. Saleh, M. S. Islam, and S. Hamdan, "Active Razor Shell CaO Catalyst Synthesis for Jatropha Methyl Ester Production via Optimized Two-Step Transesterification," *J. Chem.*, vol. 2017, pp. 1–20, 2017, doi: 10.1155/2017/1489218.

[18] R. ANR, A. A. Saleh, M. S. Islam, S. Hamdan, and M. A. Maleque, "Biodiesel Production from Crude Jatropha Oil using a Highly Active Heterogeneous Nanocatalyst by Optimizing Transesterification Reaction Parameters," *Energy & Fuels*, vol. 30, no. 1, pp. 334–343, Jan. 2016, doi: 10.1021/acs.energyfuels.5b01899.

[19] K. R. Bukkarapu and A. Krishnasamy, "A critical review on available models to predict engine fuel properties of biodiesel," *Renew. Sustain. Energy Rev.*, vol. 155, no. November 2021, p. 111925, 2022, doi: 10.1016/j.rser.2021.111925.

[20] Y. Xing, Z. Zheng, Y. Sun, and M. Agha Alikhani, "A Review on Machine Learning Application in Biodiesel Production Studies," *Int. J. Chem. Eng.*, vol. 2021, 2021, doi: 10.1155/2021/2154258.

[21] O. Awogbemi and D. V. Von Kallon, "Application of machine learning technologies in biodiesel production process—A review," *Front. Energy Res.*, vol. 11, Feb. 2023, doi: 10.3389/fenrg.2023.1122638.

[22] A. Coşgun, M. E. Günay, and R. Yıldırım, "Machine learning for algal biofuels: a critical review and perspective for the future," *Green Chem.*, vol. 25, no. 9, pp. 3354–3373, 2023, doi: 10.1039/D3GC00389B.

[23] C. Friedman and S. Sandow, *Utility-Based Learning from Data*. CRC Press, 2016. [Online]. Available: https://books.google.co.kr/books?id=CUaqDwAAQBAJ

[24] V. Bolón-Canedo and A. Alonso-Betanzos, *Intelligent Systems Reference Library 147 Recent Advances in Ensembles for Feature Selection*. [Online]. Available: http://www.kesinternational.org/organisation.php

[25] L. Abualigah, *Classification Applications with Deep Learning and Machine Learning Technologies*, vol. 1071. 2023.

[26] X. Jin *et al.*, "Investigation and optimization of biodiesel production based on multiple machine learning technologies," *Fuel*, vol. 348, p. 128546, Sep. 2023, doi: 10.1016/j.fuel.2023.128546.

[27] K. R. Bukkarapu and A. Krishnasamy, "Biodiesel composition based machine learning approaches to predict engine fuel properties," *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.*, p. 095440702311582, Mar. 2023, doi: 10.1177/09544070231158240.

[28] A. Ahmad, A. K. Yadav, and A. Singh, "Application of machine learning and genetic algorithms to the prediction and optimization of biodiesel yield from waste cooking oil," *Korean J. Chem. Eng.*, vol. 40, no. 12, pp. 2941–2956, Dec. 2023, doi: 10.1007/s11814-023-1489-9.

[29] Y. Yang *et al.*, "Innovative composite machine learning approach for biodiesel production in public vehicles," *Adv. Eng. Softw.*, vol. 184, p. 103501, Oct. 2023, doi: 10.1016/j.advengsoft.2023.103501.

[30] A. T. Hoang *et al.*, "Strategic combination of waste plastic/tire pyrolysis oil with biodiesel for natural gas-enriched HCCI engine: Experimental analysis and machine learning model," *Energy*, vol. 280, p. 128233, Oct. 2023, doi: 10.1016/j.energy.2023.128233.

[31] A. Ahmad, A. K. Yadav, and A. Singh, "Enhancing waste cooking oil biodiesel yield and characteristics through machine learning, response surface methodology, and genetic algorithms for optimal utilization in CI engines," *Int. J. Green Energy*, pp. 1–21, Sep. 2023, doi: 10.1080/15435075.2023.2253870.

[32] A. Khanna *et al.*, "Biodiesel Production from Jatropha: A Computational Approach by Means of Artificial Intelligence and Genetic Algorithm," *Sustainability*, vol. 15, no. 12, p. 9785, Jun. 2023, doi: 10.3390/su15129785.

[33] A. S. Silitonga *et al.*, "Biodiesel synthesis from Ceiba pentandra oil by microwave irradiation-assisted transesterification: ELM modeling and optimization," *Renew. Energy*, vol. 146, pp. 1278–1291, Feb. 2020, doi: 10.1016/j.renene.2019.07.065.

[34] B. Long *et al.*, "Machine learning-informed and synthetic biology-enabled semi-continuous algal cultivation to unleash renewable fuel productivity," *Nat. Commun.*, vol. 13, no. 1, p. 541, Jan. 2022, doi: 10.1038/s41467-021-27665-y.

[35] A. Banerjee, D. Varshney, S. Kumar, P. Chaudhary, and V. K. Gupta, "Biodiesel production from castor oil: ANN modeling and kinetic parameter estimation," *Int. J. Ind. Chem.*, vol. 8, no. 3, pp. 253–262, Sep. 2017,

doi: 10.1007/s40090-017-0122-3.

[36] C. Deng, S. Gong, and W. Gao, "Biodiesel production from oil-rich feedstock: A neural network modeling," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 40, no. 6, pp. 638–644, Mar. 2018, doi: 10.1080/15567036.2018.1454544.

[37] Y. Zhang and C. Niu, "Toward estimation of biodiesel production from castor oil using ANN," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 40, no. 12, pp. 1469–1476, Jun. 2018, doi: 10.1080/15567036.2018.1477873.

[38] A. Avinash and A. Murugesan, "Prediction capabilities of mathematical models in producing a renewable fuel from waste cooking oil for sustainable energy and clean environment," *Fuel*, vol. 216, pp. 322–329, Mar. 2018, doi: 10.1016/j.fuel.2017.12.029.

[39] S. Kumar, "Comparison of linear regression and artificial neural network technique for prediction of a soybean biodiesel yield," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 42, no. 12, pp. 1425–1435, Jun. 2020, doi: 10.1080/15567036.2019.1604858.

[40] F. Kusumo, A. S. Silitonga, H. H. Masjuki, H. C. Ong, J. Siswantoro, and T. M. I. Mahlia, "Optimization of transesterification process for Ceiba pentandra oil: A comparative study between kernel-based extreme learning machine and artificial neural networks," *Energy*, vol. 134, pp. 24–34, Sep. 2017, doi: 10.1016/j.energy.2017.05.196.

[41] S. Kumar, S. Jain, and H. Kumar, "Prediction of jatropha-algae biodiesel blend oil yield with the application of artificial neural networks technique," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 41, no. 11, pp. 1285–1295, Jun. 2019, doi: 10.1080/15567036.2018.1548507.

[42] S. Dhingra, K. K. Dubey, and G. Bhushan, "A Polymath Approach for the Prediction of Optimized Transesterification Process Variables of Polanga Biodiesel," *J. Am. Oil Chem. Soc.*, vol. 91, no. 4, pp. 641–653, Apr. 2014, doi: 10.1007/s11746-013-2409-7.

[43] O. S. Stamenković, K. Rajković, A. V. Veličković, P. S. Milić, and V. B. Veljković, "Optimization of base-catalyzed ethanolysis of sunflower oil by regression and artificial neural network models," *Fuel Process. Technol.*, vol. 114, pp. 101–108, Oct. 2013, doi: 10.1016/j.fuproc.2013.03.038.

[44] S. Faizollahzadeh Ardabili, B. Najafi, M. Alizamir, A. Mosavi, S. Shamshirband, and T. Rabczuk, "Using SVM-RSM and ELM-RSM Approaches for Optimizing the Production Process of Methyl and Ethyl Esters," *Energies*, vol. 11, no. 11, p. 2889, Oct. 2018, doi: 10.3390/en11112889.

[45] M. Corral Bobadilla, R. Fernández Martínez, R. Lostado Lorza, F. Somovilla Gómez, and E. Vergara González, "Optimizing Biodiesel Production from Waste Cooking Oil Using Genetic Algorithm-Based Support Vector Machines," *Energies*, vol. 11, no. 11, p. 2995, Nov. 2018, doi: 10.3390/en11112995.

[46] A. J. Yuste and M. P. Dorado, "A Neural Network Approach to Simulate Biodiesel Production from Waste Olive Oil," *Energy & Fuels*, vol. 20, no. 1, pp. 399–402, Jan. 2006, doi: 10.1021/ef050226t.