

Review

Energy-efficient machine learning approaches for enhanced biofuel (Biodiesel) production: A review

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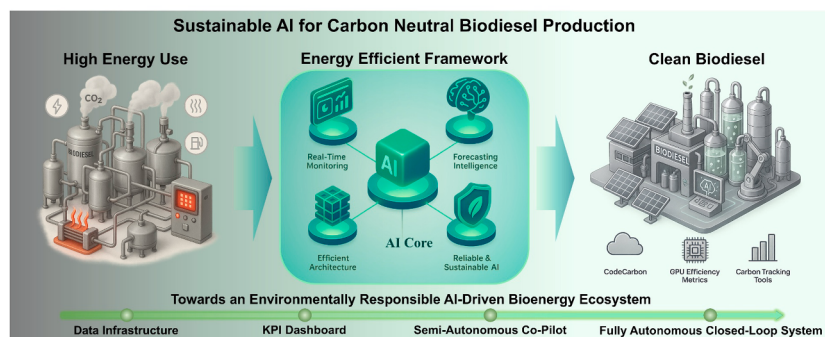
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HIGHLIGHTS

- Fossil fuel decline and climate change drive innovations in clean energy.
- AI aids in maximizing conventional yield through process control and optimization.
- Energy use and environmental impact are key concerns for developing large AI models.
- Data-driven, human-assisted, AI-validated strategies ensure safe digital transition.
- Integrating bioenergy with sustainable AI advances carbon-neutrality goals.

GRAPHICAL ABSTRACT



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ABSTRACT

Biodiesel represents a sustainable alternative to fossil fuels and aligns with long-term decarbonization goals. Integrating economic efficiency with sustainability requires a reinvention of process technology and artificial intelligence (AI)-based advanced prediction tools to maximize performance and minimize costs and carbon

Abbreviations: AI, Artificial Intelligence; ANNs, Artificial neural networks; CN, Cetane Number; DL, Deep Learning; DFT, Density functional theory; DACs, Diatomic Catalysts; DVFS, Dynamic Voltage and Frequency; ETS, Emission Trading Schemes; EER, Energy Efficiency Ratio; EPI, Energy per Inference; XAI, Explainable AI; XGB, Extreme Gradient Boosting; FAMES, Fatty acid methyl esters; FPGA, Field-Programmable Gate Array; FP, Flash Point; FTIR, Fourier Transform Infrared Spectroscopy; GPR, Gaussian process regression; GA, Genetic Algorithm; GNNs, Graph Neural Networks; GPUs, Graphics Processing Units; IAE, Integral of Absolute Error; IEA, International Energy Agency; IoT-ML, Internet of Things and ML; KPI, Key Performance Indicator; LCA, Life Cycle Assessment; LCC, Life Cycle Costing; ML, Machine Learning; MOFs, Metal-Organic Frameworks; MILP, Mixed-Integer Linear Programming; MLP, Multilayer Perceptron; NIRS, Near-Infrared Spectroscopy; NAS, Neural Architecture Search; ANFIS, Neuro-Fuzzy Inference System; NMR, Nuclear Magnetic Resonance Spectroscopy; RFs, Random forests; RL, Reinforcement Learning; RQs, Research Questions; RSM, Response Surface Methodology; SACs, Single-Atom Catalysts; SVMs, Support Vector Machines; SDGs, Sustainable Development Goals; TPUs, Tensor Processing Units; WCO, Waste cooking oil.

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