JOIV : Int. J. Inform. Visualization, 8(1) - March 2024 55-78

INTERNATIONAL JOURNAL
ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

Harnessing a Better Future: Exploring AI and ML Applications in Renewable Energy

Tien Han Nguyen [a], Prabhu Paramasivam [b], Van Huong Dong [c], Huu Cuong Le [d], Duc Chuan Nguyen [d,*]

[a] *Hanoi University of Industry, Hanoi, 100000, Vietnam*
[b] *Department of Research and Innovation, Saveetha School of Engineering, SIMATS, Chennai, Tamil Nadu, 602105, India*
[c] *Institute of Mechanical Engineering, Ho Chi Minh City University of Transport, Ho Chi Minh, 700000, Vietnam*
[d] *Institute of Maritime, Ho Chi Minh City University of Transport, Ho Chi Minh, 700000, Vietnam*
*Corresponding author: *chuan.nguyen@ut.edu.vn*

***Abstract*—Integrating machine learning (ML) and artificial intelligence (AI) with renewable energy sources, including biomass, biofuels, engines, and solar power, can revolutionize the energy industry. Biomass and biofuels have benefited significantly from implementing AI and ML algorithms that optimize feedstock, enhance resource management, and facilitate biofuel production. By applying insight derived from data analysis, stakeholders can improve the entire biofuel supply chain - including biomass conversion, fuel synthesis, agricultural growth, and harvesting - to mitigate environmental impacts and accelerate the transition to a low-carbon economy. Furthermore, implementing AI and ML in combustion systems and engines has yielded substantial improvements in fuel efficiency, emissions reduction, and overall performance. Enhancing engine design and control techniques with ML algorithms produces cleaner, more efficient engines with minimal environmental impact. This contributes to the sustainability of power generation and transportation. ML algorithms are employed in solar energy to analyze vast quantities of solar data to improve photovoltaic systems' design, operation, and maintenance. The ultimate goal is to increase energy output and system efficiency. Collaboration among academia, industry, and policymakers is imperative to expedite the transition to a sustainable energy future and harness the potential of AI and ML in renewable energy. By implementing these technologies, it is possible to establish a more sustainable energy ecosystem, which would benefit future generations.**

***Keywords*— Machine learning; artificial intelligence; renewable energy; biofuel; biomass energy.**

Manuscript received 25 Oct. 2023; revised 17 Dec. 2023; accepted 22 Feb. 2024. Date of publication 31 Mar. 2024.

I. INTRODUCTION

As we work toward a more sustainable and fair future, the synergies between the Sustainable Development Goals (SDGs), ambitions for reaching net-zero emissions, and machine learning are becoming increasingly apparent [1]–[3]. This comprehensive framework for addressing global concerns, such as poverty, inequality, and climate change, is provided by the Sustainable Development Goals (SDGs) [4], [5]. By emphasizing climate action and environmental sustainability, net-zero targets, which aim to achieve a balance between the removal of greenhouse gases and the emissions of those gases, are closely aligned with these aims [6], [7]. Machine learning is critical in accelerating progress toward the SDGs and net-zero objectives [8], [9]. Machine learning can analyze massive volumes of data and recognize complex patterns [10], [11]. Through the utilization of machine learning algorithms, we can optimize the allocation of resources, enhance the efficiency of energy use, and develop novel solutions for the sustainability of development, system protection, and the mitigation of climate change [12]–[15]. Furthermore, machine learning improves decision-making processes by offering insights and predictive analytics [16], [17]. This enables governments, companies, and communities to make educated decisions that align with the SDGs and contribute to the achievement of net-zero emissions [18]–[20]. Integrating machine learning with the SDGs and net-zero objectives provides a potent way to address urgent global concerns and drive substantial progress toward a more sustainable and resilient future for everyone [21]–[23].

Recently, there has been a significant transformation in the renewable energy sector, establishing it as a crucial element in the global energy landscape, especially during the post-COVID-19 pandemic [24]. Renewable energy sources like solar, biofuels, wind, hydropower, biomass, and geothermal energy are gaining popularity worldwide [25]–[32]. Solar power has become a significant player in the shift towards renewable energy sources [33], [34], benefiting from factors such as the decreasing costs of photovoltaic technology and supportive legislation [35], [36]. A surge in utility-scale solar installations and rooftop solar panels for residential and commercial buildings has been observed worldwide, aiming to increase the proportion of renewable energy contributing to energy systems and reduce greenhouse gas [37], [38]. In addition, solar energy could also be used for other purposes such as distillation, heat generation, and hydrogen generation [39]–[41]. Similarly, wind energy has experienced considerable growth, especially in regions with favorable wind conditions [42]–[44]. Wind farms, whether on land or at sea, are experiencing significant growth, with advancements in turbine technology enhancing their performance and output [45]–[47]. Both large-scale dams and smaller-scale projects play essential roles in harnessing hydroelectric power, a significant source of energy globally [48]. Aside from aiding in electricity production and heat generation, biomass and bioenergy, including organic and agricultural waste, play a crucial role in reducing carbon emissions across various industries [49]–[51]. In addition, municipal solid waste, including waste tire, plastic waste, and industrial waste, could also be reused to produce energy and value-added chemicals [52]–[55]. Geothermal power is used to produce electricity and hydrogen and for heating directly [56], [57]. Acquiring geothermal energy involves extracting heat from beneath the Earth's surface. Several worldwide trends fuel the growth of renewable energy sources [58], [59]. In recent years, there have been many studies relating to waste heat recovery, and the waste-to-energy path could also be a potential and promising solution for achieving green energy [60]–[63]. These trends encompass decreasing costs, technological advancements, regulatory support, efforts to combat climate change, and a growing recognition of the significance of environmental sustainability [64]–[66]. Despite facing challenges like grid integration and intermittency [67], [68], ongoing developments in energy storage [69], [70], using phase change materials [71]–[73], grid infrastructure [74], [75], and renewable energy forecasting [76]–[78] are addressing these issues and creating new opportunities for the expansion of renewable energy. Ultimately, renewable energy has transformed from a niche option to a widely adopted energy source, vital in the global shift towards a sustainable, low-carbon future [79]–[82].

There is a critical problem that requires an immediate response. That problem is the rising need for energy (used for industry, agriculture, and daily life) [83]–[85] and fuels (for transportation means such as ships, automobiles, and motive, motorcycles) [86]–[90] throughout the world. It is becoming increasingly vital for us to rely on various renewable energy sources, notably solar energy, as the requirements of humans continue to expand [91], [92]. We must switch to renewable energy sources like solar, wind, and hydrothermal energy because fossil fuels, which were previously the foundation of our energy systems, are now a large contributor to carbon dioxide released into the atmosphere [93], [94]. It is necessary to hasten the transition to clean energy as the dominant energy source to achieve global carbon neutrality [95], [96]. Not only does this need the development of new technologies, but it also necessitates the creation of superior materials that can give continuous energy output. This change is driven chiefly by solar energy, which may be converted into thermal energy by photovoltaic techniques and solar thermal conversion [97]–[99]. In addition, the technology of renewable fuel cells is gaining substantial momentum within the field of clean energy, notably in the context of battery-operated mobility. The following are recent studies discussing and summarizing various renewable energy domains as shown in Table 1.

TABLE I
RECENT STUDIES IN THE RENEWABLE ENERGY DOMAIN

Topic	Main outcomes	Study type	Sources
Solar stills	The findings indicated that the operational factors of the solar still system with an inclined weir type had a substantial effect on the amount of water produced.	Experimental and modeling	[100]
Green hydrogen production	According to thorough evaluations and computations, Canada's total capacity for green hydrogen generation is 201.12 Mt, 205.69 Mt, and 211.17 Mt, based on proton exchange membrane, alkaline, and anion exchange membrane electrolyzers.	Analytical	[101]
Solar radiation	To improve efficiency, radiation is distributed non-uniformly. Heat transmission on the cold side ought to be improved via non-uniform radiation.	Analytical	[102]
Perovskite solar cells	According to a review of research, perovskite solar cells (PSCs) have potential as photovoltaic (PV) technologies because of their high-power conversion efficiency (PCE) and cheap manufacturing costs.	Review	[103]
AI-based prognostic modeling	AI-based GEP helped in model prediction and RSM helped in accurate optimization.	Analytical modeling	[104]
Optimization approach of biohydrogen production	Optimization of biohydrogen synthesis process with high accuracy.	Analytical modeling	[105]
Management of biochar yield	Application of ML for modeling-forecasting of biochar from biomass.	Review of modeling techniques.	[106]
Photovoltaic thermal system	Application of neural networks in the complex domain of PCM-based solar system.	Analytical modeling	[107]
Prediction of biofuel properties	Model-forecasting of biofuel properties and its use in diesel engines.	Analytical modeling	[108], [109]
Optimization of fuel consumption	AI-based optimization was employed for navigation time as well as fuel consumption.	Modeling	[110]

The field of renewable energy is characterized by a great deal of uncertainty, which is caused by a variety of causes, including variations in the weather, shifts in the demand for energy, and limitations presented by technology [111], [112]. When it comes to effectively integrating renewable energy sources into the existing energy infrastructure, dealing with these uncertainties creates a significant number of hurdles [113], [114]. In spite of this, the development of technologies such as artificial intelligence (AI) and machine learning (ML) is proving a substantial influence in addressing these difficulties and releasing the full potential of renewable energy sources [115][116]. Utilizing artificial intelligence and machine learning algorithms to examine large data sets derived from weather forecasts, historical energy production data, and other relevant sources can result in more accurate predictions for the generation of renewable energy [117], [118] This can be accomplished through enhanced forecasting and planning. The provision of assistance to energy operators and grid management in the prediction of changes in supply and demand, the optimization of energy production schedules, and the effective planning for grid integration [119]–[121].

The incorporation of renewable energy sources into existing power grids requires the implementation of intricate control and optimization strategies in order to maintain the grid's stability and dependability. The application of artificial intelligence and machine learning techniques can improve grid management by dynamically modifying energy flows, monitoring energy storage installations, and predicting possible disturbances to the grid. minimizing disruptions to the system while ensuring the smooth integration of renewable energy sources of electricity [122], [123]. The application of artificial intelligence and machine learning algorithms to improve the design and operation of renewable energy systems, such as solar farms, wind turbines, and energy storage facilities, is called "enhancing energy systems." These technologies can improve energy efficiency, maximize production, and minimize operating expenditures. This may be accomplished by analyzing data about site conditions, equipment performance, and energy use patterns. The typical application of and timeline ML penetration in this domain is depicted in Fig. 1 [124].

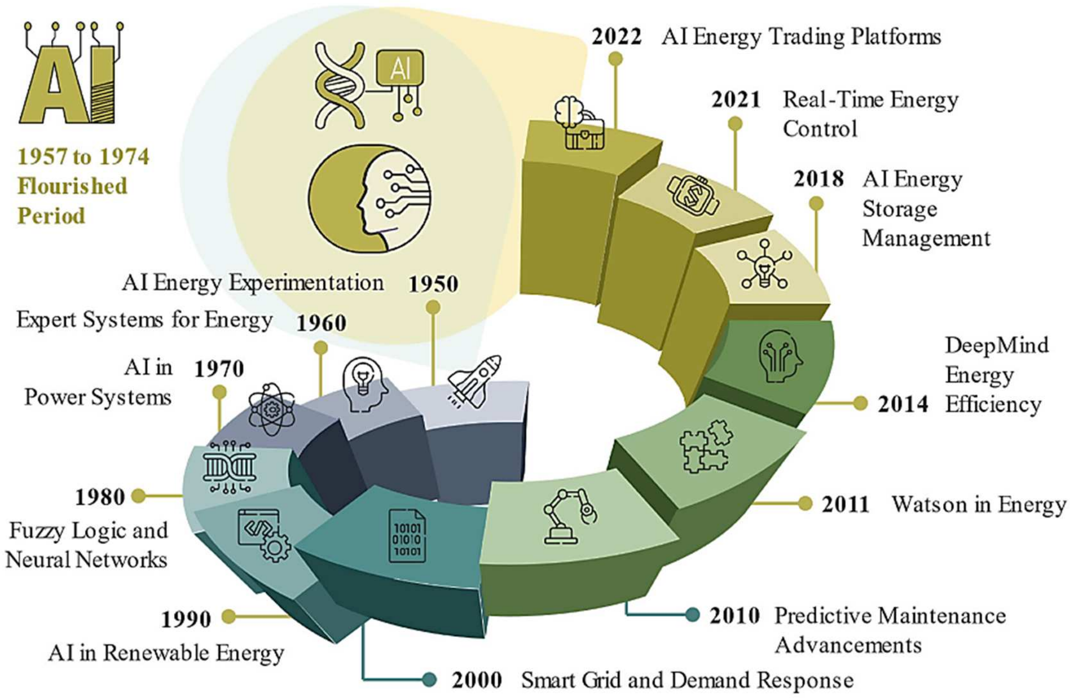

Fig. 1 Historical perspective of AI & ML penetration in the energy domain [124]

The application of artificial intelligence and machine learning algorithms has the potential to improve resource allocation in renewable energy projects. This can be accomplished by identifying the most suitable locations for new installations, selecting the renewable energy technologies that are most suitable for particular sites, and streamlining the distribution of resources such as land, materials, and labor [125], [126]. The optimization of project development procedures and the enhancement of the overall efficacy of investments in renewable energy are both positively impacted in this way. The utilization of artificial intelligence and machine learning technology enables the forecasting of maintenance needs in renewable energy infrastructure [127]–[129]. This is accomplished by analyzing data from sensors and monitoring equipment in order to identify potential equipment problems in advance. The use of this proactive strategy helps reduce the amount of time that equipment is down, extends its lifespan, and improves the reliability of the system [130], [131]. The uncertainties that exist within the sector of renewable energy provide complex issues that can be effectively addressed via the application of technologies that utilize artificial intelligence and machine learning. AI and ML are helping personnel working in the renewable energy sector to make well-informed decisions, improve system performance, and accelerate the transition toward a sustainable energy future. This is being accomplished through the utilization of data-driven insights, predictive analytics, and sophisticated optimization techniques.

Examining the utilization of Artificial Intelligence (AI) and Machine Learning (ML) in renewable energy holds significant value for various purposes. It addresses the urgent need for sustainable energy solutions by exploring how AI and machine learning technologies could enhance the effectiveness, reliability, and expandability of renewable energy systems [132]–[134]. Furthermore, this publication illuminates the interdisciplinary nature of this emerging field, connecting renewable energy research with advancements in artificial intelligence and machine learning. Through synthesizing the latest research and emphasizing key patterns and challenges, it educates policymakers, industry stakeholders, and decision-makers on the potential outcomes of implementing AI and ML in renewable energy. A review article serves as a valuable educational tool for students, researchers, and professionals looking to enhance their knowledge of renewable energy and AI/ML applications. In general, writing a review article on this topic helps to expand understanding, inspire creativity, and accelerate the shift toward clean and sustainable energy.

II. Material and Methods

When looking for scholarly articles on the subject for a review, the Boolean search tactics were employed. These tactics use keywords and operators like AND, OR, and NOT to filter search results. A researcher starts by combining keywords linked to artificial intelligence and machine learning with those connected to renewable energy, utilizing "or" to include synonyms or similar phrases to capture a broader range of relevant articles. To ensure a thorough search, they may include related topics or technologies such as deep learning, neural networks, solar, wind, hydro, or biomass was employed.

For searching particular applications of AI and ML in renewable energy, such as optimization, energy management, forecasting, or grid integration, these phrases were employed. Incorporating terminology associated with particular technologies or applications in the AI, ML, and renewable energy domains, such as smart grids, energy storage, or predictive maintenance, might also be advantageous. To discover the most recent study, the most recent years in their search were included. Combining these tactics allows a researcher to do a comprehensive search that covers all areas of their subject. However, the effectiveness of their search is heavily reliant on the database or digital library being utilized. Each platform has its syntax for Boolean searches; thus, the same was employed on platforms such as IEEE Xplore, Scopus, or Google Scholar. The related papers published in recent years have been growing at a good pace. The relationship between different terms in this domain is depicted in Fig. 2 [135].

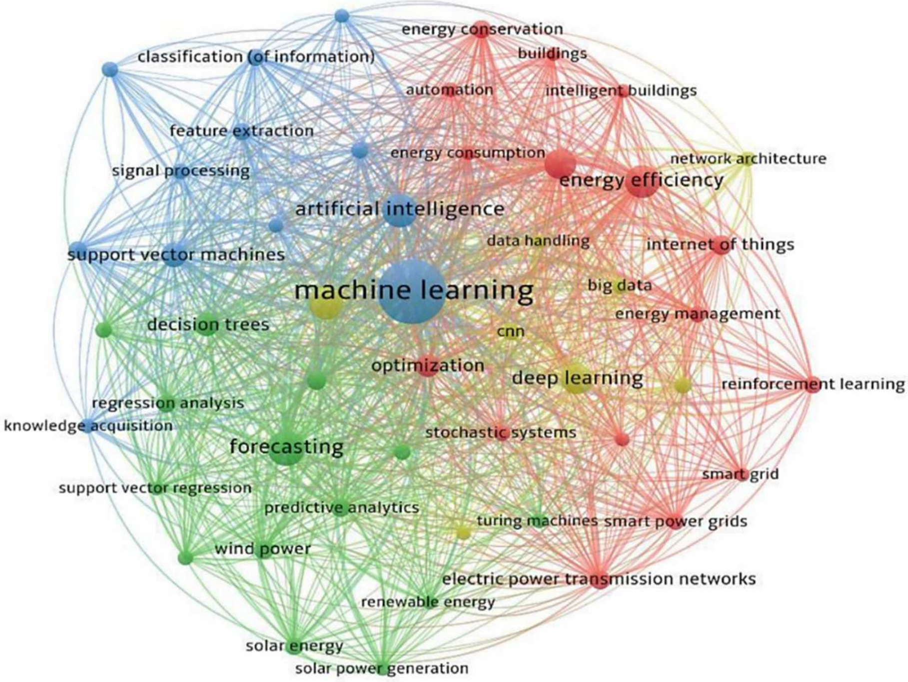

Fig. 2 An overview of ML and energy systems [135]

III. Results and Discussion

A. AI and ML Techniques in Renewable Energy Forecasting

1) Solar Power Forecasting:

The radiant energy of the sun is referred to as solar energy [136]. This energy is produced by the thermonuclear fusion of hydrogen gas, which results in massive amounts of electromagnetic energy. There is an average solar radiation intensity of 1367 W/m^2 on the surface of the planet, and the total global absorption of solar energy is around 1.8 × 1011 MW [137]. This amount of energy that is both ubiquitous and unlimited is more than sufficient to take care of the power requirements of the whole globe [138], [139]. The pursuit of a kind of energy that is both environmentally friendly and sustainable has quickly become a serious worldwide concern, especially in the world that we live in today [140]. The fast collapse of conventional energy sources such as oil and fossil fuels, together with worldwide environmental issues such as global warming and the increased need for electricity and energy, are the primary factors that have led to the emergence of this crisis [141]. Solar photovoltaic cells are the most widely used and well-established green energy systems [142]–[144], which are employed to meet the growing need for energy on a worldwide scale. This is because solar PV cells are among the many environmentally friendly and renewable energy technologies that are now accessible [145], [146]. In the same way that other energy sources have their flaws, solar photovoltaic cells have their shortcomings and face a great deal of difficulty throughout the integration process [126], [147], [148]. Solar photovoltaic cells, on the other hand, are presently being employed in a tremendous variety of contemporary applications as a result of quick technical developments [149], [150]. Some systems create just a few watts, whereas others generate megawatts of electricity on a daily capacity [151], [152].

In the field of solar energy, the use of machine learning has grown more important since it provides innovative approaches to improvements in output and efficiency [153]. The use of solar energy is becoming more dependable and simpler to incorporate into current power networks as a result of advancements in predictive analytics and panel layout optimization [154], [155]. Machine learning has made significant strides in the field of solar energy, and one of its most important applications is in predictive analytics [156]. The ability of machine learning algorithms to anticipate solar power output with exceptional accuracy is achieved by the study of historical weather patterns, levels of solar radiation, and a variety of environmental factors [157], [158]. The capacity to operate the grid effectively requires this skill, which enables solar energy to be integrated more effectively with other sources of electricity. When it comes to guaranteeing a steady energy supply and lowering dependency on non-renewable energy backups, forecasting is an essential component. This, in turn, encourages the use of solar energy to a greater extent [159]–[161]. A typical work flow of solar power forecasting using ML is depicted in Fig. 3 [162].

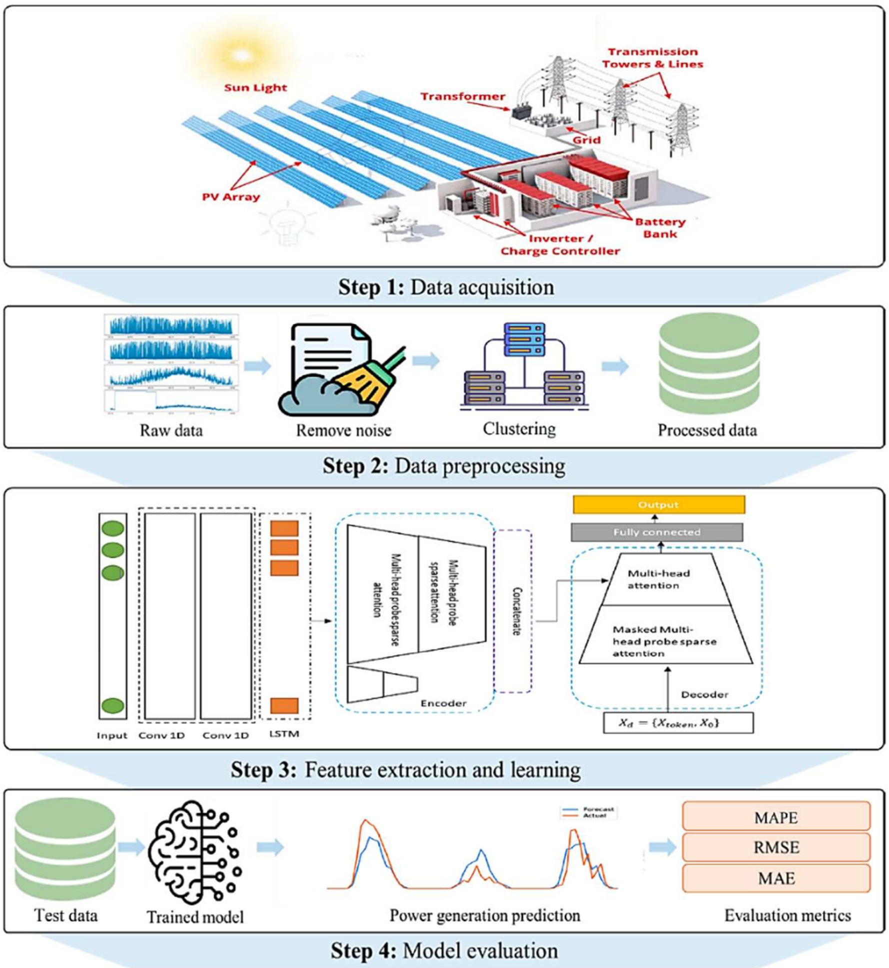

Fig. 3 A typical work flow of solar power forecasting using ML [162]

Machine learning is very necessary in order to maximize the efficiency of the positioning and orientation of solar panels [163], [164]. By analyzing the patterns of sunshine, the topography, and other geographical aspects, machine learning algorithms are able to provide recommendations for the optimal locations and angles for the deployment of solar panels in order to maximize energy capture [165], [166]. When this process is optimized, not only does it increase the efficiency of solar farms, but it also ensures that smaller, dispersed installations such as rooftop panels make a significant contribution to the production of electricity [167], [168]. An additional benefit of machine learning is that it assists with the maintenance and operation of solar power plants [169]. It is able to predict equipment faults or detect when solar panels are not performing properly due to dirt accumulation, damage, or other issues. Additionally, it can detect when solar panels are not functioning ideally. Through the use of predictive maintenance skills, issues may be rectified in a proactive manner, hence minimizing the chance of downtime and maximizing the effectiveness and durability of solar energy systems [170]–[172].

The creation of solar cells that are more efficient is another area in which machine-learning techniques aid [173]. The use of machine learning in the examination of vast amounts of data pertaining to the characteristics of materials and the designs of solar cells may reveal patterns and connections that human researchers would overlook, which ultimately leads to breakthroughs in solar cell technology [174], [175]. The results of this research might result in the creation of solar panels that are more efficient in terms of cost, which could hasten the process of solar electricity being more widely used [176]–[178].

In essence, the use of machine learning in solar energy is a major innovation that has the potential to improve the accessibility, efficiency, and integration of renewable energy into our energy systems [179]. It is projected that the use of machine learning technology in solar energy will increase as a result of its improvement, which will result in the creation of more inventive solutions in the field of renewable energy technologies [180], [181]. The following (Table II) is the summary of the use of different ML techniques in the domain of solar energy:

TABLE II
APPLICATION OF ML TECHNIQUES IN THE SOLAR ENERGY DOMAIN

Main theme	ML technique	Main outcome	Source
Prediction of daily solar radiation	Multiple MLs	Artificial neural network (ANN) was superior to other test ML techniques	[182]
Daily solar radiation mapping	Six ML techniques	Extreme learning machine (ELM) combined with particle swarm optimization provided the best predictions among six test MLs	[183]
Prediction of daily and monthly solar radiations	ANN, support vector machines (SVM), adaptive neuro-fuzzy inference system (ANFIS), Gaussian process regression (GPR), Multiple linear regression (MLR), Radial basis function (RBF)	With a mean absolute percentage error (MAPE) of 5.1% and a root mean squared error (RMSE) of 0.29, the RBF model was able to predict solar radiation efficiently.	[184]
Use of Pearson correlation for solar energy forecasting	Random forest (RF), ANN, LR and SVM	ANN was superior with robust predictions	[185]
Photovoltaic (PV) power forecasting	GPR and SVM	Matern 5/2 GPR was superior in forecasting	[186]
Site selection and power forecasting using ML	Long short-term memory (LSTM), Gated recurrent unit (GRU), ANN	ML models outperformed conventional approaches by as much as 38% in the site adaptation test.	[187]
Comparative analysis of ML and conventional approaches for solar radiation and PV power	Maxwell and transportation models, SVM, RF RNN, LSTM, and GRU	The best prediction was by LSTM and GRU.	[188]
Application of multiple MLs for solar radiation	SVM, LSTM, GPR, ELM, and k-nearest neighbor (KNN)	LSTM and GPR could provide the best prediction results.	[189]

The incorporation of machine learning (ML) into solar energy systems ushers in a new age of efficiency and sustainability in the field of renewable energy [190]. The solar business is overcoming conventional difficulties, maximizing energy output, and improving system maintenance by using the predictive capabilities of machine learning (ML) [191]–[193]. Solar energy can be more successfully incorporated into the global energy mix thanks to the ability of machine learning to evaluate and learn from enormous quantities of data. This will result in a reduction in dependency on fossil fuels and will help mitigate climate change. The role that machine learning technologies play in enhancing the efficiency and dependability of solar energy systems will likely expand as these technologies continue to advance [194], [195]. This holds the promise of a more positive and environmentally friendly future powered by renewable energy [196]–[198].

2) Biofuel-based Energy Forecasting

As the principal source of energy, traditional fossil fuels continue to hold a dominant position [199]. Because of the ever-increasing demand and the ever-increasing population of the world, the dwindling stocks of fossil fuels provide a problem for the future supply of these resources [200], [201]. The ever-increasing need for energy may be satisfied by the effective production of biofuel that could be used for transportation means [202], [203]. The problem is further attenuated by the increasing greenhouse gases (GHGs) caused by the use of fossil fuels [199], [204]. Taking a holistic approach to addressing global environmental concerns and advancing sustainable development may be accomplished by analyzing the relationship between the Sustainable Development Goals (SDGs), the achievement of net-zero emissions, the exploration of alternative fuels, and the distinctive contribution of biodiesel [205], [206]. There is a need for several measures to combat climate change, reduce emissions, and ensure that everyone has access to sustainable energy sources [207], [208]. This interconnection underscores the need for these initiatives [117], [209]–[211].

Goal 7 of the Sustainable Development Goals, which focuses on providing affordable and clean energy, and Goal 13 of the Sustainable Development Goals, which focuses on climate action, offer the foundation for a global transition to renewable energy sources and reducing carbon footprints [212]. Maintaining a balance between the greenhouse gases that are released into the atmosphere and those that are removed from the atmosphere is an essential component of achieving net-zero emissions, which will contribute to a future that is both sustainable and climate-resilient. The investigation of alternative fuels, such as biodiesel, biogas, bioethanol, and furan, is vital in the process of shifting to more sustainable choices that have the potential to successfully reduce emissions from transportation [213]–[216], which is a significant contributor to global greenhouse gas emissions [7], [217], [218].

The practical application of these relationships is shown by biodiesel, which is a sustainable biofuel that may be generated from vegetable oils, animal fats, or recycled cooking grease [219], [220]. In comparison to conventional fossil fuels, this product is not only non-toxic but also biodegradable and produces far less emissions. Making the switch from conventional fuels to biodiesel may be of great assistance to nations in achieving their net-zero objectives, improving energy security, reducing their dependency on imported fuels, and providing support to the local agricultural and recycling industries [221][222]. As an additional point of interest, the production and consumption of biodiesel contributes to Sustainable Development Goal 12 (Responsible Consumption and Production) by promoting resource efficiency and reducing waste. SDG 8 is advanced via the creation of job opportunities in the area of renewable energy, while SDG 9 is advanced through the promotion of scientific developments in the production and consumption of biofuels. Both of these goals are advanced through the inclusion into the energy mix [6], [23], [223].

The use of machine learning, a subfield of artificial intelligence, has revolutionized a wide range of sectors via the analysis of enormous amounts of data and the generation of predictions or judgments without the need for explicit programming for specific tasks [224]. The applications of this technology span a broad variety of domains, with the primary emphasis being placed on forecasting engine performance and emission frameworks, in addition to optimization.

When it comes to the performance of engines and the emissions they produce, machine learning algorithms are applied to foresee and improve engine operations in various circumstances. The engine's efficiency, the amount of fuel it uses, and the pollution levels may all be predicted by these algorithms via the analysis of sensor data and historical performance reports [225]–[227]. The literature reveals that engine researchers mainly focused on engine performance metrics like brake thermal efficiency (BTE), brake-specific fuel/energy consumption (BSFC/BSEC), peak cylinder pressure (PCP), and heat release rate (HRR) [228]–[232]. Also, on the emission side oxides of nitrogen (NOx), carbon mono oxide (CO), unburnt hydrocarbons (UHC), and carbon dioxide (CO_2), particulate matter (PM) [233]–[236] were reported. However, these parameters are quite sensitive to changes in engine operating parameters like compression ratio, fuel supply, fuel injection parameters, and engine hardware [237], [238]. The conventional methods of simulation and modeling are time-consuming and tiresome. Also, to support global activities aimed at lowering carbon footprints and tackling climate change, it is vital to place a primary emphasis on the development of engines that are both sustainable and efficient [239]–[241]. The use of machine learning models enables the modeling of a variety of situations, which in turn reveals ideal configurations that conventional experimentation techniques would overlook. Machine learning finds applications in mainly two domains: firstly, the model-prediction of engine performance and emission framework, and secondly in the optimization [242]. Some studies showed the usefulness and applicability of ML in this domain to effectively apply ANN for model and prediction of engine performance and emissions [110], [238], [243]. It could be observed that ANN was mainly used in this domain. Besides this other ML techniques like ANFIS [244], [245], XGBoost [246], GPR [247], Gene expression programming (GEP) [248], [249], SVM, and RF [250], [251] are being applied for model predictions.

On the other hand, optimization is a prominent application field that focuses on using machine learning to enhance processes and systems in various industries. In many industries, including manufacturing, logistics, and energy distribution, machine learning algorithms are particularly adept at evaluating complex information to identify the most efficient routes, production schedules, and distribution management techniques [242][252]. We can save costs and decrease our environmental impact if we optimize our performance. The use of machine learning to improve diesel engines that are fuelled by biodiesel includes predictive modeling, optimization of fuel injection, modeling of combustion, fault detection, and optimum control techniques [253], [254]. As an example, machine learning algorithms scrutinize biodiesel blends' compositions, the engine's state, and environmental elements to anticipate performance and emissions. Through the use of sophisticated models that mimic combustion in a variety of settings, they fine-tune the timing and pressure of fuel injection to maximize combustion efficiency. When it comes to defect detection, machine learning enables the rapid identification of abnormalities, which in turn facilitates the fast repair of infrastructure. Continuous optimization of engine settings is performed to improve fuel economy and lower emissions via the use of optimum control systems [255]. Machine learning enhances the performance of biodiesel engines, which results in these engines being more environmentally friendly and efficient than conventional diesel engines.

Even though the biofuel business has the potential to make a substantial contribution to the development of sustainable energy solutions, it is often confronted with several challenges that prevent its expansion and general adoption [256], [257]. The dispute that is usually referred to as the "food versus fuel" debate is a serious topic since it involves the struggle for agricultural land and water resources between biofuel production and food production [258]. There is a possibility that this rivalry may lead to a rise in the cost of food and will inspire concerns about food security, especially in regions with a scarcity of agricultural resources.

Furthermore, biofuels' consequences on the ecosystem are a complicated topic. Even though they could reduce greenhouse gas emissions in contrast to fossil fuels, the benefits can be nullified by the carbon footprint associated with changes in land use, farming, and the manufacturing of biofuels [259], [260]. Deforestation and a reduction in biodiversity are two consequences that might result from the transformation of land for the cultivation of biofuel crops under certain circumstances [261]–[263].

There is one additional challenge to take into consideration, and that is the financial viability of biofuels [264][265]. Biofuels typically depend on government subsidies and policy support to compete with conventional fuels. As a result of fluctuations in oil prices, the cost-competitiveness of biofuels might be affected, which can result in unclear market prospects [266]–[268]. In addition, the biofuel industry requires significant advancements in both technology and infrastructure to improve efficiency and reduce costs [269], [270]. This includes the production of biofuels from non-food sources such as agricultural waste and algae, as well as the establishment of the necessary distribution and retailing networks to make biofuels accessible to consumers [271], [272]. Last but not least, it is essential to consider the social and ethical issues, such as the impact that widespread biofuel production has on the communities located nearby, the rights of landowners, and the development of rural areas. To successfully address these difficulties, it is essential to adopt a holistic strategy that considers the economic, environmental, and social elements of the production and use of biofuels. In this way, it will be possible to guarantee that the expansion of the biofuel business plays a positive part in the global move toward energy systems that are both sustainable and environmentally friendly [273]. A typical flow chart showing the application of intelligent approaches in this domain is depicted in Fig. 4 [274].

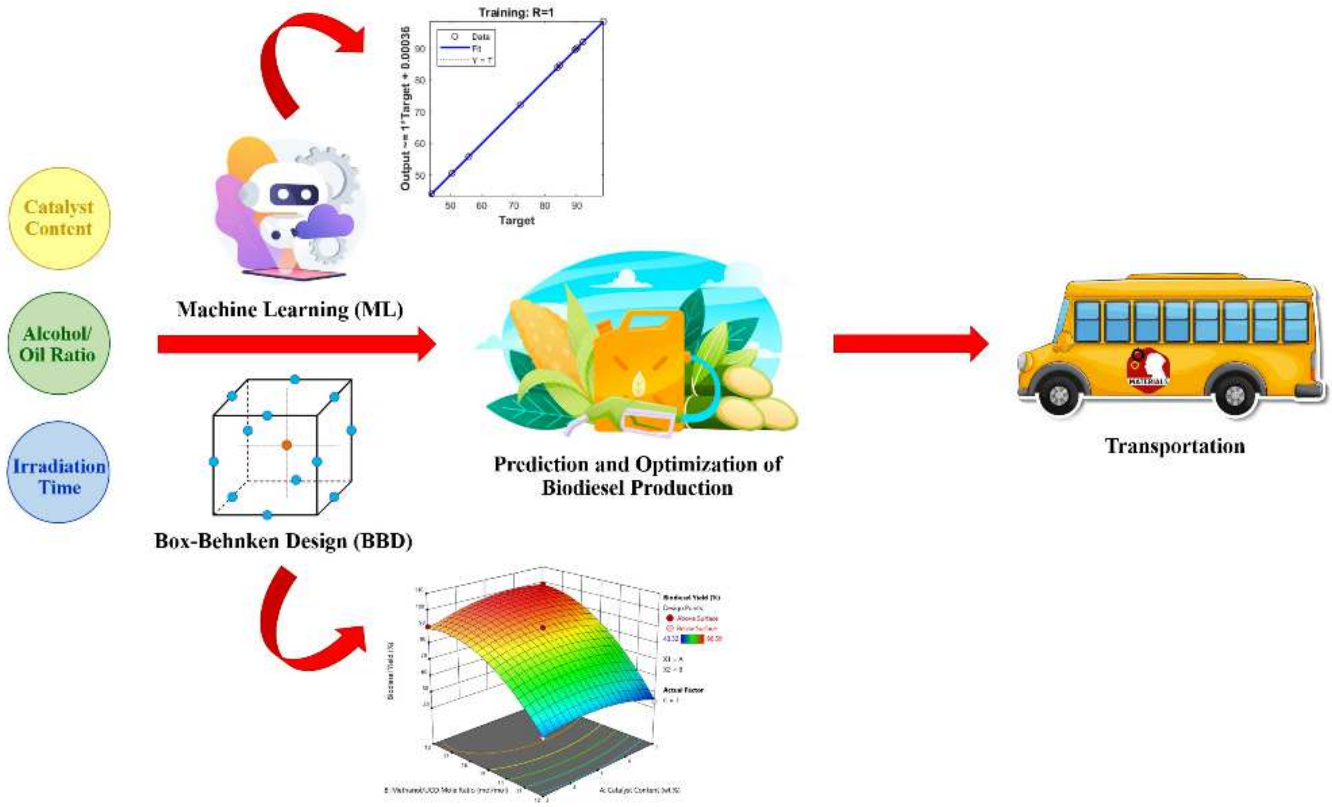

Fig. 4 Application of intelligent approaches in the biofuel domain [274]

The biofuel sector has a wide variety of challenges, and machine learning offers several intriguing opportunities to address and overcome these challenges. Through data analysis and predictive modeling, machine learning has the potential to enhance the efficiency, sustainability, and economic viability of the production and consumption of biofuels. Here are some of the ways that machine learning might be beneficial to the biofuel industry:

- Large amounts of agricultural data, including weather patterns, soil conditions, and crop health, may be examined with the use of machine learning algorithms to anticipate and improve crop yields, notably for the production of biofuels [275]. By optimizing this process, we can solve the argument over the "food versus fuel" issue by increasing the efficiency of the production of biofuel crops. Consequently, this might result in the creation of greater output with less amount of land, thus protecting more area for the production of food.
- Through the use of machine learning models, one may improve their understanding of the complex biochemical processes that are involved in the synthesis of biofuels [276]. Due to the fact that these models are able to forecast the most efficient processing methods and ideal conditions for converting biomass into biofuels, they are able to reduce the amount of energy that is used and the amount of waste that is produced throughout the manufacturing process [277]. The

manufacture of biofuels has the potential to have a smaller carbon footprint and fewer negative impacts on the environment if artificial intelligence is used to optimize these methods.

- By using machine learning, the process of developing advanced biofuels from non-food sources such as agricultural residue, algae, and cellulosic materials may be accelerated, resulting in much faster advancement. The most advantageous feedstocks and growing techniques may be identified by machine learning algorithms via the examination of genetic data and growth circumstances. This helps to improve sustainability and reduce the amount of rivalry with food production [278].
- It is possible to develop accurate projections for biofuel demand, pricing, and competitiveness by using machine learning algorithms to undertake an analysis of market patterns, oil prices, and policy influences. To improve the economic viability of biofuels, this research may be of assistance to biofuel producers and investors in making choices that are well-informed, getting finance, and reacting to changing market circumstances [279].
- For biofuels to be widely used, it is necessary to ensure that they are distributed effectively from production facilities to end-users. Machine learning has the potential to improve logistics and supply chain operations, resulting in reduced transportation costs and emissions. Additionally, it will ensure that biofuels are delivered to high-demand markets in an efficient manner [280].
- Machine learning algorithms are able to evaluate the environmental consequences of biofuels over their whole lifespan. These effects include but are not limited to changes in land usage, water consumption, and emissions of greenhouse gases [281].

By addressing these difficulties, machine learning improves the efficiency and long-term viability of the biofuel business and contributes to the sector's growth and integration into the global energy environment. With the ongoing development of machine learning technologies, it is anticipated that their influence on the biofuel business will increase dramatically, ultimately resulting in the creation of more environmentally friendly and economically viable biofuel solutions. Table III lists the summary of the application of different ML techniques in the domain of solar energy:

TABLE III
APPLICATION OF ML TECHNIQUES IN THE BIOFUEL ENERGY DOMAIN

Main theme	ML technique	Main outcome	Source
Prediction of biodiesel characteristics and fatty acid profile	LR, RF, XGboost, and SVM	Using a machine learning framework to forecast biodiesel fuel properties based on its fatty acid composition	[282]
Predictive modeling of biodiesel production	RF and AdaBoost	AdaBoost was efficient in the optimization of process parameters	[283]
Model forecasting of engine operation	ANN and response surface methodology	The study uncovered that ANN-RSM is a valuable hybrid technique for model- prediction.	[284]
Evaluation and forecasting to determine biodiesel purity	Alternating model tree, RF, MLP-ANN, and least median square	Results reveal that the AMT stands out as the top forecasting technique.	[285]
Forecasting of biodiesel production	Bayesian-optimized SVR and ANN	Hybrid SVR approach outperformed the other approach	[286]
Model-prediction of engine performance	ANN-Fuzzy	The hybrid approach could accurately predict the engine performance	[287]
The modeling forecasting of biofuel-powered engine	ANN-Genetic algorithm – RSM	A triple-blended biofuel-powered engine performance could be modeled with more than 90% accuracy.	[288]
Emission and performance prediction of engine running on biofuel blends	ANN-RSM	It was observed that RSM could optimize, and ANN could accurately predict the biofuel-powered engine.	[289]

Using machine learning (ML) in the biofuel industry is a significant step toward creating an energy environment that is more environmentally friendly and efficient. Artificial intelligence (ML) provides exciting solutions for tackling issues in the biofuel business because of its capacity to evaluate big datasets, forecast results, and enhance procedures. Machine learning is vital for the economic and environmental success of biofuel production since it allows for the optimization of crop yields, the enhancement of production procedures, and the development of new feedstocks. In addition, machine learning makes it possible to do market research, optimize supply chain operations, and evaluate environmental impact, which provides stakeholders along the biofuel value chain with helpful information [290]. As the need for renewable energy continues to rise, the role that machine learning plays in fostering innovation and speeding the adoption of biofuels is becoming more critical. To unlock the full possibilities of machine learning in the biofuel business, academics, industry participants, and policymakers will need to collaborate to overcome technological, economic, and regulatory constraints. Biofuels that have been enhanced via ML-based optimization and innovation might make a big contribution to the transition to a more sustainable energy future [291], [292]. This is because considerable focus has been placed on addressing difficulties, which has led to breakthroughs in machine learning technology.

3) Biomass Energy Forecasting

A comprehensive approach to combating climate change and achieving sustainable development goals may be accomplished by investigating the relationship between biomass usage, the pursuit of net-zero emissions, the generation of renewable energy, and the reduction of greenhouse gas emissions [293]–[295]. Energy generation may benefit greatly from the use of organic materials such as agricultural leftovers, by-products of forestry, and crops cultivated explicitly for energy production. In addition to facilitating the transition to a low-carbon economy, they provide a variety of strategies for reducing greenhouse gas emissions [296]–[298].

One of the most critical aspects of this synergy is the concept of biomass as a source of energy that is either carbon-negative or carbon-neutral [299], [300]. During the process of photosynthesis, biomass crops can remove carbon dioxide from the atmosphere when they are handled correctly. A closed carbon cycle is completed when these materials are converted into bioenergy by processes such as combustion, gasification, or anaerobic digestion [301]–[304]. By these processes, carbon dioxide is released into the atmosphere. As a result of this process, carbon absorption and release are brought into equilibrium, which ultimately results in either net-zero emissions or maybe even net-negative emissions when biomass residues are used as fuel by the process [106], [305]. As an additional benefit, biofuels that are generated from biomass, such as biodiesel and bioethanol, provide environmentally friendly alternatives for the transportation and industrial sectors, resulting in a significant reduction in emissions of greenhouse gases. These biofuels have the potential to be combined with conventional fuels or employed in machines and power plants that are designed specifically for that purpose [306]. This provides an energy source that is less harmful to the environment and has a longer lifespan while also promoting energy independence and safeguarding the environment [307]–[310].

The storage of carbon dioxide in long-lasting biomass products or the use of carbon capture and storage (CCS) technology are two ways in which biomass energy systems may function as carbon sinks in addition to their ability to reduce direct greenhouse gas emissions [259]. Biochar, for example, is a stable form of carbon that is produced by the pyrolysis of biomass. When applied as a soil supplement, biochar can potentially increase soil fertility and carbon sequestration properties [311], [312]. Similarly, CCS systems can sequester carbon dioxide (CO_2) emissions from biomass power plants or bioenergy facilities beneath the ground, effectively removing carbon from the atmosphere [313], [314]. In addition, biomass energy is compatible with other renewable energy sources, such as solar and wind power, and it provides reliable electricity production, which contributes to the maintenance of grid stability and the fulfillment of shifting energy needs [212]. Because power plants that use biomass can quickly modify their output to complement intermittent renewable sources, they are able to provide a consistent energy supply and reduce the need for backup power from fossil fuels [315], [316]. Additionally, sustainable land management techniques are included in the relationship between the use of biomass and the reduction of greenhouse gas emissions [317], [318]. This connection extends beyond the production of electricity. For the purpose of increasing biomass production, improving carbon sequestration, and promoting biodiversity conservation, the implementation of agroforestry, reforestation, and afforestation initiatives might be beneficial. The production of biomass in conjunction with environmentally responsible land management methods is an approach that plays a significant part in bolstering the resilience of ecosystems and aiding attempts to adapt to climate change [319], [320].

Therefore, it is vital to carefully examine sustainability criteria to fully harness the potential of biomass in terms of achieving net-zero emissions and mitigating greenhouse gas emissions [321]. When it comes to producing sustainable biomass, it is of the utmost importance to prioritize preserving the environment, preserving biodiversity, and the promotion of social fairness. This should be done without disrupting food production or the natural ecosystems. When it comes to ensuring the responsible sourcing and exploitation of biomass, it is essential to establish certification programs that are open and transparent, robust regulatory frameworks, and the participation of stakeholders [322]–[324].

The use of biomass, the pursuit of net-zero emissions, the implementation of renewable energy, and the reduction of greenhouse gas emissions constitute a holistic strategy for combating climate change and furthering sustainable development [325]. Exploring biomass energy systems may provide a flexible and sustainable energy source that plays a vital part in reducing greenhouse gas emissions, assisting in the transition towards a low-carbon economy, and enhancing the resilience of ecosystems [326], [327]. Through the strategic usage of biomass in a way that is both sustainable and integrated, communities have the opportunity to achieve ambitious climate targets while simultaneously fostering economic growth, energy stability, and environmental conservation [328], [329].

Even though biomass energy has the potential to be a source of renewable energy, the industry faces several severe hurdles that prevent it from being widely adopted and from being scalable [330], [331]. One of the most significant challenges is the rivalry for biomass resources that exists between other industries, such as the production of food and the preservation of land [332], [333]. The "food versus fuel" debate is sparked when agricultural land formerly used for food production is diverted to produce energy crops [294], [334]. This raises concerns about food security, changes in land usage, and deforestation. It is necessary to engage in careful land-use planning and sustainable management methods to avoid unfavorable impacts on the environment and society and achieve a balance between biomass production for energy and other essential requirements [335]–[337].

The variable nature of biomass feedstocks and their accessibility is another challenge the biomass energy business must contend with [338]. The availability of biomass is affected by seasonal variables, weather conditions, and agricultural cycles, in contrast to fossil fuels, which can be collected and stored for lengthy periods [339]. Because of this fluctuation, there are uncertainties in the supply chains of biomass, which ultimately affects the reliability and cost-efficiency of the generation of biomass energy. When it comes to the logistics and transportation of biomass feedstock, issues arise, especially in rural and distant places that have little or inadequate infrastructure [340], [341].

In addition, the widespread adoption of biomass energy systems is hampered by difficulties of technological and technical character. Combustion, gasification, and anaerobic digestion are examples of technologies that may be used to convert biomass [342][343]. These technologies need sophisticated machinery and complex procedures, which can be costly to set up. Because the use of either inefficient or obsolete technologies may impede the economic viability of biomass energy projects, efficiency and scalability are two of the most important elements to consider. The inclusion of biomass energy into existing energy systems and grids involves some technological challenges, particularly about grid stability, energy storage, and system flexibility [344], [345]. This is especially true when biomass is exploited in conjunction with intermittent renewable energy sources such as solar and wind power.

Addressing the issue of environmental sustainability continues to be a big concern for business that deals with biomass energy [346], [347]. However, inappropriate ways of producing and using biomass may lead to undesirable environmental impacts such as deforestation, soil degradation, and the loss of biodiversity. This is even though biomass has the potential to reduce greenhouse gas emissions in contrast to fossil fuels [348]. The implementation of stringent sustainability standards, the performance of lifecycle assessments, and the establishment of regulatory frameworks to guarantee the responsible sourcing, production, and utilization of biomass feedstocks are all necessary steps to take to ensure that the environmental benefits of biomass energy are balanced with its potential environmental drawbacks.

Several factors play a key role in determining the growth and development of the biomass energy industry, including economic and regulatory problems. There are several factors that might present obstacles to the development of biomass energy projects and investments, including policy frameworks, government backing, and changes in the energy market [349], [350]. Additionally, the lack of financial incentives and market strategies to capitalize on the environmental and social benefits of biomass energy adds to the complexity of its economic viability and attraction to investors. This is because there are no market methods to profit from these benefits [351], [352].

In order to effectively address these difficulties, a complete approach is required, one that incorporates technical improvements, regulatory support, the participation of stakeholders, and sustainable management practices [353]. By overcoming these challenges, the biomass energy industry has the potential to have a stronger influence in the fight against climate change, the enhancement of energy security, and the promotion of sustainable development [354]. Machine learning offers promising solutions for overcoming the many challenges that the biomass energy business faces, to enhance its efficiency, environmental friendliness, and viability from a financial standpoint [355], [356]. Machine learning may help handle these difficulties in a number of different ways, including the following:

- Improving the Management of Biomass Resources**:** Machine learning algorithms are able to analyze a wide variety of data sources, including satellite imaging, climate data, and soil information, in order to improve the management of biomass resources [357]. An improvement in decision-making about land usage, crop selection, and harvest schedules may be supported by machine learning [358]–[360]. This can be accomplished via the study of biomass availability, growth patterns, and quality. The goal is to increase biomass output while simultaneously reducing environmental damage [361].
- Improving the Logistics of the Biomass Supply Chain: Machine learning has the potential to improve the logistics of the biomass supply chain by predicting demand, optimizing routes, and scheduling operations in an efficient manner. In the end, machine learning algorithms have the potential to improve inventory management, reduce transportation costs, and reduce the amount of biomass that is lost during storage and transit. This will eventually lead to an increase in the efficiency of the generation of biomass energy [322], [362].
- Improving the Processes of Biomass Conversion: Machine learning has the potential to improve the efficiency and functionality of several technologies that are used for the conversion of biomass [363]. These technologies include combustion, gasification, and analytical digestion. Machine learning algorithms may improve operating parameters, discover abnormalities, and anticipate equipment problems by analyzing process data and sensor readings [364], [365]. This eventually results in a reduction in downtime and an increase in energy output. It is also possible for machine learning to assist in the development of technologies for the conversion of biomass by accelerating the identification of materials, the optimization of processes, and the enhancement of designs [366], [367].
- Support for environmental sustainability: With the use of machine learning, environmental sustainability may be supported. Machine learning can assist in the prediction of environmental consequences, the optimization of land use, and the assistance of regulatory compliance for sustainable biomass production and consumption methods [368], [369]. Machine learning algorithms can analyze the environmental effects of biomass energy projects by conducting an analysis of environmental data and simulating ecosystem dynamics [370], [371]. The planning of land use and the formulation of policies may both benefit from this knowledge. In addition, machine learning may be of assistance in the monitoring and protection of ecosystems, providing support for projects that aim to preserve sustainable biomass production while also being responsible to society and the environment [372].
- Providing Assistance with Market Analysis and Policy Development: Machine learning can analyze market patterns, assess the consequences of policies, and provide assistance with decision-making about investments in biomass energy and formulation of policies [373], [374]. Machine learning algorithms can identify market opportunities, estimate energy demand, and assess the economic viability of biomass energy projects. This is accomplished by studying market data, customer preferences, and regulatory frameworks. Furthermore, machine learning may be used to aid in policy analysis and scenario modeling [375], [376]. This can provide policymakers with insights into the possible implications of different policy interventions and assist in developing effective strategies for increasing the use of biomass energy.

A summary of different ML techniques used for biomass energy is listed in Table IV.

TABLE IV
APPLICATION OF ML TECHNIQUES IN THE BIOMASS ENERGY DOMAIN

Main theme	Machine learning technique	Main result	Source
Biochar yield from biomass.	RF and Gradient boosting regression (GBR)	The coefficient of determinates (R^2) was in the range of 0.89 to 0.94	[377]
Biomass to hydrogen production and its prediction	LR, KNN, SVM, and DT	LR was best in model prediction.	[378]
Algal biomass to biochar yield	XGBoost	R^2 was 0.84	[379]
Biomass pyrolysis yield prediction	GBR and RF	GBR was superior to RF with R^2 in the range of 0.9 to 0.95	[380]
Biomass and coal co-pyrolysis and output prediction	Extra-Trees (ET) and RF	ET was better owing to lower errors and improved generalization	[381]
Prediction of biomass-derived biochar	ANN and ANFIS	ANN was superior to ANFIS with R^2 in the range of 0.964.	[382]
Use of biomass-derived biochar for water remediation	Support vector machine (SVM), ANN, and RF	RF was superior to ANN and SVM with a forecasting accuracy of 94.89%.	[383]
Biomass to hydrogen production prediction	DT, GPR, and ELT with GA and PSO	The ELT-PSO outperformed other models by achieving the $R^2 = 0.99$	[384]
Biomass to biochar production prediction	MLR, SVM, DT, RF, and KNN	The random forest model was the best-performing model.	[385]
Biomass to syngas production	Multi-layer perceptron ANN	Bayesian-optimized ANN could predict with high accuracy.	[386]

In general, machine learning offers a variety of opportunities to solve difficulties that are often encountered in the biomass energy business. These include the enhancement of resource management, supply chain logistics, conversion processes, and environmental sustainability. Through the use of machine learning technology, the biomass energy business has the potential to uncover novel opportunities for progress, efficiency, and environmental friendliness, so contributing to the transition towards a more sustainable and strong energy landscape [12], [14].

B. Future Perspectives and Challenges

An investigation into the use of machine learning (ML) techniques in the area of renewable energy indicates a future that is both complicated and exciting, with a variety of views and obstacles. To successfully navigate the route towards renewable energy systems that are more efficient, reliable, and sustainable, boosted by machine learning technologies, it is essential to have a solid understanding of these dynamics.

1) Future perspectives

Recent Developments in Algorithms for ML: The development of machine learning in the field of renewable energy is contingent on developing sophisticated algorithms built expressly for the unique characteristics of renewable energy systems. Deep learning architectures, reinforcement learning approaches, and hybrid models are being investigated to improve the management of complex and nonlinear interactions in energy data [48], [387].

Real-time predictive analytics**:** In the case of renewable energy systems, the improvement will be made possible via the use of machine learning technology, which will increase the accuracy of energy production, demand, and grid operations forecasting [12], [388]. The management of energy, the stability of the grid, and the inclusion of variable renewable energy sources like solar and wind power into existing power systems will all be improved as a result of this [389], [390].

Autonomous energy system**:** It is anticipated that energy systems will evolve to be self-sufficient and driven by machine learning. These systems will be able to optimize themselves, adapt to changing conditions, and continue to be robust in the face of environmental shifts, variations in energy consumption, and market volatility. The purpose of these systems is to improve the efficiency of energy production, distribution, and consumption, with the eventual goal of fostering enhanced energy independence and sustainability [391], [392].

Integrated approach: Decentralized intelligence and decision-making inside renewable energy systems will be made possible via the process of connecting machine learning algorithms with Internet of Things sensors and edge computing technologies. Real-time monitoring, control, and optimization of energy assets at the local level will be made possible as a result of this, which will result in improving energy efficiency and grid resilience [393], [394].

Collaboration**:** In the future, research will emphasize interdisciplinary cooperation among experts in renewable energy, data scientists, and domain specialists to develop complete solutions for the difficulties that are found at the intersection of energy, the environment, and society. Moreover, enhancing the awareness of understanding of the importance of environmental protection is very important [395]. Through collaborative efforts, we will be able to develop cutting-edge machine-learning applications that will have a substantial influence on the field of renewable energy.

2) Challenges

Quality and availability of data: Quantity and quality of the data that is accessible is one of the problems that must be overcome [396]. When it comes to using machine learning for renewable energy, one of the most significant challenges is the need for a large quantity of diverse data to properly train machine learning models [397]. It is very necessary to have access to data sets that are dependable, comprehensive, and representative to construct machine learning models that are accurate and robust for applications using renewable energy [398], [399].

Understanding and Clarity**:** To establish trustworthy relationships with stakeholders and win their support, machine learning models that are used in renewable energy systems need to be simple to understand and straightforward to comprehend. It will be vital to improve the understandability of machine learning models and explain the decision-making methods associated with them in order to ensure that they are widely accepted in energy planning, policy-making, and operational procedures [400], [401].

Scalability and Generalization**:** To be effective, machine learning algorithms need to be able to scale up and generalize over a wide range of geographical locations, climates, and renewable energy technologies. As a prerequisite for their use in real-world renewable energy systems, the development of machine learning solutions that are capable of scaling and adapting to a wide range of settings and data sources is essential.

Energy efficiency**:** When it comes to machine learning algorithms and computer infrastructure, the consumption of energy may be a major worry because of the environmental and economic ramifications it has, especially when it is used on a big scale [402]. For the purpose of minimizing the impact that machine learning technologies have on the environment, it is vital to develop energy-efficient machine learning algorithms and hardware accelerators, as well as to fine-tune computing resources for applications that include renewable energy [403], [404].

Ethical issues**:** Take into account the following about the ethical and social impacts: Concerns surrounding privacy, prejudice, fairness, and accountability are raised when machine learning technologies are used in the field of renewable energy [405]. It is vital to develop ethical principles, legal frameworks, and governance structures to encourage the responsible and equitable application of machine learning technology in the field of renewable energy. This will allow for the resolution of these difficulties [406].

To address these forthcoming opportunities and challenges, it is necessary for academics, policymakers, industry stakeholders, and members of civil society to work together. This will allow them to capitalize on the revolutionary influence that machine learning can have in driving renewable energy toward a more sustainable and equitable future ahead. By overcoming these challenges and making the most of the opportunities presented by machine learning, we will be able to accelerate the transition to a more sustainable energy environment that is driven by advancements in renewable energy [407].

IV. Conclusion

It is concluded that the use of AI and ML in the field of renewable energy, especially in biomass, biofuels, engines, and solar power, has the potential to substantially transform the energy industry. A significant amount of progress has been made in boosting efficiency, dependability, and sustainability in a variety of industries via the combination of artificial intelligence and machine learning technologies with renewable energy sources. When it comes to biomass and biofuels, developments in artificial intelligence and machine learning algorithms have significantly improved approaches to managing biomass resources, optimizing feedstock, and the generation of biofuels. Using data-driven insights and predictive analytics, researchers and industry stakeholders can improve the efficiency of the biofuel supply chain. This includes the growth and harvesting of crops, as well as the conversion of biomass and the synthesis of fuel. The optimization of this process not only increases the economic viability of biofuel production but also reduces the negative impacts on the environment and accelerates the transition toward a low-carbon economy.

In addition, using artificial intelligence and machine learning in both engines and combustion systems has led to considerable improvements in engine performance, emissions reductions, and fuel economy improvements. These advancements have a significant potential to enhance the sustainability of transportation and power production, which will eventually contribute to the worldwide measures being undertaken to battle climate change and reduce harmful levels of air pollution. Artificial intelligence and machine learning are valuable tools within the solar energy sector, particularly in enhancing the efficiency and reliability of solar photovoltaic (PV) systems. Machine learning algorithms can analyze vast amounts of solar data, including irradiance levels, weather patterns, and system performance indicators, to improve the design, operation, and maintenance of photovoltaic (PV) systems. This optimization aims to optimize energy output, decrease downtime, and boost overall system efficiency. As a result, the cost-effectiveness and accessibility of solar energy will be increased.

As we look to the future, it will be essential to continue research and innovation in artificial intelligence and machine learning for renewable energy to overcome the challenges that still exist and uncover new opportunities. To put these achievements into practice in a realistic manner and accelerate the global transition toward a sustainable energy future powered by renewable sources, it is vital to collaborate with academics, industrial partners, and policymakers. By using artificial intelligence and machine learning, we can build a more sustainable energy ecology for the generations who will come after us.

References

[1] M. Yu, J. Kubiczek, K. Ding, A. Jahanzeb, and N. Iqbal, "Revisiting SDG-7 under energy efficiency vision 2050: the role of new economic models and mass digitalization in OECD," *Energy Effic.*, vol. 15, no. 1, p. 2, Jan. 2022, doi: 10.1007/s12053-021-10010-z.

[2] M. Mulligan, A. van Soesbergen, D. G. Hole, T. M. Brooks, S. Burke, and J. Hutton, "Mapping nature's contribution to SDG 6 and implications for other SDGs at policy relevant scales," *Remote Sens. Environ.*, vol. 239, p. 111671, Mar. 2020, doi: 10.1016/j.rse.2020.111671.

[3] T. T. Le, J. C. Priya, H. C. Le, N. V. L. Le, T. B. N. Nguyen, and D. N. Cao, "Harnessing artificial intelligence for data-driven energy predictive analytics: A systematic survey towards enhancing sustainability," *Int. J. Renew. Energy Dev.*, vol. 13, no. 2, 2024, doi: 10.61435/ijred.2024.60119.

[4] A. L. Salvia, W. Leal Filho, L. L. Brandli, and J. S. Griebeler, "Assessing research trends related to Sustainable Development Goals: local and global issues," *J. Clean. Prod.*, vol. 208, pp. 841–849, 2019, doi: 10.1016/j.jclepro.2018.09.242.

[5] M. del C. Pérez-Peña, M. Jiménez-García, J. Ruiz-Chico, and A. R. Peña-Sánchez, "Analysis of Research on the SDGs: The Relationship between Climate Change, Poverty and Inequality," *Appl. Sci.*, vol. 11, no. 19, p. 8947, Sep. 2021, doi: 10.3390/app11198947.

[6] P. Thapa, B. Mainali, and S. Dhakal, "Focus on Climate Action: What Level of Synergy and Trade-Off Is There between SDG 13; Climate Action and Other SDGs in Nepal?," *Energies*, vol. 16, no. 1, p. 566, Jan. 2023, doi: 10.3390/en16010566.

[7] IEA, "Tracking SDG7: The Energy Progress Report, 2022," 2022.

[8] R. Feng, X. Xu, Z.-T. Yu, and Q. Lin, "A machine-learning assisted multi-cluster assessment for decarbonization in the chemical fiber

industry toward net-zero: A case study in a Chinese province," *J. Clean. Prod.*, vol. 425, p. 138965, Nov. 2023, doi: 10.1016/j.jclepro.2023.138965.

[9] V. G. Nguyen *et al.*, "An extensive investigation on leveraging machine learning techniques for high-precision predictive modeling of CO 2 emission," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 45, no. 3, pp. 9149–9177, Aug. 2023, doi: 10.1080/15567036.2023.2231898.

[10] S. L. Goldenberg, G. Nir, and S. E. Salcudean, "A new era: artificial intelligence and machine learning in prostate cancer," *Nat. Rev. Urol.*, vol. 16, no. 7, pp. 391–403, Jul. 2019, doi: 10.1038/s41585-019-0193-3.

[11] C. Janiesch, P. Zschech, and K. Heinrich, "Machine learning and deep learning," *Electron. Mark.*, vol. 31, no. 3, pp. 685–695, Sep. 2021, doi: 10.1007/s12525-021-00475-2.

[12] T. Ahmad, R. Madonski, D. Zhang, C. Huang, and A. Mujeeb, "Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm," *Renew. Sustain. Energy Rev.*, vol. 160, p. 112128, May 2022, doi: 10.1016/j.rser.2022.112128.

[13] N. Milojevic-Dupont and F. Creutzig, "Machine learning for geographically differentiated climate change mitigation in urban areas," *Sustain. Cities Soc.*, vol. 64, p. 102526, 2021.

[14] D. Rangel-Martinez, K. D. P. Nigam, and L. A. Ricardez-Sandoval, "Machine learning on sustainable energy: A review and outlook on renewable energy systems, catalysis, smart grid and energy storage," *Chem. Eng. Res. Des.*, vol. 174, pp. 414–441, 2021.

[15] P. Khandare, S. Deokar, and A. Dixit, "Improvement of Traditional Protection System in the Existing Hybrid Microgrid with Advanced Intelligent Method," *Int. J. Data Sci.*, vol. 1, no. 2, pp. 72–81, May 2020, doi: 10.18517/ijods.1.2.72-81.2020.

[16] M. Sharifzadeh, A. Sikinioti-Lock, and N. Shah, "Machine-learning methods for integrated renewable power generation: A comparative study of artificial neural networks, support vector regression, and Gaussian Process Regression," *Renew. Sustain. Energy Rev.*, vol. 108, pp. 513–538, Jul. 2019, doi: 10.1016/j.rser.2019.03.040.

[17] M. Pan, Q. Xing, Z. Chai, H. Zhao, Q. Sun, and D. Duan, "Real-time digital twin machine learning-based cost minimization model for renewable-based microgrids considering uncertainty," *Sol. Energy*, vol. 250, pp. 355–367, Jan. 2023, doi: 10.1016/j.solener.2023.01.006.

[18] T. A. Kurniawan *et al.*, "Decarbonization in waste recycling industry using digitalization to promote net-zero emissions and its implications on sustainability," *J. Environ. Manage.*, vol. 338, p. 117765, 2023.

[19] J. D. Sachs, G. Schmidt-Traub, M. Mazzucato, D. Messner, N. Nakicenovic, and J. Rockström, "Six transformations to achieve the sustainable development goals," *Nat. Sustain.*, vol. 2, no. 9, pp. 805–814, 2019.

[20] S. Yadav, A. Samadhiya, A. Kumar, A. Majumdar, J. A. Garza-Reyes, and S. Luthra, "Achieving the sustainable development goals through net zero emissions: Innovation-driven strategies for transitioning from incremental to radical lean, green and digital technologies," *Resour. Conserv. Recycl.*, vol. 197, p. 107094, 2023.

[21] IEA, "Tracking SDG7: The Energy Progress Report, 2020," 2020.

[22] C. W. Sadoff, E. Borgomeo, and S. Uhlenbrook, "Rethinking water for SDG 6," *Nat. Sustain.*, vol. 3, no. 5, pp. 346–347, May 2020, doi: 10.1038/s41893-020-0530-9.

[23] M. Beccarello and G. Di Foggia, "Sustainable Development Goals Data-Driven Local Policy: Focus on SDG 11 and SDG 12," *Adm. Sci.*, vol. 12, no. 4, p. 167, Nov. 2022, doi: 10.3390/admsci12040167.

[24] M. Munasinghe, "COVID-19 and sustainable development," *Int. J. Sustain. Dev.*, vol. 23, no. 1–2, pp. 1–24, 2020.

[25] A. T. Hoang and V. D. Tran, "Experimental Analysis on the Ultrasound-based Mixing Technique Applied to Ultra-low Sulphur Diesel and Bio-oils," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 9, no. 1, p. 307, Feb. 2019, doi: 10.18517/ijaseit.9.1.7890.

[26] A. T. Hoang and V. T. Nguyen, "Emission Characteristics of a Diesel Engine Fuelled with Preheated Vegetable Oil and Biodiesel," *Philipp. J. Sci.*, vol. 146, no. 4, pp. 475–482, 2017.

[27] X. P. Nguyen, "A strategy development for optimal generating power of small wind-diesel-solar hybrid microgrid system," in *2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)*, IEEE, 2020, pp. 1329–1334.

[28] Z. Said *et al.*, "Improving the thermal efficiency of a solar flat plate collector using MWCNT-Fe3O4/water hybrid nanofluids and ensemble machine learning," *Case Stud. Therm. Eng.*, vol. 40, p. 102448, Dec. 2022, doi: 10.1016/j.csite.2022.102448.

[29] X. P. Nguyen and V. H. Dong, "A study on traction control system for solar panel on vessels," in *International Conference on Emerging Applications in Material Science and Technology, ICEAMST 2020*, 2020, p. 020016. doi: 10.1063/5.0007708.

[30] T. Sathish *et al.*, "Waste to fuel: Synergetic effect of hybrid nanoparticle usage for the improvement of CI engine characteristics fuelled with waste fish oils," *Energy*, vol. 275, p. 127397, Jul. 2023, doi: 10.1016/j.energy.2023.127397.

[31] M. Ghodbane *et al.*, "Thermal performance assessment of an ejector air-conditioning system with parabolic trough collector using R718 as a refrigerant: A case study in Algerian desert region," *Sustain. Energy Technol. Assessments*, vol. 53, p. 102513, Oct. 2022, doi: 10.1016/j.seta.2022.102513.

[32] T. T. Bui, H. Q. Luu, A. T. Hoang, O. Konur, T. Huu, and M. T. Pham, "A review on ignition delay times of 2,5-Dimethylfuran," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 44, no. 3, pp. 7160–7175, Sep. 2022, doi: 10.1080/15567036.2020.1860163.

[33] A. A. Salem and I. S. Seddiek, "Techno-Economic Approach to Solar Energy Systems Onboard Marine Vehicles," *Polish Marit. Res.*, vol. 23, no. 3, pp. 64–71, Sep. 2016, doi: 10.1515/pomr-2016-0033.

[34] Y. Shi and W. Luo, "Application of Solar Photovoltaic Power Generation System in Maritime Vessels and Development of Maritime Tourism," *Polish Marit. Res.*, vol. 25, no. s2, pp. 176–181, Aug. 2018, doi: 10.2478/pomr-2018-0090.

[35] M. Karteris and A. M. Papadopoulos, "Legislative framework for photovoltaics in Greece: A review of the sector's development," *Energy Policy*, vol. 55, pp. 296–304, 2013.

[36] L. De Boeck, S. Van Asch, P. De Bruecker, and A. Audenaert, "Comparison of support policies for residential photovoltaic systems in the major EU markets through investment profitability," *Renew. Energy*, vol. 87, pp. 42–53, 2016.

[37] M. Jurčević *et al.*, "Techno-economic and environmental evaluation of photovoltaic-thermal collector design with pork fat as phase change material," *Energy*, vol. 254, p. 124284, Sep. 2022, doi: 10.1016/j.energy.2022.124284.

[38] S. F. Ahmed *et al.*, "Perovskite solar cells: Thermal and chemical stability improvement, and economic analysis," *Mater. Today Chem.*, vol. 27, p. 101284, Jan. 2023, doi: 10.1016/j.mtchem.2022.101284.

[39] N. Franzese, I. Dincer, and M. Sorrentino, "A new multigenerational solar-energy based system for electricity, heat and hydrogen production," *Appl. Therm. Eng.*, vol. 171, p. 115085, 2020.

[40] T. Chitsomboon, A. Koonsrisook, A. T. Hoang, and T. H. Le, "Experimental investigation of solar energy-based water distillation using inclined metal tubes as collector and condenser," *Energy Sources, Part A Recover. Util. Environ. Eff.*, pp. 1–17, 2021, doi: 10.1080/15567036.2021.1966139.

[41] S. E. Hosseini and M. A. Wahid, "Hydrogen from solar energy, a clean energy carrier from a sustainable source of energy," *Int. J. Energy Res.*, vol. 44, no. 6, pp. 4110–4131, 2020.

[42] E. Ciba, P. Dymarski, and M. Grygorowicz, "Heave Plates with Holes for Floating Offshore Wind Turbines," *Polish Marit. Res.*, vol. 29, no. 1, pp. 26–33, Mar. 2022, doi: 10.2478/pomr-2022-0003.

[43] H. Zhang, Y. Hu, and J. He, "Wind Tunnel Experiment of Multi-Mode ARC Sail Device," *Polish Marit. Res.*, vol. 28, no. 4, pp. 20–29, Jan. 2022, doi: 10.2478/pomr-2021-0046.

[44] I. Ismail, A. H. Ismail, and G. H. N. Nur Rahayu, "Wind Energy Feasibility Study of Seven Potential Locations in Indonesia," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 10, no. 5, pp. 1970–1978, 2020, doi: 10.18517/ijaseit.10.5.10389.

[45] W.-H. Chen *et al.*, "Two-stage optimization of three and four straight-bladed vertical axis wind turbines (SB-VAWT) based on Taguchi approach," *e-Prime - Adv. Electr. Eng. Electron. Energy*, vol. 1, p. 100025, 2021, doi: 10.1016/j.prime.2021.100025.

[46] M. A. Hassoine, F. Lahlou, A. Addaim, and A. A. Madi, "Improved Evaluation of The Wind Power Potential of a Large Offshore Wind Farm Using Four Analytical Wake Models.," *Int. J. Renew. Energy Dev.*, vol. 11, no. 1, pp. 35–48, 2022.

[47] M. M. Riaz and B. H. Khan, "Techno-Economic Analysis and Planning for the Development of Large Scale Offshore Wind Farm in India.," *Int. J. Renew. Energy Dev.*, vol. 10, no. 2, pp. 257–268, 2021.

[48] V. N. Nguyen *et al.*, "Potential of Explainable Artificial Intelligence in Advancing Renewable Energy: Challenges and Prospects," *Energy & Fuels*, vol. 38, no. 3, pp. 1692–1712, Feb. 2024, doi: 10.1021/acs.energyfuels.3c04343.

[49] A. E. Atabani *et al.*, "Emerging potential of spent coffee ground valorization for fuel pellet production in a biorefinery," *Environ. Dev. Sustain.*, May 2022, doi: 10.1007/s10668-022-02361-z.

[50] R. Aniza, W.-H. Chen, A. Pétrissans, A. T. Hoang, V. Ashokkumar, and M. Pétrissans, "A review of biowaste remediation and valorization for environmental sustainability: Artificial intelligence approach," *Environ. Pollut.*, vol. 324, p. 121363, May 2023, doi: 10.1016/j.envpol.2023.121363.
[51] K.-T. Lee *et al.*, "Energy-saving drying strategy of spent coffee grounds for co-firing fuel by adding biochar for carbon sequestration to approach net zero," *Fuel*, vol. 326, p. 124984, Oct. 2022, doi: 10.1016/j.fuel.2022.124984.
[52] A. T. Hoang, T. H. Nguyen, and H. P. Nguyen, "Scrap tire pyrolysis as a potential strategy for waste management pathway: a review," *Energy Sources, Part A Recover. Util. Environ. Eff.*, pp. 1–18, Mar. 2020, doi: 10.1080/15567036.2020.1745336.
[53] J. Kandasamy and I. Gökalp, "Pyrolysis, Combustion, and Steam Gasification of Various Types of Scrap Tires for Energy Recovery," *Energy & Fuels*, vol. 29, no. 1, pp. 346–354, Jan. 2015, doi: 10.1021/ef502283s.
[54] S. Varjani *et al.*, "Sustainable management of municipal solid waste through waste-to-energy technologies," *Bioresour. Technol.*, vol. 355, p. 127247, Jul. 2022, doi: 10.1016/j.biortech.2022.127247.
[55] M. Q. Chau, A. T. Hoang, T. T. Truong, and X. P. Nguyen, "Endless story about the alarming reality of plastic waste in Vietnam," *Energy Sources, Part A Recover. Util. Environ. Eff.*, pp. 1–9, 2020.
[56] M.-E. Ramazankhani, A. Mostafaeipour, H. Hosseininasab, and M.-B. Fakhrzad, "Feasibility of geothermal power assisted hydrogen production in Iran," *Int. J. Hydrogen Energy*, vol. 41, no. 41, pp. 18351–18369, Nov. 2016, doi: 10.1016/j.ijhydene.2016.08.150.
[57] L. Zhang, Y. Qiu, Y. Chen, and A. T. Hoang, "Multi-objective particle swarm optimization applied to a solar-geothermal system for electricity and hydrogen production; Utilization of zeotropic mixtures for performance improvement," *Process Saf. Environ. Prot.*, vol. 175, pp. 814–833, Jul. 2023, doi: 10.1016/j.psep.2023.05.082.
[58] Z. Said *et al.*, "Nanotechnology-integrated phase change material and nanofluids for solar applications as a potential approach for clean energy strategies: Progress, challenges, and opportunities," *J. Clean. Prod.*, vol. 416, p. 137736, Sep. 2023, doi: 10.1016/j.jclepro.2023.137736.
[59] C. Wang, W. Lu, C. Xi, and X. P. Nguyen, "Research on green building energy management based on BIM and FM," *Nat. Environ. Pollut. Technol*, vol. 18, no. 5, pp. 1641–1646, 2019.
[60] A. T. Hoang *et al.*, "Power generation characteristics of a thermoelectric modules-based power generator assisted by fishbone-shaped fins: Part II – Effects of cooling water parameters," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 43, no. 3, pp. 381–393, Feb. 2021, doi: 10.1080/15567036.2019.1624891.
[61] T. H. Huan, A. T. Hoang, and V. S. Vladimirovich, "Power generation characteristics of a thermoelectric modules-based power generator assisted by fishbone-shaped fins: Part I – effects of hot inlet gas parameters," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 43, no. 5, pp. 588–599, Feb. 2021, doi: 10.1080/15567036.2019.1630035.
[62] V. A. Ferraz de Campos, V. B. Silva, J. S. Cardoso, P. S. Brito, C. E. Tuna, and J. L. Silveira, "A review of waste management in Brazil and Portugal: Waste-to-energy as pathway for sustainable development," *Renew. Energy*, vol. 178, pp. 802–820, Nov. 2021, doi: 10.1016/j.renene.2021.06.107.
[63] G. F. Ghesti, E. A. Silveira, M. G. Guimarães, R. B. W. Evaristo, and M. Costa, "Towards a sustainable waste-to-energy pathway to pequi biomass residues: Biochar, syngas, and biodiesel analysis," *Waste Manag.*, vol. 143, pp. 144–156, Apr. 2022, doi: 10.1016/j.wasman.2022.02.022.
[64] N. Imanuella *et al.*, "Interfacial-engineered CoTiO3-based composite for photocatalytic applications: a review," *Environ. Chem. Lett.*, vol. 20, no. 5, pp. 3039–3069, Oct. 2022, doi: 10.1007/s10311-022-01472-3.
[65] Z. Xu, S. Zhai, and N. X. Phuong, "Research on green transition development of energy enterprises taking mining industry as an example," *Nat. Environ. Pollut. Technol*, vol. 18, no. 5, pp. 1512–1526, 2019.
[66] W. Chen *et al.*, "Effects of material doping on the performance of thermoelectric generator with / without equal segments," *Appl. Energy*, vol. 350, p. 121709, 2023, doi: 10.1016/j.apenergy.2023.121709.
[67] S. D. Ahmed, F. S. M. Al-Ismail, M. Shafiullah, F. A. Al-Sulaiman, and I. M. El-Amin, "Grid Integration Challenges of Wind Energy: A Review," *IEEE Access*, vol. 8, pp. 10857–10878, 2020, doi: 10.1109/ACCESS.2020.2964896.
[68] Y. Seo, S. yeob Lee, J. Kim, C. Huh, and D. Chang, "Determination of optimal volume of temporary storage tanks in a ship-based carbon capture and storage (CCS) chain using life cycle cost (LCC) including unavailability cost," *Int. J. Greenh. Gas Control*, 2017, doi: 10.1016/j.ijggc.2017.06.017.
[69] X. P. Nguyen and A. T. Hoang, "The Flywheel Energy Storage System: An Effective Solution to Accumulate Renewable Energy," in *2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)*, IEEE, Mar. 2020, pp. 1322–1328. doi: 10.1109/ICACCS48705.2020.9074469.
[70] T. Kousksou, P. Bruel, A. Jamil, T. El Rhafiki, and Y. Zeraouli, "Energy storage: Applications and challenges," *Sol. Energy Mater. Sol. Cells*, vol. 120, pp. 59–80, Jan. 2014, doi: 10.1016/j.solmat.2013.08.015.
[71] M. Jurčević, S. Nižetić, D. Čoko, A. T. Hoang, and A. M. Papadopoulos, "Experimental investigation of novel hybrid phase change materials," *Clean Technol. Environ. Policy*, vol. 24, no. 1, pp. 201–212, Jan. 2022, doi: 10.1007/s10098-021-02106-y.
[72] R. Senthil, B. M. S. Punniakodi, D. Balasubramanian, X. P. Nguyen, A. T. Hoang, and V. N. Nguyen, "Numerical investigation on melting and energy storage density enhancement of phase change material in a horizontal cylindrical container," *Int. J. Energy Res.*, vol. 46, no. 13, pp. 19138–19158, 2022, doi: 10.1002/er.8228.
[73] Y. Liu *et al.*, "Improvement of cooling of a high heat flux CPU by employing a cooper foam and NEPCM/water suspension," *J. Energy Storage*, vol. 55, p. 105682, Nov. 2022, doi: 10.1016/j.est.2022.105682.
[74] K. A. Khan, M. M. Quamar, F. H. Al-Qahtani, M. Asif, M. Alqahtani, and M. Khalid, "Smart grid infrastructure and renewable energy deployment: A conceptual review of Saudi Arabia," *Energy Strateg. Rev.*, vol. 50, p. 101247, Nov. 2023, doi: 10.1016/j.esr.2023.101247.
[75] R. Sinnott, M. Bayer, D. Houghton, D. Berry, and M. Ferrier, "Development of a Grid Infrastructure for Functional Genomics," in *Lecture Notes in Computer Science*, A. Konagaya and K. Satou, Eds., Springer, Berlin, Heidelberg, 2005, pp. 125–139. doi: 10.1007/978-3-540-32251-1_12.
[76] H. Wang, Z. Lei, X. Zhang, B. Zhou, and J. Peng, "A review of deep learning for renewable energy forecasting," *Energy Convers. Manag.*, vol. 198, p. 111799, Oct. 2019, doi: 10.1016/j.enconman.2019.111799.
[77] C. Sweeney, R. J. Bessa, J. Browell, and P. Pinson, "The future of forecasting for renewable energy," *WIREs Energy Environ.*, vol. 9, no. 2, Mar. 2020, doi: 10.1002/wene.365.
[78] R. Ghasempour, M. A. Nazari, M. Ebrahimi, M. H. Ahmadi, and H. Hadiyanto, "Multi-Criteria Decision Making (MCDM) Approach for Selecting Solar Plants Site and Technology: A Review.," *Int. J. Renew. Energy Dev.*, vol. 8, no. 1, 2019.
[79] S. E. Hosseini, "Transition away from fossil fuels toward renewables: lessons from Russia-Ukraine crisis," *Futur. Energy*, vol. 1, no. 1, pp. 2–5, May 2022, doi: 10.55670/fpll.fuen.1.1.8.
[80] Enerdata, "Global Energy Transition Statistics: Share of renewables in electricity production," Enerdata.
[81] Y. Chang, Y. Wei, J. Zhang, X. Xu, L. Zhang, and Y. Zhao, "Mitigating the greenhouse gas emissions from urban roadway lighting in China via energy-efficient luminaire adoption and renewable energy utilization," *Resour. Conserv. Recycl.*, vol. 164, p. 105197, Jan. 2021, doi: 10.1016/j.resconrec.2020.105197.
[82] S. Nižetić, M. Arıcı, and A. T. Hoang, "Smart and Sustainable Technologies in energy transition," *J. Clean. Prod.*, vol. 389, p. 135944, Feb. 2023, doi: 10.1016/j.jclepro.2023.135944.
[83] P. A. Owusu and S. Asumadu-Sarkodie, "A review of renewable energy sources, sustainability issues and climate change mitigation," *Cogent Eng.*, vol. 3, no. 1, p. 1167990, Dec. 2016, doi: 10.1080/23311916.2016.1167990.
[84] W. Chen, M. Alharthi, J. Zhang, and I. Khan, "The need for energy efficiency and economic prosperity in a sustainable environment," *Gondwana Res.*, vol. 127, pp. 22–35, 2024.
[85] R. Kümmel, D. Lindenberger, and F. Weiser, "The economic power of energy and the need to integrate it with energy policy," *Energy Policy*, vol. 86, pp. 833–843, 2015.
[86] A. . Hoang, Q. . Tran, and X. . Pham, "Performance and emission characteristics of popular 4-stroke motorcycle engine in Vietnam fuelled with biogasoline compared with fossil gasoline," *Int. J. Mech. Mechatronics Eng.*, vol. 18, no. 2, pp. 97–103, 2018.
[87] M. Q. Chau, V. V. Le, A. T. Hoang, A. R. M. S. Al-Tawaha, and V. V. Pham, "A simulation research of heat transfers and chemical reactions in the fuel steam reformer using exhaust gas energy from motorcycle engine," *J. Mech. Eng. Res. Dev.*, vol. 43, no. 5, pp. 89–102, 2020.
[88] L. Changxiong, Y. Hu, Z. Yang, and H. Guo, "Experimental Study of Fuel Combustion and Emission Characteristics of Marine Diesel

Engines Using Advanced Fuels," *Polish Marit. Res.*, vol. 30, no. 3, pp. 48–58, Sep. 2023, doi: 10.2478/pomr-2023-0038.

[89] Y. Li, B. Li, F. Deng, Q. Yang, and B. Zhang, "Research on the Application of Cold Energy of Largescale Lng-Powered Container Ships to Refrigerated Containers," *Polish Marit. Res.*, vol. 28, no. 4, pp. 107–121, Jan. 2022, doi: 10.2478/pomr-2021-0053.

[90] T. P. Ogundunmade and A. A. Adepoju, "Modelling Liquified Petroleum Gas Prices in Nigeria Using Machine Learning Models," *Int. J. Data Sci.*, vol. 3, no. 2, pp. 93–100, Dec. 2022, doi: 10.18517/ijods.3.2.93-100.2022.

[91] A. N. Olimat, "Study of fabricated solar dryer of tomato slices under Jordan climate condition," *Int. J. Renew. Energy Dev.*, vol. 6, no. 2, pp. 93–101, 2017, doi: 10.14710/ijred.6.2.93-101.

[92] S. Suherman, H. Widuri, S. Patricia, E. E. Susanto, and R. J. Sutrisna, "Energy analysis of a hybrid solar dryer for drying coffee beans," *Int. J. Renew. Energy Dev.*, vol. 9, no. 1, pp. 131–139, 2020, doi: 10.14710/ijred.9.1.131-139.

[93] N. T. Hung, "Remittance, Renewable Energy, and CO2 Emissions: a Vietnamese Illustration," *J. Knowl. Econ.*, Mar. 2023, doi: 10.1007/s13132-023-01238-4.

[94] M. Amir and S. Z. Khan, "Assessment of renewable energy: Status, challenges, COVID-19 impacts, opportunities, and sustainable energy solutions in Africa," *Energy Built Environ.*, vol. 3, no. 3, pp. 348–362, Jul. 2022, doi: 10.1016/j.enbenv.2021.03.002.

[95] L. Chen *et al.*, "Strategies to achieve a carbon neutral society: a review," *Environ. Chem. Lett.*, vol. 20, no. 4, pp. 2277–2310, Aug. 2022, doi: 10.1007/s10311-022-01435-8.

[96] F. Wang *et al.*, "Technologies and perspectives for achieving carbon neutrality," *Innov.*, vol. 2, no. 4, p. 100180, Nov. 2021, doi: 10.1016/j.xinn.2021.100180.

[97] Y. Xin and D. Long, "Linking eco-label knowledge and sustainable consumption of renewable energy: A roadmap towards green revolution," *Renew. Energy*, vol. 207, pp. 531–538, May 2023, doi: 10.1016/j.renene.2023.02.102.

[98] A. Franco and P. Salza, "Strategies for optimal penetration of intermittent renewables in complex energy systems based on techno-operational objectives," *Renew. Energy*, vol. 36, no. 2, pp. 743–753, Feb. 2011, doi: 10.1016/J.RENENE.2010.07.022.

[99] R. Syahyadi, N. Safitri, R. Widia, Safriadi, and Azwar, "Building Integrated Photovoltaic (BIPV): Implementing Artificial Intelligent (AI) on Designing Rooftile Photovoltaic," *Int. J. Data Sci.*, vol. 4, no. 1, pp. 60–66, May 2023, doi: 10.18517/ijods.4.1.60-66.2023.

[100] M. Samimi and H. Moghadam, "Investigation of structural parameters for inclined weir-type solar stills," *Renew. Sustain. Energy Rev.*, vol. 190, p. 113969, Feb. 2024, doi: 10.1016/j.rser.2023.113969.

[101] G. K. Karayel and I. Dincer, "Green hydrogen production potential of Canada with solar energy," *Renew. Energy*, vol. 221, p. 119766, Feb. 2024, doi: 10.1016/j.renene.2023.119766.

[102] Z. Xuan, M. Ge, C. Zhao, Y. Li, S. Wang, and Y. Zhao, "Effect of nonuniform solar radiation on the performance of solar thermoelectric generators," *Energy*, vol. 290, p. 130249, Mar. 2024, doi: 10.1016/j.energy.2024.130249.

[103] X. Li *et al.*, "Dimensional diversity (0D, 1D, 2D, and 3D) in perovskite solar cells: exploring the potential of mixed-dimensional integrations," *J. Mater. Chem. A*, vol. 12, no. 8, pp. 4421–4440, 2024, doi: 10.1039/D3TA06953B.

[104] P. Sharma and A. K. Sharma, "AI-Based Prognostic Modeling and Performance Optimization of CI Engine Using Biodiesel-Diesel Blends," *Int. J. Renew. Energy Res.*, no. v11i2, 2021, doi: 10.20508/ijrer.v11i2.11854.g8191.

[105] P. Sharma, M. Sivaramakrishnaiah, B. Deepanraj, R. Saravanan, and M. V. Reddy, "A novel optimization approach for biohydrogen production using algal biomass," *Int. J. Hydrogen Energy*, vol. 52, pp. 94–103, Jan. 2024, doi: 10.1016/j.ijhydene.2022.09.274.

[106] V. G. Nguyen *et al.*, "Machine learning for the management of biochar yield and properties of biomass sources for sustainable energy," *Biofuels, Bioprod. Biorefining*, Feb. 2024, doi: 10.1002/bbb.2596.

[107] M. J. Deka *et al.*, "Enhancing the performance of a photovoltaic thermal system with phase change materials: Predictive modelling and evaluation using neural networks," *Renew. Energy*, vol. 224, p. 120091, Apr. 2024, doi: 10.1016/j.renene.2024.120091.

[108] A. T. Hoang and D. C. Nguyen, "Properties of DMF-fossil gasoline RON95 blends in the consideration as the alternative fuel," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 8, no. 6, pp. 2555–2560, 2018.

[109] A. T. Hoang and M. T. Pham, "Influences of heating temperatures on physical properties, spray characteristics of bio-oils and fuel supply system of a conventional diesel engine," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 8, no. 5, pp. 2231–2240, 2018, doi: 10.18517/ijaseit.8.5.5487.

[110] K. Rudzki, P. Gomulka, and A. T. Hoang, "Optimization Model to Manage Ship Fuel Consumption and Navigation Time," *Polish Marit. Res.*, vol. 29, no. 3, pp. 141–153, Sep. 2022, doi: 10.2478/pomr-2022-0034.

[111] A. Zakaria, F. B. Ismail, M. S. H. Lipu, and M. A. Hannan, "Uncertainty models for stochastic optimization in renewable energy applications," *Renew. Energy*, vol. 145, pp. 1543–1571, 2020.

[112] A. Palzer and H.-M. Henning, "A comprehensive model for the German electricity and heat sector in a future energy system with a dominant contribution from renewable energy technologies–Part II: Results," *Renew. Sustain. Energy Rev.*, vol. 30, pp. 1019–1034, 2014.

[113] A. Q. Al-Shetwi, "Sustainable development of renewable energy integrated power sector: Trends, environmental impacts, and recent challenges," *Sci. Total Environ.*, vol. 822, p. 153645, May 2022, doi: 10.1016/j.scitotenv.2022.153645.

[114] A. Sajadi, L. Strezoski, V. Strezoski, M. Prica, and K. A. Loparo, "Integration of renewable energy systems and challenges for dynamics, control, and automation of electrical power systems," *Wiley Interdiscip. Rev. Energy Environ.*, vol. 8, no. 1, p. e321, 2019.

[115] T. Ahmad *et al.*, "Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities," *J. Clean. Prod.*, vol. 289, no. January, 2021, doi: 10.1016/j.jclepro.2021.125834.

[116] Z. Fan, Z. Yan, and S. Wen, "Deep learning and artificial intelligence in sustainability: a review of SDGs, renewable energy, and environmental health," *Sustainability*, vol. 15, no. 18, p. 13493, 2023.

[117] P. W. Khan, Y.-C. Byun, S.-J. Lee, D.-H. Kang, J.-Y. Kang, and H.-S. Park, "Machine Learning-Based Approach to Predict Energy Consumption of Renewable and Nonrenewable Power Sources," *Energies*, vol. 13, no. 18, p. 4870, Sep. 2020, doi: 10.3390/en13184870.

[118] S. E. Haupt *et al.*, "Combining artificial intelligence with physics-based methods for probabilistic renewable energy forecasting," *Energies*, vol. 13, no. 8, p. 1979, 2020.

[119] K. S. Perera, Z. Aung, and W. L. Woon, "Machine Learning Techniques for Supporting Renewable Energy Generation and Integration: A Survey," 2014, pp. 81–96. doi: 10.1007/978-3-319-13290-7_7.

[120] K. Kumar, R. Rao, O. Kaiwartya, S. Kaiser, and P. Sanjeevikumar, *Sustainable Developments by Artificial Intelligence and Machine Learning for Renewable Energies*. Elsevier, 2022. doi: 10.1016/C2020-0-04074-0.

[121] S. Chandrasekaran, "Feasibility study on machine-learning-based hybrid renewable energy applications for engineering education," *Comput. Appl. Eng. Educ.*, vol. 29, no. 2, pp. 465–473, Mar. 2021, doi: 10.1002/cae.22237.

[122] X. Fu, X. Wu, C. Zhang, S. Fan, and N. Liu, "Planning of distributed renewable energy systems under uncertainty based on statistical machine learning," *Prot. Control Mod. Power Syst.*, vol. 7, no. 1, p. 41, Dec. 2022, doi: 10.1186/s41601-022-00262-x.

[123] A. Al-Dahoud, M. Fezari, and A. Aldahoud, "Machine Learning in Renewable Energy Application: Intelligence System for Solar Panel Cleaning," *WSEAS Trans. Environ. Dev.*, vol. 19, pp. 472–478, May 2023, doi: 10.37394/232015.2023.19.45.

[124] M. S. S. Danish, "AI in Energy: Overcoming Unforeseen Obstacles," *AI*, vol. 4, no. 2, pp. 406–425, May 2023, doi: 10.3390/ai4020022.

[125] N. Salleh, S. S. Yuhaniz, and N. F. Mohd Azmi, "Modeling Orbital Propagation Using Regression Technique and Artificial Neural Network," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 12, no. 3, p. 1279, May 2022, doi: 10.18517/ijaseit.12.3.15366.

[126] A. Kurniawan and E. Shintaku, "Estimation of Hourly Solar Radiations on Horizontal Surface from Daily Average Solar Radiations Using Artificial Neural Network," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 12, no. 6, pp. 2336–2341, Dec. 2022, doi: 10.18517/ijaseit.12.6.12940.

[127] E. H. Flaieh, F. O. Hamdoon, and A. A. Jaber, "Estimation the Natural Frequencies of a Cracked Shaft Based on Finite Element Modeling and Artificial Neural Network," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 10, no. 4, pp. 1410–1416, Aug. 2020, doi: 10.18517/ijaseit.10.4.12211.

[128] R. Concepcion II, E. Dadios, A. Bandala, J. Cuello, and Y. Kodama, "Hybrid Genetic Programming and Multiverse-based Optimization of Pre-Harvest Growth Factors of Aquaponic Lettuce Based on Chlorophyll Concentration," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 11, no. 6, p. 2128, Dec. 2021, doi: 10.18517/ijaseit.11.6.14991.

[129] A. Bustamam, D. Sarwinda, B. Abdillah, and T. P. Kaloka, "Detecting Lesion Characteristics of Diabetic Retinopathy Using Machine

Learning and Computer Vision," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 10, no. 4, p. 1367, Aug. 2020, doi: 10.18517/ijaseit.10.4.8876.
[130] R. I. Perwira, M. Y. Florestiyanto, I. R. Nurjanah, - Heriyanto, and D. B. Prasetyo, "Implementation of Gabor Wavelet and Support Vector Machine for Braille Recognition," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 12, no. 4, p. 1449, Aug. 2022, doi: 10.18517/ijaseit.12.4.14445.
[131] J. Capote-Leiva, M. Villota-Rivillas, and J. MuÃ±oz-OrdÃ³Ã±ez, "Access Control System based on Voice and Facial Recognition Using Artificial Intelligence," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 12, no. 6, pp. 2342–2348, Dec. 2022, doi: 10.18517/ijaseit.12.6.16049.
[132] Sumarsono, F. A. N. Farida Afiatna, and N. Muflihah, "The Monitoring System of Soil PH Factor Using IoT-Webserver-Android and Machine Learning: A Case Study," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 14, no. 1, pp. 118–130, Feb. 2024, doi: 10.18517/ijaseit.14.1.18745.
[133] R. Fredyan, M. R. N. Majiid, and G. P. Kusuma, "Spatiotemporal Analysis for Rainfall Prediction Using Extreme Learning Machine Cluster," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 13, no. 6, pp. 2240–2248, Dec. 2023, doi: 10.18517/ijaseit.13.6.18214.
[134] Desniorita, N. Nazir, R. Youfa, M. T. E. Prasada, and E. Pelita, "Sustainable Biorefinery: Effect of Time Fermentation on Hidrolisis Product from Cocoa Pod Husk," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 14, no. 1, pp. 151–156, Feb. 2024, doi: 10.18517/ijaseit.14.1.18401.
[135] M. M. Forootan, I. Larki, R. Zahedi, and A. Ahmadi, "Machine Learning and Deep Learning in Energy Systems: A Review," *Sustainability*, vol. 14, no. 8, p. 4832, Apr. 2022, doi: 10.3390/su14084832.
[136] T. V. Ramachandra, R. K. Jha, S. V. Krishna, and B. V. Shruthi, "Solar energy decision support system," *Int. J. Sustain. Energy*, vol. 24, no. 4, pp. 207–224, Dec. 2005, doi: 10.1080/14786450500292105.
[137] A. S. Bin Mohd Shah, H. Yokoyama, and N. Kakimoto, "High-Precision Forecasting Model of Solar Irradiance Based on Grid Point Value Data Analysis for an Efficient Photovoltaic System," *IEEE Trans. Sustain. Energy*, vol. 6, no. 2, pp. 474–481, Apr. 2015, doi: 10.1109/TSTE.2014.2383398.
[138] Z. Şen, "Solar energy in progress and future research trends," *Prog. Energy Combust. Sci.*, vol. 30, no. 4, pp. 367–416, Jan. 2004, doi: 10.1016/j.pecs.2004.02.004.
[139] N. I. Ilham, M. Z. Hussin, N. Y. Dahlan, and E. A. Setiawan, "Prospects and Challenges of Malaysia's Distributed Energy Resources in Business Models Towards Zero – Carbon Emission and Energy Security," *Int. J. Renew. Energy Dev.*, vol. 11, no. 4, pp. 1089–1100, Nov. 2022, doi: 10.14710/ijred.2022.45662.
[140] B. Wattana and P. Aungyut, "Impacts of Solar Electricity Generation on the Thai Electricity Industry," *Int. J. Renew. Energy Dev.*, vol. 11, no. 1, pp. 157–163, Feb. 2022, doi: 10.14710/ijred.2022.41059.
[141] E. Kabir, P. Kumar, S. Kumar, A. A. Adelodun, and K.-H. Kim, "Solar energy: Potential and future prospects," *Renew. Sustain. Energy Rev.*, vol. 82, pp. 894–900, Feb. 2018, doi: 10.1016/j.rser.2017.09.094.
[142] T. H. Le, M. T. Pham, H. Hadiyanto, V. V. Pham, and A. T. Hoang, "Influence of Various Basin Types on Performance of Passive Solar Still: A Review," *Int. J. Renew. Energy Dev.*, vol. 10, no. 4, pp. 789–802, Nov. 2021, doi: 10.14710/ijred.2021.38394.
[143] J. Liu, R. Song, S. Nasreen, and A. T. Hoang, "Analysis of the complementary property of solar energy and thermal power based on coupling model," *Nat. Environ. Pollut. Technol.*, vol. 18, no. 5, pp. 1675–1681, 2019.
[144] F. Hyder, K. Sudhakar, and R. Mamat, "Solar PV tree design: A review," *Renew. Sustain. Energy Rev.*, vol. 82, pp. 1079–1096, Feb. 2018, doi: 10.1016/j.rser.2017.09.025.
[145] S. Hayat, A. Safi, S. Wahab, K. Shahzad, and Y. Chen, "Renewable energy R&D and natural resources: A success story of environmentally friendly financing in OECD economies," *Resour. Policy*, vol. 83, p. 103655, Jun. 2023, doi: 10.1016/j.resourpol.2023.103655.
[146] M. Ahmad, M. A. Khan, M. Zafar, and S. Sultana, "Environment-friendly Renewable Energy from Sesame Biodiesel," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 32, no. 2, pp. 189–196, Nov. 2009, doi: 10.1080/15567030802467480.
[147] A. Y. Kian and S. C. Lim, "On the Potential of Solar Energy for Chemical and Metal Manufacturing Plants in Malaysia," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 13, no. 5, pp. 1898–1904, 2023, doi: 10.18517/ijaseit.13.5.19052.
[148] N. S. Asefa, "Computer Programming to Estimate the Global Daily and Hourly solar Radiation of any location around the Globe," *Int. J. Data Sci.*, vol. 3, no. 2, pp. 101–106, May 2023, doi: 10.18517/ijods.3.2.101-106.2022.
[149] S. Sargunanathan, A. Elango, and S. T. Mohideen, "Performance enhancement of solar photovoltaic cells using effective cooling methods: A review," *Renew. Sustain. Energy Rev.*, vol. 64, pp. 382–393, Oct. 2016, doi: 10.1016/j.rser.2016.06.024.
[150] N. Rathore, N. L. Panwar, F. Yettou, and A. Gama, "A comprehensive review of different types of solar photovoltaic cells and their applications," *Int. J. Ambient Energy*, vol. 42, no. 10, pp. 1200–1217, Jul. 2021, doi: 10.1080/01430750.2019.1592774.
[151] K. Obaideen *et al.*, "Solar Energy: Applications, Trends Analysis, Bibliometric Analysis and Research Contribution to Sustainable Development Goals (SDGs)," *Sustainability*, vol. 15, no. 2, p. 1418, Jan. 2023, doi: 10.3390/su15021418.
[152] A. Gopi, P. Sharma, K. Sudhakar, W. K. Ngui, I. Kirpichnikova, and E. Cuce, "Weather Impact on Solar Farm Performance: A Comparative Analysis of Machine Learning Techniques," *Sustainability*, vol. 15, no. 1, p. 439, Dec. 2022, doi: 10.3390/su15010439.
[153] A. Shirole, M. Wagh, and V. Kulkarni, "Thermal Performance Comparison of Parabolic Trough Collector (PTC) Using Various Nanofluids," *Int. J. Renew. Energy Dev.*, vol. 10, no. 4, pp. 875–889, Nov. 2021, doi: 10.14710/ijred.2021.33801.
[154] A. M. Ghaithan, A. Al-Hanbali, A. Mohammed, A. M. Attia, H. Saleh, and O. Alsawafy, "Optimization of a solar-wind- grid powered desalination system in Saudi Arabia," *Renew. Energy*, vol. 178, pp. 295–306, Nov. 2021, doi: 10.1016/j.renene.2021.06.060.
[155] A. Behzadi and S. Sadrizadeh, "A rule-based energy management strategy for a low-temperature solar/wind-driven heating system optimized by the machine learning-assisted grey wolf approach," *Energy Convers. Manag.*, vol. 277, p. 116590, Feb. 2023, doi: 10.1016/j.enconman.2022.116590.
[156] Z. Yao *et al.*, "Machine learning for a sustainable energy future," *Nat. Rev. Mater.*, vol. 8, no. 3, pp. 202–215, Oct. 2022, doi: 10.1038/s41578-022-00490-5.
[157] T. Cheng, X. Zhu, F. Yang, and W. Wang, "Machine learning enabled learning based optimization algorithm in digital twin simulator for management of smart islanded solar-based microgrids," *Sol. Energy*, vol. 250, pp. 241–247, Jan. 2023, doi: 10.1016/j.solener.2022.12.040.
[158] A. S. Al-Buraiki and A. Al-Sharafi, "Technoeconomic analysis and optimization of hybrid solar/wind/battery systems for a standalone house integrated with electric vehicle in Saudi Arabia," *Energy Convers. Manag.*, vol. 250, p. 114899, Dec. 2021, doi: 10.1016/j.enconman.2021.114899.
[159] A. Singh, P. Baredar, and B. Gupta, "Computational Simulation & Optimization of a Solar, Fuel Cell and Biomass Hybrid Energy System Using HOMER Pro Software," *Procedia Eng.*, vol. 127, pp. 743–750, 2015, doi: 10.1016/j.proeng.2015.11.408.
[160] S. Jafari, S. Hoseinzadeh, and A. Sohani, "Deep Q-Value Neural Network (DQN) Reinforcement Learning for the Techno-Economic Optimization of a Solar-Driven Nanofluid-Assisted Desalination Technology," *Water*, vol. 14, no. 14, p. 2254, Jul. 2022, doi: 10.3390/w14142254.
[161] H. Adun *et al.*, "Estimation of thermophysical property of hybrid nanofluids for solar Thermal applications: Implementation of novel Optimizable Gaussian Process regression (O-GPR) approach for Viscosity prediction," *Neural Comput. Appl.*, pp. 1–22, 2022, doi: 10.1007/s00521-022-07038-2.
[162] E. M. Al-Ali *et al.*, "Solar Energy Production Forecasting Based on a Hybrid CNN-LSTM-Transformer Model," *Mathematics*, vol. 11, no. 3, p. 676, Jan. 2023, doi: 10.3390/math11030676.
[163] P. Vengatesh Ramamurthi and E. Rajan Samuel Nadar, "IoT-based Energy Monitoring and Controlling of an Optimum Inclination Angle of the Solar Panels," *IETE J. Res.*, vol. 68, no. 4, pp. 3108–3118, Jul. 2022, doi: 10.1080/03772063.2020.1754301.
[164] I. Segovia Ramírez, A. Pliego Marugán, and F. P. García Márquez, "A novel approach to optimize the positioning and measurement parameters in photovoltaic aerial inspections," *Renew. Energy*, vol. 187, pp. 371–389, Mar. 2022, doi: 10.1016/j.renene.2022.01.071.
[165] Y. Wang, Z. Rao, J. Liu, and S. Liao, "An optimized control strategy for integrated solar and air-source heat pump water heating system with cascade storage tanks," *Energy Build.*, vol. 210, p. 109766, Mar. 2020, doi: 10.1016/j.enbuild.2020.109766.
[166] Z. Said, P. Sharma, L. Syam Sundar, V. G. Nguyen, V. D. Tran, and V. V. Le, "Using Bayesian optimization and ensemble boosted regression trees for optimizing thermal performance of solar flat plate collector under thermosyphon condition employing MWCNT-Fe3O4/water hybrid nanofluids," *Sustain. Energy Technol. Assessments*, vol. 53, p. 102708, Oct. 2022, doi:

10.1016/j.seta.2022.102708.
[167] W. Quitiaquez, J. Estupinán-Campos, C. Nieto-Londoño, C. A. Isaza-Roldán, P. Quitiaquez, and F. Toapanta-Ramos, "CFD Analysis of Heat Transfer Enhancement in a Flat-Plate Solar Collector with Different Geometric Variations in the Superficial Section," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 11, no. 5, p. 2039, Oct. 2021, doi: 10.18517/ijaseit.11.5.15288.
[168] A. Damayanti, F. Arifianto, and T. L. Indra, "Development Area for Floating Solar Panel and Dam in The Former Mine Hole (Void) Samarinda City, East Kalimantan Province," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 11, no. 5, p. 1713, Oct. 2021, doi: 10.18517/ijaseit.11.5.14097.
[169] M. S. Ibrahim, W. Dong, and Q. Yang, "Machine learning driven smart electric power systems: Current trends and new perspectives," *Appl. Energy*, vol. 272, p. 115237, Aug. 2020, doi: 10.1016/j.apenergy.2020.115237.
[170] C. Zhang, Y. Zhang, J. Pu, Z. Liu, Z. Wang, and L. Wang, "An hourly solar radiation prediction model using eXtreme gradient boosting algorithm with the effect of fog-haze," *Energy Built Environ.*, Aug. 2023, doi: 10.1016/j.enbenv.2023.08.001.
[171] S. Kallio and M. Siroux, "Photovoltaic power prediction for solar micro-grid optimal control," *Energy Reports*, vol. 9, pp. 594–601, Mar. 2023, doi: 10.1016/j.egyr.2022.11.081.
[172] D. Chakraborty, J. Mondal, H. B. Barua, and A. Bhattacharjee, "Computational solar energy – Ensemble learning methods for prediction of solar power generation based on meteorological parameters in Eastern India," *Renew. Energy Focus*, vol. 44, pp. 277–294, Mar. 2023, doi: 10.1016/j.ref.2023.01.006.
[173] N. V. Sridharan and V. Sugumaran, "Visual fault detection in photovoltaic modules using decision tree algorithms with deep learning features," *Energy Sources, Part A Recover. Util. Environ. Eff.*, pp. 1–17, Dec. 2021, doi: 10.1080/15567036.2021.2020379.
[174] M. M. Najafabadi, F. Villanustre, T. M. Khoshgoftaar, N. Seliya, R. Wald, and E. Muharemagic, "Deep learning applications and challenges in big data analytics," *J. Big Data*, vol. 2, no. 1, p. 1, Dec. 2015, doi: 10.1186/s40537-014-0007-7.
[175] S. Paliwal, A. Sharma, S. Jain, and S. Sharma, "Machine learning and deep learning in bioinformatics," in *Bioinformatics and Computational Biology*, Chapman and Hall/CRC, 2024, pp. 63–74.
[176] Y. Zhou, Y. Li, D. Wang, and Y. Liu, "A multi-step ahead global solar radiation prediction method using an attention-based transformer model with an interpretable mechanism," *Int. J. Hydrogen Energy*, vol. 48, no. 40, pp. 15317–15330, May 2023, doi: 10.1016/j.ijhydene.2023.01.068.
[177] V. Nikolaeva and E. Gordeev, "SPAM: Solar Spectrum Prediction for Applications and Modeling," *Atmosphere (Basel).*, vol. 14, no. 2, p. 226, Jan. 2023, doi: 10.3390/atmos14020226.
[178] M. Gao *et al.*, "Temperature prediction of solar greenhouse based on NARX regression neural network," *Sci. Rep.*, vol. 13, no. 1, p. 1563, Jan. 2023, doi: 10.1038/s41598-022-24072-1.
[179] W. Chen, W. Zou, K. Zhong, and A. Aliyeva, "Machine learning assessment under the development of green technology innovation: A perspective of energy transition," *Renew. Energy*, vol. 214, pp. 65–73, Sep. 2023, doi: 10.1016/j.renene.2023.05.108.
[180] Y. Gao, S. Miyata, Y. Matsunami, and Y. Akashi, "Spatio-temporal interpretable neural network for solar irradiation prediction using transformer," *Energy Build.*, vol. 297, p. 113461, Oct. 2023, doi: 10.1016/j.enbuild.2023.113461.
[181] D. El Bourakadi, H. Ramadan, A. Yahyaouy, and J. Boumhidi, "A novel solar power prediction model based on stacked BiLSTM deep learning and improved extreme learning machine," *Int. J. Inf. Technol.*, vol. 15, no. 2, pp. 587–594, Feb. 2023, doi: 10.1007/s41870-022-01118-1.
[182] Ü. Ağbulut, A. E. Gürel, and Y. Biçen, "Prediction of daily global solar radiation using different machine learning algorithms: Evaluation and comparison," *Renew. Sustain. Energy Rev.*, vol. 135, p. 110114, Jan. 2021, doi: 10.1016/j.rser.2020.110114.
[183] Y. Feng, W. Hao, H. Li, N. Cui, D. Gong, and L. Gao, "Machine learning models to quantify and map daily global solar radiation and photovoltaic power," *Renew. Sustain. Energy Rev.*, vol. 118, p. 109393, Feb. 2020, doi: 10.1016/j.rser.2019.109393.
[184] M. Taki, A. Rohani, and H. Yildizhan, "Application of machine learning for solar radiation modeling," *Theor. Appl. Climatol.*, vol. 143, no. 3–4, pp. 1599–1613, Feb. 2021, doi: 10.1007/s00704-020-03484-x.
[185] I. Jebli, F. Z. Belouadha, M. I. Kabbaj, and A. Tilioua, "Prediction of solar energy guided by pearson correlation using machine learning," *Energy*, vol. 224. 2021. doi: 10.1016/j.energy.2021.120109.
[186] B. Zazoum, "Solar photovoltaic power prediction using different machine learning methods," *Energy Reports*, vol. 8, pp. 19–25, Apr. 2022, doi: 10.1016/j.egyr.2021.11.183.
[187] G. Narvaez, L. F. Giraldo, M. Bressan, and A. Pantoja, "Machine learning for site-adaptation and solar radiation forecasting," *Renew. Energy*, vol. 167, pp. 333–342, Apr. 2021, doi: 10.1016/j.renene.2020.11.089.
[188] R. A. A. Ramadhan, Y. R. J. Heatubun, S. F. Tan, and H.-J. Lee, "Comparison of physical and machine learning models for estimating solar irradiance and photovoltaic power," *Renew. Energy*, vol. 178, pp. 1006–1019, Nov. 2021, doi: 10.1016/j.renene.2021.06.079.
[189] V. Demir and H. Citakoglu, "Forecasting of solar radiation using different machine learning approaches," *Neural Comput. Appl.*, vol. 35, no. 1, pp. 887–906, Jan. 2023, doi: 10.1007/s00521-022-07841-x.
[190] A. Rajagopalan *et al.*, "Empowering power distribution: Unleashing the synergy of IoT and cloud computing for sustainable and efficient energy systems," *Results Eng.*, vol. 21, p. 101949, Mar. 2024, doi: 10.1016/j.rineng.2024.101949.
[191] D. Wilantara, N. B. Mulyono, and D. Winarso, "Automate Short Cyclic Well Job Candidacy Using Artificial Neural Networks–Enabled Lean Six Sigma Approach: A Case Study in Oil and Gas Company," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 12, no. 4, p. 1639, Aug. 2022, doi: 10.18517/ijaseit.12.4.12845.
[192] D. Rosiani, M. Gibral Walay, P. Rahalintar, A. D. Candra, A. Sofyan, and Y. Arison Haratua, "Application of Artificial Intelligence in Predicting Oil Production Based on Water Injection Rate," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 13, no. 6, pp. 2338–2344, Dec. 2023, doi: 10.18517/ijaseit.13.6.19399.
[193] I. P. Astuti, A. Yudaputra, D. S. Rinandio, and A. Y. Yuswandi, "Biogeographical Distribution Model of Flowering Plant Capparis micracantha Using Support Vector Machine (SVM) and Generalized Linear Model (GLM) and its Ex-situ Conservation Efforts," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 11, no. 6, p. 2328, Dec. 2021, doi: 10.18517/ijaseit.11.6.14582.
[194] S. M. Padmaja *et al.*, "Stability and Reliability Analysis for Multiple WT Using Deep Reinforcement Learning," *Electr. Power Components Syst.*, vol. 52, no. 2, pp. 308–321, Jan. 2024, doi: 10.1080/15325008.2023.2220313.
[195] P. Ashok Babu, J. L. Mazher Iqbal, S. Siva Priyanka, M. Jithender Reddy, G. Sunil Kumar, and R. Ayyasamy, "Power Control and Optimization for Power Loss Reduction Using Deep Learning in Microgrid Systems," *Electr. Power Components Syst.*, vol. 52, no. 2, pp. 219–232, Jan. 2024, doi: 10.1080/15325008.2023.2217175.
[196] J. Wang *et al.*, "Upstream Solar Wind Prediction up to Mars by an Operational Solar Wind Prediction System," *Sp. Weather*, vol. 21, no. 1, Jan. 2023, doi: 10.1029/2022SW003281.
[197] F. Nawab, A. S. Abd Hamid, A. Ibrahim, K. Sopian, A. Fazlizan, and M. F. Fauzan, "Solar irradiation prediction using empirical and artificial intelligence methods: A comparative review," *Heliyon*, vol. 9, no. 6, p. e17038, Jun. 2023, doi: 10.1016/j.heliyon.2023.e17038.
[198] L. Goliatt and Z. M. Yaseen, "Development of a hybrid computational intelligent model for daily global solar radiation prediction," *Expert Syst. Appl.*, vol. 212, p. 118295, Feb. 2023, doi: 10.1016/j.eswa.2022.118295.
[199] H. Zhang, E. Hu, C. Duan, and J. Qin, "An improved model to evaluate the performance of solar-aided power generation plants," *Int. J. Green Energy*, vol. 19, no. 3, pp. 300–313, Feb. 2022, doi: 10.1080/15435075.2021.1946810.
[200] Z. Said *et al.*, "Modeling-optimization of performance and emission characteristics of dual-fuel engine powered with pilot diesel and agricultural-food waste-derived biogas," *Int. J. Hydrogen Energy*, vol. 48, no. 18, pp. 6761–6777, Feb. 2023, doi: 10.1016/j.ijhydene.2022.07.150.
[201] Q. B. Doan, X. P. Nguyen, T. M. H. Dong, M. T. Pham, and T. S. Le, "Performance and emission characteristics of diesel engine using ether additives: A review," *Int. J. Renew. Energy Dev.*, vol. 11, no. 1, pp. 255–274, 2022.
[202] J. C. Juan, A. T. Hoang, and C. K. Cheng, "Sustainable aviation fuel," *Fuel*, vol. 347, p. 128369, Sep. 2023, doi: 10.1016/j.fuel.2023.128369.
[203] T. T. Truong, X. P. Nguyen, V. V. Pham, V. V. Le, A. T. Le, and V. T. Bui, "Effect of alcohol additives on diesel engine performance: a review," *Energy Sources, Part A Recover. Util. Environ. Eff.*, pp. 1–25, Dec. 2021, doi: 10.1080/15567036.2021.2011490.
[204] R. Zhao *et al.*, "A Numerical and Experimental Study of Marine Hydrogen–Natural Gas–Diesel Tri–Fuel Engines," *Polish Marit. Res.*, vol. 27, no. 4, pp. 80–90, Dec. 2020, doi: 10.2478/pomr-2020-0068.

[205] R. Alawneh, F. Ghazali, H. Ali, and M. Asif, "A new index for assessing the contribution of energy efficiency in LEED 2009 certified green buildings to achieving UN sustainable development goals in Jordan," *Int. J. Green Energy*, vol. 16, no. 6, pp. 490–499, May 2019, doi: 10.1080/15435075.2019.1584104.

[206] A. Chatterjee, A. Brent, R. Rayudu, and P. Verma, "Microgrids for rural schools: An energy-education accord to curb societal challenges for sustainable rural developments," *Int. J. Renew. Energy Dev.*, vol. 8, no. 3, pp. 231–241, Oct. 2019, doi: 10.14710/ijred.8.3.231-241.

[207] H. Liu and F. Yan, "Quantitative analysis of impact factors and scenario prediction of energy related carbon emissions at county level," *Int. J. Green Energy*, vol. 20, no. 12, pp. 1342–1351, Sep. 2023, doi: 10.1080/15435075.2022.2110379.

[208] D. R. Adhikari, K. Techato, and R. Jariyaboon, "A systematic literature review on renewable energy technologies for energy sustainability in Nepal: Key challenges and opportunities," *Int. J. Renew. Energy Dev.*, vol. 13, no. 2, pp. 206–222, Mar. 2024, doi: 10.61435/ijred.2024.60032.

[209] F. Müller, M. Neumann, C. Elsner, and S. Claar, "Assessing African Energy Transitions: Renewable Energy Policies, Energy Justice, and SDG 7," *Polit. Gov.*, vol. 9, no. 1, pp. 119–130, Feb. 2021, doi: 10.17645/pag.v9i1.3615.

[210] D. Firoiu, G. H. Ionescu, R. Pîrvu, L. M. Cismaș, S. Tudor, and I. C. Patrichi, "Dynamics of Implementation of SDG 7 Targets in EU Member States 5 Years after the Adoption of the Paris Agreement," *Sustainability*, vol. 13, no. 15, p. 8284, Jul. 2021, doi: 10.3390/su13158284.

[211] M. J. Burke and R. Melgar, "SDG 7 requires post-growth energy sufficiency," *Front. Sustain.*, vol. 3, Aug. 2022, doi: 10.3389/frsus.2022.940958.

[212] J. Che, Z. An, Y. Zheng, and F. Song, "The dynamic complementarity of renewable energy sources: A Bayesian vector autoregressive approach," *Int. J. Green Energy*, vol. 20, no. 13, pp. 1501–1513, Oct. 2023, doi: 10.1080/15435075.2022.2160933.

[213] M. Q. Chau, D. C. Nguyen, A. T. Hoang, Q. V. Tran, and V. V. Pham, "A Numeral Simulation Determining Optimal Ignition Timing Advance of SI Engines Using 2.5-Dimethylfuran-Gasoline Blends," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 10, no. 5, pp. 1933–1938, Oct. 2020, doi: 10.18517/ijaseit.10.5.13051.

[214] Semin, R. A. Bakar, and L. P. A. RFC, "Analysis of the Effect of Intake Valve Fin Adding of Dual Fuel Engine on the Performance-Based Experiment," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 10, no. 5, pp. 1939–1945, 2020, doi: 10.18517/ijaseit.10.5.6632.

[215] S. A. Rahman, A. Meryandini, A. B. Juanssilfero, and Fahrurrozi, "Cocoa Pod Husk (CPH) for Biomass on Bioethanol Production," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 13, no. 3, pp. 828–836, 2023, doi: 10.18517/ijaseit.13.3.18794.

[216] N. U. Utami, M. Said, M. Faizal, and L. N. Komariah, "Conversion of palm oil mill effluent on biogas production with consortium bacteria," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 9, no. 6, pp. 2035–2041, 2019, doi: 10.18517/ijaseit.9.6.10461.

[217] IRENA, "Tracking SDG7: The Energy Progress Report (2018)," 2018.

[218] C.-W. Shyu, "A framework for 'right to energy' to meet UN SDG7: Policy implications to meet basic human energy needs, eradicate energy poverty, enhance energy justice, and uphold energy democracy," *Energy Res. Soc. Sci.*, vol. 79, p. 102199, Sep. 2021, doi: 10.1016/J.ERSS.2021.102199.

[219] S. A. Mohd Johari, M. Ayoub, J. Z. Lee, N. A. Rashidi, and M. R. Shamsuddin, "Utilization of Dairy Waste Scum Oil for Microwave-Assisted Biodiesel Production over KOH-Waste Eggshell based Calcium Oxide Catalyst," *Int. J. Renew. Energy Dev.*, Mar. 2024, doi: 10.61435/ijred.2024.59995.

[220] O. Balli and A. Dalkiran, "Comparative thermodynamic, environmental and sustainability performance assessments of an aero turboprop engine utilizing jet fuel and biofuel," *Int. J. Green Energy*, vol. 19, no. 13, pp. 1466–1485, Oct. 2022, doi: 10.1080/15435075.2021.2005606.

[221] L. Saini, C. S. Meena, B. P. Raj, N. Agarwal, and A. Kumar, "Net Zero Energy Consumption building in India: An overview and initiative toward sustainable future," *Int. J. Green Energy*, vol. 19, no. 5, pp. 544–561, Apr. 2022, doi: 10.1080/15435075.2021.1948417.

[222] P. Das, C. K. Jha, S. Saxena, and R. K. Ghosh, "Can biofuels help achieve sustainable development goals in India? A systematic review," *Renew. Sustain. Energy Rev.*, vol. 192, p. 114246, Mar. 2024, doi: 10.1016/j.rser.2023.114246.

[223] C. R. Canavan, L. Graybill, W. Fawzi, and J. Kinabo, "The SDGs Will Require Integrated Agriculture, Nutrition, and Health at the Community Level," *Food Nutr. Bull.*, vol. 37, no. 1, pp. 112–115, Mar. 2016, doi: 10.1177/0379572115626617.

[224] R. Cioffi, M. Travaglioni, G. Piscitelli, A. Petrillo, and F. De Felice, "Artificial Intelligence and Machine Learning Applications in Smart Production: Progress, Trends, and Directions," *Sustainability*, vol. 12, no. 2, p. 492, Jan. 2020, doi: 10.3390/su12020492.

[225] M. Liang and M. Chen, "Monitoring the Performance of a Ship's Main Engine Based on Big Data Technology," *Polish Marit. Res.*, vol. 29, no. 3, pp. 128–140, 2022.

[226] Z. Korczewski, "Energy and Emission Quality Ranking of Newly Produced Low-Sulphur Marine Fuels," *Polish Marit. Res.*, vol. 29, no. 4, pp. 77–87, Dec. 2022, doi: 10.2478/pomr-2022-0045.

[227] V. H. Dong and P. Sharma, "Optimized conversion of waste vegetable oil to biofuel with Meta heuristic methods and design of experiments," *J. Emerg. Sci. Eng.*, vol. 1, no. 1, pp. 22–28, Sep. 2023, doi: 10.61435/jese.2023.4.

[228] A.-T. Le, Y.-L. T. Nguyen, K. N. Duc, T.-D. Nghiem, H.-T. Pham, and N.-D. Bui, "Applying a neural network-based approach for estimating instantaneous emissions of the heavy-duty buses: A case study," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 44, no. 3, pp. 8012–8023, Sep. 2022, doi: 10.1080/15567036.2022.2118903.

[229] A. T. Hoang and V. V. Pham, "A study of emission characteristic, deposits, and lubrication oil degradation of a diesel engine running on preheated vegetable oil and diesel oil," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 41, no. 5, pp. 611–625, Mar. 2019, doi: 10.1080/15567036.2018.1520344.

[230] A. T. Hoang, A. T. Le, and V. V. Pham, "A core correlation of spray characteristics, deposit formation, and combustion of a high-speed diesel engine fueled with Jatropha oil and diesel fuel," *Fuel*, vol. 244, pp. 159–175, May 2019, doi: 10.1016/j.fuel.2019.02.009.

[231] A. T. Hoang, V. V. Le, V. V. Pham, and B. C. Tham, "An investigation of deposit formation in the injector, spray characteristics, and performance of a diesel engine fueled with preheated vegetable oil and diesel fuel," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 41, no. 23, pp. 2882–2894, Dec. 2019, doi: 10.1080/15567036.2019.1582731.

[232] C. Sik Lee *et al.*, "Experimental study on the effects of ethanol blends on the combustion process, power performance and emission reduction of a motorcycle spark-ignition engine," *Int. J. Ambient Energy*, vol. 43, no. 1, pp. 7150–7160, Dec. 2022, doi: 10.1080/01430750.2022.2063383.

[233] V. N. Nguyen *et al.*, "Understanding fuel saving and clean fuel strategies towards green maritime," *Polish Marit. Res.*, vol. 30, no. 2, pp. 146–164, 2023, doi: 10.2478/pomr-2023-0030.

[234] Z. Korczewski, "Health Monitoring of a Compression Ignition Engine Fed with Different Low-Sulphur Marine Fuels by Endoscopic Image Processing and Analysis," *Polish Marit. Res.*, vol. 30, no. 2, pp. 85–94, Jun. 2023, doi: 10.2478/pomr-2023-0024.

[235] Z. Domachowski, "Minimizing Greenhouse Gas Emissions From Ships Using a Pareto Multi-Objective Optimization Approach," *Polish Marit. Res.*, vol. 28, no. 2, pp. 96–101, Jun. 2021, doi: 10.2478/pomr-2021-0026.

[236] T. Le Anh, K. Nguyen Duc, H. Tran Thi Thu, and T. Cao Van, "Improving Performance and Reducing Pollution Emissions of a Carburetor Gasoline Engine by Adding HHO Gas into the Intake Manifold," Mar. 2013. doi: 10.4271/2013-01-0104.

[237] Z. Hu and W. Qin, "Fuzzy Method and Neural Network Model Parallel Implementation of Multi-Layer Neural Network Based on Cloud Computing for Real Time Data Transmission in Large Offshore Platform," *Polish Marit. Res.*, vol. 24, no. s2, pp. 39–44, Aug. 2017, doi: 10.1515/pomr-2017-0062.

[238] V. G. Nguyen *et al.*, "Using Artificial Neural Networks for Predicting Ship Fuel Consumption," *Polish Marit. Res.*, vol. 30, no. 2, pp. 39–60, Jun. 2023, doi: 10.2478/pomr-2023-0020.

[239] O. M. Butt, M. S. Ahmad, H. S. Che, and N. A. Rahim, "Usage of on-demand oxyhydrogen gas as clean/renewable fuel for combustion applications: a review," *Int. J. Green Energy*, vol. 18, no. 13, pp. 1405–1429, Oct. 2021, doi: 10.1080/15435075.2021.1904944.

[240] P. Saha *et al.*, "Grey, blue, and green hydrogen: A comprehensive review of production methods and prospects for zero-emission energy," *Int. J. Green Energy*, pp. 1–15, Aug. 2023, doi: 10.1080/15435075.2023.2244583.

[241] M. I. Lamas, R. C.G., T. J., and R. J.D., "Numerical Analysis of Emissions from Marine Engines Using Alternative Fuels," *Polish Marit. Res.*, vol. 22, no. 4, pp. 48–52, Dec. 2015, doi: 10.1515/pomr-2015-0070.

[242] L. Zhou, Y. Song, W. Ji, and H. Wei, “Machine learning for combustion,” *Energy AI*, vol. 7, p. 100128, Jan. 2022, doi: 10.1016/j.egyai.2021.100128.
[243] Q. Shi, Y. Hu, and G. Yan, “Fault Diagnosis of ME Marine Diesel Engine Fuel Injector with Novel IRCMDE Method,” *Polish Marit. Res.*, vol. 30, no. 3, pp. 96–110, Sep. 2023, doi: 10.2478/pomr-2023-0043.
[244] K. Janardhana *et al.*, “ANFIS modeling of biodiesels’ physical and engine characteristics: A review,” *Heat Transf.*, vol. 50, no. 8, pp. 8052–8079, Dec. 2021, doi: 10.1002/htj.22266.
[245] G. Najafi *et al.*, “SVM and ANFIS for prediction of performance and exhaust emissions of a SI engine with gasoline–ethanol blended fuels,” *Appl. Therm. Eng.*, vol. 95, pp. 186–203, Feb. 2016, doi: 10.1016/j.applthermaleng.2015.11.009.
[246] H. Darmawan, M. Yuliana, and M. Z. S. Hadi, “GRU and XGBoost Performance with Hyperparameter Tuning Using GridSearchCV and Bayesian Optimization on an IoT-Based Weather Prediction System,” *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 13, no. 3, pp. 848–859, 2023, doi: 10.18517/ijaseit.13.3.18377.
[247] M. Alruqi, P. Sharma, B. Deepanraj, and F. Shaik, “Renewable energy approach towards powering the CI engine with ternary blends of algal biodiesel-diesel-diethyl ether: Bayesian optimized Gaussian process regression for modeling-optimization,” *Fuel*, vol. 334, p. 126827, Feb. 2023, doi: 10.1016/j.fuel.2022.126827.
[248] P. Sharma, “Artificial intelligence-based model prediction of biodiesel-fueled engine performance and emission characteristics: A comparative evaluation of gene expression programming and artificial neural network,” *Heat Transf.*, vol. 50, no. 6, pp. 5563–5587, Sep. 2021, doi: 10.1002/htj.22138.
[249] P. Sharma, “Gene expression programming-based model prediction of performance and emission characteristics of a diesel engine fueled with linseed oil biodiesel/diesel blends: An artificial intelligence approach,” *Energy Sources, Part A Recover. Util. Environ. Eff.*, 2020, doi: 10.1080/15567036.2020.1829204.
[250] A. Semic and S. Karamehic, “Stroke Analysis and Prediction Using PySpark, Suport Vector Machine and Random Forest Regression,” *Int. J. Data Sci.*, vol. 3, no. 2, pp. 62–70, 2022.
[251] N. A. Zakaria, Z. Ali Shah, and S. Kasim, “Protein Structure Prediction Using Robust Principal Component Analysis and Support Vector Machine,” *Int. J. Data Sci.*, vol. 1, no. 1, pp. 14–17, May 2020, doi: 10.18517/ijods.1.1.14-17.2020.
[252] W. Peng and O. Karimi Sadaghiani, “Machine learning for sustainable reutilization of waste materials as energy sources – a comprehensive review,” *Int. J. Green Energy*, pp. 1–26, Sep. 2023, doi: 10.1080/15435075.2023.2255647.
[253] D. Raising Rathod *et al.*, “Prospects of novel heterogeneous base catalysts and nanocatalysts in achieving sustainable biodiesel production,” *Int. J. Green Energy*, vol. 21, no. 5, pp. 1017–1042, Apr. 2024, doi: 10.1080/15435075.2023.2228886.
[254] S. Salni, P. L. Hariani, and H. M. Hanifa, “Influence of the Rubber Seed Type and Altitude on Characteristic of Seed, Oil and Biodiesel,” *Int. J. Renew. Energy Dev.*, vol. 6, no. 2, pp. 157–163, Jun. 2017, doi: 10.14710/ijred.6.2.157-163.
[255] D. Jiang, Y. Long, P. Fu, C. Guo, Y. Tang, and H. Huang, “A novel multi-stack fuel cell hybrid system energy management strategy for improving the fuel cell durability of the hydrogen electric Multiple Units,” *Int. J. Green Energy*, pp. 1–10, Oct. 2023, doi: 10.1080/15435075.2023.2266724.
[256] O. Adeleke, S. A. Akinlabi, T.-C. Jen, and I. Dunmade, “Sustainable utilization of energy from waste: A review of potentials and challenges of Waste-to-energy in South Africa,” *Int. J. Green Energy*, vol. 18, no. 14, pp. 1550–1564, Nov. 2021, doi: 10.1080/15435075.2021.1914629.
[257] R. V. N. Seutche, M. Sawadogo, and F. N. Ngassam, “Valuation of CO2 Emissions Reduction from Renewable Energy and Energy Efficiency Projects in Africa: A Case Study of Burkina Faso,” *Int. J. Renew. Energy Dev.*, vol. 10, no. 4, pp. 713–729, Nov. 2021, doi: 10.14710/ijred.2021.34566.
[258] M. Kügemann and H. Polatidis, “Multi-criteria decision analysis of alternative fuel buses: methodology and case-study,” *Int. J. Green Energy*, pp. 1–21, Feb. 2024, doi: 10.1080/15435075.2024.2316768.
[259] M. Younis, S. Y. Alnouri, B. J. Abu Tarboush, and M. N. Ahmad, “Renewable biofuel production from biomass: a review for biomass pelletization, characterization, and thermal conversion techniques,” *Int. J. Green Energy*, vol. 15, no. 13, pp. 837–863, Oct. 2018, doi: 10.1080/15435075.2018.1529581.
[260] P. Varma, J. Otageri, and B. Kandasubramanian, “Biodiesel from fats: Fatty acid feedstock as a circular economy solution,” *Int. J. Green Energy*, pp. 1–21, Feb. 2024, doi: 10.1080/15435075.2024.2319219.
[261] X. Zhu, W. Guo, Z. Luo, X. Zhu, W. Cai, and X. Zhu, “Combined with co-hydrothermal carbonation of wood waste and food waste digestate for enhanced gasification of wood waste,” *Fuel*, vol. 331, p. 125789, Jan. 2023, doi: 10.1016/j.fuel.2022.125789.
[262] M. Melikoglu, “Reutilisation of food wastes for generating fuels and value added products: A global review,” *Environ. Technol. Innov.*, vol. 19, p. 101040, Aug. 2020, doi: 10.1016/j.eti.2020.101040.
[263] P. Ganguly, S. Sengupta, P. Das, and A. Bhowal, “Valorization of food waste: Extraction of cellulose, lignin and their application in energy use and water treatment,” *Fuel*, vol. 280, p. 118581, Nov. 2020, doi: 10.1016/j.fuel.2020.118581.
[264] K. Shu, J. Scheffran, U. A. Schneider, L. E. Yang, and J. Elflein, “Reconciling food and bioenergy feedstock supply in emerging economies: Evidence from Jiangsu Province in China,” *Int. J. Green Energy*, vol. 14, no. 6, pp. 509–521, May 2017, doi: 10.1080/15435075.2017.1297307.
[265] Y. S. Chandrasiri, W. M. L. I. Weerasinghe, D. A. T. Madusanka, and P. M. Manage, “Waste-Based Second-Generation Bioethanol: A Solution for Future Energy Crisis,” *Int. J. Renew. Energy Dev.*, vol. 11, no. 1, pp. 275–285, Feb. 2022, doi: 10.14710/ijred.2022.41774.
[266] S. Zullaikah *et al.*, “Experimental Investigation and Optimization of Non-Catalytic In-Situ Biodiesel Production from Rice Bran Using Response Surface Methodology Historical Data Design,” *Int. J. Renew. Energy Dev.*, vol. 10, no. 4, pp. 803–810, Nov. 2021, doi: 10.14710/ijred.2021.34138.
[267] A. Dubey, R. S. Prasad, and J. K. Singh, “An Analytical and Economical Assessment of the Waste Cooking Oil based Biodiesel using Optimized Conditions on the Process Variables,” *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 00, no. 00, pp. 1–16, 2020, doi: 10.1080/15567036.2020.1839600.
[268] T. Mizik and G. Gyarmati, “Economic and Sustainability of Biodiesel Production—A Systematic Literature Review,” *Clean Technol.*, vol. 3, no. 1, pp. 19–36, Jan. 2021, doi: 10.3390/cleantechnol3010002.
[269] T. G. Ambaye, M. Vaccari, A. Bonilla-Petriciolet, S. Prasad, E. D. van Hullebusch, and S. Rtimi, “Emerging technologies for biofuel production: A critical review on recent progress, challenges and perspectives,” *J. Environ. Manage.*, vol. 290, p. 112627, 2021.
[270] M V Rodionova *et al.*, “Biofuel production: challenges and opportunities,” *Int. J. Hydrogen Energy*, vol. 42, no. 12, pp. 8450–8461, 2017.
[271] S. Singh, G. Pandey, G. K. Rath, H. P. Veluswamy, and N. Molokitina, “Life cycle assessment of biomass-based hydrogen production technologies: A review,” *Int. J. Green Energy*, pp. 1–16, Aug. 2023, doi: 10.1080/15435075.2023.2245453.
[272] B. Samantaray, S. Mohapatra, R. R. Mishra, B. C. Behera, and H. Thatoi, “Bioethanol production from agro-wastes: a comprehensive review with a focus on pretreatment, enzymatic hydrolysis, and fermentation,” *Int. J. Green Energy*, pp. 1–27, Sep. 2023, doi: 10.1080/15435075.2023.2253871.
[273] A. Demirbas, “Biofuels sources, biofuel policy, biofuel economy and global biofuel projections,” *Energy Convers. Manag.*, vol. 49, no. 8, pp. 2106–2116, Aug. 2008, doi: 10.1016/j.enconman.2008.02.020.
[274] A. Buasri, P. Sirikoom, S. Pattane, O. Buachum, and V. Loryuenyong, “Process Optimization of Biodiesel from Used Cooking Oil in a Microwave Reactor: A Case of Machine Learning and Box–Behnken Design,” *ChemEngineering*, vol. 7, no. 4, p. 65, Jul. 2023, doi: 10.3390/chemengineering7040065.
[275] L. M. Colla, M. Zaparoli, F. de S. Sossella, N. E. Kreling, and A. Rempel, “Cellular stress strategies and harvesting methods to improve the feasibility of microalgae biofuel,” *Int. J. Green Energy*, vol. 19, no. 10, pp. 1098–1117, Aug. 2022, doi: 10.1080/15435075.2021.1983726.
[276] P. R. Jeon *et al.*, “Recent advances and future prospects of thermochemical biofuel conversion processes with machine learning,” *Chem. Eng. J.*, vol. 471, p. 144503, Sep. 2023, doi: 10.1016/j.cej.2023.144503.
[277] M. Mowbray *et al.*, “Machine learning for biochemical engineering: A review,” *Biochem. Eng. J.*, vol. 172, p. 108054, Aug. 2021, doi: 10.1016/j.bej.2021.108054.
[278] J. Poore and T. Nemecek, “Reducing food’s environmental impacts through producers and consumers,” *Science (80-.).*, vol. 360, no. 6392, pp. 987–992, Jun. 2018, doi: 10.1126/science.aaq0216.
[279] D. C. Makepa, C. H. Chihobo, T. T. Manhongo, and D. Musademba, “Life-cycle assessment of microwave-assisted pyrolysis of pine sawdust as an emerging technology for biodiesel production,” *Results Eng.*, vol. 20, p. 101480, Dec. 2023, doi: 10.1016/j.rineng.2023.101480.

[280] R. de la Torre, C. G. Corlu, J. Faulin, B. S. Onggo, and A. A. Juan, "Simulation, Optimization, and Machine Learning in Sustainable Transportation Systems: Models and Applications," *Sustainability*, vol. 13, no. 3, p. 1551, Feb. 2021, doi: 10.3390/su13031551.
[281] I. Ahmad *et al.*, "Machine Learning Applications in Biofuels' Life Cycle: Soil, Feedstock, Production, Consumption, and Emissions," *Energies*, vol. 14, no. 16, p. 5072, Aug. 2021, doi: 10.3390/en14165072.
[282] M. Suvarna *et al.*, "Predicting biodiesel properties and its optimal fatty acid profile via explainable machine learning," *Renew. Energy*, vol. 189, pp. 245–258, Apr. 2022, doi: 10.1016/j.renene.2022.02.124.
[283] 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.
[284] P. Sharma *et al.*, "Application of machine learning and Box-Behnken design in optimizing engine characteristics operated with a dual-fuel mode of algal biodiesel and waste-derived biogas," *Int. J. Hydrogen Energy*, vol. 48, no. 18, pp. 6738–6760, Feb. 2023, doi: 10.1016/j.ijhydene.2022.04.152.
[285] H. Moayedi, B. Aghel, L. K. Foong, and D. T. Bui, "Feature validity during machine learning paradigms for predicting biodiesel purity," *Fuel*, vol. 262, p. 116498, Feb. 2020, doi: 10.1016/j.fuel.2019.116498.
[286] N. Sultana, S. M. Z. Hossain, M. Abusaad, N. Alanbar, Y. Senan, and S. A. Razzak, "Prediction of biodiesel production from microalgal oil using Bayesian optimization algorithm-based machine learning approaches," *Fuel*, vol. 309, p. 122184, Feb. 2022, doi: 10.1016/j.fuel.2021.122184.
[287] S. Dey, N. M. Reang, A. Majumder, M. Deb, and P. K. Das, "A hybrid ANN-Fuzzy approach for optimization of engine operating parameters of a CI engine fueled with diesel-palm biodiesel-ethanol blend," *Energy*, 2020, doi: 10.1016/j.energy.2020.117813.
[288] H. Karimmaslak, B. Najafi, S. S. Band, S. Ardabili, F. Haghighat-Shoar, and A. Mosavi, "Optimization of performance and emission of compression ignition engine fueled with propylene glycol and biodiesel–diesel blends using artificial intelligence method of ANN-GA-RSM," *Eng. Appl. Comput. Fluid Mech.*, vol. 15, no. 1, pp. 413–425, Jan. 2021, doi: 10.1080/19942060.2021.1880970.
[289] M. Aydın, S. Uslu, and M. B. Çelik, "Performance and emission prediction of a compression ignition engine fueled with biodiesel-diesel blends: A combined application of ANN and RSM based optimization," *Fuel*, vol. 269, p. 117472, 2020.
[290] T. Wang, H. Huang, X. Li, X. Guo, M. Liu, and H. Lei, "Optimal estimation of proton exchange membrane fuel cell model parameters based on an improved chicken swarm optimization algorithm," *Int. J. Green Energy*, vol. 20, no. 9, pp. 946–965, Jul. 2023, doi: 10.1080/15435075.2022.2131432.
[291] A. I. Hassane, D. H. Didane, A. M. Tahir, R. M. Mouangue, J. G. Tamba, and J.-M. Hauglustaine, "Comparative Analysis of Hybrid Renewable Energy Systems for Off-Grid Applications in Chad.," *Int. J. Renew. Energy Dev.*, vol. 11, no. 1, 2022.
[292] M. Soltani *et al.*, "A comprehensive review of geothermal energy evolution and development," *Int. J. Green Energy*, vol. 16, no. 13, pp. 971–1009, Oct. 2019, doi: 10.1080/15435075.2019.1650047.
[293] T. B. N. Nguyen and N. V. L. Le, "Biomass resources and thermal conversion biomass to biofuel for cleaner energy: A review," *J. Emerg. Sci. Eng.*, vol. 1, no. 1, pp. 6–13, Sep. 2023, doi: 10.61435/jese.2023.2.
[294] M. Usman, S. Cheng, and J. S. Cross, "Biomass Feedstocks for Liquid Biofuels Production in Hawaii & Tropical Islands: A Review," *Int. J. Renew. Energy Dev.*, vol. 11, no. 1, pp. 111–132, Feb. 2022, doi: 10.14710/ijred.2022.39285.
[295] M. Sivaramakrishnaiah *et al.*, "Numerical and experimental investigations on a bladeless turbine: Tesla's cohesion-type innovation," *Int. J. Renew. Energy Dev.*, vol. 13, no. 1, pp. 110–121, Jan. 2024, doi: 10.14710/ijred.2024.55455.
[296] J. Viglasky, O. Barborak, J. Suchomel, and N. Langova, "Status and Vision for the Biomass-To-Energy Sector," *World Futures*, vol. 65, no. 5–6, pp. 389–405, Sep. 2009, doi: 10.1080/02604020903021594.
[297] K. Parmar, "Biomass- An Overview on Composition Characteristics and Properties," *IRA-International J. Appl. Sci. (ISSN 2455-4499)*, vol. 7, no. 1, p. 42, May 2017, doi: 10.21013/jas.v7.n1.p4.
[298] J. Han, X. Yao, Y. Zhan, S.-Y. Oh, L.-H. Kim, and H.-J. Kim, "A method for estimating higher heating value of biomass-plastic fuel," *J. Energy Inst.*, vol. 90, no. 2, pp. 331–335, Apr. 2017, doi: 10.1016/j.joei.2016.01.001.
[299] A. T. Hoang and O. Konur, "Microwave Pretreatment of the Biomass," in *Bioethanol Fuel Production Processes. I*, CRC Press, 2023, p. 18.
[300] G. S. Ghodake *et al.*, "Review on biomass feedstocks, pyrolysis mechanism and physicochemical properties of biochar: State-of-the-art framework to speed up vision of circular bioeconomy," *J. Clean. Prod.*, vol. 297, p. 126645, May 2021, doi: 10.1016/j.jclepro.2021.126645.
[301] M. Brooks, M. Abdellatif, and R. Alkhaddar, "Application of life cycle carbon assessment for a sustainable building design: a case study in the UK," *Int. J. Green Energy*, vol. 18, no. 4, pp. 351–362, Mar. 2021, doi: 10.1080/15435075.2020.1865360.
[302] M. Shahbaz, A. Inayat, D. O. Patrick, and M. Ammar, "The influence of catalysts in biomass steam gasification and catalytic potential of coal bottom ash in biomass steam gasification: a review," *Renew. Sustain. Energy Rev.*, vol. 73, pp. 468–476, 2017.
[303] B. Bushra and N. Remya, "Biochar from pyrolysis of rice husk biomass—characteristics, modification and environmental application," *Biomass Convers. Biorefinery*, pp. 1–12, 2020.
[304] H. M. U. Ayub, A. Ahmed, S. S. Lam, J. Lee, P. L. Show, and Y.-K. Park, "Sustainable valorization of algae biomass via thermochemical processing route: An overview," *Bioresour. Technol.*, vol. 344, p. 126399, 2022.
[305] V. G. Nguyen, P. Sharma, Ü. Ağbulut, H. S. Le, V. D. Tran, and D. N. Cao, "Precise prognostics of biochar yield from various biomass sources by Bayesian approach with supervised machine learning and ensemble methods," *Int. J. Green Energy*, pp. 1–25, Dec. 2023, doi: 10.1080/15435075.2023.2297776.
[306] A. Callegari, S. Bolognesi, D. Cecconet, and A. G. Capodaglio, "Production technologies, current role, and future prospects of biofuels feedstocks: A state-of-the-art review," *Crit. Rev. Environ. Sci. Technol.*, vol. 50, no. 4, pp. 384–436, Feb. 2020, doi: 10.1080/10643389.2019.1629801.
[307] I. Ryzhikov, M. Liukkonen, A. Kettunen, and Y. Hiltunen, "Risk Estimation in Data-driven Fault Prediction for a Biomass-fired Power Plant," in *Proceedings of the 12th International Joint Conference on Computational Intelligence*, SCITEPRESS - Science and Technology Publications, 2020, pp. 423–429. doi: 10.5220/0010113104230429.
[308] J. Popp, S. Kovács, J. Oláh, Z. Divéki, and E. Balázs, "Bioeconomy: Biomass and biomass-based energy supply and demand," *N. Biotechnol.*, vol. 60, pp. 76–84, Jan. 2021, doi: 10.1016/j.nbt.2020.10.004.
[309] M. A. Helal, N. Anderson, Y. Wei, and M. Thompson, "A Review of Biomass-to-Bioenergy Supply Chain Research Using Bibliometric Analysis and Visualization," *Energies*, vol. 16, no. 3, p. 1187, Jan. 2023, doi: 10.3390/en16031187.
[310] M. Balat, "Thermochemical Routes for Biomass-based Hydrogen Production," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 32, no. 15, pp. 1388–1398, May 2010, doi: 10.1080/15567030802706796.
[311] S. Mona, S. K. Malyan, N. Saini, B. Deepak, A. Pugazhendhi, and S. S. Kumar, "Towards sustainable agriculture with carbon sequestration, and greenhouse gas mitigation using algal biochar," *Chemosphere*, vol. 275, p. 129856, 2021, doi: 10.1016/j.chemosphere.2021.129856.
[312] F. Rosalina and I. Febriadi, "A Novel Ameliorant Biochar of Areca Nuts Skin and Sago Bark Waste for Increasing Soil Chemical Fertility," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 13, no. 3, pp. 1184–1189, 2023, doi: 10.18517/ijaseit.13.3.18315.
[313] R. Shaw and S. Mukherjee, "The development of carbon capture and storage (CCS) in India: A critical review," *Carbon Capture Sci. Technol.*, vol. 2, p. 100036, Mar. 2022, doi: 10.1016/j.ccst.2022.100036.
[314] L. Rosa and M. Mazzotti, "Potential for hydrogen production from sustainable biomass with carbon capture and storage," *Renew. Sustain. Energy Rev.*, vol. 157, p. 112123, Apr. 2022, doi: 10.1016/j.rser.2022.112123.
[315] M. H. Saeed, W. Fangzong, and B. A. Kalwar, "RETRACTED: Control of Bidirectional DC-DC Converter for Micro-Energy Grid's DC Feeders' Power Flow Application," *Int. J. Renew. Energy Dev.*, vol. 11, no. 2, pp. 533–546, May 2022, doi: 10.14710/ijred.2022.41952.
[316] Y. Wang, G. Chen, B. Yan, and R. Bastiaans, "A coupling energy system of 10 clean-energy heating systems: A case study in Shandong province in China," *Int. J. Green Energy*, vol. 18, no. 13, pp. 1323–1338, Oct. 2021, doi: 10.1080/15435075.2021.1897826.
[317] H. Asgedom and E. Kebreab, "Beneficial management practices and mitigation of greenhouse gas emissions in the agriculture of the Canadian Prairie: a review," *Agron. Sustain. Dev.*, vol. 31, no. 3, pp. 433–451, Jul. 2011, doi: 10.1007/s13593-011-0016-2.
[318] P. Smith *et al.*, "How much land-based greenhouse gas mitigation can be achieved without compromising food security and environmental goals?," *Glob. Chang. Biol.*, vol. 19, no. 8, pp. 2285–2302, Aug. 2013, doi: 10.1111/gcb.12160.

[319] K. Owebor, E. O. Diemuodeke, and T. A. Briggs, "Thermo-economic and environmental analysis of integrated power plant with carbon capture and storage technology," *Energy*, vol. 240, p. 122748, Feb. 2022, doi: 10.1016/j.energy.2021.122748.

[320] A. H. El-Kady, M. T. Amin, F. Khan, and M. M. El-Halwagi, "Analysis of CO2 pipeline regulations from a safety perspective for offshore carbon capture, utilization, and storage (CCUS)," *J. Clean. Prod.*, vol. 439, p. 140734, Feb. 2024, doi: 10.1016/j.jclepro.2024.140734.

[321] O. C. Anika, S. G. Nnabuife, A. Bello, E. R. Okoroafor, B. Kuang, and R. Villa, "Prospects of low and zero-carbon renewable fuels in 1.5-degree net zero emission actualisation by 2050: A critical review," *Carbon Capture Sci. Technol.*, vol. 5, p. 100072, Dec. 2022, doi: 10.1016/j.ccst.2022.100072.

[322] A. Shafizadeh *et al.*, "Machine learning-based characterization of hydrochar from biomass: Implications for sustainable energy and material production," *Fuel*, vol. 347, p. 128467, Sep. 2023, doi: 10.1016/j.fuel.2023.128467.

[323] T. Kalak, "Potential Use of Industrial Biomass Waste as a Sustainable Energy Source in the Future," *Energies*, vol. 16, no. 4, p. 1783, Feb. 2023, doi: 10.3390/en16041783.

[324] P. J. García-Nieto, E. García-Gonzalo, B. M. Paredes-Sánchez, and J. P. Paredes-Sánchez, "Modelling hydrogen production from biomass pyrolysis for energy systems using machine learning techniques," *Environ. Sci. Pollut. Res.*, vol. 30, no. 31, pp. 76977–76991, May 2023, doi: 10.1007/s11356-023-27805-5.

[325] N. Hodžić and K. Kadic, "Co-firing of coal and woody biomass under conditions of reburning technology with natural gas," *Int. J. Renew. Energy Dev.*, vol. 12, no. 3, pp. 440–447, May 2023, doi: 10.14710/ijred.2023.50250.

[326] F. Amiraslani and D. Dragovich, "Exporting electricity – a review of Iran's experience on water and energy development within a regional perspective," *Int. J. Green Energy*, vol. 21, no. 4, pp. 871–882, Mar. 2024, doi: 10.1080/15435075.2023.2222169.

[327] K. Sapkota, Shabbiruddin, and K. S. Sherpa, "Wind farm site suitability assessment & validation using geospatially explicit multi-criteria approach: A case study of South Sikkim, India," *Int. J. Green Energy*, vol. 21, no. 2, pp. 300–327, Jan. 2024, doi: 10.1080/15435075.2023.2195926.

[328] Y. Wang, Y. Dong, and X. Sun, "Can environmental regulations facilitate total-factor efficiencies in OECD countries? Energy-saving target VS emission-reduction target," *Int. J. Green Energy*, vol. 20, no. 13, pp. 1488–1500, Oct. 2023, doi: 10.1080/15435075.2022.2160932.

[329] V. Duc Bui *et al.*, "Techno-economic assessment and logistics management of biomass in the conversion progress to bioenergy," *Sustain. Energy Technol. Assessments*, vol. 55, p. 102991, Feb. 2023, doi: 10.1016/j.seta.2022.102991.

[330] V. N. Nguyen *et al.*, "Biochar-based catalysts derived from biomass waste: production, characterization, and application for liquid biofuel synthesis," *Biofuels, Bioprod. Biorefining*, Feb. 2024, doi: 10.1002/bbb.2593.

[331] Aisman, Santosa, R. A. Hadiguna, and N. Nazir, "Design of Sustainable Agricultural-Based Biomass Electrification Model in the Islands Area: Prospect of Bamboo Biomass," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 10, no. 5, pp. 2145–2151, 2020, doi: 10.18517/ijaseit.10.5.13421.

[332] A. Adetoyinbo, S. Gupta, V. O. Okoruwa, and R. Birner, "The role of institutions in sustaining competitive bioeconomy growth in Africa – Insights from the Nigerian maize biomass value-web," *Sustain. Prod. Consum.*, vol. 30, pp. 186–203, Mar. 2022, doi: 10.1016/j.spc.2021.11.013.

[333] G. Sahoo, A. Sharma, and A. Chandra Dash, "Biomass from trees for bioenergy and biofuels – A briefing paper," *Mater. Today Proc.*, vol. 65, pp. 461–467, 2022, doi: 10.1016/j.matpr.2022.02.639.

[334] E. Aykut and Ü. K. Terzi, "Techno-economic and environmental analysis of grid connected hybrid wind/photovoltaic/biomass system for Marmara University Goztepe campus," *Int. J. Green Energy*, vol. 17, no. 15, pp. 1036–1043, Dec. 2020, doi: 10.1080/15435075.2020.1821691.

[335] S. Zhu, N. Preuss, and F. You, "Advancing sustainable development goals with machine learning and optimization for wet waste biomass to renewable energy conversion," *J. Clean. Prod.*, vol. 422, p. 138606, Oct. 2023, doi: 10.1016/j.jclepro.2023.138606.

[336] C. Wang, S. A. Raza, T. S. Adebayo, S. Yi, and M. I. Shah, "The roles of hydro, nuclear and biomass energy towards carbon neutrality target in China: A policy-based analysis," *Energy*, vol. 262, p. 125303, Jan. 2023, doi: 10.1016/j.energy.2022.125303.

[337] M. M. Soltani, P. Ahmadi, and M. Ashjaee, "Techno-economic optimization of a biomass gasification energy system with Supercritical CO2 cycle for hydrogen fuel and electricity production," *Fuel*, vol. 333, p. 126264, Feb. 2023, doi: 10.1016/j.fuel.2022.126264.

[338] D. Ilic, K. Williams, R. Farnish, E. Webb, and G. Liu, "On the challenges facing the handling of solid biomass feedstocks," *Biofuels, Bioprod. Biorefining*, vol. 12, no. 2, pp. 187–202, Mar. 2018, doi: 10.1002/bbb.1851.

[339] A. Dunnett, C. Adjiman, and N. Shah, "Biomass to Heat Supply Chains," *Process Saf. Environ. Prot.*, vol. 85, no. 5, pp. 419–429, 2007, doi: 10.1205/psep07022.

[340] S. M. Zahraee, N. Shiwakoti, and P. Stasinopoulos, "Biomass supply chain environmental and socio-economic analysis: 40-Years comprehensive review of methods, decision issues, sustainability challenges, and the way forward," *Biomass and Bioenergy*, vol. 142, p. 105777, 2020.

[341] S. Ko, P. Lautala, and R. M. Handler, "Securing the feedstock procurement for bioenergy products: a literature review on the biomass transportation and logistics," *J. Clean. Prod.*, vol. 200, pp. 205–218, Nov. 2018, doi: 10.1016/j.jclepro.2018.07.241.

[342] P. Sittisun, N. Tippayawong, and S. Shimpalee, "Gasification of Pelletized Corn Residues with Oxygen Enriched Air and Steam," *Int. J. Renew. Energy Dev.*, vol. 8, no. 3, pp. 215–224, Oct. 2019, doi: 10.14710/ijred.8.3.215-224.

[343] F. N. Rahma, C. Tamzysi, A. Hidayat, and M. A. Adnan, "Investigation of Process Parameters Influence on Municipal Solid Waste Gasification with CO2 Capture via Process Simulation Approach," *Int. J. Renew. Energy Dev.*, vol. 10, no. 1, pp. 1–10, Feb. 2021, doi: 10.14710/ijred.2021.31982.

[344] T. M. Gür, "Review of electrical energy storage technologies, materials and systems: challenges and prospects for large-scale grid storage," *Energy Environ. Sci.*, vol. 11, no. 10, pp. 2696–2767, 2018, doi: 10.1039/C8EE01419A.

[345] M. A. Basit, S. Dilshad, R. Badar, and S. M. Sami ur Rehman, "Limitations, challenges, and solution approaches in grid-connected renewable energy systems," *Int. J. Energy Res.*, vol. 44, no. 6, pp. 4132–4162, May 2020, doi: 10.1002/er.5033.

[346] M. R. Anuar and A. Z. Abdullah, "Challenges in biodiesel industry with regards to feedstock, environmental, social and sustainability issues: A critical review," *Renew. Sustain. Energy Rev.*, vol. 58, pp. 208–223, May 2016, doi: 10.1016/j.rser.2015.12.296.

[347] S. K. Sansaniwal, M. A. Rosen, and S. K. Tyagi, "Global challenges in the sustainable development of biomass gasification: An overview," *Renew. Sustain. Energy Rev.*, vol. 80, pp. 23–43, 2017.

[348] A. W. Bhutto *et al.*, "Progress in the production of biomass-to-liquid biofuels to decarbonize the transport sector-prospects and challenges," *RSC Adv.*, vol. 6, no. 38, pp. 32140–32170, 2016, doi: 10.1039/c5ra26459f.

[349] M. Banja, R. Sikkema, M. Jégard, V. Motola, and J.-F. Dallemand, "Biomass for energy in the EU – The support framework," *Energy Policy*, vol. 131, pp. 215–228, Aug. 2019, doi: 10.1016/j.enpol.2019.04.038.

[350] S. Sen and S. Ganguly, "Opportunities, barriers and issues with renewable energy development – A discussion," *Renew. Sustain. Energy Rev.*, vol. 69, pp. 1170–1181, Mar. 2017, doi: 10.1016/j.rser.2016.09.137.

[351] A. Halba, S. K. Thengane, and P. Arora, "A Critical Outlook on Lignocellulosic Biomass and Plastics Co-Gasification: A Mini-Review," *Energy & Fuels*, vol. 37, no. 1, pp. 19–35, Jan. 2023, doi: 10.1021/acs.energyfuels.2c02907.

[352] B. Ercan, K. Alper, S. Ucar, and S. Karagoz, "Comparative studies of hydrochars and biochars produced from lignocellulosic biomass via hydrothermal carbonization, torrefaction and pyrolysis," *J. Energy Inst.*, vol. 109, p. 101298, Aug. 2023, doi: 10.1016/j.joei.2023.101298.

[353] F. Haleem, S. Farooq, Y. Cheng, and B. V. Waehrens, "Sustainable Management Practices and Stakeholder Pressure: A Systematic Literature Review," *Sustainability*, vol. 14, no. 4, p. 1967, Feb. 2022, doi: 10.3390/su14041967.

[354] F. Bilgili, E. Koçak, Ü. Bulut, and S. Kuşkaya, "Can biomass energy be an efficient policy tool for sustainable development?," *Renew. Sustain. Energy Rev.*, vol. 71, pp. 830–845, May 2017, doi: 10.1016/j.rser.2016.12.109.

[355] A. D. A. Bin Abu Sofian *et al.*, "Advances, Synergy, and Perspectives of Machine Learning and Biobased Polymers for Energy, Fuels, and Biochemicals for a Sustainable Future," *Energy & Fuels*, vol. 38, no. 3, pp. 1593–1617, Feb. 2024, doi: 10.1021/acs.energyfuels.3c03842.

[356] Z. Allal, H. N. Noura, O. Salman, and K. Chahine, "Machine learning solutions for renewable energy systems: Applications, challenges, limitations, and future directions," *J. Environ. Manage.*, vol. 354, p. 120392, Mar. 2024, doi: 10.1016/j.jenvman.2024.120392.

[357] I. Ali, F. Greifeneder, J. Stamenkovic, M. Neumann, and C. Notarnicola, "Review of Machine Learning Approaches for Biomass and Soil Moisture Retrievals from Remote Sensing Data," *Remote Sens.*, vol. 7, no. 12, pp. 16398–16421, Dec. 2015, doi: 10.3390/rs71215841.

[358] Y. Pristyanto, Z. Mukarabiman, and A. F. Nugraha, "Extreme Gradient Boosting Algorithm to Improve Machine Learning Model Performance on Multiclass Imbalanced Dataset," *JOIV Int. J. Informatics Vis.*, vol. 7, no. 3, pp. 710–715, Sep. 2023, doi: 10.30630/joiv.7.3.1102.

[359] H. P. Nguyen, P. Q. P. Nguyen, D. K. P. Nguyen, V. D. Bui, and D. T. Nguyen, "Application of IoT Technologies in Seaport Management," *JOIV Int. J. Informatics Vis.*, vol. 7, no. 1, pp. 228–240, Mar. 2023, doi: 10.30630/joiv.7.1.1697.

[360] - Andrizal, R. Chadry, and A. I. Suryani, "Embedded System Using Field Programmable Gate Array (FPGA) myRIO and LabVIEW Programming to Obtain Data Patern Emission of Car Engine Combustion Categories," *JOIV Int. J. Informatics Vis.*, vol. 2, no. 2, pp. 56–62, Mar. 2018, doi: 10.30630/joiv.2.2.50.

[361] H. Li *et al.*, "Machine-learning-aided thermochemical treatment of biomass: a review," *Biofuel Res. J.*, vol. 10, no. 1, pp. 1786–1809, Mar. 2023, doi: 10.18331/BRJ2023.10.1.4.

[362] F. Elmaz, Ö. Yücel, and A. Y. Mutlu, "Predictive modeling of biomass gasification with machine learning-based regression methods," *Energy*, vol. 191, p. 116541, Jan. 2020, doi: 10.1016/J.ENERGY.2019.116541.

[363] Z. Wang *et al.*, "The role of machine learning to boost the bioenergy and biofuels conversion," *Bioresour. Technol.*, vol. 343, p. 126099, Jan. 2022, doi: 10.1016/j.biortech.2021.126099.

[364] M. Syafrudin, G. Alfian, N. Fitriyani, and J. Rhee, "Performance Analysis of IoT-Based Sensor, Big Data Processing, and Machine Learning Model for Real-Time Monitoring System in Automotive Manufacturing," *Sensors*, vol. 18, no. 9, p. 2946, Sep. 2018, doi: 10.3390/s18092946.

[365] A. Diez-Olivan, J. Del Ser, D. Galar, and B. Sierra, "Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0," *Inf. Fusion*, vol. 50, pp. 92–111, Oct. 2019, doi: 10.1016/j.inffus.2018.10.005.

[366] W. Zhang *et al.*, "Machine learning for hydrothermal treatment of biomass: A review," *Bioresour. Technol.*, vol. 370, p. 128547, Feb. 2023, doi: 10.1016/j.biortech.2022.128547.

[367] Q. Liu *et al.*, "Machine learning-aided hydrothermal carbonization of biomass for coal-like hydrochar production: Parameters optimization and experimental verification," *Bioresour. Technol.*, vol. 393, p. 130073, Feb. 2024, doi: 10.1016/j.biortech.2023.130073.

[368] A. Rao, A. Talan, S. Abbas, D. Dev, and F. Taghizadeh-Hesary, "The role of natural resources in the management of environmental sustainability: Machine learning approach," *Resour. Policy*, vol. 82, p. 103548, May 2023, doi: 10.1016/j.resourpol.2023.103548.

[369] D. Radočaj and M. Jurišić, "GIS-Based Cropland Suitability Prediction Using Machine Learning: A Novel Approach to Sustainable Agricultural Production," *Agronomy*, vol. 12, no. 9, p. 2210, Sep. 2022, doi: 10.3390/agronomy12092210.

[370] A. Karthik, P. Kalita, A. Garg, L. Gao, S. Chen, and X. Peng, "A Novel MOGA approach for power saving strategy and optimization of maximum temperature and maximum pressure for liquid cooling type battery thermal management system," *Int. J. Green Energy*, vol. 18, no. 1, pp. 80–89, Jan. 2021, doi: 10.1080/15435075.2020.1831507.

[371] B. Chakma, L. Serto, S. Kharpude, P. Narale, and M. S. Seveda, "Life cycle assessment analysis, embodied energy evaluation and economic aspect study of double mirror reflector box type solar cooker for NEH region of Sikkim," *Int. J. Green Energy*, vol. 19, no. 9, pp. 1005–1022, Jul. 2022, doi: 10.1080/15435075.2021.1978446.

[372] S. Ascher, X. Wang, I. Watson, W. Sloan, and S. You, "Interpretable machine learning to model biomass and waste gasification," *Bioresour. Technol.*, vol. 364, p. 128062, Nov. 2022, doi: 10.1016/j.biortech.2022.128062.

[373] T. M. Alabi *et al.*, "A review on the integrated optimization techniques and machine learning approaches for modeling, prediction, and decision making on integrated energy systems," *Renew. Energy*, vol. 194, pp. 822–849, Jul. 2022, doi: 10.1016/j.renene.2022.05.123.

[374] A. Entezari, A. Aslani, R. Zahedi, and Y. Noorollahi, "Artificial intelligence and machine learning in energy systems: A bibliographic perspective," *Energy Strateg. Rev.*, vol. 45, p. 101017, Jan. 2023, doi: 10.1016/j.esr.2022.101017.

[375] C. Angione, E. Silverman, and E. Yaneske, "Using machine learning as a surrogate model for agent-based simulations," *PLoS One*, vol. 17, no. 2, p. e0263150, Feb. 2022, doi: 10.1371/journal.pone.0263150.

[376] S. Razavi *et al.*, "The Future of Sensitivity Analysis: An essential discipline for systems modeling and policy support," *Environ. Model. Softw.*, vol. 137, p. 104954, Mar. 2021, doi: 10.1016/j.envsoft.2020.104954.

[377] H. Li *et al.*, "Machine learning assisted predicting and engineering specific surface area and total pore volume of biochar," *Bioresour. Technol.*, vol. 369, p. 128417, Feb. 2023, doi: 10.1016/j.biortech.2022.128417.

[378] E. E. Ozbas, D. Aksu, A. Ongen, M. A. Aydin, and H. K. Ozcan, "Hydrogen production via biomass gasification, and modeling by supervised machine learning algorithms," *Int. J. Hydrogen Energy*, vol. 44, no. 32, pp. 17260–17268, Jun. 2019, doi: 10.1016/j.ijhydene.2019.02.108.

[379] A. Pathy, S. Meher, and B. P, "Predicting algal biochar yield using eXtreme Gradient Boosting (XGB) algorithm of machine learning methods," *Algal Res.*, vol. 50, p. 102006, Sep. 2020, doi: 10.1016/j.algal.2020.102006.

[380] L. Leng *et al.*, "Machine learning predicting and engineering the yield, N content, and specific surface area of biochar derived from pyrolysis of biomass," *Biochar*, vol. 4, no. 1, p. 63, Dec. 2022, doi: 10.1007/s42773-022-00183-w.

[381] H. Wei, K. Luo, J. Xing, and J. Fan, "Predicting co-pyrolysis of coal and biomass using machine learning approaches," *Fuel*, vol. 310, p. 122248, Feb. 2022, doi: 10.1016/j.fuel.2021.122248.

[382] Y. Li, R. Gupta, and S. You, "Machine learning assisted prediction of biochar yield and composition via pyrolysis of biomass," *Bioresour. Technol.*, vol. 359, p. 127511, Sep. 2022, doi: 10.1016/j.biortech.2022.127511.

[383] C. Chen *et al.*, "Characteristics prediction of hydrothermal biochar using data enhanced interpretable machine learning," *Bioresour. Technol.*, vol. 377, p. 128893, Jun. 2023, doi: 10.1016/j.biortech.2023.128893.

[384] Z. U. Haq, H. Ullah, M. N. A. Khan, S. Raza Naqvi, A. Ahad, and N. A. S. Amin, "Comparative study of machine learning methods integrated with genetic algorithm and particle swarm optimization for bio-char yield prediction," *Bioresour. Technol.*, vol. 363, p. 128008, Nov. 2022, doi: 10.1016/j.biortech.2022.128008.

[385] A. Hai *et al.*, "Machine learning models for the prediction of total yield and specific surface area of biochar derived from agricultural biomass by pyrolysis," *Environ. Technol. Innov.*, vol. 30, p. 103071, May 2023, doi: 10.1016/j.eti.2023.103071.

[386] R. Kanthasamy *et al.*, "Bayesian optimized multilayer perceptron neural network modelling of biochar and syngas production from pyrolysis of biomass-derived wastes," *Fuel*, vol. 350, p. 128832, Oct. 2023, doi: 10.1016/j.fuel.2023.128832.

[387] V. Belle and I. Papantonis, "Principles and Practice of Explainable Machine Learning," *Front. Big Data*, vol. 4, Jul. 2021, doi: 10.3389/fdata.2021.688969.

[388] S. Salcedo-Sanz, L. Cornejo-Bueno, L. Prieto, D. Paredes, and R. García-Herrera, "Feature selection in machine learning prediction systems for renewable energy applications," *Renew. Sustain. Energy Rev.*, vol. 90, pp. 728–741, Jul. 2018, doi: 10.1016/j.rser.2018.04.008.

[389] S. Wenninger, C. Kaymakci, and C. Wiethe, "Explainable long-term building energy consumption prediction using QLattice," *Appl. Energy*, vol. 308, p. 118300, Feb. 2022, doi: 10.1016/j.apenergy.2021.118300.

[390] J. Ferraz-Caetano, F. Teixeira, and M. N. D. S. Cordeiro, "Explainable Supervised Machine Learning Model To Predict Solvation Gibbs Energy," *J. Chem. Inf. Model.*, Aug. 2023, doi: 10.1021/acs.jcim.3c00544.

[391] H. F. Posada-Quintero and J. B. Bolkhovsky, "Machine Learning models for the Identification of Cognitive Tasks using Autonomic Reactions from Heart Rate Variability and Electrodermal Activity," *Behav. Sci. (Basel).*, vol. 9, no. 4, p. 45, Apr. 2019, doi: 10.3390/bs9040045.

[392] A. Lamkaddem *et al.*, "System for powering autonomous solar cookers by batteries," *Sci. African*, vol. 17, p. e01349, Sep. 2022, doi: 10.1016/j.sciaf.2022.e01349.

[393] M. Mammeri, L. Dehimi, H. Bencherif, and F. Pezzimenti, "Paths towards high perovskite solar cells stability using machine learning techniques," *Sol. Energy*, vol. 249, pp. 651–660, Jan. 2023, doi: 10.1016/j.solener.2022.12.002.

[394] Z. Hui, M. Wang, X. Yin, Y. Wang, and Y. Yue, "Machine learning for perovskite solar cell design," *Comput. Mater. Sci.*, vol. 226, p.

112215, Jun. 2023, doi: 10.1016/j.commatsci.2023.112215.

[395] A. T. Hoang, A. R. Al-Tawaha, Lan Anh Vu, Van Viet Pham, A. M. Qaisi, and J. Křeček, “Integrating Environmental Protection Education in the Curriculum: A Measure to Form Awareness of Environmental Protection for the Community,” in *Environmental Sustainability Education for a Changing World*, Cham: Springer International Publishing, 2021, pp. 191–207. doi: 10.1007/978-3-030-66384-1_12.

[396] L. Zhou, S. Pan, J. Wang, and A. V. Vasilakos, “Machine learning on big data: Opportunities and challenges,” *Neurocomputing*, vol. 237, pp. 350–361, May 2017, doi: 10.1016/j.neucom.2017.01.026.

[397] Xue-Wen Chen and Xiaotong Lin, “Big Data Deep Learning: Challenges and Perspectives,” *IEEE Access*, vol. 2, pp. 514–525, 2014, doi: 10.1109/ACCESS.2014.2325029.

[398] O. Usman, A. A. Alola, and S. Saint Akadiri, “Effects of domestic material consumption, renewable energy, and financial development on environmental sustainability in the EU-28: Evidence from a GMM panel-VAR,” *Renew. Energy*, vol. 184, pp. 239–251, Jan. 2022, doi: 10.1016/j.renene.2021.11.086.

[399] B. Surya *et al.*, “Economic Evaluation, Use of Renewable Energy, and Sustainable Urban Development Mamminasata Metropolitan, Indonesia,” *Sustainability*, vol. 13, no. 3, p. 1165, Jan. 2021, doi: 10.3390/su13031165.

[400] W. Wedashwara, M. S. Yadnya, I. W. Sudiarta, I. W. A. Arimbawa, and T. Mulyana, “Solar Powered Vibration Propagation Analysis System using nRF24l01 based WSN and FRBR,” *JOIV Int. J. Informatics Vis.*, vol. 7, no. 1, pp. 15–21, Mar. 2023, doi: 10.30630/joiv.7.1.1592.

[401] E. V. Maliberan, “NComputing Adoption: Issues and Challenges,” *JOIV Int. J. Informatics Vis.*, vol. 2, no. 4, pp. 257–261, Aug. 2018, doi: 10.30630/joiv.2.4.162.

[402] D. Mhlanga, “Artificial Intelligence and Machine Learning for Energy Consumption and Production in Emerging Markets: A Review,” *Energies*, vol. 16, no. 2, p. 745, Jan. 2023, doi: 10.3390/en16020745.

[403] F. J. Wang, H. W. Lin, W. D. Tu, C. H. Shiau, and Y. C. Hung, “Energy-efficient HVAC system through chillers’ capacity sizing for a library building,” *Int. J. Green Energy*, vol. 14, no. 2, pp. 157–161, Jan. 2017, doi: 10.1080/15435075.2016.1253576.

[404] M. Iqbal, J. Ma, N. Ahmad, Z. Ullah, and A. Hassan, “Energy-Efficient supply chains in construction industry: An analysis of critical success factors using ISM-MICMAC approach,” *Int. J. Green Energy*, vol. 20, no. 3, pp. 265–283, Feb. 2023, doi: 10.1080/15435075.2022.2038609.

[405] D. Rangel-Martinez, K. D. P. Nigam, and L. A. Ricardez-Sandoval, “Machine learning on sustainable energy: A review and outlook on renewable energy systems, catalysis, smart grid and energy storage,” *Chem. Eng. Res. Des.*, vol. 174, pp. 414–441, Oct. 2021, doi: 10.1016/j.cherd.2021.08.013.

[406] R. Gupta, A. K. Yadav, S. Jha, and P. K. Pathak, “A robust regressor model for estimating solar radiation using an ensemble stacking approach based on machine learning,” *Int. J. Green Energy*, pp. 1–21, Nov. 2023, doi: 10.1080/15435075.2023.2276152.

[407] N. Yilmaz, “Comparative energy and environmental assessment of battery technologies and alternative fuels in sustainable aviation,” *Int. J. Green Energy*, pp. 1–10, May 2022, doi: 10.1080/15435075.2022.2075226.