Review Article

# Unlocking renewable energy potential: Harnessing machine learning and intelligent algorithms

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**Abstract**. This review article examines the revolutionary possibilities of machine learning (ML) and intelligent algorithms for enabling renewable energy, with an emphasis on the energy domains of solar, wind, biofuel, and biomass. Critical problems such as data variability, system inefficiencies, and predictive maintenance are addressed by the integration of ML in renewable energy systems. Machine learning improves solar irradiance prediction accuracy and maximizes photovoltaic system performance in the solar energy sector. ML algorithms help to generate electricity more reliably by enhancing wind speed forecasts and wind turbine efficiency. ML improves the efficiency of biofuel production by optimizing feedstock selection, process parameters, and yield forecasts. Similarly, ML models in biomass energy provide effective thermal conversion procedures and real-time process management, guaranteeing increased energy production and operational stability. Even with the enormous advantages, problems such as data quality, interpretability of the models, computing requirements, and integration with current systems still remain. Resolving these issues calls for interdisciplinary cooperation, developments in computer technology, and encouraging legislative frameworks. This study emphasizes the vital role of ML in promoting sustainable and efficient renewable energy systems by giving a thorough review of present ML applications in renewable energy, highlighting continuing problems, and outlining future prospects.

Keywords: Machine learning; Artificial Intelligence; Renewable energy; Waste-to-energy path; Sustainable energy

## 1. Introduction

The economy has been growing quickly, and the need for energy is also rising quickly to meet people's daily demands and activities (Hoang *et al.*, 2022d; Yoro *et al.*, 2021), in which the immediate result of the growing energy demand has been a notable rise in the quantity of electricity generated (IEA, 2022a; IRENA, 2013). Due to the ever-increasing energy demand for human activities, the fossil fuel has been thoroughly exploited and used (Nguyen *et al.*, 2021b; Zou *et al.*, 2016). As a result, the use of these fossil fuels contribute to numerous other serious environmental issues, which the emissions of greenhouse gases produced by these fossil fuels may be partly blamed for both the phenomena of climate change and global warming (Bakır *et al.*, 2022; Martins *et al.*, 2019; V. G. Nguyen *et al.*, 2023a; Nguyen *et al.*, 2021a). Meanwhile, the cornerstones of a sustainable future are the development of technology that uses renewable energy sources and the execution of a policy that seeks to reach "zero carbon emission" (Li and Haneklaus, 2022; Vats and Mathur, 2022). In this regard, a large number of studies have pledged to

work on developing renewable energy systems (RES), which are those that employ renewable energy sources to generate power (Bui *et al.*, 2022; Kaur *et al.*, 2021; Nguyen-Thi and Bui, 2023). The International Energy Agency (IEA) projects that by 2040, renewable energy sources will account for about 60% of the total capacity for the production of new power (IEA, 2022b, 2015).

The Energy Status Report 2021 on Sustainable Development Goal 7 (SDG-7), intends to encourage policymakers on global cooperation to provide affordable and universal access to sustainable energy by 2030. Important energy targets included in the 2021 SDG-7 report are universal access to affordable energy, clean cooking fuels, and an increased proportion of renewable energy (IEA, 2019; Trinh and Chung, 2023a). In 2010, 10.6 billion USD in foreign funding was invested in developing countries for clean energy production. Globally, the production of renewable energy has increased considerably from 16.4% in 2010 to 17.1% in 2018, out of the total energy consumption (Trinh and Chung, 2023b). The

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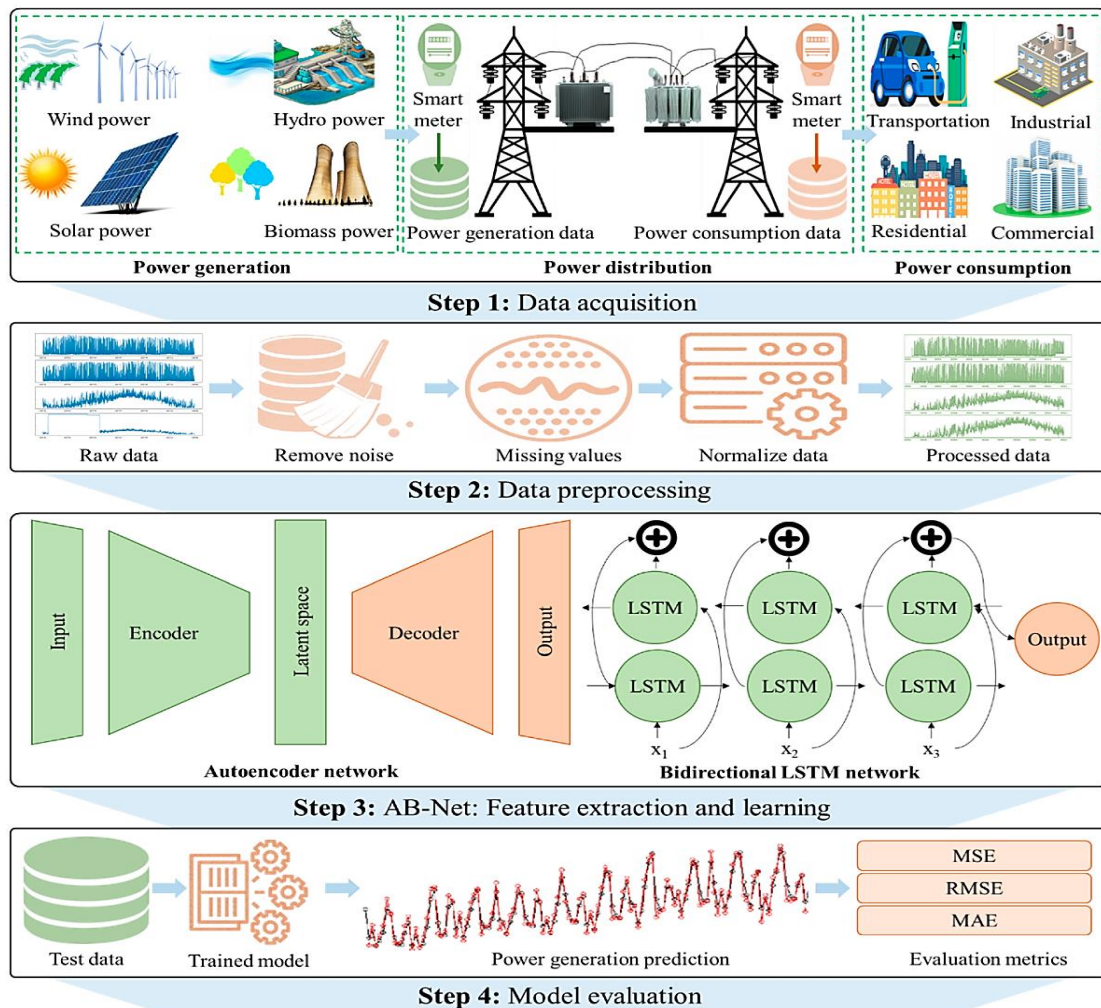
**Fig. 1** Schematics of model development using ML (Khan *et al.*, 2021)

statistics indicate the global attempts to generate renewable energy to provide us access to electricity for industrial uses, transportation, and daily needs (V. G. Nguyen *et al.*, 2024e; Philibert, 2017). The objective of achieving SDG-7 by 2030 requires consistent efforts from the private sector, government, and civil society as well as international organizations. It involves investment in renewable energy, policy reforms, technological innovations, and enhanced energy efficiency (Burke and Melgar, 2022; UNDP *et al.*, 2021; Yu *et al.*, 2022).

Renewable energy sources still face inherent issues like weather dependency, intermittency, and high upfront costs even with enormous technological advances (Bandh *et al.*, 2024; Demirbas, 2009; Medina *et al.*, 2022). Still, the long-term advantages of renewable energy—including the protection of the environment, lower greenhouse gas emissions, and the financial challenges often exceed the disadvantages (Fan and Li, 2023; Franco and Salza, 2011). Integration of renewables with energy storage possibilities, smarter grid approaches, and preserving energy security become increasingly crucial as the world's energy landscape shifts toward sustainability (Hoang *et al.*, 2021a; Tan *et al.*, 2021). The IEA projects that yearly spending on renewable energy must surpass $1 trillion in order to meet the global sustainable energy needs by 2030. Governments, international organizations, and private companies have created a range of financial tools, including crowdsourcing, green bonds, and public-private partnerships, to support these initiatives (IEA, 2021; Smirnova *et al.*, 2021).

The renewable energy sector may be assisted by artificial intelligence (AI), especially in terms of improving management and distribution systems, increasing environmental monitoring, and optimizing energy production (T. Ahmad *et al.*, 2021; Yan *et al.*, 2022). Applications of AI have shown the capacity to enhance offshore wind energy production, speed up decision-making, and manage renewable energy production (Ferrero Bermejo *et al.*, 2019; Han *et al.*, 2024). Systems for different energy production techniques are quickly adapting machine learning (ML) to boost efficiency, save costs, and enhance prediction abilities (Andrizal *et al.*, 2018; H. P. Nguyen *et al.*, 2023). Renewable energy systems can be deployed and managed in a better way if assisted by ML. This approach can increase their viability in supplying energy. ML algorithms are used in solar energy systems to maximize energy storage, improve energy projections, and increase solar panel performance (Balsora *et al.*, 2022; Tchandao *et al.*, 2023). Through the identification and isolation of flaws in solar panels, these methods may greatly reduce the amount of time needed for maintenance. Additionally demonstrating remarkable accuracy are ML-based solar energy forecasting systems (Alassery *et al.*, 2022; Utama *et al.*, 2023). ML has improved energy generation from wind energy farms by accurately forecasting the wind speed, direction, and other weather information (Ponkumar *et al.*, 2023; Zafar *et al.*, 2022). ML has been used to optimize wind farm design for more effective operations (Nascimento *et al.*, 2023). Using the prognostic and

optimizing abilities of ML, the RES can be more efficiently controlled, which is crucial to meeting global energy needs and achieving sustainable development goals (Le *et al.*, 2024b; Stetco *et al.*, 2019). Similar gains are observed in different renewable energy sectors like biofuel and geothermal (Buster *et al.*, 2021; Shakibi *et al.*, 2023). A flow of ML-based model development is illustrated in Figure 1 (Khan *et al.*, 2021).

The literature review was conducted using an organized approach that comprises several crucial phases: literature search, selection criteria, data extraction, analysis, and synthesis of important findings. Using well-known academic databases like Web of Science, Springer Link, IEEE Xplore, ScienceDirect, and Google Scholar, the literature in this domain was searched. A search was directed by using particular terms and combinations, like "machine learning," "renewable energy," "solar energy," "wind energy," "biofuel", "biomass", "intelligent algorithms," "energy optimization," "energy forecasting," and "AI in energy systems." Although fundamental papers providing fundamental knowledge will also be taken into account, the focus will be on recent research within the last five years to guarantee the inclusion of current material. Selected papers will be peer-reviewed and excellent conference papers on the use of intelligent algorithms and machine learning in RES. Studies ought to incorporate case studies that show how to use the material practically, theoretical analysis, or real data. Research not immediately related to the intersection of ML and renewable energy, papers not available in English, and papers lacking adequate methodological detail or empirical data will be ignored.

To methodically collect relevant data from every study, a standard data extraction form was developed. Authors, publication year, goals, methods, kinds of ML algorithms used, applications of renewable energy, results, and conclusions were retrieved. Methodologies for the analysis were both quantitative and qualitative. This helped in assessing different strategies in detail and their effectiveness in the published studies. The information was combined to provide a logical story that emphasizes the status of present research, significant achievements, and unresolved problems in the area. Gaps in current research will be noted, along with themes for further

investigation and the value of interdisciplinary approaches and cooperation between AI researchers and renewable energy experts. At last, practical suggestions for academics, professionals, and legislators will be offered, with an emphasis on applying ML to fully exploit renewable energy sources, as well as best practices and new developments that could influence future studies and applications in this field. The goal of this systematic approach is to give a thorough and educational analysis of how ML and intelligent algorithms may improve RES, therefore contributing valuable information to both academic study and real-world energy applications.

This review paper investigates how ML could help progress renewable energy, focusing on developments in biofuel, biomass, solar, organic waste utilization, and wind energy systems. It talks about the limitations and restrictions of current renewable energy technologies with AI and highlights significant breakthroughs in the field led by AI. Among the issues discussed is the viability of wind and solar energy for an eco-friendly and greener future. Ultimately, this work seeks to demonstrate how ML interacts with RES, influencing the direction of these technologies and energy storage developments and advancing knowledge of AI's capacity to drive the RES industry toward a cleaner and greener future.

## 2. Machine learning algorithms

Numerous studies investigating the combination of ML with different renewable energy (RE) study fields can be found in the scholarly literature (W. Ahmed *et al.*, 2020; Chen *et al.*, 2024b; Ding *et al.*, 2022; Rangel-Martinez *et al.*, 2021). The type of ML methods used in these papers allow for a methodical classification of them. Supervised algorithms are a main class; they are trained on labeled datasets to forecast results from input data (Saravanan and Sujatha, 2018; Sen *et al.*, 2020). Semi-supervised algorithms fall into another group and enhance learning accuracy by combining labeled and unlabelled input (Roscher *et al.*, 2020; P. Sharma *et al.*, 2022a). Stochastic and statistically supervised algorithms are also reported in the literature, which improve prediction performance by using
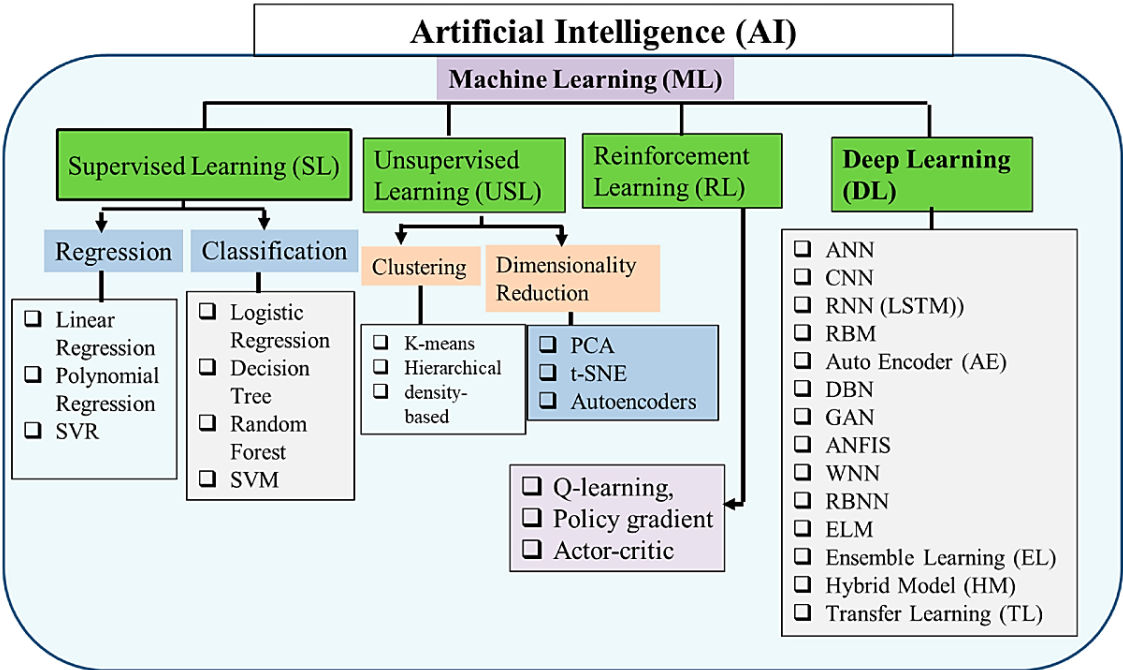


**Fig. 2** Classification of AI & ML algorithms (Benti *et al.*, 2023)

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statistical and probabilistic models (Haksoro *et al.*, 2023; Palanichamy and Palani, 2014; Premalatha and Baskar, 2012). A classification of AI & ML approaches is depicted in Figure 2 (Benti *et al.*, 2023).

A second important class is unsupervised algorithms, which find underlying patterns and structures by analyzing data without specified labels. Finally, reinforced algorithms concentrate on learning the best courses of action by trial and error and improving their decision-making techniques with input (Sierra-García and Santos, 2020; Yeter *et al.*, 2022). This categorization scheme not only helps to arrange a large amount of research but also emphasizes the various methodological approaches and breakthroughs in the use of ML for renewable energy problems. Through this kind of classification of the literature, academics and practitioners can better comprehend and negotiate the many approaches and their distinct benefits in using ML to advance renewable energy solutions (Cervantes *et al.*, 2020; Shi *et al.*, 2012). A few approaches commonly reported in the literature are discussed:

### 2.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) are computer systems models that simulate the way that the human brain processes information through layers of interconnected nodes (neurons) (Okumuş *et al.*, 2021; Su *et al.*, 2023; Veza *et al.*, 2022a). ANNs are one of the efficient approaches to modeling and forecasting datasets with complex, non-linear interactions in the domain of RES (Afridi *et al.*, 2022; Al Mamun *et al.*, 2020). With significant volatility and non-linearity in input factors like weather, ANNs appear to be particularly helpful in predicting the output of energy from renewable sources like wind and solar (V. N. Nguyen *et al.*, 2024b; Tuan Hoang *et al.*, 2021). Learning from historical data, artificial neural networks (ANNs) may produce intricate patterns and improve prediction accuracy (Cepowski *et al.*, 2021; Ihsan *et al.*, 2023). Since they can generalize from trained data, they are perfect for scenarios involving large, diverse datasets and enable better operational planning, prediction, and management for a large number of fields such as education (Haque *et al.*, 2024; Yaqin *et al.*, 2021), society and human (Capote-Leiva *et al.*, 2022; Kannan *et al.*, 2023), energy and fuels (Le *et al.*, 2023; Notton *et al.*, 2019; Taghavifar and Perera, 2023), economy (Moonlight *et al.*, 2023; Suvon *et al.*, 2023), medicine (Puri *et al.*, 2023; Yeo *et al.*, 2023), manufacturing and industry (Cong My *et al.*, 2023; Radonjić *et al.*, 2020; Rosiani *et al.*, 2023), environment (Biswas *et al.*, 2024; Zarra *et al.*, 2019), food and agriculture (Chaivivatrakul *et al.*, 2022; Swasono *et al.*, 2022), transportation (Abramowski, 2008; H. P. Nguyen *et al.*, 2024a; V. G. Nguyen *et al.*, 2023b), and others (Sigiel *et al.*, 2024; Sumari *et al.*, 2022). While artificial neural networks (ANNs) are computationally demanding and need a lot of training data, their potential for enhancing the performance of RES and their integration into existing power grids seems bright. Figure 3 illustrates the application of ANN in solar energy harvesting (Janarthanan *et al.*, 2021).

### 2.2 Gaussian Process Regression

Gaussian Process Regression (GPR) provides a non-parametric, Bayesian method of regression with its probabilistic framework for prediction and uncertainty quantification (Ma *et al.*, 2022; Marrel and Iooss, 2024). GPR is used to estimate and forecast the fundamentally variable and environment-dependent outputs of renewable energy sources such as solar panels and wind turbines (Ferkous *et al.*, 2021; Lio *et al.*, 2021). Since GPR can produce confidence intervals in addition to point estimates, it truly excels in assessing the accuracy of energy estimates (Baiz *et al.*, 2020; Huang *et al.*, 2019). This knowledge is highly helpful in the field of managing the integration of renewable energy into the grid, which calls for reducing uncertainty. GPR can handle datasets of small to medium size with efficiency and is flexible enough to integrate domain knowledge through kernel functions (Boyle, 2007; Gibbs, 1997; Keerthi and Lin, 2003). GPR's strong prediction performance and uncertainty estimation—especially with large datasets—make it a necessary tool for renewable energy research and applications despite its computing requirements. Figure 4 depicts the schematics of the GPR framework applied for solar forecasting.
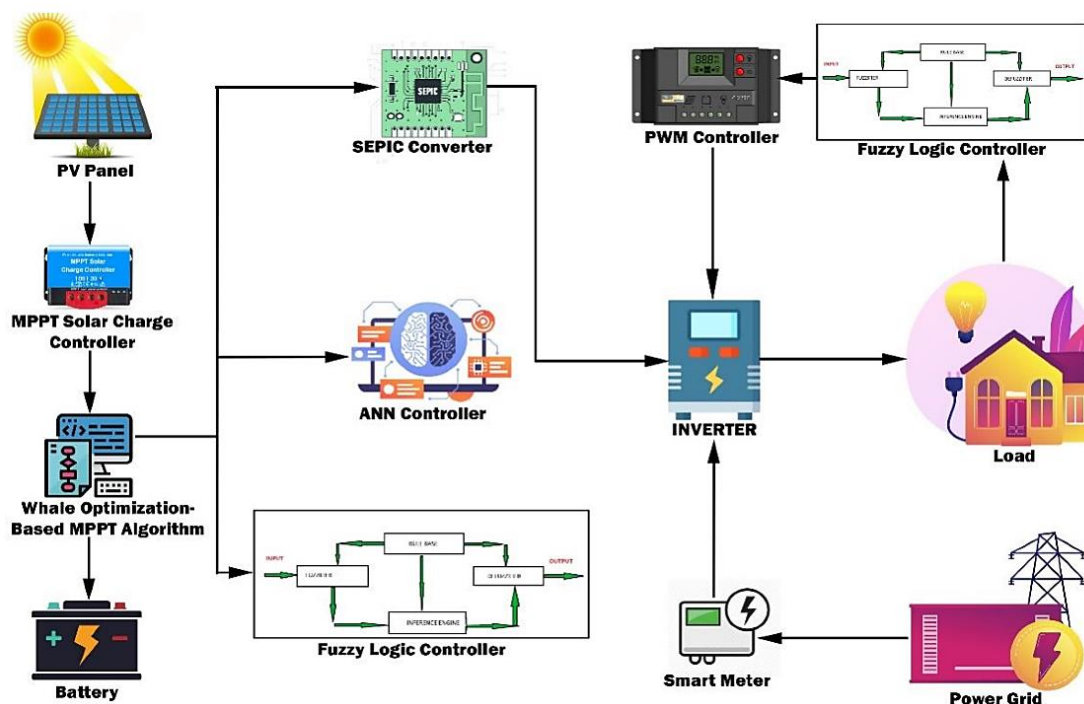


**Fig. 3** Application of ANN-based controller in solar energy (Janarthanan *et al.*, 2021)

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**Fig. 4** GPR framework's schematic diagram
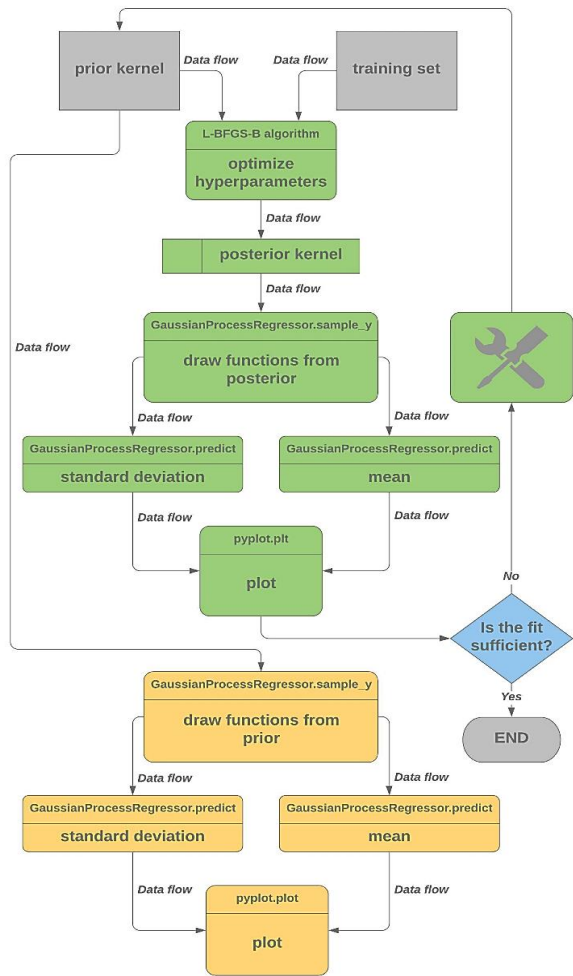


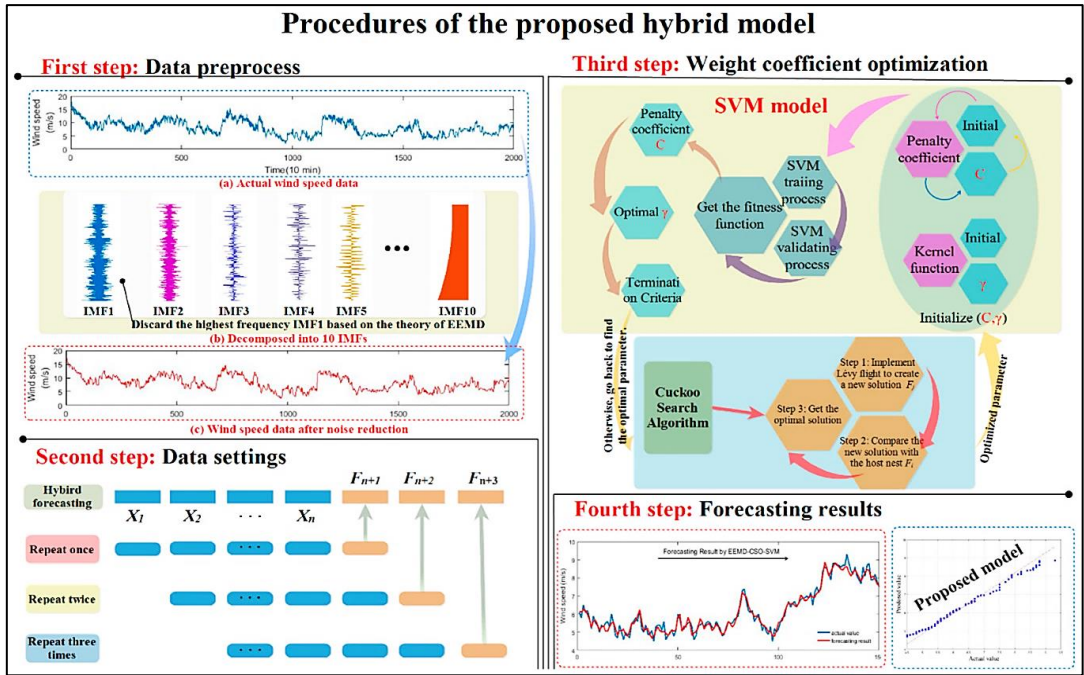**Fig. 5** Wind speed prediction with SVM (Liu *et al.*, 2018)

*2.3 Support Vector Machine*

The Support Vector Machine (SVM) is one of the prominently used supervised learning models in the domain of RES and energy management (Ahmad *et al.*, 2022; Said *et al.*, 2023b). SVM makes use of Kernel functions to handle high-dimensional data and non-linear relationships quite well (Cortes

and Vapnik, 1995; Liao *et al.*, 2024). It can efficiently handle model-prediction tasks like classification and regression (Astuti *et al.*, 2021; Secilmis *et al.*, 2023). It can be used in RES for the prediction of solar radiation (Meenal and Selvakumar, 2018), wind speed (Sarp *et al.*, 2022), and patterns of energy consumption (You *et al.*, 2022). SVMs help identify complex patterns in datasets related to renewable energy as they can identify the optimum hyperplane that splits data into many groups (Gangwar *et al.*, 2018; Liu *et al.*, 2020). Their resistance against overfitting and ability to manage non-linear data distributions increase the accuracy of their forecasts. SVMs perform exceptionally well when the dataset is small and the processing power is limited. But optimizing SVM performance calls for careful parameter modification and choosing appropriate kernel functions. Support vector machines (SVMs) are nevertheless a practical and reliable approach to improve the predictability and administration of RES in spite of these challenges (Tuerxun *et al.*, 2021; Wang *et al.*, 2020). Figure 5 depicts the application of metaheuristic approach optimized SVM for wind speed prediction (Liu *et al.*, 2018).
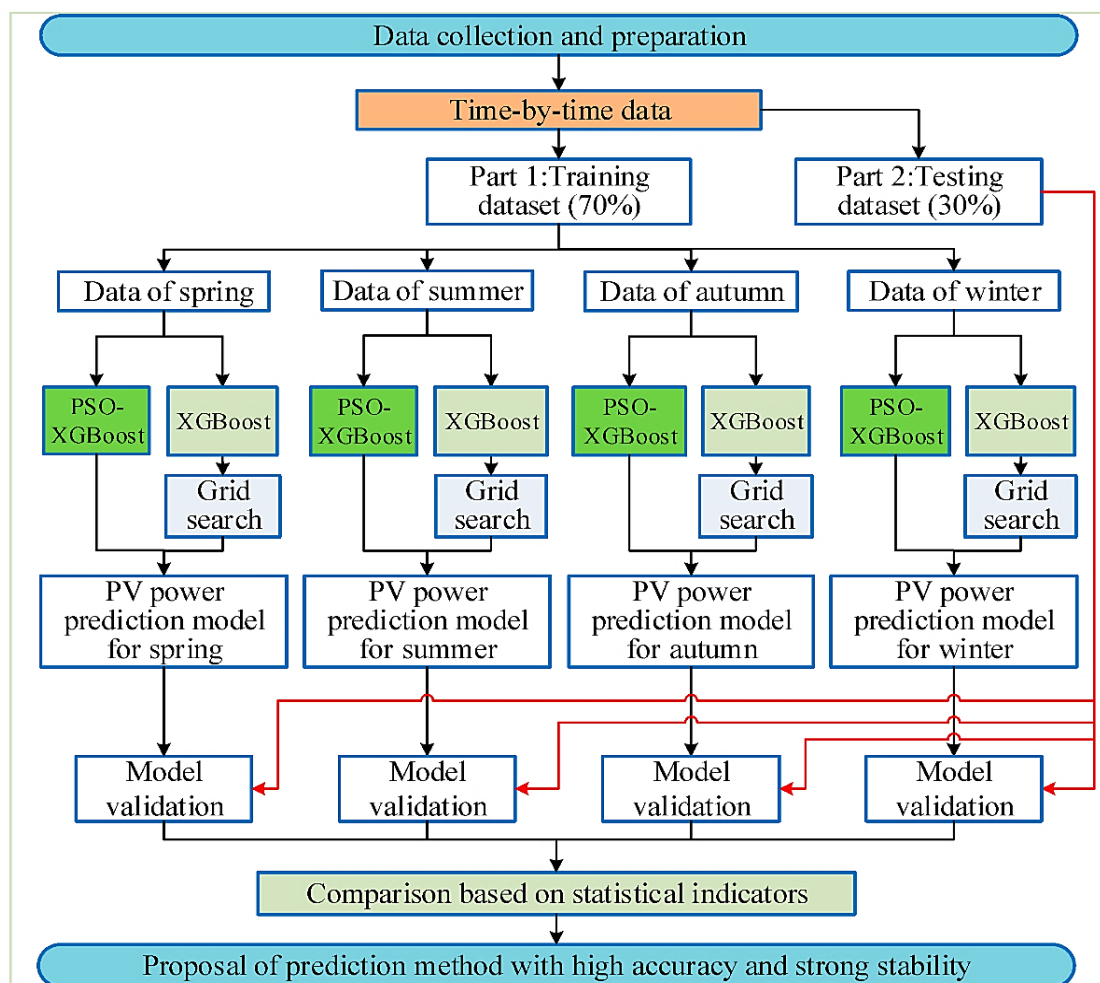
### 2.4 XGBoost

Extreme Gradient Boosting (XGBoost) makes use of ensembles of decision trees for high-performance prognostics (Hartanto et al., 2023; Wicaksono et al., 2023). The XGBoost truly excels in the renewable energy industry in the case of predictive modeling and optimization (Chen and Guestrin, 2016; Dong et al., 2022). XGBoost-based models can be efficiently employed in optimizing energy storage systems, and

forecasting solar as well as wind energy output. XGBoost has a unique advantage that it can handle large datasets quickly while maintaining high precision levels (Akbar et al., 2024; Aksoy and Genc, 2023; X. Li et al., 2022). This is achieved by boosting trees, which are built one after the other, each of which fixes the errors of the one before it. This helps in optimizing the loss function. Regularization techniques in XGBoost provide resistance to overfitting and suitability for a broad spectrum of applications (Bae et al., 2021; Huang et al., 2021). Improved forecasts of renewable energy sources result in better control and integration of these resources into energy systems because of the efficiency and scalability of XGBoost. A flowchart as Figure 6 depicts the model development process using annual data in the case of solar energy (D. Li et al., 2023).

### 2.5 Adaptive Neuro Fuzzy Inference System

In the case of Adaptive Neuro-Fuzzy Inference System (ANFIS) a qualitative method of fuzzy logic is combined with neural network learning capabilities to form an efficient hybrid intelligence system (P. Sharma *et al.*, 2022b; Yadav *et al.*, 2021). ANFIS does exceptionally well at modeling and forecasting complex, non-linear phenomena like wind speed prediction and solar irradiance forecasts in renewable energy applications (Purwanto *et al.*, 2021; Safari *et al.*, 2021; Wasista *et al.*, 2023). By fusing fuzzy systems and neural networks, ANFIS can handle the inherent uncertainties and variations in renewable energy data (Baghban *et al.*, 2019; Sharma and Sahoo, 2022). Accurate and reliable forecasts are offered by ANFIS as it gets trained using historical data and adjusting to any change in



**Fig. 6** A hybrid approach of PSO-XGBoost for PV system (D. Li *et al.*, 2023)
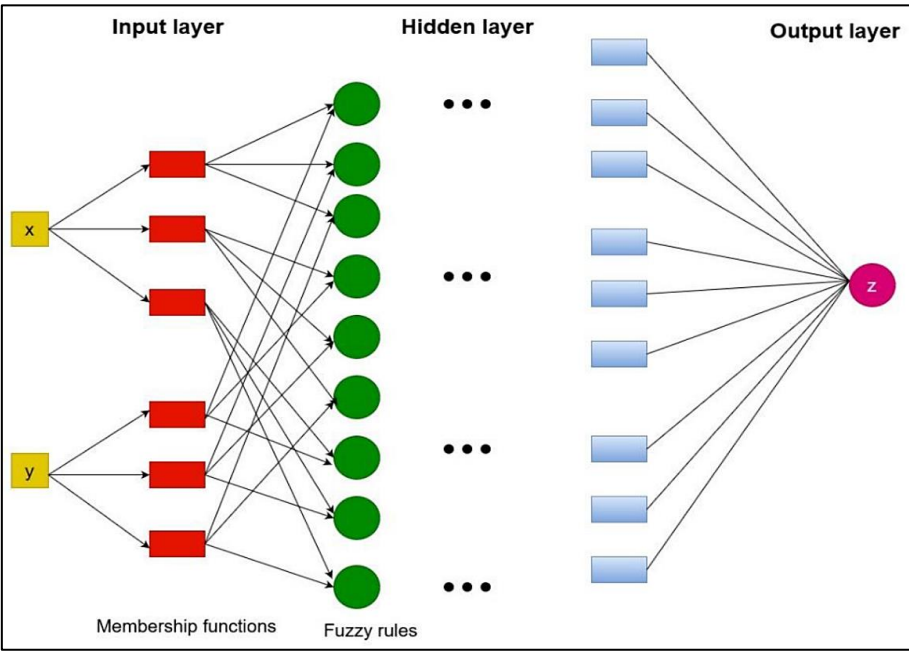
**Fig. 7** ANFIS architecture for energy prediction from solar farm (Gopi *et al.*, 2022)

environmental conditions. Because ANFIS can handle noise in data and approximate non-linear processes, it is a useful tool for raising the dependability and efficiency of RES. Its capacity for modeling and analysis of the connection between different input and output parameters enhances energy management and optimization decision-making (Nassef *et al.*, 2020; Pitalúa-Díaz *et al.*, 2019). Figure 7 depicts the ANFIS architecture used in the case of an energy prediction from a solar farm (Gopi *et al.*, 2022).
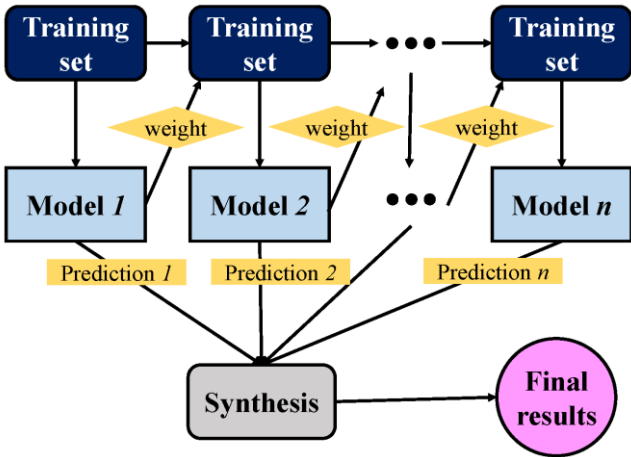
*2.6 AdaBoost*

The ensemble learning method known as AdaBoost (Adaptive Boosting) builds a better classifier by combining the predictions of multiple weak classifiers (Ilham *et al.*, 2023; Liu *et al.*, 2022; Shahraki *et al.*, 2020). In renewable energy, AdaBoost is used to classify energy use patterns, forecast solar energy, and estimate wind speed. Through iteratively changing the weights of falsely detected samples, the system is able to concentrate on more challenging cases in subsequent iterations (R. Li *et al.*, 2022). The general expected robustness and

accuracy of the model are increased by this approach. AdaBoost is quite efficient in handling varied and complicated datasets as are generally reported in renewable energy research, (Yang and Liu, 2022). It is a crucial method for strengthening the baseline model's performance and therefore improving the dependability and predictability of RES (Shao *et al.*, 2016; Yang and Liu, 2022). Flexibility and adaptability of the algorithm support decision-making procedures in RES management and help to generate more precise projections. A schematic of AdaBoost is illustrated in Figure 8 (Wang *et al.*, 2021).

*2.7 Tweedie Regression*

Tweedie Regression is a type of generalized linear model that does especially well with data having both positive and zero continuous values (V. G. Nguyen *et al.*, 2024b; Parveen *et al.*, 2016). Its applications are reported in renewable energy research, such as wind turbine and solar panel simulation. Precise and trustworthy forecasts are obtained by Tweedie Regression, which successfully captures the underlying



**Fig. 8** Schematics of AdaBoost-based model (Wang *et al.*, 2021)

distribution of energy generation data (Bonat and Kokonendji, 2017; Petterle *et al.*, 2019). Applications where the response variable is a non-negative value with a lot of zeros, such as daily energy production interrupted by weather-related intervals of no output, benefit particularly from it. Tweedie Regression enhances the accuracy of predictive models by accounting for the particular distribution of data on renewable energy, therefore facilitating better planning, optimization, and integration of renewable energy into the power system (Alawi *et al.*, 2024; Tweedie and Reynolds, 2016).

### 2.8 Huber Regression

Huber Regression is especially useful for handling outliers in data. Huber is a robust regression technique that blends the features of absolute deviation regression and conventional least squares (Feng and Wu, 2022; Sun *et al.*, 2020). In applications for renewable energy, Huber Regression is used to estimate the energy output from wind turbines and solar panels, where data may be noisy and include large outliers brought on by fast changes in meteorological circumstances. The Huber loss function balances the robustness of absolute deviation with the sensitivity of least squares; it is quadratic for small errors and linear for large errors (Huang *et al.*, 2018; Jiang, 2023). As it guarantees that outliers do not have a disproportionate effect on the model, Huber Regression is, therefore, a reliable method for modeling and forecasting renewable energy outputs (Ibidoja *et al.*, 2023; Lin *et al.*, 2022). Through the improvement of prediction robustness and accuracy, Huber Regression facilitates the better management and integration of renewable energy sources into the power system.

## 3. Application of ML in solar energy

Solar energy is considered as the most abundant renewable energy source in the world. As reported, solar energy could be harvested for a large number of use purposes such as electricity production (Ghodbane *et al.*, 2020; Y. Khan *et al.*, 2024; L. Zhang *et al.*, 2023), heat production (Faisal Ahmed *et al.*, 2021;

Franzese *et al.*, 2020; Said *et al.*, 2022b), distillation (Gandhi *et al.*, 2022; Larik *et al.*, 2019; Tri Le *et al.*, 2020), food drying (Lingayat *et al.*, 2020; Madhankumar *et al.*, 2023; Murugavelh *et al.*, 2019), and hydrogen production (Hoang *et al.*, 2023c; Okonkwo *et al.*, 2022; Phap *et al.*, 2022). However, weather variables vary throughout the year, photovoltaic (PV) electricity output is by nature stochastic and experiences sporadic swings. The projection of PV generation is made more challenging by these oscillations in data. PV generation forecasting accuracy need must be improved since forecasting errors are far larger (15–20%) during energy generation in comparison with load forecasting errors (1-3%). (Behzadi and Sadrizadeh, 2023; Tian *et al.*, 2023). Solar energy forecasting is classified as short-term (a few minutes to a few hours) and medium-term (a few hours to a few days) forecasts, as well as long-term (a few days to several months). Out of these, since short-term forecasting calls for making results predictions quickly, it is the most difficulty to be precise (Allal *et al.*, 2024; Heidari and Khovalyg, 2020; Rabehi *et al.*, 2020; Venkateswaran and Cho, 2024). However, short-term forecasting is, therefore, the most accurate and dependable approach to PV forecasting, offering a reliable and reliable way to project PV production. Short-term forecasting has therefore generated a lot of interest in solving the integration and operational issues related to solar power penetration. Enhancing grid stability and dependability, optimizing market participation, and raising solar power generating efficiency all depend on it (Akilu *et al.*, 2018; Hayajneh *et al.*, 2024; Said *et al.*, 2022a; S. Zhang *et al.*, 2023).

Statistical, and ML models are the most often used models for solar PV power forecasts to improve upon the physical models (Le *et al.*, 2024a; Wedashwara *et al.*, 2023). Physical models simulate PV systems employing complicated equations, but they are expensive to compute and can fall short of capturing the subtleties of actual circumstances, which leads to less precise forecasts. Similar short-term variations and quick changes in meteorological conditions, which have a significant effect on solar PV generation and lead to inaccurate predictions, are also difficult for statistical techniques based on historical data patterns and statistical algorithms to capture (Antonopoulos and Antonopoulos, 2024; Marzouq *et al.*, 2018;
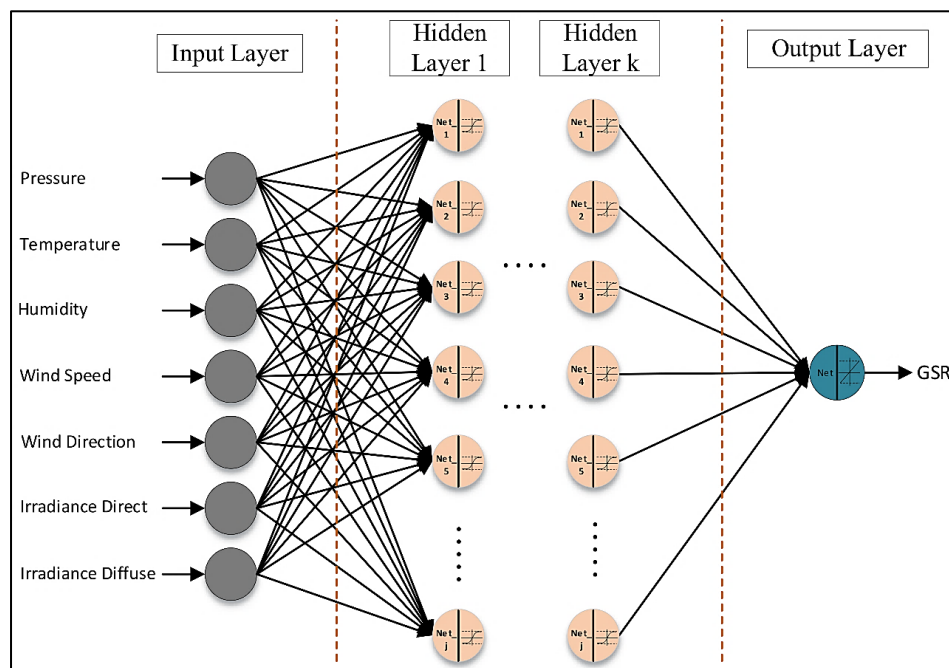

**Fig. 9** ANN architecture for GSR prediction (Aljanad *et al.*, 2021)

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**Table 1**
Application of ML in solar energy domain

| Name of ML | The main theme of the study | Parameters | Main outcomes | Source |
|---|---|---|---|---|
| Linear regression, SVM, Random Forest (RF), and ANN | Solar energy forecasting | Energy, wind speed (WS), humidity, solar radiation (SR), wind direction (WD), wind pressure (WP) | On the basis of statistical metrics, ANN was superior to other ML | (Jebli et al., 2021) |
| ANN | Hourly solar radiation | Mean ambient temperature, hourly global and direct irradiation, mean speed of wind, location coordinates | R values of 0.9340 could be achieved during model testing. | (Geetha et al., 2022) |
| ANN | Performance prediction of solar thermal collectors | Type of heaters, Input temperature and irradiance | An R-value of 0.9956 was achieved for ANN 15 model | (Çerçi et al., 2024) |
| LSTM + CNN | Solar irradiance and plan of array (POA) | Solar irradiance and POA data | The stacking of LSTM and CNN was superior to individual CNN and LSTM models | (Elizabeth Michael et al., 2022) |
| Gradient boosting regression trees (GBRT), ANN, k-near test neighbor (kNN), and lasso regression | Model-prediction of solar energy | Seasonal meteorological data | GBRT and kNN were superior to other models. | (Sivakumar et al., 2022) |
| LSTM + CNN + transformer model | Grid integration-based solar energy | Hourly basis data adopted from the Fin grid comprising meteorological data | A combined approach of LSTM-CNN-transformer led to superior results compared to individual models | (Al-Ali et al., 2023) |
| Hybrid ML + statistical approach | Forecasting of solar energy generation from a large-scale RE plant | Five-minute resolution dataset from 10 MW thin-film solar cells and polycrystalline solar panels | Hybrid model, combining ML and statistics. It showed superior performance and accuracy compared to standard individual models and an ML-only model. | (Vennila et al., 2022) |
| SVM based classifier | City scale classification of roof scale for PV application | Solar radiation and roof shape data set | The SVM classifier identified 6 kinds of roof forms with a mean accuracy of 66%. | (Mohajeri et al., 2018) |
| GPR | Forecasting of solar radiation | One week of weather data from Stellenbosch, SA | Results were accurate up to 95%. | (Lubbe et al., 2020) |

A. Sharma *et al.*, 2022). ML models, on the other hand, can enhance accuracy by combining historical trends, incorporating real-time data, and adapting to changing circumstances (Jathar *et al.*, 2024). ML-based methods work particularly well at identifying the connections between non-linear trends, which leads to more precise short-term solar PV projections. ML techniques most often used include artificial neural networks (ANN), support vector machines (SVM), Gaussian process regression (GPR), and regression trees. The comprehension of the intricate and dynamic character of solar PV generation is greatly enhanced by these techniques, which also raise the precision and effectiveness of solar power forecasts (R. Ahmed *et al.*, 2020; Luo *et al.*, 2021). A lot of researchers have concentrated on encouraging the application of ML in the domain of solar energy including photovoltaic (PV) array layout optimization (Subhashini *et al.*, 2023), PV energy predictions (Mellit and Pavan, 2010), solar irradiance predictions (Hameed *et al.*, 2019; Hou *et al.*, 2023) and enhancing the efficiency of solar chimney facilities (Mandal *et al.*, 2024; Taki *et al.*, 2021). An ANN architecture employed for the prediction of global solar irradiance (GSR) depicts the way it is employed in Figure 9 (Aljanad *et al.*, 2021). A summary of studies using ML in the solar energy domain is listed in Table 1.

**4. Application of machine learning in wind energy**

Wind energy is one of the significant RES, it has high potential for long-term power production (Barus and Dalimi, 2021; Chen *et al.*, 2021; Zhang *et al.*, 2021). Wind turbines make

use of the kinetic energy present in the wind to transform it into electrical energy, it offers a clean and plentiful alternative to fossil fuels (Chen *et al.*, 2022c; Oueslati, 2023; Tumenbayar and Ko, 2023). Among other energy sources, wind energy is especially favorable because of its low environmental effect, low greenhouse gas emissions, and falling prices as technology advances (Chaurasiya *et al.*, 2019; Chen *et al.*, 2024c; Sayed *et al.*, 2021). It may also be used both onshore and offshore, offering flexibility in deployment. As wind energy capacity grows worldwide, it plays an important role in providing energy security, lowering carbon footprints, and facilitating the shift to a sustainable energy future (Kumara *et al.*, 2017; Sitharthan *et al.*, 2018).

Using AI to improve the efficiency of these systems creates prospects for future improvement. Investigations in the domain of wind energy systems comprising the design of turbine blades, and precise wind speed predictions, may enhance wind farm performance and environmental sustainability. In the domain of wind energy, it has been employed for wind energy prediction, wind speed forecasting, peak power point tracking, prediction of wind energy quantification, and prediction of wind pressure and energy (Dosdoğru and Boru İpek, 2022; Ju *et al.*, 2019; Wu *et al.*, 2022). Wind power prediction techniques fall into three categories: long-term, medium-term, and short-term. Real-time wind power scheduling relies on short-term forecasts during the next few hours (De Caro *et al.*, 2020; Jiang *et al.*, 2017). Medium-term wind power forecasts are utilized for unit mix and standby arrangements in the next week. Long-term wind power forecasting, often done in months or quarters, is crucial for assessing and maintaining wind resources (Carvalho *et al.*, 2017;
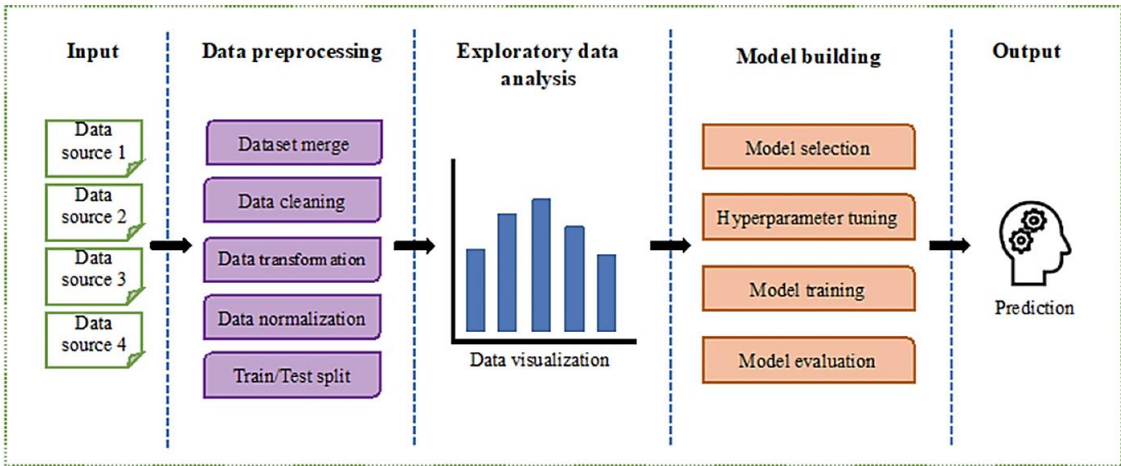
**Fig. 10** ML architecture for wind energy prediction

**Table 2**
Application of ML in the wind energy domain

| Algorithm employed | The main theme of the research | Main outcomes | Source |
|---|---|---|---|
| Gaussian Process | Measurement of unsteady wind characteristics | Indirect dynamic GP outperformed deterministic and probabilistic wind power prediction modes, resulting in lower errors. | (Xue et al., 2020) |
| Autoregressive Integrated Moving Average (ARIMA) | Precision of wind speed forecasting | A study found that ML-based frameworks were superior to traditional approaches for predicting wind energy. | (Shawon et al., 2021) |
| kNN, XGBoost, Random Forest, LASSO, and SVR | Wind power forecasting | The algorithms correctly forecasted daily wind power outputs for places other than the model-trained location. | (Demolli et al., 2019) |
| Echo state networks (ESN) | Wind direction as well as speed forecasting | The proposed method could predict the data with high accuracy. | (Chitsazan et al., 2019) |
| LSTM + Grey wolf optimizer | Wind speed forecasting | The LSTM-GWO combined model predicted with high accuracy also filled in missing data and flattened WSTs data. | (Altan et al., 2021) |
| Ensemble approach of ML + mayfly optimization | Wind speed prediction | Point and interval forecasting are employed for more intelligent grid management. The optimal distribution is an excellent way to assess uncertainty. | (Liu et al., 2021) |
| Elman and Elastic wavelets transform (EWT) | Wind speed forecasting | ENN was developed to anticipate sub-signals. A new error rectification approach was developed to enhance prediction capabilities for decomposition-based models. | (Y. Deng et al., 2020) |
| Deep learning bi-directional LSTM | Handing uncertainty and overfitting in the prediction model of wind speed | Boruta wrapper feature selection was used to extract critical meteorological data for wind speed predictions (BFS), forecasting wind speed based on previous and subsequent time steps. | (Sankari Subbiah et al., 2023) |

Haghshenas et al., 2023). All forecasting approaches aim to improve the precision of wind power predictions. Traditional prediction of wind power methods includes physical and statistical approaches, whereas intelligent methods include ML and deep learning techniques (X. Deng et al., 2020; Jiang et al., 2021; Lipu et al., 2021). Physical models use numerical weather prediction data to compute wind power production by estimating wind speed time series in a given environment (Li and Zhang, 2022; Simankov et al., 2023). Figure 10 illustrates how an ML-based architecture is employed in the wind energy domain for model-prediction. Table 2 summarizes works that used ML in wind energy and related research prognostics.

## 5. Application of Machine learning in biofuels

Biofuels are renewable and alternative fuels derived from organic materials like plants and organic waste. Biofuels are attractive substitutes for fossil fuels since they reduce greenhouse gas emissions (Ahmed et al., 2023; Hoang et al., 2023d; Istadi et al., 2021). As reported, biofuels are beneficial in reducing dependence on costly fossil fuel imports and offer a sustainable substitute for fossil fuels (Hoang and Pham, 2021; Wei et al., 2024; Zeńczak and Gromadzińska, 2020). Indeed, ancohol (methanol, ethanol, n-propanol, butanol, pentanol, hexanol), biodiesel, bio-oil, furan-based biofuels, ether, and biogas are typical examples (Bui et al., 2021; Cao and Johnson, 2024; Changxiong et al., 2023a; De Poures et al., 2023; Doan et al., 2022; Fayad et al., 2022; Hoang et al., 2023a, 2021c; Jia et al., 2024; Yusuf et al., 2023). Biofuels may be used to generate electricity, heat, and transport, therefore ensuring environmental sustainability and energy source diversity (Hoang et al., 2021e; Veza et al., 2022b). A sustainable for of fuel for use in diesel engines, biodiesel is made from vegetable oils, animal fats, and waste cooking oils. Use of it in diesel engines, either in pure form (B100) or as a blend with petroleum fuel

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(often B20, which contains 20% biodiesel), helps in the reduction of sulfur, particulate matter, and greenhouse gas emissions (Sunil Kumar *et al.*, 2024). Biodiesel offers a cleaner combustion having less environmental impact. Besides, biodiesel provides superior lubrication than conventional diesel, which may extend the life of engine parts (Manimaran *et al.*, 2023; Paramasivama *et al.*, 2024). The use of biodiesel does, however, provide several challenges. Biodiesel has a higher viscosity in comparison with petroleum diesel, thus it may need to be modified in older engines and may provide running difficulties in colder climates that call for the usage of additives or lower biodiesel mixtures (Changxiong *et al.*, 2023b; Hoang, 2021; N *et al.*, 2023; V. N. Nguyen *et al.*, 2023). Even with these drawbacks, employing biodiesel into diesel engines is a significant step in the direction of more environmentally friendly and sustainable transportation options (Gebremariam, 2023; Hoang *et al.*, 2022f; P. Singh *et al.*, 2020).

A significant number of biofuels such as biogas, methanol, and ethanol are helping to produce environmentally friendly energy substitutes (P. Sharma *et al.*, 2023; Truong *et al.*, 2021). The sugars from maize and sugarcane can be fermented to produce ethanol, which is then added to gasoline to raise octane levels and cut emissions. Its renewable nature and ability to be carbon neutral make it a vital part of the creation of sustainable fuel strategies (W.-H. Chen *et al.*, 2023; Kazemi Shariat Panahi *et al.*, 2020; Manochio *et al.*, 2017; Megawati *et al.*, 2022). Methanol as a flex-fuel can be produced from biomass or as a waste organic product of industrial operations. It is them mixed with gasoline or used straight in fuel cells. Its high hydrogen content and effective combustion properties help to lower emissions and strengthen energy security (Deka *et al.*, 2022; Yadav *et al.*, 2020). A plentiful supply of biogas containing methane may be used for heating, electricity generation, and car fuel (Dahlgren, 2022; Korberg *et al.*, 2020). The anaerobic digestion (AD) process is employed to produce biogas from

organic waste. Through the reduction of greenhouse gas emissions and the mitigation of waste disposal issues, its production advances the circular economy (Hoang *et al.*, 2022a; Kapoor *et al.*, 2020). Collectively, these biofuels provide a substantial contribution to the creation of renewable energy sources and the lessening of environmental harmful impacts (Nguyen-Thi and Bui, 2023; Yilmaz, 2012; Yuvenda *et al.*, 2022).

In the biofuel industry, ML has become a revolutionary technique that greatly improves several phases of biofuel production and use. Improved overall efficiency and sustainability of biofuel production may be achieved by ML algorithms optimizing feedstock choices, process parameters, and yield forecasts (Okolie, 2024; V. Sharma *et al.*, 2023b). Large dataset analysis allows ML models to find correlations and patterns that are not immediately obvious using conventional techniques. For example, supervised learning algorithms like SVM and ANN can forecast the ideal feedstock combination to optimize biofuel production with the least amount of environmental effect (I. Ahmad *et al.*, 2021; Sharmila *et al.*, 2024; Shelare *et al.*, 2023).

ML methods enable the monitoring and control of parameters like temperature, pH, and nutrient content during fermentation, guaranteeing the best possible conditions for microbial activity and thereby raising conversion rates. Reinforcement learning may also be used to improve bioreactor operational parameters, which can adjust to changing circumstances to preserve high efficiency (Agrawal *et al.*, 2020; Sharma, 2021). Moreover, by forecasting the characteristics of the finished product depending on the input features and process factors, ML models may improve the quality control of biofuels. Complying with regulations and guaranteeing constant fuel quality depends on this predictive capacity. ML approaches help save costs and increase efficiency in biofuel logistics and supply chain management since they can help in optimizing routes and inventory management (Ayoola *et al.*, 2019;
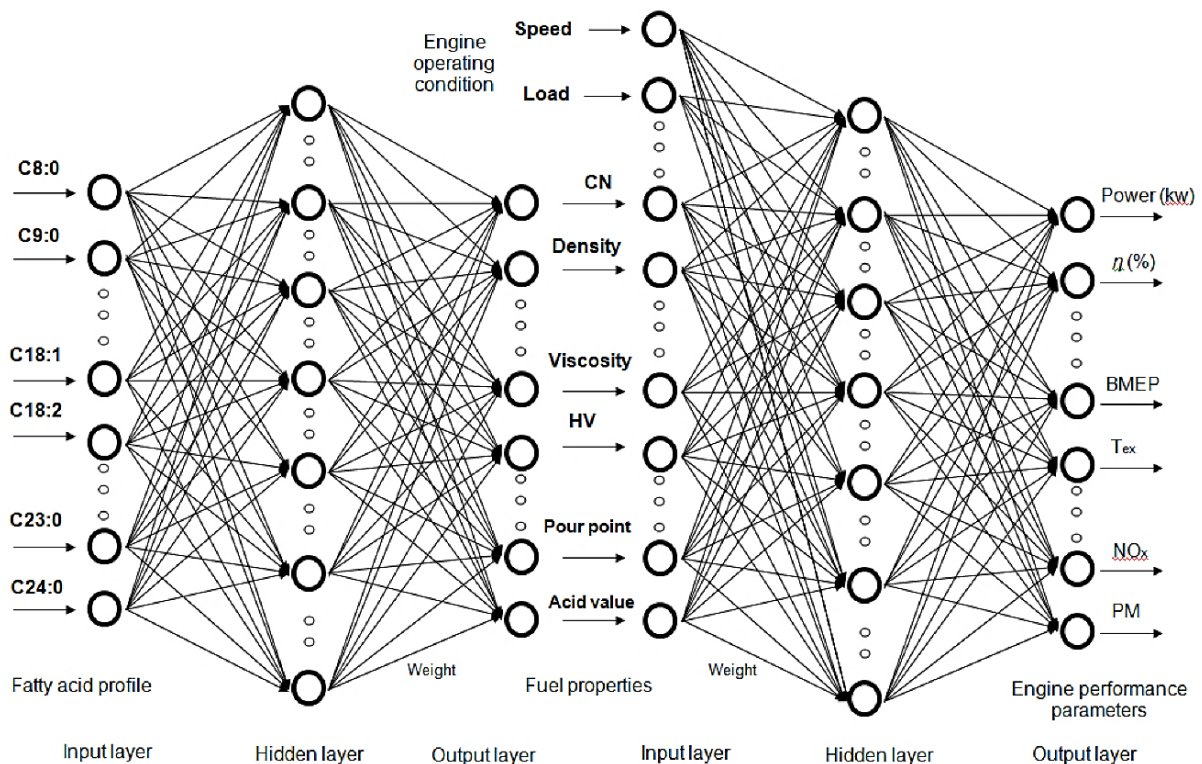


**Fig. 11** ANN in biodiesel synthesis and use in the engine (Jahirul *et al.*, 2013)

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**Table 3**
Application of ML in the biofuel sector

| ML/AI used | The main theme of the research | Main outcomes | Source |
|---|---|---|---|
| ANN | Biodiesel yield and properties estimation | A high-precision model having R as 0.958 could be achieved | (Giwa *et al.*, 2015) |
| RSM and ANN | Biodiesel yield from castor oil | The developed model could predict well within 8% of the actual yield. | (Banerjee *et al.*, 2017) |
| ANN | Alage-Jatropha Biodiesel yield model prediction | $R^2 = 0.9976$ could be achieved in this study. | (Kumar *et al.*, 2019) |
| ANFIS | Biodiesel synthesis employing | The model's high R-squared value (0.9978) along with a small absolute deviation (1.14%) indicate the recommended ANFIS model as an effective technique for predicting biodiesel yields. | (Guo and Baghban, 2017) |
| Genetic Algorithm (GA) + SVM | Biodiesel blends properties | A highly precise model with 97.4% accuracy was established. | (Cheng *et al.*, 2016) |
| GA + ANN +RSM | Biodiesel production output | This approach helped in the identification of the best setting for the highest yield for Simarouba glauca methyl ester. | (Sivamani *et al.*, 2019) |
| GBDT and ANN | Ethanol fermentation prediction | Yeast morphological data was employed. The model could predict with more than 90% accuracy. | (Itto-Nakama *et al.*, 2021) |
| XGBoost, kNN, RF, SVM, and logistic regression | Biogas production prognostics | Boruta wrapper feature selection was used to extract critical meteorological data for wind speed predictions (BFS), forecasting wind speed based on previous and subsequent time steps. | (De Clercq *et al.*, 2019) |
| Continuous wavelet transformation (CWT) | Cycle-to-cycle variation in biodiesel-powered engine | Statistical as well as CWT helped in the analysis of the coefficient of variation during biodiesel-diesel combustion | (Sharma and Sharma, 2022) |
| Taguchi L 16 and RSM | Water Hyacinth biodiesel-powered engine model prediction | Models could predict in the range of 0.849 to 0.9985 as measured in terms of $R^2$. | (Jain *et al.*, 2023) |
| Bayesian optimized GPR | Prognostic of biogas-biodiesel powered engine | The Bayesian hyperparameter-optimized models achieved 99.9% accuracy in predicting engine emission and performance. | (Said *et al.*, 2023a) |

Muhammad *et al.*, 2022; Prasada Rao *et al.*, 2017). Figure 11 shows how model-prediction in the domain of biofuel production and utilization in engines is achieved using an ML-based architecture (Jahirul *et al.*, 2013). The biofuel production, its utilization, and associated research prognostics studies that employed ML are compiled in Table 3.

## 6. Application of machine learning in biomass

Biomass is known as the major source of renewable energy, it has been produced around $146 \times 10^6$ metric tons per year (Balat and Ayar, 2005; Duc Bui *et al.*, 2023). As predicted, biomass energy could account for more than 50% of energy demand in the developping countries by 2050 (Demirbas, 2008). Indeed, the main biomass sources in the world include farm waste, woodworking wastes, forestry and agricultural residue, and aquatic plants (Ağbulut *et al.*, 2023; Alzamora and Barros, 2020; Bandh *et al.*, 2023; Dhyani and Bhaskar, 2018; Güleç *et al.*, 2023). The variety in feedstock processing, shorter reaction times, cheap capital costs, wide product range, high process yield, $CO_2$ neutrality, and possibility for product improvements have made the thermal conversion of biomass into bioenergy a viable approach (Chen *et al.*, 2022b; Hoang *et al.*, 2023b, 2021b; Saravanakumar *et al.*, 2023). Owing to these positive gains, biomass is receiving a lot of interests in the conversion of biomass to value-added chemicals and biofuels (Hoang *et al.*, 2022e; Rathore and Singh, 2022; Seo *et al.*, 2022). The broad classification of biomass conversion to energy can take the route of any of the following: pyrolysis, torrefaction, hydrothermal treatment, gasification, and combustion (Chen *et al.*, 2022a; V. G. Nguyen *et al.*, 2024f; Umer *et al.*, 2024). At 300–650 °C in the absence of air, biomass feedstock pyrolyzes to produce bio-oil, charcoal, and pyrolytic gas (Chen *et al.*, 2024a; Hoang *et al.*, 2021d). Torrefied biomass is produced when pyrolysis, a milder kind, takes place without oxygen at 200–320 °C under air pressure (Niu *et al.*, 2019; Tang *et al.*, 2020). Depending on the intended products such as bio-oil, bio-gas, or bio-char, parameters for hydrothermal treatment are varied between 250 and 374 °C and 4 and 22 MPa (Tekin *et al.*, 2014). In regulated oxygen flow at high temperatures (550–1000 °C), gasification converts carbon-based materials into synthetic gas. Burning biomass with too much air causes a chain of chemical processes that produce heat (García Nieto *et al.*, 2019; Hoang *et al.*, 2022b; V. G. Nguyen *et al.*, 2024c).

The energy recovered from biomass and waste feedstock may be economically recovered using these thermal conversion techniques to produce biochar, bulk chemicals, liquid transport fuels, heat, and electricity (Emenike *et al.*, 2024; Gil, 2022; Okolie *et al.*, 2022; Yang *et al.*, 2017). These solutions provide more demand management options and may significantly lessen the carbon footprint of related activities (Nguyen and Le, 2023; V. N. Nguyen *et al.*, 2024a). The environmental effect of the transportation industry may be reduced by using efficient manufacturing methods for fuels like biodiesel. The combined heat and power (CHP) system also employs syngas from biomass gasification as an appropriate substitute for fossil fuel (J. Singh *et al.*, 2020; Thi *et al.*, 2024; Zhang *et al.*, 2022). The byproduct of biomass gasification, a porous organic residue
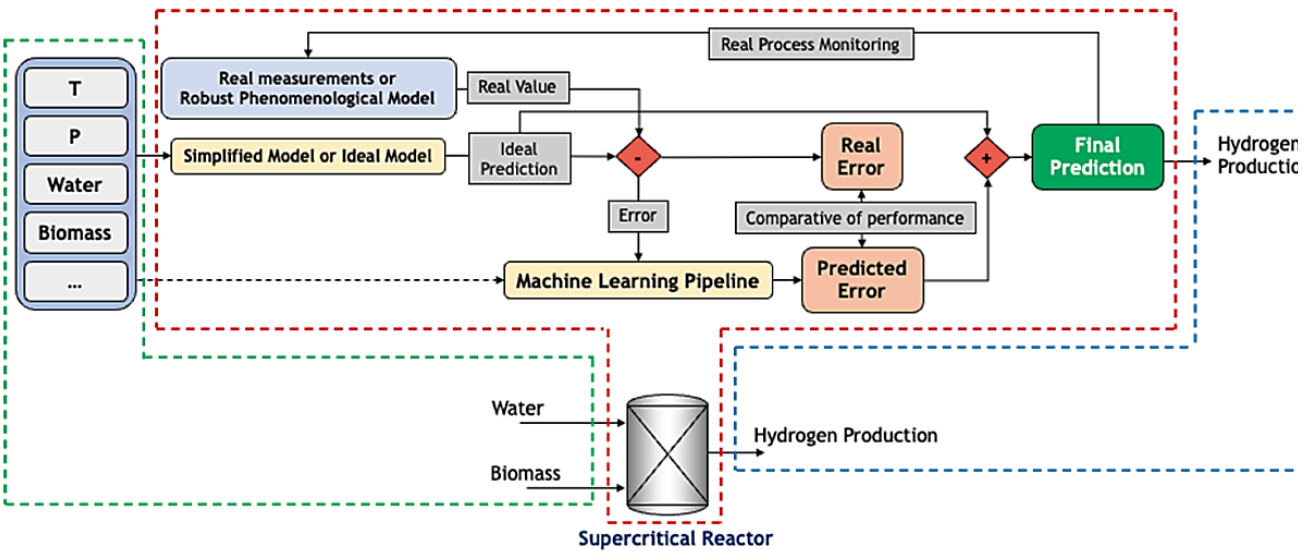
**Fig. 12** ML-based modeling architecture for biomass gasification (dos Santos Junior *et al.*, 2023)

**Table 4**
ML-based investigation in biomass to the energy sector

| ML/AI used | The main theme of the research | Main outcomes | Source |
|---|---|---|---|
| SVR, ANFIS, and ANN | Biomass higher heating value (HHV) forecasting | An adaptive neuro-fuzzy inference system is superb in prediction model development. | (Dodo *et al.*, 2022b) |
| MLR, ANFIS, SVM, and ANN | Prediction of HHV | Not one of the proximate analysis elements can individually provide an accurate HHV prediction provided they are coupled as input to the established models. | (Dodo *et al.*, 2022a) |
| SVR, polynomial egression, Decision tree (DT), and ANN | Prognostic models for the biomass gasification process | $R^2 > 0.9$ for almost all outputs of the process could be achieved in this study. | (Elmaz *et al.*, 2020) |
| ANN | Biomass gasification process | The model's high R-squared value (0.99) in the case of methane and carbon monoxide and 0.98 in the case of hydrogen and $CO_2$ was attained using ANN. | (Baruah *et al.*, 2017) |
| ANN | Prediction of tar formation in bubbling fluidized gasifier | $R^2 > 0.9$ for the tar prediction model developed using ANN showed as robust model. | (Serrano and Castelló, 2020) |
| ANN | Effect of bed material on bubbling fluidized-based gasification | $R^2 > 0.9$ for the tar prediction model developed using ANN showed as robust model. | (Serrano *et al.*, 2020) |
| ANN | Estimation and prediction of producer gas in fluidized bed gasifier | R = 0.987 and MSE was 0.71 for the models developed with ANN. | (George *et al.*, 2018) |
| ANN | Exergy prediction of raw biomass using ML | For the exergy model, the $R^2$ value was higher than 0.92 in model training and 0.79 in the testing phase. The mean absolute percentage error was less than 4%. | (Kartal and Özveren, 2022) |
| RF, SVM, DT, and MLR | Biomass to Bio-oil yield prognostic model using pyrolysis data | RF-based bio-oil yield prediction model with R = 0.98 was superior to the other three ML approaches. | (Ullah *et al.*, 2021) |

known as biochar finds use in soil carbon sequestration, pollution absorption, pollution remediation, and the synthesis of carbon-based products (Fiore *et al.*, 2020; Gonçalves *et al.*, 2019; Hoang *et al.*, 2022c; Richardson *et al.*, 2015).

Since these conversion processes are very complex and contain non-linear factors, process design, optimization, and intensification depend on mathematical models. Through the use of these models, one may forecast important process performance metrics, enable improved management and optimization, and evaluate the effect of different variables on outputs (Elmaz *et al.*, 2020; Liu *et al.*, 2024; W. Zhang *et al.*, 2023). However, the conventional approaches are time-consuming and difficult, and the data-derived ML is an

attractive option (Agrafiotis *et al.*, 2014; Kousheshi *et al.*, 2020). ML and AI have shown to be very helpful in the area of biomass-to-energy conversion (García-Nieto *et al.*, 2023; Wang and Yao, 2023). This is attributed to their ability to handle complex, high-dimensional data and enhance nonlinear processes (V. G. Nguyen *et al.*, 2024d; Tang *et al.*, 2023). Accurate simulation of conversion processes like as pyrolysis, gasification, and combustion made possible by these technologies enables one to predict and enhance system performance (Alruqi *et al.*, 2024; Ge *et al.*, 2023). AI-powered models may be able to identify the best operating conditions, which might increase productivity and efficiency while reducing expenses at the same moment. Furthermore, real-time process control and monitoring made

feasible by ML algorithms ensures the stability and quality of the manufacturing process (khan *et al.*, 2023; H. Li *et al.*, 2023). AI may be used to develop new catalysts and materials that will further increase the rate of conversion and product quality. Huge data from many sources is integrated using ML and artificial intelligence to provide predictive maintenance and fault identification. That reduces operational risks and downtime. A summary of studies showing the application of ML & AI in the domain of biomass to energy is given in Table 4. The flowchart of how the ML models are developed in biomass energy is depicted in Figure 12 (dos Santos Junior *et al.*, 2023).

## 7. Application of ML in waste-to-energy path

Waste management in the present era is not just concerned with its disposal but also has been already acknowledged as a crucial asset for the circular economy (Atabani *et al.*, 2022; Salmenperä *et al.*, 2021; Son Le *et al.*, 2022). Every year, around 2 billion tons of municipal solid waste (MSW) are created across the world, with nearly one-third of this material not being properly handled from an environmental aspect (Hoang *et al.*, 2022f; Kahan, 2020). Most countries are facing major waste management challenges as a result of the huge amount of MSW being generated. Meanwhile, population expansion and a desire for higher living standards have driven up energy consumption (Dong *et al.*, 2014). According to the EU's waste hierarchy principle, reuse of materials and recovery take precedence above energy recovery from trash, generally known as 'Waste-to-Energy' (WtE). Nonetheless, WtE is needed to valorize and treat waste portions which may not be financially or technically recoverable, to divert streams away from garbage dumps, and to function as a safe sink for hazardous substances (Gil, 2022; Sharma *et al.*, 2020). WtE is an umbrella term used for several types of processes of transforming waste materials into usable energy, like heat energy, electricity, or fuel (Dal Pozzo *et al.*, 2023). However, the generation of greenhouse gases, gaseous pollutants, and toxic ash fractions along with comparatively poor energy efficiency provide a major obstacle for WtE in the shift to a circular and climate-neutral economy (Gautam and Agrawal, 2021; Kumar *et al.*, 2020). Incineration facilities have been established since the late nineteenth century to improve

cleanliness and reduce waste volume/weight (Reis, 2011). Since the late 1960s, the duty of guaranteeing safe garbage disposal was combined with energy recovery, using incinerators being outfitted with industrial steam boilers (Kaltschmitt, 2019). Electricity and heat created from the produced steam; may be utilized to replace an equivalent quantity of energy generated locally. This may provide an indirect environmental advantage by avoiding emissions from power grids and heat networks that have a greater carbon intensity than energy generated from garbage (Ferraz de Campos *et al.*, 2021). As the carbon intensity of electricity and heat output decreases in the future, owing to climate legislation, the advantages of replacing carbon-intensive power or heat generation are projected to reduce (O. Khan *et al.*, 2024; Lisbona *et al.*, 2023). However, WtE plants are expected to continue to play an important role as heat suppliers, such as in industrial steam networks, while also maximizing the additional value that may be derived from the material recuperation of unrecyclable waste streams (Makarichi *et al.*, 2018; Ronda *et al.*, 2023). The different routes of WtE in the case of MSW are depicted in Figure 13 (Rezania *et al.*, 2023).

ML has emerged as a quite useful technology in different aspects of life, including the WtE domain. Integrating ML into WtE processes may improve efficiency, optimize operations, and contribute to sustainable energy solutions (Zhu *et al.*, 2023). The sorting of garbage is one of the significant phases in the WtE process. The reliability and efficiency of a WtE process are hugely dependent on the quality of waste sorting (Kumar and Samadder, 2017). Efficient sorting ensures that the most recyclable and combustible material is recovered from the waste stream. The conventional methods of waste sorting methods are time-consuming and labor-intensive. In these circumstances, ML is found useful approach for enhancing the quality and reliability of the process (Li *et al.*, 2020; Zhihong *et al.*, 2017). Initially, the prognostic model is trained on massive waste image-based datasets to identify between constituents of waste items like organic waste, plastics, metals, and non-recyclables (Hossen *et al.*, 2024). The classification approach of ML especially image recognition techniques enables the model to accurately recognize and categorize various sorts of garbage. The ML-enhanced automated sorting systems help accelerate the waste sorting system without much human intervention. It also improves the purity of the sorted materials, which is a
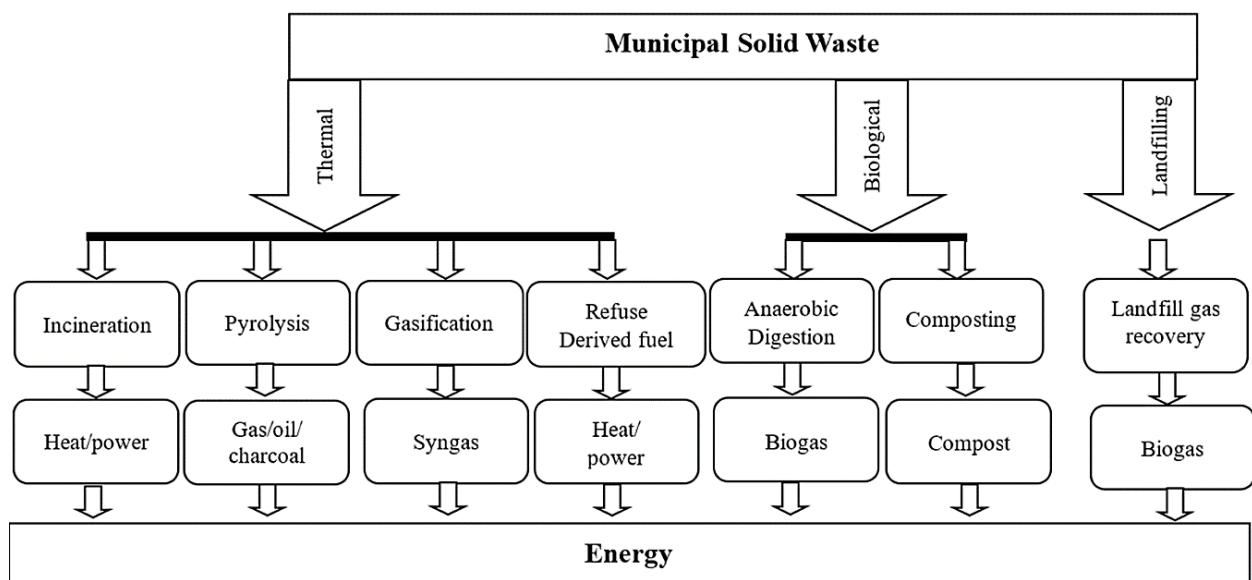


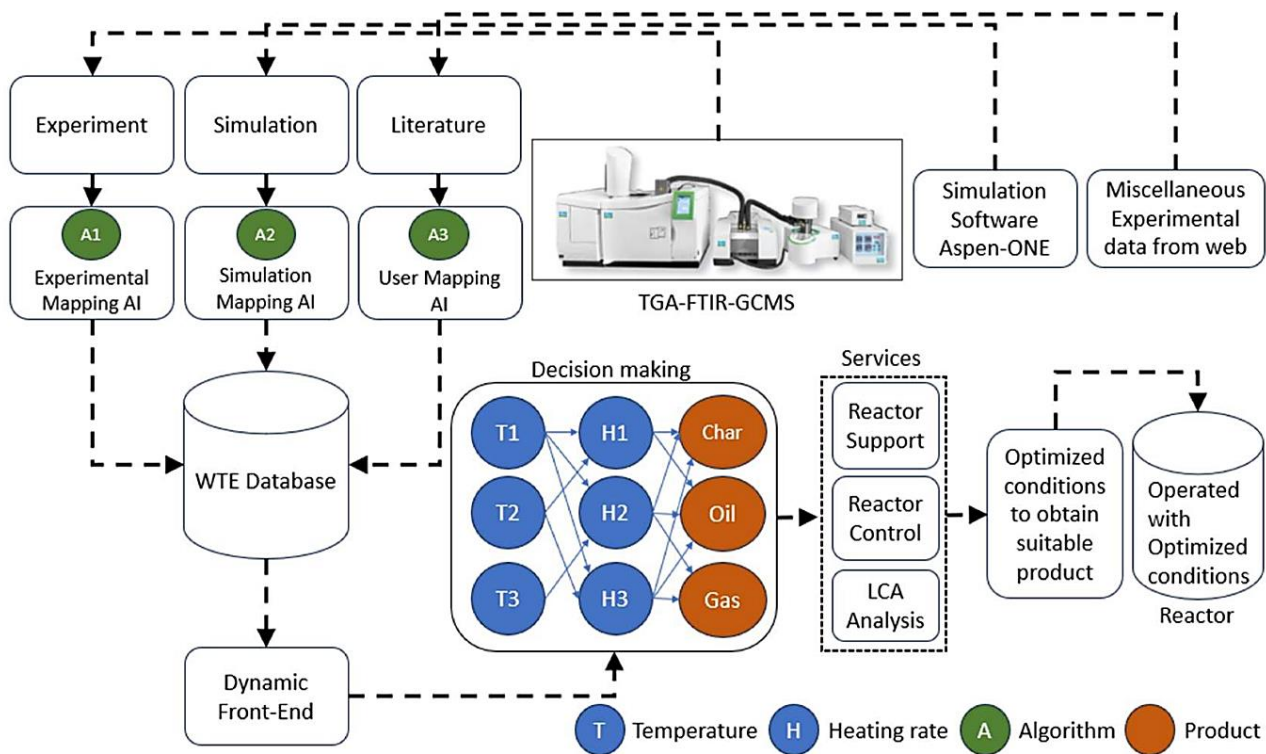**Fig. 13**. Different WtE routed for MSW (Rezania *et al.*, 2023)

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**Fig. 14**. Intelligent framework for the pyrolysis process (A. Gabbar and Ahmad, 2024)

worthy parameter for effective energy conversion (Jin *et al.*, 2023; Lv *et al.*, 2023).

Another aspect of ML application in the WtE domain is to improve the energy conversion process from sorted waste to useful energy (Al-Ruzouq *et al.*, 2022). This is achieved by employing a variety of techniques, including gasification, incineration, and anaerobic digestion. Each one of these approaches has its own set of inherent characteristics that need to be modeled to optimize the energy output while minimizing the negative environmental effect caused by these processes (Chiu *et al.*, 2022; Peng and Karimi Sadaghiani, 2024). In this scenario, ML can play an important role in the WtE process optimization (Taki and Rohani, 2022a). For example, in the case of the incineration process, ML algorithms are employed to monitor and control the combustion process in real-time. ML assistance ensures that waste is burnt at the optimized oxygen level and ideal temperature for best results (Ali *et al.*, 2023; Zaki *et al.*, 2023). Similarly, in the case of the anaerobic digestion process, the ML approaches can assist in maintaining optimal microbial conditions, such optimized settings help in increasing the biogas output (Andrade Cruz *et al.*, 2022). The continuous process data evaluation employing advanced ML approaches helps in the detection of trends and abnormalities (Ge *et al.*, 2021). It thus offers a solution in the form of proactive modifications, in turn helping to improve overall efficiency. An intelligent framework in this regard is depicted in Figure 14 (A. Gabbar and Ahmad, 2024).

The process as well as system reliability is crucial in WtE plants because equipment downtime can lead to significant energy loss. ML helps in efficient predictive maintenance to offer a robust solution to this challenging issue. ML algorithms can help in the near accurate forecast when a piece of equipment may break by examining data from sensors installed in it (Achouch *et al.*, 2023; Saraswat and Agrawal, 2023). This enables prompt maintenance, preventing unexpected malfunctions and increasing the life of the equipment. Furthermore, predictive maintenance eliminates the need for frequent inspections, which may be disruptive and expensive. The use of ML in this context not only assures continuous operation but also improves the safety and sustainability of the WtE plant (J. Li *et al.*, 2022; Pehlken *et al.*, 2022).

The environmental effect of waste-to-energy operations is a key problem, particularly in terms of emissions and residue management. ML can help to reduce these consequences by improving process control and optimization. For example, emission control systems can utilize machine learning algorithms to continually monitor and regulate the quantities of pollutants released throughout the energy conversion process (V. Sharma *et al.*, 2023a; Ünal Uyar *et al.*, 2023). This guarantees that the facility complies with environmental laws while minimizing its carbon footprint. Furthermore, machine learning may optimize the treatment and disposal of leftovers, such as incinerator ash, ensuring that these byproducts are managed in an ecologically sustainable manner (Ghosh *et al.*, 2023; Zhang *et al.*, 2024).

The use of ML in WtE goes beyond operational gains to drive research and innovation. By evaluating massive volumes of data from diverse WtE processes, ML can discover insights that lead to new approaches and technologies (Huang and Koroteev, 2021; Li *et al.*, 2024). For example, machine learning can aid in the identification of the most efficient biogas feedstocks or the development of novel gasification catalysts. These developments have the potential to improve WtE processes' efficiency, cost-effectiveness, and scalability. Furthermore, ML can help integrate WtE systems with other renewable energy sources like solar and wind, resulting in a more robust and sustainable energy infrastructure. The

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**Table 5**
A summary of recent ML based WtE studies

| Main theme | ML used | Main outcomes | Source |
|---|---|---|---|
| Higher heating value model prediction of waste biomass | ANN and Multivariate linear regression | 1. Well précised and robust prediction models were developed.<br>2. ANN model had only 1.17527 root mean squared error (RMSE) | (Ezzahra Yatim *et al.*, 2022) |
| Higher heating value of MSW | MLP-ANN, Radial bias function-ANN, ANFIS, SVM | 1. RBF-ANN-based model was superior to others.<br>2. RBF-ANN had RMSE as just 0.02 during training and 0.03 during model test. | (Taki and Rohani, 2022b) |
| Forecasting of gas yield from MSW | Deep NN and Moth-flame optimization (MFO) | 1. DNN was used for prognostic and MFO was used to improve the precision of DNN. | (Yang *et al.*, 2021) |
| Waste sorting | You only look once (YoLo5s) and ShuffleNet V2 | The proposed model was 62% more efficient in prediction compared with model developed with YoLo5s based model alone | (Y. Chen *et al.*, 2023) |
| Garbage classification for effective sorting | RestNet-34 | The results shows that classification accuracy was as high as 99%. | (Kang *et al.*, 2020) |
| Hydrothermal gasification of waste biomass: optimization | Adaptive multivariate random forest + Adaptive weighted rank aggregation + Tunable decision support system | The hybrid approach helped in achieving 94% accuracy in hydrothermal gasification process | (Gopirajan *et al.*, 2021) |
| Olive pit waste gasification for hydrogen fuel | Supervised ML (kNN, LR, DT, and SVM) | LR and SVR were superior to other two ML approaches based on $R^2$ and MSE values.<br>LR and SVR achieved $R^2$ values of 0.999 and 0.997, respectively while MSE was 0.008 and 2.66, respectively. | (Ozbas *et al.*, 2019) |
| MSW gasification model-prediction | SVM, RF and Gradient Boosting Regression (RGR) | GBr was superior in prediction with $R^2$ more than 0.926 and RMSE less than 6.318. | (Yang *et al.*, 2023) |
| Model-prediction of polyethylene waste | Central composite design of RSM | Model could be developed with less than 5% error. | (Hasanzadeh *et al.*, 2023) |

following studies listed in Table 5 summarize recent works showing the application of ML for effective WtE transformation.

## 8. Challenges and perspective

ML is making rapid inroads in the domain of the renewable energy sector. However, there exist some challenges in employing ML and intelligent algorithms to improve the energy production from RES. Data gathering, interpretability, model consistency, computation capabilities, and solution scalability are only a few of the problems. This section provides an examination of these issues and also discusses how these challenges can be overcome.

### 8.1 Data Quality and Acquisition

Obtaining and relying on the data is a major challenge for employing ML in renewable energy installations. With the use of sensors and monitoring equipment, renewable energy sources like solar and wind generate large amounts of data (Koutroulis and Kalaitzakis, 2003). Still, this data often runs into issues like noise, inaccuracy, and incompleteness. Training ML models that provide accurate results requires giving top priority to gathering data of outstanding quality and dependability. The solutions to these issues need data preparation techniques like as cleansing, normalization, and imputation, but they may be resource- and complexity-demanding (Aslam *et al.*, 2021; Qaiyum *et al.*, 2023).

Another significant challenge is the variety of data sources. Several sources—including weather stations, satellite photography, and Internet of Things devices—provide data on renewable energy, all in different forms and standards. The integration of this heterogeneous data into a single dataset suitable for ML applications requires sophisticated techniques

and presents significant technical and logistical difficulties (Kahia *et al.*, 2022; J. Li *et al.*, 2023).

### 8.2 Model Validation and Accuracy

High model accuracy is essential for ML to be used in RES effectively. Nevertheless, this project has a great difficulty because of the complex and varied features of renewable energy sources. Because solar and wind energy is intermittent and affected by weather and geography, building prediction models is made more difficult. Using a wide range of datasets that cover a wide range of scenarios, models must be thoroughly trained to guarantee accurate predictions of energy demand and output (Hu and You, 2022; Pan *et al.*, 2023).

Another important aspect is the model validation. ML models need to be rigorously validated using techniques like split-sample testing, bootstrapping, and cross-validation. Still, this process is made more difficult by the lack of globally recognized standards for RES. To properly evaluate the efficiency of ML models, recognized validation procedures and standards must be established (Ahmad *et al.*, 2022).

### 8.3 Transparency and Interpretability

The acceptance of ML models in applications related to renewable energy depends on their understandability. Engineers, legislators, and investors are among the stakeholders who need to understand how models come up with their predictions and suggestions. Nevertheless, several advanced ML techniques, notably deep learning, operate as "black boxes," making it difficult to understand their underlying principles (Hassija *et al.*, 2024; Shams Amiri *et al.*, 2021).

A lack of openness may lead to mistrust and hesitation to use ML technology. Explainable AI (XAI) and other comprehensible ML models and techniques are being developed more and more by researchers in response to this

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problem. These tactics are meant to provide an understanding of the model's decisions and guarantee that the projections are precise and understandable. It is somewhat difficult to strike the ideal balance between interpretability and model complexity (Cortiñas-Lorenzo and Lacey, 2024; Qin *et al.*, 2023).

### 8.4 Computational infrastructure

ML techniques in RES often need large computer resources to be implemented. Complex models, particularly those using large neural networks, need a significant amount of memory and processing power to develop. This may be problematic, especially for smaller companies and research groups with less access to powerful computer technology (Kapp *et al.*, 2023; Khan *et al.*, 2020).

Moreover, applications that need fast processing of enormous amounts of data include dynamic energy management and predictive maintenance. Accurately achieving the necessary computer efficiency is a complex process. Using hardware developments like Tensor Processing Units (TPUs) and Graphics Processing Units (GPUs) as well as optimization techniques like distributed computing and parallel processing is essential to meeting these demands (Chammas *et al.*, 2023; Routis *et al.*, 2024).

### 8.5 Scalability

ML technology deployment in RES is heavily reliant on scalability. The solutions have to be able to handle an increasing volume of data and expand to cover larger geographic areas or include more renewable energy sources. Achieving scalability while maintaining dependability and performance calls for careful planning and robust structures (Cerquitelli *et al.*, 2019; Torres *et al.*, 2018).

For instance, when used for other wind farms with different characteristics, an ML model built with data from one wind farm may not perform as well. It will be necessary to develop models that can be used in many contexts and modified as needed. Though they still require more research and development, transfer learning and federated learning are potential new approaches for addressing scaling issues.

### 8.6 Easy Integration with Existing Systems

Using ML models in the present renewable energy infrastructure and operational processes is another significant challenge (Resch *et al.*, 2014). Complex networks of renewable energy comprise a number of stakeholders, including grid operators, energy providers, and regulatory bodies. It takes a thorough understanding and efficient coordination to integrate ML solutions smoothly without interfering with ongoing activities.

Different technological stacks, data formats, and communication protocols make it difficult to integrate current ML solutions with outmoded systems (Raschka *et al.*, 2020). Integration cannot be enabled until compatibility and standard interfaces are ensured. Moreover, sufficient training of employees is necessary to guarantee their effective use and administration of these recently acquired instruments, which is necessary for the project to be completed successfully.

### 8.7 Protection and Privacy

Concerns about privacy and security also arise when ML is included in RES. IoT sensors and devices are widely used in these systems, which creates several cyberattack weaknesses. Achieving data and ML model security is crucial to prevent

unauthorized access and modification (Kokila and Reddy K, 2025).

Furthermore, privacy issues arise from the collecting and usage of large amounts of data. It takes careful balance to effectively use data for ML applications while nevertheless adhering to regulations like the General Data Protection Regulation (GDPR) (Hoofnagle *et al.*, 2019). Differential privacy and secure multi-party computing are two techniques being looked at to address these issues, but they complicate the development and deployment of ML systems even more.

### 8.8 Ethical issues

ML applications in RES are increasingly requiring the consideration of ethical concerns. The decisions ML algorithms take might have a significant impact on the environment and communities. It is essential that these models work impartially and do not inadvertently exacerbate already-existing biases or inequalities (Malhotra *et al.*, 2018; Stahl, 2021).

Energy pricing and allocation ML models need to be designed especially to provide equitable and fair access to energy supply. Tackling these issues requires the establishment of ethical standards and frameworks for the use of ML in renewable energy. Important components of ethical ML adoption include also active engagement with stakeholders and ensuring transparency in decision-making processes.

### 8.9 Regulating and policy issues

Regulation and policy frameworks have a big impact on how ML is used in RES. One has to be completely aware of both national and international laws and regulations to properly negotiate the intricate regulatory environment. Finding the right mix between encouraging innovation and guaranteeing compliance is essential (Fernandes and Silva, 2022).

Artificial intelligence and ML technologies integration in the renewable energy industry should be encouraged by the policies (Antonopoulos *et al.*, 2020). This includes setting up standards and recommendations, allocating funds for research and development, and promoting collaboration between the corporate world and academic institutions (Nam *et al.*, 2020). Still, the rapid advancement of ML technology often outpaces regulatory frameworks, leading to misunderstanding and major implementation barriers.

A multidisciplinary approach including collaboration among data scientists, engineers, policymakers, and other stakeholders is required to address these challenges. Overcoming these obstacles and fully using the ability of ML in the RES need continuous research and development as well as the application of set standards and ethical guidelines (Malhotra *et al.*, 2018; Ximenes and Ramalho, 2021). By efficiently overcoming these challenges, the renewable energy industry may employ ML to boost production, foster innovation, and significantly advance the cause of a more ecologically friendly future.

## 9. Conclusion

The integration of ML and intelligent algorithms in RES presents a transformative opportunity. It helps in enhancing reliability, efficiency, and sustainability. This review paper has explored the application of ML across several RES like solar, wind, biofuel, and biomass energy domains. The study highlights significant progress and concerning challenges. ML techniques are instrumental in addressing key issues like data variability, system optimization, predictive maintenance, and process control. However, to fully harness these benefits,

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several challenges must be overcome through multidisciplinary collaboration, technological innovation, and supportive policy frameworks. ML contributes to the improvement of solar irradiance forecasts, which raises the precision of estimates of energy generation. The performance and efficiency of solar systems are maximized via optimization techniques. Inaddition, better wind speed forecasts made possible by advanced machine learning algorithms lead to increased turbine efficiency and energy dependability. Algorithms for predictive maintenance lowers wind farm downtime and operating expenses. For biofuels, by optimizing feedstock selection, process parameters, and yield forecasts, ML improves the production of biofuels. Data-driven strategies raise the economic and environmental sustainability of biofuel production. In the case of biomass energy, effective thermal conversion procedures made possible by machine learning guarantee increased energy production and stable operations. ML-based real-time process control lowers waste and improves system efficiency.

In order to properly train machine learning models, it is necessary to offer data that is reliable and of high quality. Indeed, to win over stakeholders and be accepted, it is important to improve the understanding of complex machine learning models. Managing the high computational requirements of complex machine learning models is one of the computing demands that must be met. Establishing frameworks that will make it easier to incorporate machine learning into renewable energy sources is a requirement for receiving support from policy and regulation. Moreover, ensure the confidentiality and safety of the data stored in machine learning systems. This is an ethical issue. The future of renewable energy lies in the successful integration of ML and intelligent algorithms, promising a cleaner, more efficient, and resilient energy system. Continued research, innovation, and collaboration are imperative to overcome challenges and fully unlock the potential of renewable energy through ML.

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