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Review

Potential of Explainable Artificial Intelligence in Advancing Renewable Energy: Challenges and Prospects

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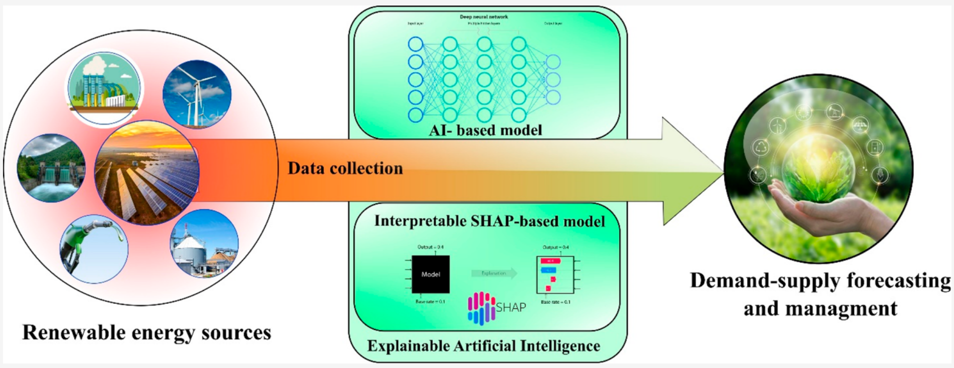

ABSTRACT: Modern machine learning (ML) techniques are making inroads in every aspect of renewable energy for optimization and model prediction. The effective utilization of ML techniques for the development and scaling up of renewable energy systems needs a high degree of accountability. However, most of the ML approaches currently in use are termed black box since their work is difficult to comprehend. Explainable artificial intelligence (XAI) is an attractive option to solve the issue of poor interoperability in black-box methods. This review investigates the relationship between renewable energy (RE) and XAI. It emphasizes the potential advantages of XAI in improving the performance and efficacy of RE systems. It is realized that although the integration of XAI with RE has enormous potential to alter how energy is produced and consumed, possible hazards and barriers remain to be overcome, particularly concerning transparency, accountability, and fairness. Thus, extensive research is required to address the societal and ethical implications of using XAI in RE and to create standardized data sets and evaluation metrics. In summary, this paper shows the potential, perspectives, opportunities, and challenges of XAI application to RE system management and operation aiming to target the efficient energy-use goals for a more sustainable and trustworthy future.

1. INTRODUCTION

1.1. Background and Motivation. Fossil fuels are nonrenewable energy sources that have been used for many years to power numerous transportation, industrial, and home activities.[1,2] Oil, natural gas, and coal are three primary forms of fossil fuels;[3] these are the principal energy sources for most of the world's population, and their utilization has resulted in enormous advances in human progress. The last few decades have witnessed considerable growth in the demand for and consumption of fossil fuels.[4,5] As reported by the International Energy Agency (IEA), fossil fuels continue to account for more than 80% of total universal energy usage, with oil and gas being the most common. Coal consumption has declined over the past decade owing to environmental anxieties, but it remains a crucial energy source, particularly in developing countries.[6] The combustion of fossil fuels emits significant volumes of greenhouse gases (GHGs) into the atmosphere, contributing to global warming and disrupting weather patterns;[7,8] international efforts have been thus made to minimize GHGs and to move toward cleaner, more sustainable energy sources.[9,10] Another issue arising from the use of fossil fuels is that the combustion of fossil fuels emits pollutants such as oxides of nitrogen, carbon monoxide, sulfur dioxide, and particulate matter, which may lead to serious health consequences, especially for vulnerable people such as children, older people, and those suffering from respiratory ailments.[11] Aside from the environmental and health outcomes, the usage of fossil fuels entails economic and geopolitical dangers.[12] Indeed, fossil fuel

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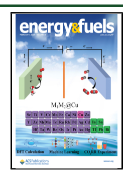

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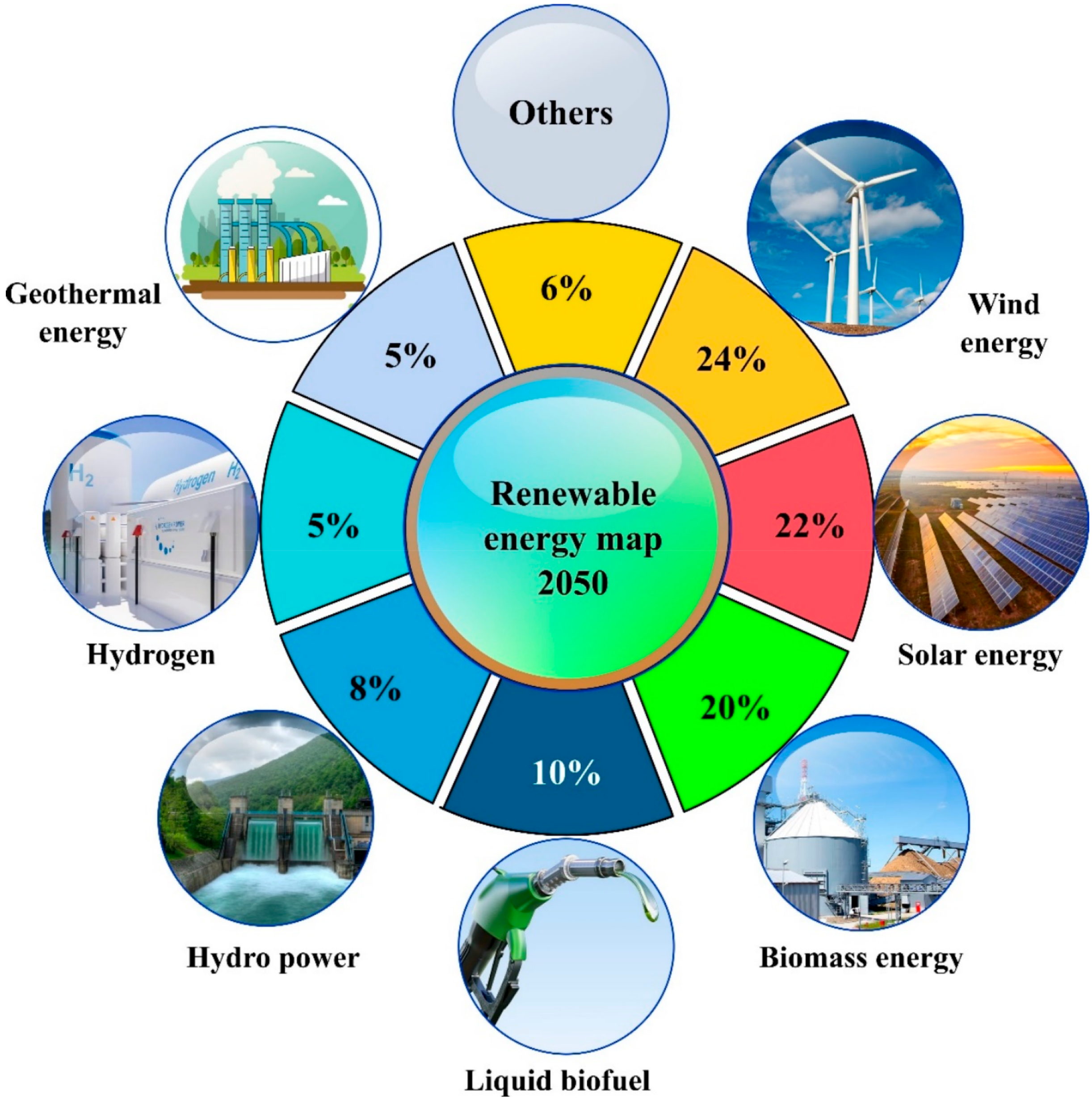

Figure 1. Map of predicted renewable energy usage by 2050[15,16]

reserves are frequently found in politically unstable areas, and their prices can be variable, resulting in financial instability and uncertainty.[13,14] For this reason, Sustainable Development Goals (SDGs) were proposed by the United Nations as a universal call for sustainable action to end poverty, safeguard the environment, and guarantee energy security. Reaching net-zero targets by 2050, in particular, is a critical task that will necessitate significant efforts from all sectors of the economy. In this context, strategies that involve the use of renewable energy (RE) have attracted attention from a large number of policymakers, researchers, and end-users. A map showing the predicted usage of RE in 2050 is shown in Figure 1.[15,16]

Reaching these goals will necessitate a combination of regulatory initiatives, technology innovation, and greater public knowledge and participation. In addition to RE sources, alternative technologies such as hydrogen fuel cells and carbon capture storage (CCS) can be used.[17−19] Hydrogen fuel cells create electricity using hydrogen as a fuel source and produce only heat and water as byproducts. CCS refers to the process of collecting CO_2 emissions via fossil-fuel power stations and burying them underground to lessen their environmental effects.[20,21] Although RE systems may offer many advantages in terms of achieving net-zero emissions, sources such as the wind and the sun are inherently unpredictable, making accurate forecasting of energy generation difficult. Machine learning (ML) has emerged as a potent tool for RE research as it can scan vast amounts of data and uncover patterns that would otherwise go unnoticed. ML can be applied in the context of RE to predict energy production, optimize energy storage, and increase the performance of RE systems. These algorithms can be used to examine previous weather patterns and energy generation data to anticipate future energy generation more accurately and can assist grid operators and energy firms in managing the supply and demand of energy. A pictorial representation of the different types of ML is shown in Figure 2.

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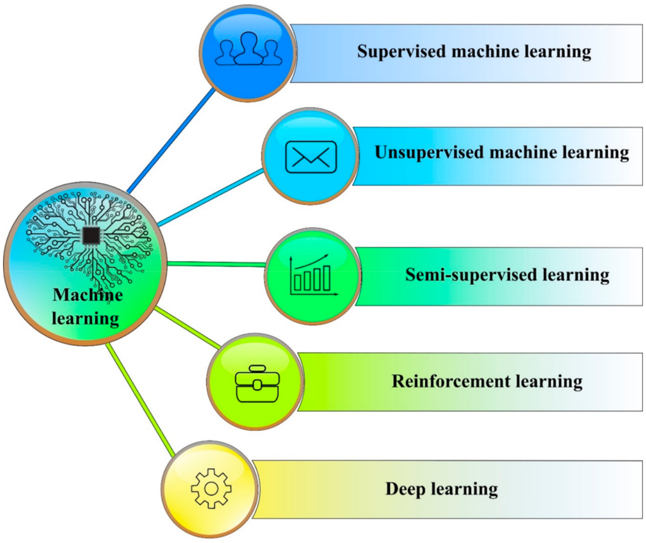

Figure 2. Types of machine learning.

Energy storage optimization is another area of application for ML in RE research. In RE systems, energy storage is important, as it allows energy to be generated and stored for later consumption. ML algorithms can analyze energy demand and supply patterns, thus helping to improve the functioning of energy storage devices and reducing the waste of energy while also increasing the general effectiveness of RE systems. ML models may also be employed to enhance the efficiency of RE systems, anticipate energy output, and optimize energy storage. For instance, an ML algorithm can be used to analyze data on the efficiency of solar panels and wind turbines to detect areas for improvement.[22−24] As a result, more efficient and cost-effective RE solutions may emerge. However, despite the numerous advantages of ML in RE research, several potential downsides must be considered. One source of concern is that an ML model needs a significant amount of data to function correctly, which can pose difficulties in RE research as data are often scant or difficult to collect.[25,26] Another potential disadvantage of employing ML in RE research is the risk of becoming overly reliant on technology; although ML can provide valuable insights and increase the performance of RE systems, it is critical to remember that it is only one tool among many. Finding a balance between technology innovation and human competence in RE research is critical.[26] It is therefore essential to examine the possible disadvantages of ML, such as the need for enormous volumes of data and the risk of overdependence. The power of ML to drive progress in RE research can be harnessed by striking a balance between technical innovation and human knowledge.[25] Table 1 summarizes the latest studies on the use of ML in the RE domain.

The issue of "black box" models currently poses a momentous challenge in the field of ML. This term refers to the user's incapacity to grasp or explain the decisions made by complicated ML algorithms. Although these models are very suited to tackling complex problems, their lack of openness and interpretability has been a rising source of concern.[37] The black box dilemma originates from the fact that ML algorithms frequently employ complex mathematical and statistical techniques to discover patterns from vast data sets, with results that may be highly accurate but are often challenging to explain. A deep learning neural network, for example, may be able to reliably identify an image of a cat, but it may be unclear how the model reached that conclusion. This makes it difficult to comprehend how the model works, what elements it considers, and whether it is drawing the correct conclusions. One of the foremost significant challenges related to the black box problem is the question of trust. ML-based models are employed in sensitive areas such as healthcare, banking, forensics, and law enforcement, and are increasingly employed to make crucial decisions that affect people's lives. This lack of transparency can also raise ethical concerns, especially if the model makes biased or unfair decisions.[38−40]

Numerous approaches can be taken to remedy the black box issue. One involves employing more straightforward, visible, and interpretable models. Models based on a decision tree or linear

Table 1. Recent Studies on the Use of "Black Box" ML Methods

Objectives	ML models used	Main outcomes	Source
Prediction of hydrogen content and bio-oil yield	Random forest (RF) and multiple linear regression (MLR)	RF was more robust for the prediction of H-bio-oil and bio-oil output	27
Model-based predictions of monthly solar radiation	Support vector regression (SVR), Gaussian process regression (GPR), K-nearest neighbors (KNN), long short-term memory (LSTM), and extreme learning machine (ELM)	LSTM and GPR models proved the most successful for this work	28
Solar irradiance prediction	8-stacking regression cross-validation	The model could provide predictions that were more than 98% accurate	29
Forecasting wind power through meteorological characterization	Decision tree (DT)	DT integrating rotor-equivalent wind speed enhanced the accuracy of prediction by 22%	30
Prediction of solar and wind resources	Cascade forward back-propagation (Cfbp), multilayer perceptron (MLP), self-organizing map (SOM), and radial basis function (RBF)	When applied separately to Brazilian wind data, CFBP was superior to the other ML techniques tested	31
Optimization of geothermal system	ANN and genetic algorithm	The exergy efficiency achieved by thermo-economic optimization was 23.34%.	32
Prediction of geothermal-based heat flow	SVM, generalized linear model (GLM), DNN, and gradient-boosted regression tree (GBRT)	A hybrid DNN-SVM approach improved the results	33
Prediction of biodiesel properties	XGB, SVR, MLR, and SVR for cold filter plugging point and cetane number	XGB and RF-based ML frameworks were superior to the others, with good accuracy (R^2 0.9)	34
Biofuel-powered engine	LSTM	LSTM yielded good predictions for engine performance and emission characteristics	35
Prediction of biomass pyrolysis	Different ANNs	The models were shown to have a competitive prediction capacity (R^2 0.99)	36

regression, for example, are reasonably uncomplicated and can be used to create accurate predictions, although simpler models may not be as effective at dealing with complicated problems or vast data sets.[41] Another approach is to employ strategies that allow the user to understand how the model makes decisions. One example is the use of feature importance algorithms to determine which features of a data set are important when making a specific forecast, which can help users understand which elements are considered by the model.[42,43] Alternative approaches to addressing the black box problem include the use of model-agnostic techniques to create explanations for specific predictions such as local interpretable model-agnostic explanations (LIME) or Shapley Additive Explanations (SHAP). These strategies provide local interpretable models that explain the outcome of the original model. While these explanations are not guaranteed to be correct or complete, they may provide helpful information about how the model makes decisions.[44,45] Finally, efforts are being made to improve the clarity and interpretability of the ML models. This includes creating explainable AI (XAI) techniques to facilitate an understanding of how a model makes decisions. Examples of these techniques include methods of providing human-readable descriptions of the behavior of a model, which simplify the model's internal workings and interfaces, thus allowing users to engage with it and study its decision-making process. In summary, the black box phenomenon is a significant problem faced by researchers in ML. While complicated ML models can be relatively effective at tackling complex issues, their lack of transparency and interpretability can make it difficult to understand how they make decisions. To address this problem, a combination of measures will be required, including simpler models, tools for generating explanations, and efforts to boost the transparency and interpretability of ML models. Researchers and practitioners can collaborate to create more reliable, ethical, and transparent ML systems to benefit society.

1.2. Scope and Objectives of This Work. This work critically evaluates XAI strategies for advancement in the RE sector. We review current RE XAI methods and tools and evaluate their usefulness in improving energy efficiency, carbon emissions, and the reliability and stability of the energy grid. In addition, we discuss the flaws of current XAI techniques and suggest avenues for further research. The main contents of this work are as follows:

- To present an overview of the most modern XAI approaches and technologies employed in the RE market.
- To critically assess the effectiveness of XAI techniques in improving energy efficiency, lowering carbon emissions, and improving the reliability and stability of the energy grid.
- To highlight the limitations of current XAI techniques and to identify future research directions to overcome these limitations.
- To identify the key challenges and opportunities related to the adoption of XAI in the RE domain.
- To provide a roadmap for researchers and practitioners who are interested in applying XAI techniques to RE applications.

2. RENEWABLE ENERGY TECHNOLOGIES

2.1. Solar Energy. Solar energy has become an attractive choice for REs. It uses several technologies to transform the sun's energy into electricity or heat energy.[46] Solar energy can deliver a clean, long-term, economical solution to the world's growing energy needs, and its greatest benefit is the fact that it is a completely renewable resource.[47,22] This implies that solar energy can offer future generations a reliable and copious source of energy. Another significant advantage of solar energy is that it does not emit GHGs or pollute the air;[48,49] unlike fossil fuels, it emits no harmful particulates or chemicals into the air, making it a clean and environmentally friendly energy source.[50] As a result, solar energy is an excellent option for combating climate change and lowering global carbon footprints.[51,52]

Photovoltaic (PV) panels, concentrating solar power (CSP), and solar heating systems are examples of technologies that can harness solar energy. PV panels immediately transform sunlight into energy, whereas CSP systems focus sunlight into a narrow space, creating heat that can then be used to generate steam or electricity. Solar heating systems harness the energy of the sun to heat water or air, which is then used for heating or cooling.[53] Solar energy has recently become more affordable, making it more competitive with traditional fossil fuels.[54,55] Despite the numerous advantages of solar-based energy conversion systems, several issues need to be addressed.[56] The main challenge is that solar energy is intermittent and weather-dependent, meaning that energy storage and backup systems are needed to ensure a consistent and dependable electricity supply.[57−59] Overall, solar energy offers enormous promise as a clean, sustainable, and cost-effective energy source and may play a vital part in satisfying global energy requirements while conserving the environment, with ongoing investment and technological breakthroughs.

2.2. Wind Energy. Wind energy is a RE source that is growing quickly and could meet a large proportion of current energy needs. It is a renewable and clean resource, and its use can cut GHG emissions, reduce reliance on fossil-based fuels, and generate employment and economic prosperity.[60,61] Wind energy is produced by harnessing the power of wind turbines, which gather and transform the kinetic energy of the wind.[62,63] These turbines are often built in regions with strong winds, such as mountain peaks or offshore in the ocean. The most prominent benefit of wind energy is that it can be used on a large scale. There are many different types of wind turbines, from small ones that can supply electricity to a single home or business to large ones that can fuel whole towns. Wind energy is a very adaptable RE source that can be used in a variety of contexts. The low cost of wind energy is a further advantage; the cost of this resource has gradually declined in recent decades, due in part to scientific and industrial breakthroughs.[64,65]

The use and development of wind energy can generate jobs and augment economic growth in addition to its environmental and economic benefits. Thousands of people are currently employed in the wind energy industry worldwide, working in many areas from manufacturing and installation to maintenance and operations. Despite its many advantages, however, there are several challenges associated with wind energy;[66,67] one of the most difficult is that wind turbines only generate electricity when the wind blows, making it problematic to integrate this energy into the grid. Advancements in technologies related to energy storage, such as pumped hydro storage and batteries, are assisting in addressing this issue and making wind energy a more reliable source of electricity.[68,69]

2.3. Geothermal Energy. Geothermal energy is an environmentally friendly form of energy that has recently gained attention due to its capacity to reduce GHG emissions and ameliorate the influences of climate change. Unlike other RE sources such as solar and wind, geothermal energy is accessible

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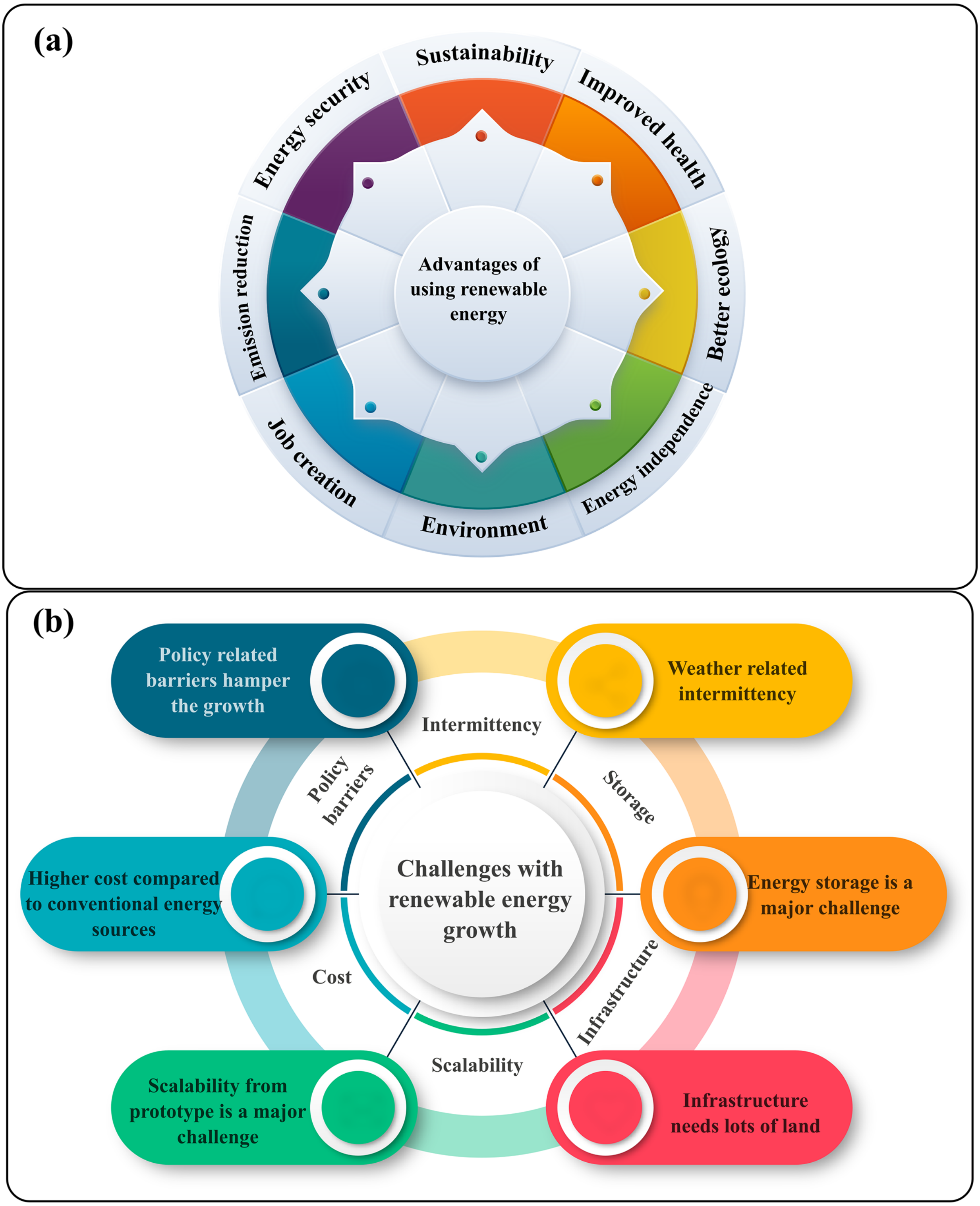

Figure 3. (a) Advantages of using renewable energy; (b) challenges hindering the growth of renewable energy.

24 h per day and can provide the baseload electricity needed to fulfill the demands of whole towns and industries. Geothermal energy is generated by the breakdown of radioactive elements inside the Earth and the heat that remains from the origin of the planet. This heat remains trapped inside the Earth's crust and can be accessed through geothermal reservoirs or deep drilling into the surface. Geothermal energy systems can be classified into three types: direct usage, geothermal heat pumps, and power generation. Direct-use geothermal water is used to heat or cool structures such as greenhouses and industrial operations, whereas geothermal heat pumps use the constant temperature of the Earth to heat or cool buildings.[70] Finally, in power production systems, geothermal reservoirs are used to create electricity.[71,72]

Depending on the type of reservoir used, geothermal power plants can be categorized as binary, flash, or dry steam plants. Hot water is used in a binary system to heat a secondary fluid that vaporizes and drives a turbine to produce electricity. In a

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flash system, hot water is flashed to steam to power a turbine, while in a dry steam system, steam is drawn straight from a geothermal reservoir and used to drive a turbine. Geothermal energy provides several advantages over typical fossil fuels such as a low carbon footprint, high efficiency, and low cost. Furthermore, geothermal energy has a smaller physical footprint than other renewable sources, making it ideal for urban areas with limited space.[73,74] However, geothermal energy does have some drawbacks: access to geothermal resources is geographically limited, and drilling and exploration can be costly. Furthermore, geothermal power plants require significant amounts of water for cooling, which can be difficult in water-stressed areas. Finally, geothermal energy offers excellent potential as an RE source, especially in places with abundant geothermal resources.[75,76] It provides a sustainable and economical source of electricity and can assist in the reduction of GHG emissions. Further research and investment are still required to improve exploration and drilling techniques and tackle water-related issues.

2.4. Hydroenergy. Hydroenergy is an RE source that has been used by humans for thousands of years. In this section, we present a brief introduction to hydroenergy and its place in the RE landscape. The energy produced by moving water is known as hydro power. A dam can be constructed across a river or other body of water, thereby creating a reservoir of water that is discharged through turbines, which spin and produce electricity.[77,78] Run-of-the-river systems, which do not need a reservoir or a dam, can also be used to generate hydroenergy; in this case, water is diverted from a river and passed through turbines, generating electricity as it flows downstream. The reliability of hydroelectric power is one of the key advantages. In contrast to wind and solar energy, which are impacted by weather, hydro energy can be created constantly all year round. As a result, it is a valuable source of baseload power, defined as the bare minimum level of power required to meet daily energy demand.[79,80]

Hydroenergy is also a low-cost source, particularly in areas with abundant water resources. While the initial costs of constructing a dam or run-of-the-river system may be high, the ongoing prices of producing electricity are relatively low, and as a result, hydro energy is an attractive option for countries seeking to expand their energy infrastructure.[81] Hydroenergy can also provide ancillary services, such as grid stabilization and frequency regulation. The use of hydro power plants can help to balance the supply and demand for electricity via the grid, thus preventing blackouts and brownouts. However, there are some drawbacks to this approach, as dams and reservoirs can have serious ecological consequences, such as the destruction of habitats and alterations in water flows. Furthermore, storing water behind a dam can cause the buildup of silt, which lowers the effectiveness of the turbines over time.[82,83] Despite these obstacles, hydroelectricity remains a valuable RE source, currently providing approximately 16% of the world's electricity generation, and this sector has excellent room for expansion. Hydroenergy is expected to play a larger role in the global mix of energy sources as technology progresses and the spending on RE rises.

2.5. Other Renewable Energy Sources. While other technologies, such as wind and solar, can transform our world, some technologies, such as wind and solar, can change our world. In addition to the sources of RE described above, there are other options, as follows:

- Tidal power: Electricity can be generated by harnessing the energy of ocean tides, as these move large amounts of water back and forth, which can be used to turn turbines and generate power. While this technology is still in its infancy, several countries, including France, South Korea, and Canada, have begun experimenting with tidal power systems.[84,85]
- Biomass: The term "organic" refers to the employment of RE sources such as biomass. Biomass can be burned directly to provide heat or can be processed into a gas or liquid fuel to power generators.[86] Although biomass energy shows promise as a good low-carbon source of energy, it still has some environmental drawbacks, such as the likelihood of deforestation and changes in land use.[87,88]
- Wave power, like tidal power, harnesses the energy of ocean waves to generate electricity. This type of system uses buoys or other devices positioned on the top surface of the water that can convert the motion of the tides into electricity. Although this technology is in its infancy, several countries, including the United Kingdom and Australia, have begun testing wave power systems.[89,90]
- Fuel cells: These are a type of energy conversion mechanism that turns chemical energy into electrical energy.[91] Unlike batteries, which store electrical energy, fuel cells can produce electricity indefinitely if fed fuel.[92] A range of fuels, including hydrogen, natural gas, and methanol, can power fuel cells. They are becoming increasingly common in buildings and as backup power sources for vehicles.[21]

In summary, although solar, wind, geothermal, and hydropower are some of the most well-known RE sources, many other technologies can potentially transform the energy landscape. A diversified and robust energy mix should be created for the future by investigating these lesser-known technologies and investing in their development.

2.6. Characteristics and Challenges of Renewable Energy. RE, or clean energy, is derived from replenishable natural resources such as sunlight, wind, rain, geothermal heat, and tidal waves. It is becoming more popular as people around the world become more aware of the negative environmental impacts of fossil fuels. RE has the following advantages, as depicted in Figure 3a:[93−96]

- RE sources emit few to no emissions, making them a more environmentally friendly alternative to fossil fuels. This reduces air pollution and GHG emissions, which cause global warming.
- Renewable and plentiful: Unlike fossil fuels, RE sources can be replenished naturally, and will not be depleted in the foreseeable future.
- Cost-effective: Over time, RE technologies have become more cost-effective, allowing them to compete with fossil fuels. Technological advancements and economies of scale have aided in this development.
- Job creation: The RE sector can offer a large number of jobs in different kinds of industrial operations, including energy provision, manufacturing, and construction.
- Energy independence: Countries can improve their energy security by reducing reliance on foreign energy sources.

The challenges associated with the use of RE are illustrated in Figure 3b.[97−99] The key points are as follows:

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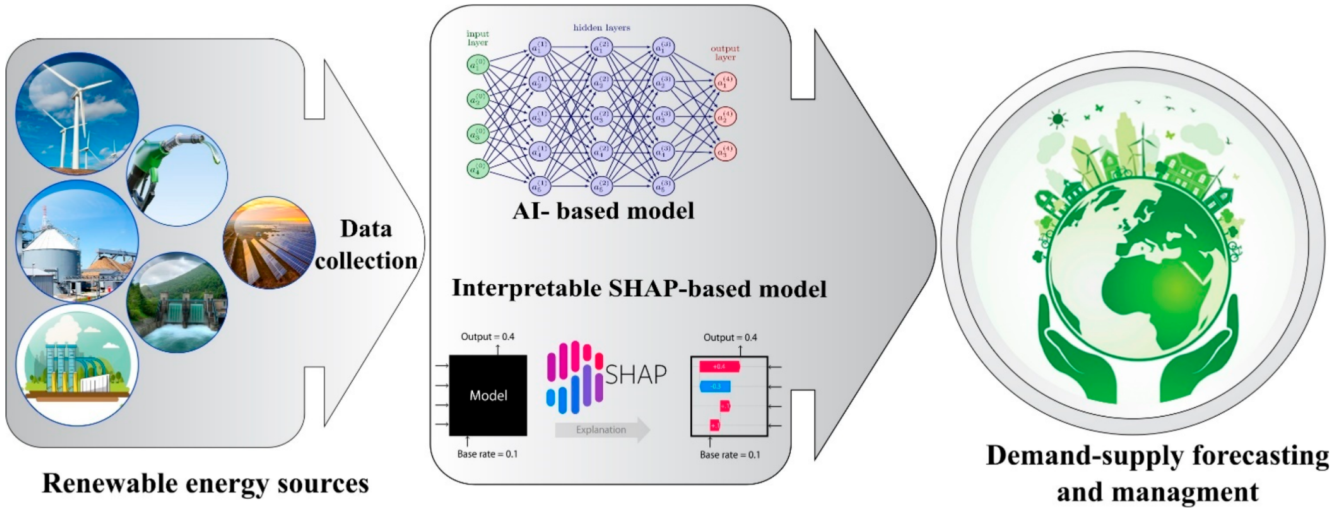

Figure 4. Applications of ML and AI in RE systems.

- Intermittence: Most RE-based energy sources, such as wind and solar power, are intermittent, meaning that their energy output varies with weather conditions. This can make the provision of a consistent and reliable energy supply difficult. To solve the issue of intermittency, energy storage technologies are needed to store excess energy for use at times when RE sources are unavailable.
- High initial costs: Although RE technologies are growing less expensive, a significant initial investment is required, which can pose a barrier to entry for some individuals or businesses.
- Grid integration: For technical and regulatory reasons, RE sources must be integrated into the existing power grid.
- Land use: Several RE sources, such as wind and solar, require large amounts of land for their installation, meaning that conflicts may arise over land used for agriculture or conservation.

In summary, RE has numerous benefits compared to fossil fuels, as it is cleaner, renewable, and more cost-effective and can foster job creation and energy independence. However, issues such as intermittency, energy storage, high upfront costs, grid integration, and land use must be addressed.

3. INTRODUCTION TO AI AND ITS APPLICATIONS IN RENEWABLE ENERGY

Artificial intelligence (AI) is a subfield of soft computing that covers the development of algorithms and computer systems that are capable of activities that generally require the involvement of the human intellect, such as the interpretation of natural language, classifying images, decision-making, and resolving complicated problems. In recent years, AI has become one of the most important and swiftest-growing domains of research and development activities, with enormous potential to transform many aspects of daily life.[100]

The most significant research areas concerning AI include ML, natural language processing (NLP), robotics, computer vision, and cognitive computing. Robotics is concerned with developing intelligent machines that are capable of interacting with the physical world, whereas cognitive computing seeks to create systems that are capable of simulating human thought processes. One of the most difficult challenges in AI research is the development of algorithms and systems that are capable of performing complex tasks with high accuracy and reliability, which frequently necessitates the use of large data sets and sophisticated algorithms that are capable of learning from these data and making accurate predictions. Deep learning has emerged in recent years as an influential technique for solving many engineering problems, particularly those involving image and speech recognition.[101,102]

AI has been successfully employed in areas such as banking, entertainment, healthcare, transportation, finance, and education and can be used to improve traffic flow and security in transportation. In the field of education, AI can be used to personalize learning and offer students personalized feedback and help. Despite the enormous potential of AI, however, there are numerous ethical and societal concerns associated with its development and application, including issues related to privacy, bias, transparency, and accountability concerns. There is a risk, for example, that AI systems will be used to discriminate against specific groups or perpetuate existing social inequalities. As a result, AI researchers and developers must collaborate closely with ethicists, policymakers, and other stakeholders to ensure that AI is created and employed in ethical and responsible ways.[103,104] A graphical representation of the use of ML and AI in RE is shown in Figure 4.

In a nutshell, AI is a rapidly emerging and interesting field of research with a huge capability to revolutionize the entirety of daily life. However, there are challenges and ethical concerns related to its development and operation. As a consequence, scientists and other interested parties must work together to ensure AI is created sensibly and ethically and to benefit society.

3.1. Machine Learning and Deep Learning.

Deep learning and ML are among the most recent significant technological advances. Although these two terms are frequently used interchangeably, they are not synonymous. Both are subclasses of AI that involve the creation of intelligent systems that can perform tasks without the need for explicit human intervention. ML seeks to allow computers to make decisions based on patterns and trends in data, rather than on explicit instructions from a human programmer.[105] Based on the type of data and the task at hand, ML algorithms can be supervised, reinforced, or unsupervised.[106]

Deep learning is a subset of ML in which the aim is to model and resolve complicated engineering problems using an artificial neural network (ANN). Deep learning algorithms are designed to automatically learn data representations and can be used for classification, prediction, and other tasks. The term "deep" refers to the number of layers of the neural networks, which allow them to extract high-level features from input data.[107] Deep learning models can handle large amounts of data, which are essential for many modern applications such as speech and image recognition, NLP, and autonomous vehicles. Research on deep learning has also resulted in significant advances in other fields, such as healthcare, as this approach can be used to improve disease diagnosis and drug discovery. Despite its advantages, however, it has some limitations, with one of the most difficult challenges being the need for large amounts of labeled data to train neural networks. Furthermore, deep learning algorithms can be computationally intensive, meaning that robust hardware is required to train and run these models.[108]

In summary, ML and deep learning have revolutionized the domain of AI and enabled significant advances in various domains. Whereas ML is concerned with creating algorithms that can learn from data, deep learning goes further by employing neural networks to extract higher-level features from the data. In the future, these technologies may change how humans live, work, and interact with technology.

3.2. Applications of AI in Renewable Energy.

AI has become an indispensable tool for optimizing RE systems, as these algorithms can forecast RE production, manage energy storage systems, and optimize energy consumption. ML algorithms, for example, can be used to analyze weather patterns and historical energy production data to make accurate predictions for future RE production. These forecasts can assist grid operators in managing the supply demand balance and ensuring that RE sources are exploited to their full capacity. AI algorithms may also be employed to manage energy storage systems, which can aid in smoothing out fluctuations in RE production and ensuring that energy is available when needed. Overall, AI has the potential to transform the way RE is generated and used, making it more efficient, dependable, and cost-effective.

3.2.1. Solar Energy.

AI can learn and dissect huge data sets in real-time, perform regression, classify images and voice recordings, and identify patterns and insights. These models can make predictions and recommendations to enhance the performance of solar energy systems. Examples of how AI is used in solar energy applications include its use to enhance the efficiency of a solar panel; AI algorithms can predict how much energy a solar panel will produce under various conditions by analyzing temperature, weather, and shading patterns.[109,110] These data can then be used to optimize the panel placement, tilt, and orientation to maximize energy production. A study conducted based on AI can also aid in detecting maintenance issues such as faulty panels or connections, thus allowing for quick repairs and preventing energy loss. Furthermore, AI can predict and forecast energy demand, allowing for better solar energy integration into the power grid.[111,112] Nwokolo et al.[113] employed six different techniques for performance prediction of several solar PV systems in Australia, using a radial basis function (RBF), MLP-ANN, switched and controlled auto regression integrated moving averages (SARIMA and CARIMA), and boosting and bagging ensemble ML models. The suggested hybrid model, which used only the quantifiable parameter of solar radiation, is most comparable to all systems' recorded PV energy output, with a comprehensive R^2 of 0.9998% and an RMSE of 0.0063 kWh.

Second, AI can improve solar energy storage technologies. Storage of solar energy is essential to supply energy when the sun does not shine. AI models can optimize energy storage by analyzing data from energy usage patterns and weather forecasts to predict when energy storage systems need to be charged and discharged, and can also help in optimizing the sizes of these energy storage systems, thus lowering costs while ensuring adequate energy storage.[24,114] Khan et al.[107] proposed an enhanced, generally applicable stacked ensemble approach (DSE-XGB) for solar energy forecasting based on two deep learning techniques, long short-term memory (LSTM) and an ANN. The suggested model was tested on four different solar generation data sets to enable a full assessment. In addition, the Shapley Additive Explanations (SHAP) framework was used in this study to provide a deeper understanding of the algorithm's learning process. The suggested DSE-XGB technique achieved the best trade-off between reliability and stability across various case studies, regardless of the variables used, and gave an improvement in the R2 value of 10−12% over previous models.

In summary, we note that AI is revolutionizing the solar energy sector by enabling new ways to optimize the production of energy, lowering costs, and improving system efficiency. With the growing popularity of solar energy, AI is poised to play a more significant role in ensuring that solar energy is a dependable and cost-effective RE source.

3.2.2. Wind Energy.

AI can successfully enhance the efficiency, trustworthiness, and safety of wind energy systems. Its potential applications in these systems include predictive maintenance, among others. Wind turbines require routine maintenance to ensure that they operate at peak efficiency and maintenance schedules are traditionally determined based on the manufacturer's recommendations, environmental conditions, and inspection reports.[115] However, by analysis of data from sensors embedded in turbines, AI can be employed to adjust maintenance schedules as necessary. Temperature, vibration, and other parameters that can indicate potential faults are collected by these sensors, and based on these data, AI algorithms can forecast the precise time at which maintenance will be required, thereby reducing downtime and improving turbine performance.[116] Wind farm optimization is another area where AI can have a significant impact. Wind farms are typically designed using historical wind data; however, wind patterns can change over time, resulting in suboptimal performance. AI algorithms can analyze real-time data from wind turbines and weather sensors to optimize the positioning and operation of individual turbines, which can increase the energy yielded by a wind farm by up to 20%, making them more profitable and sustainable.[117] AI can also improve the safety of wind turbines. Wind turbines are frequently located in remote and challenging locations, making maintenance and repair difficult. AI can be used to monitor turbine components and detect anomalies that could pose a safety risk; for example, if a blade is damaged, an AI model can detect changes in vibration and alert technicians to take action before the damage becomes severe.[31]

Power grid management is another application of AI in the domain of wind energy, particularly because it is an intermittent power source, where the output varies according to weather conditions. AI algorithms can forecast wind energy output and adjust the power grid to balance supply and demand; this process can help to reduce the need for fossil-fuel-powered backup generators, lower greenhouse gas emissions, and improve the overall sustainability of the energy system. Finally, AI can be used to improve the efficiency of the wind turbine

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design. AI algorithms can identify areas for improvement by analyzing data on wind patterns and turbine performance. This data-driven approach to turbine design can result in more efficient and dependable turbines, thus lowering the cost of wind energy and making it more competitive with other energy sources.[118,119]

In summary, the use of AI can transform the wind energy sector by improving efficiency, dependability, and safety, while decreasing costs and GHG emissions. It can help in the development of a more sustainable and renewable energy system that benefits the environment and society. However, as with any technology, AI must be used responsibly with appropriate safeguards and ethical considerations to ensure that its benefits are realized while avoiding unintended consequences.

3.2.3. Geothermal Energy. Geothermal energy is a clean, renewable, and reliable source of energy where electricity is generated by harnessing the Earth's natural heat. The harnessing of geothermal energy can be improved with the help of AI. The heat generated by the Earth's core is stored in the rocks and fluids in the Earth's crust, and geothermal power plants are built to extract and use this energy to generate electricity. However, with the help of AI, the efficiency of these plants can be significantly improved. One of the most important applications of AI in geothermal energy is in the exploration phase. The traditional method of exploration involves drilling a well and testing the temperature and flow rate of the fluid, which can be time-consuming and costly. Geologists can use AI to create a detailed subsurface map by integrating data from various sources, such as seismic activity, gravity, and magnetic fields. This enables more focused and efficient drilling, thereby lowering the costs and risks associated with exploration.[120,121] Another application of AI in geothermal energy is related to the monitoring and maintenance of power plants. AI models can be used to monitor the real-time performance of a plant and detect anomalies or inefficiencies, which enables timely maintenance and repairs, reduces downtime, and increases the overall efficiency of the plant. These models can also optimize power plant operations by adjusting the output to match demand, thereby reducing waste. AI models can be used to forecast the performance of a geothermal reservoir and can predict the temperature, pressure, and flow rate of the reservoir by analyzing data from sensors and other sources, thus allowing for better management and optimization of the plant's operation. This can assist operators in making informed decisions about when to extract and inject fluid and can maximize the plant's energy output.[122,123] Finally, AI can be used to enhance the overall competence of a geothermal power plant by identifying inefficiencies and suggesting ways to improve them based on an analysis of data from various sources. For example, the placement of heat exchangers can be optimized to reduce heat loss and increase the plant efficiency. AI has numerous applications in geothermal energy that can help enhance the efficacy and cost-effectiveness of this clean RE source. Geothermal power plants can achieve increased output and reduced costs and can provide a reliable energy source for future generations by using AI to improve exploration, monitoring, maintenance, and optimization.

3.2.4. Hydro-energy. For decades, hydro-energy has been an essential source of RE. It entails converting the energy generated by moving water into electrical power. With the ever-increasing global demand for energy, hydro-energy has become an appealing option for many countries. However, efficient and effective hydro-energy management relies on sophisticated control systems that are capable of optimizing the performance of hydro power plants.[85,124]

AI is a powerful tool that can help in this process, and this section explores its applications in hydro energy. One of the most important of these applications is turbine control. Turbines are the heart of any hydro-energy plant, and their proper operation is crucial to the overall efficiency of the system. AI algorithms can monitor the performance of a turbine and make real-time adjustments to improve it; for example, AI can be used to adjust the flow rate of water to a turbine based on real-time data about the water level and weather conditions. This can help maximize the power output of the turbine while minimizing wear and tear to the equipment.[125,126]

Another application of AI in hydro-energy is the prediction of energy output. Accurate predictions of the energy output of a hydropower plant are essential for energy supply planning and management. To predict the energy output, an AI algorithm analyzes historical data on the performance of the hydropower plant, water levels, turbine efficiency, and weather conditions.[127,128] Its output can assist energy companies in better managing the energy supply and demand and optimizing energy production. AI can also be used in the maintenance of hydroelectric plants as this needs to be done routinely to ensure peak performance. AI algorithms can monitor the condition of equipment and predict when maintenance will be required, for example, by scanning the vibration and temperature of a turbine and detecting any anomalies that could indicate a problem. This can assist in minimizing downtime and lowering maintenance costs.[129−131] Finally, AI can be used to improve the design and construction of hydroelectric power plants by analyzing data on the terrain, water flow, and weather conditions. This can help to maximize the plant's power output while minimizing its environmental impact. There are numerous ways in which AI can be applied in the field of hydro-energy, from optimizing turbine performance to predicting energy output and optimizing plant design. As the demand for renewable energy grows, AI will play a growing role in the efficient and effective management of hydro-energy plants.

3.3. Benefits and Challenges of AI Application in Renewable Energy.

AI has made significant contributions to various industries including RE. AI can help with RE in multiple ways, including predicting power output and optimizing energy storage. The ability to predict the power output is one of its primary benefits. RE sources such as wind and solar power depend on weather conditions, meaning that the prediction of energy generation is challenging; however, AI algorithms can accurately forecast the energy output by analyzing several forms of data such as weather predictions, historical weather patterns, and energy production. This can assist grid operators in efficiently balancing supply and demand, minimizing the necessity for backup power sources and reducing the overall cost of energy.[132−134]

Energy storage optimization is another area in which AI can be used in RE. For instance, batteries can help compensate for the sporadic nature of RE generation. By predicting when the energy demand will be high and storing excess energy during low-demand periods, AI can help to optimize the employment of energy storage systems, which can in turn reduce the need for backup power from fossil fuels and make RE sources more reliable and cost-effective. AI can also aid in optimizing the design and operation of RE systems. These algorithms can assist engineers in designing more efficient RE systems by analyzing data from diverse sources, such as the inherent patterns in

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weather conditions, energy usage information, and grid data, and can also optimize the operation of a system by adjusting the power output based on the weather conditions and energy demand.[132,135,136] The use of AI models can help to lower the cost of RE systems by reducing the need for expensive backup power sources and can make RE more cost-effective by optimizing energy storage and predicting power output. Furthermore, these models can identify the areas in which RE systems should be installed for the highest efficiency, thereby lowering the overall cost of these systems.[137] In summary, there is a diverse range of applications for AI in the RE sector, from predicting power output to optimizing energy storage and system design. These algorithms can help to reduce the cost of RE systems, while increasing their reliability and cost-effectiveness. As the use of RE becomes more prevalent, AI will play an increasingly significant role in ensuring that these systems operate efficiently and reliably.[138] However, several challenges must be overcome before these models can be widely adopted in RE, and the most important of these is the lack of high-quality data. AI algorithms require large amounts of data to train the model and allow it to make precise predictions, but RE systems frequently generate sparse and irregular data, making it challenging to train AI models. Furthermore, the available data may be of low quality or unstandardized, which can affect the accuracy of an AI model.[106] As a result, efforts must be made to collect and standardize high-quality data to develop accurate AI models. The complex and dynamic nature of RE systems, which have many interconnected components that interact, poses another challenge. AI models must capture these interactions to optimize the system as a whole, which requires the creation of sophisticated algorithms that are capable of dealing with these levels of complexity and variability. In addition, the integration of RE into the grid is a significant challenge. RE sources, such as wind and solar power, are intermittent and variable, which can cause grid instability. AI can be used to predict energy production and enable grid integration, but sophisticated algorithms need to be developed that are capable of dealing with the uncertainty and variability inherent in RE production.[139,112,131] A further issue is the scarcity of skilled workers. The development and deployment of AI models require specialized personnel such as data scientists, software developers, and engineers, and the current shortage of skilled labor in the RE domain may impede their wider adoption. The use of black box AI in the RE sector also raises social and ethical concerns; there is a risk, for example, that AI will be used to automate decision-making and replace human workers, resulting in job losses. AI may also be used to optimize the operation of RE systems at the expense of social and environmental concerns.[140,141]

In summary, although AI has the potential to transform the RE sector, several challenges must be met before these models can be universally adopted. Such challenges include a lack of high-quality data, the complexity of RE systems, problems with grid integration, a shortage of skilled personnel, and ethical and social concerns. To address these issues, scientists, engineers, policymakers, and stakeholders must work together to guarantee the sustainable and responsible deployment of AI.

4. EXPLAINABLE AI TECHNIQUES

XAI represents an improvement to conventional black box AI systems, as these models are transparent and understandable to humans. The aim is to develop AI models and systems that can provide clearer and interpretable explanations for their actions and decisions. Most of the AI systems currently in use have traditionally been regarded as "black boxes" because they rely on complex algorithms that are difficult for humans to comprehend. This lack of transparency has made it difficult for users to trust and effectively manage AI systems, particularly in sensitive domains, such as healthcare, finance, and security applications. XAI aims to address this issue by developing AI models that can explain their decision-making processes. Methods such as rule-based systems, decision trees, and symbolic reasoning enable users to comprehend how an AI model makes a specific decision or recommendation. XAI can help users build trust in AI systems and make more informed decisions by providing clear explanations.[43,142,143]

XAI has significant implications in the RE domain for several reasons. A graphical representation of the main XAI techniques employed in the RE domain is shown in Figure 5. RE systems

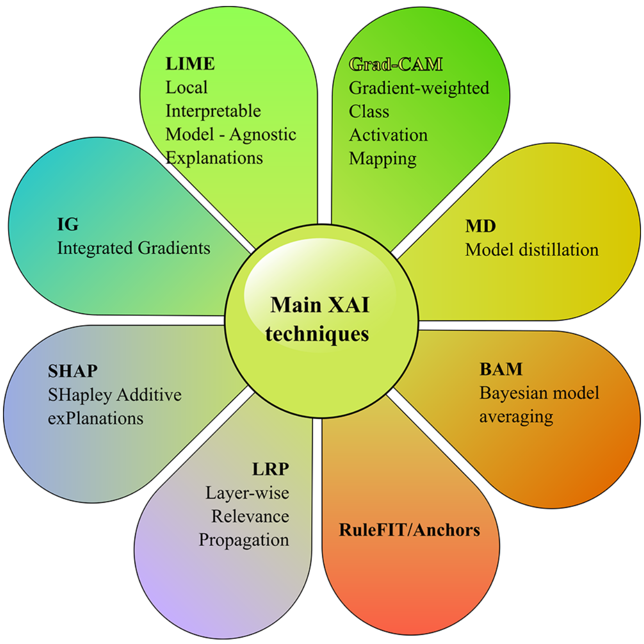

Figure 5. Main XAI techniques employed in the renewable energy domain.

rely heavily on data-driven decision-making to optimize energy production and lower costs. Among other things, AI models are used to forecast the energy demand, predict weather patterns, and optimize power distribution. However, because these systems frequently involve complex algorithms and large amounts of data, humans may struggle to understand how decisions are made.[144,145] XAI can address this issue by explaining the factors influencing the decisions of an AI model. A solvable AI model, for example, could provide a detailed breakdown of how it predicts energy demand for a specific region including specific weather data, historical usage patterns, and other relevant factors. This could provide energy professionals with a better understanding of how to optimize their RE systems, resulting in increased efficiency and cost savings.[41,146]

Another significant advantage of the use of XAI in RE is the possibility of increasing public trust in these systems. Local communities and environmental groups frequently oppose RE projects, citing concerns about their impacts on wildlife, natural habitats, and local economies. The use of XAI models can help

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Table 2. Summary of the Main XAI Techniques

XAI technique	Main features	Source
Local interpretable model-agnostic explanations (LIME)	This approach can explain the predictions of a model within a specific, local context around a given instance. This is useful when dealing with models that are inherently difficult to interpret, such as DNN or ensemble methods.	147
Integrated gradients (IG)	IG can provide feature significance scores by integrating the gradients of the model's predictions concerning the input features across a path from a reference point to the input sample.	148
SHapley Additive exPlanations (SHAP)	Based on cooperative game theory, it provides a unified measure of the relevance of a feature.	149
Layer-wise relevance propagation (LRP)	This method assigns relevance ratings to input characteristics based on the contribution of each feature to the model's output.	150
Model distillation (MD)	The main feature of MD is its capacity to transfer knowledge from a more complicated ("teacher") model to a less complicated ("student") model.	151
Bayesian model averaging (BAM)	BMA is a more sophisticated and robust system for decision-making and prediction in cases where uncertainty in terms of model selection is a crucial issue, by examining an ensemble of simulations and assigning probabilities to their contributions.	152
Descriptive machine learning explanations (DALEX)	This provides a set of tools for model-independent and model-specific explanations.	153
Concept activation vectors (CAV)	This can aid in an understanding of which properties of a neural network are relevant to a specific concept.	154
Local rule-based explanations (LORE)	This approach discovers simple, human-understandable principles to explain the forecasts made by models.	155
Anchor explanations (AE)	This focuses on discovering simple, interpretable rule-based explanations for model predictions.	156
Evaluating counterfactual explanations (Ecco)	Ecco is a framework for evaluating the efficacy of counterfactual explanations.	157

to address these concerns and build support for RE initiatives by providing transparent and understandable explanations of how RE systems are managed. Overall, XAI has the potential to play a significant role in advancing RE technologies and assisting in the transition to a more sustainable and environmentally friendly energy system. Table 2 summarizes the main XAI techniques and their features.

4.1. Local Interpretable Model-Agnostic Explanations. Local interpretable model-agnostic explanation (LIME) is a prominent explainable AI strategy that can provide insights into the decision-making processes of complex machine learning models. It is a model-agnostic method and can be used with deep neural networks, support vector machines, and decision trees.[158] LIME generates a set of interpretable features around a specific prediction before training a local interpretable model on this feature set to explain the prognosis. The feature set is created using a process known as a perturbation, in which the original input is successively adjusted to produce a set of similar but slightly different occurrences.[159] The local model then learns to anticipate the output from the original model for each of these cases and utilizes this knowledge to create an explanation for the initial forecast. LIME is an excellent technique for increasing the transparency and interpretability of complicated machine learning models in a variety of applications, including natural language processing, image recognition, and healthcare.[160]

4.2. Integrated Gradients. This is a popular approach to XAI that is particularly useful for explaining the predictions of deep neural networks. In this technique, feature attributions are generated by calculating the gradients of the prediction model concerning the input features and incorporating these gradients into the input space. Integrated gradients (IG) give a more nuanced view of how each input feature contributes to the model's output by accounting for the magnitude of a feature and the change in its value as it travels from a baseline input to the actual input. This allows the user to identify the most relevant factors driving the model's predictions and offers an understandable explanation of how the algorithm makes its judgments.[161,162] IG has been utilized in various applications, including image identification, natural language processing, and healthcare, and is widely regarded as one of the most successful XAI approaches available today, as it offers various advantages over other attribution methods: it is model-independent, meaning it can be used to clarify the forecasts of any ML framework, irrespective of its architecture or training approach; it gives a quantifiable measure of the relevance of a feature, thus providing an accurate understanding of how each feature contributes to the output of the model; it has many applications because it can handle continuous and discrete input data; and it provides smooth, consistent explanations that are simple to understand, which is essential for establishing trust in AI models and ensuring that they are used responsibly.[163,164] IG is a robust and adaptable XAI approach that is popular among researchers and practitioners.

4.3. SHapley Additive exPlanations. SHapley Additive exPlanations (SHAP) is a framework for describing the output of any machine learning model in which a significant value is assigned to each feature based on its contribution to the model output. The central concept underpinning this approach is the use of game theory to award significance ratings that meet a set of desirable qualities. This approach is based on Shapley values, which were first created in the context of cooperative game theory to determine each player's contribution to the ultimate reward of a coalition.[165] In ML, the "players" are the input features, while the "payoff" is the output of the model. The Shapley value for a feature is defined as its average contribution across all possible coalitions of features; in other words, it reflects the feature's marginal contribution to the model output while accounting for all potential feature combinations. The SHAP framework evaluates all likely subsets of features and computes the average contribution of each feature to the model output over all possible subsets to compute the SHAP value for a single prediction. This yields a series of SHAP values, one for each feature, which indicates the extent to which each feature contributes to the model's prediction for that instance.[166,167]

SHAP has the advantage of providing a consistent framework for understanding the output of any ML model independent of its architecture or training method. It also has several desirable qualities, including consistency, local accuracy, missingness, and additivity, which guarantee that the feature significance ratings are both meaningful and dependable.[168,169] Overall, it is a strong

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and adaptable framework for describing the output of ML models. It is extensively used in business and academia to improve the transparency and accountability of AI systems.

4.4. Layer-Wise Relevance Propagation. Layer-wise relevance propagation (LRP) is a simple AI approach for assigning relevance scores to deep neural network input data. The goals of this approach are to determine which input elements contribute the most to the network's output and to offer a human-readable explanation for the decision made by the model. LRP works by propagating the network's output relevance score back through the network and giving relevance ratings to each input feature. The relevance score represents the significance of each feature in terms of contributing to the network's output.[170,171]

To execute LRP, the input is first sent through the network to create an output. The significance score of the production is then set to one and is transmitted layer by layer across the network, with relevance scores being awarded based on each layer's input. To allocate the relevance score back across the network, the LRP algorithm follows a set of rules that are intended to guarantee that the relevance score is distributed in a manner consistent with the behavior of the network. For instance, if a specific input feature is substantially engaged in a given layer, resulting in a high output score, that feature will be assigned a high relevance value. LRP has been effectively used in a variety of deep neural network designs including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs). It has been used to explain the predictions of these networks over a wide range of applications, such as image classification, natural language processing, and speech recognition.[170,172]

In general, LRP has the benefit of providing a clear and interpretable rationale for the network's choice, which can aid in developing confidence and comprehension of the model's behavior. However, it is a computationally costly approach, and the relevance ratings that it generates are not always easy to comprehend, particularly for large and complicated networks.

4.5. Gradient-Weighted Class Activation Mapping. Gradient-weighted class activation mapping (Grad-CAM) is a simple AI approach for visualizing the parts of an image that are most significant in terms of the prediction of a deep neural network. It is valuable in comprehending the behavior of CNNs used in image classification applications. The central idea of Grad-CAM is to use the gradient information coming into the final convolutional layer of the CNN to identify the significance of each spatial position in the input picture for a particular class; in other words, a given class prediction is used to create a heatmap of the most relevant areas of the image.[173,174]

Grad-CAM first computes the gradients of the output class score concerning the activations of the final convolutional layer to generate the heatmap. These gradients represent the extent to which each feature map in the last convolutional layer contributes to the target class prediction. The feature maps and their accompanying gradients are then combined to form a weighted sum and used to highlight the most important parts of the picture in terms of the forecast. A rectified linear unit (ReLU) activation function is applied to process this weighted total to remove any negative values, and a heatmap is created that highlights the most relevant areas of the picture. This heatmap may be superimposed over the original input picture to enable the user to see the most significant image regions. This gives a visible and interpretable reason for CNN's choice and can contribute to the development of trust and comprehension.[174,175]

Grad-CAM is helpful for various image classification tasks, including object recognition, scene comprehension, and medical picture analysis. It is also computationally efficient, making it useful for real-world applications.

4.6. Model Distillation. Model distillation (MD) is a method of producing a simpler, more explainable model that replicates the behavior of a more complicated, opaque model. MD-based XAI involves using these distilled models to explain the details of the original models' predictions. A simpler model, such as a decision tree or a linear regression model, is trained to gain insight into the predictions of the more complicated model. The less complex model is trained to predict the same outcomes as the detailed model but with fewer parameters and a more straightforward structure.[176,177] Once trained, the simplified model can be used to explain the predictions of the original, more complicated model as it is easier to understand and more explainable, and the user can more readily observe its structure and parameters. A more transparent and intelligible explanation of the complicated model's behavior may be obtained by using the simpler model to explain its predictions. XAI based on MD has been employed in various applications including speech recognition, NLP, and image classification. In image classification, for example, a complex CNN can be reduced to a more straightforward linear model or decision tree, which can explain why the original network categorized a specific image in a particular way.[177]

MD-based XAI has the benefit of providing clearer and more interpretable explanations for the behavior of complicated models without losing accuracy. However, it is crucial to remember that the distilled model may not precisely reflect all features of the original model's behavior, and its explanations may not always be correct or complete. Furthermore, the simpler model used for distillation might alter the explanations' quality.

4.7. Bayesian Model Averaging. Bayesian model averaging (BMA) is an XAI approach that combines the predictions from many models to obtain a more accurate and robust forecast. It aims to account for the uncertainty in the model predictions and to offer a trustworthy assessment of the underlying links between the input and output variables. In BMA, the model parameters are assigned a prior distribution, which indicates the user's existing ideas about the relationship between the input and output variables. Based on the available data, the initial allocation is modified to produce the posterior distribution, which reflects the user's revised ideas about the connections between the variables.[172,152]

The predictions of many models, each with a separate set of parameter values taken from the posterior distribution, are then connected via BMA. The uncertainty in the model predictions is accounted for by averaging over these numerous models, providing a relatively trustworthy approximation of the underlying connections between the output and input variables.[152,178] BMA can also be used to assess the uncertainty in model predictions in a natural way. This approach can provide a spread of anticipated values rather than a single point estimate by using the posterior distribution to construct several models. This distribution may be used to create confidence or prediction intervals, which can aid in transparency and the development of trust in the model's behavior. This approach can be applied to various model designs, including linear models, decision trees, and neural networks and can also be used to carry out

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classification and regression tasks. BMA has been used effectively in several domains, including financial forecasting, medical diagnosis, and climate modeling.[152,178] One possible disadvantage of BMA is that it can be computationally costly, particularly when working with massive data sets or sophisticated models. Furthermore, there is a need to define a previous distribution, which can be a complex process in practice.[179]

In addition to the XAI techniques described above, several others have been reported in the literature. Anchors is an XAI approach that includes creating human-readable *if-then* rules that define the conditions under which a model's prediction changes. These guidelines can aid in the development of trust in the model and a comprehension of its behavior. The counterfactual explanations technique involves producing hypothetical inputs that might cause the model to respond differently; these explanations can aid in identifying the exact characteristics of the information that drive the model's choice.[180] RuleFit is an XAI approach that combines linear models with decision trees to construct *if-then* rules that explain the model's behavior. These guidelines can enable the user to develop trust in and comprehension of the model's behavior. Determination of the causal linkages between variables in a model is known as causal inference and can aid in the identification of specific components influencing the model's choice.[181] Concept activation vectors are a technique for identifying the ideas that a deep neural network has learned using labeled examples. This method can assist in explaining the behavior of a deep neural network and in identifying the elements that drive its decisions.[182] ProtoNN is an XAI approach for learning a low-dimensional representation of input data that captures critical characteristics. The choice-theoretic explanation is a process of explaining a model's behavior based on trade-offs between several choice criteria and can aid in identifying the elements that influence a model's choice and finding opportunities for improvement.[183]

In summary, it is hard to classify any specific XAI strategies as excellent or poor since each methodology has advantages and disadvantages, and the most suitable technique will depend on the unique situation. Some XAI algorithms, such as LIME and SHAP, are model-independent and can be used with various models, such as decision trees, deep neural networks, and linear models. These strategies are often regarded as particularly useful in terms of describing the behavior of complicated models and offering insights into the elements influencing the model's conclusion. Other XAI approaches, such as BAM and causal inference, depend on detailed data and model assumptions; these approaches can be effective in certain situations but may not be suitable in others. Furthermore, some XAI strategies may be more or less interpretable to various stakeholders; for example, decision trees and *if-then* rules may be more understandable to nontechnical stakeholders, whereas a gradient-based strategy may be more suited to technical audiences. Overall, the efficacy of an XAI approach will be determined by several criteria such as the complexity of the model, the amount and structure of the data, and the stakeholders involved. It is important to thoroughly assess the strengths and weaknesses of each approach before selecting the optimal technique for a given problem and situation.

5. EXPLAINABLE AI IN RENEWABLE ENERGY

5.1. Importance of Transparency and Interpretability in Renewable Energy. The transparency and interpretability of ML models are key aspects in terms of ensuring that RE systems work successfully and efficiently. In this context, ML algorithms can assist in optimizing energy production, enhancing energy storage efficiency, and reducing the total energy production costs. However, these algorithms can inject uncertainty and unpredictability into energy systems, leading to unexpected repercussions or errors. The capacity of ML models to be understood by people is termed transparency, and the capacity for them to be described is known as interpretability. In other words, these aspects refer to the user's ability to trace back the model's judgments or forecasts and comprehend how it arrived at those conclusions. Transparency and interpretability are especially crucial in RE systems, as these frequently involve complicated interactions between elements such as weather conditions, energy demand, and energy supply.[170,184]

RE systems can be optimized and controlled more successfully by employing transparent and interpretable ML models; for example, energy producers may use these models to anticipate how much energy will be generated by solar panels or wind turbines, which can help them decide when to sell electricity to the grid and when to store extra energy in batteries. Similarly, energy users may use these models to estimate energy demand, which can help them change their energy usage habits to take advantage of decreased energy costs or to minimize their overall energy consumption.[156,158] In addition to increasing the performance of RE systems, transparency and interpretability may assist in the development of confidence and credibility among stakeholders such as policymakers, regulators, and the public. These stakeholders are frequently concerned about the hazards and uncertainties in RE systems. Explaining how these systems function may soothe their fears and increase their support for these technologies.[185,186] Openness and interpretability are essential to ensuring that ML-based RE systems run successfully and efficiently. These principles aid in the development of stakeholder trust, improvements in system performance, and the reduction of total energy production costs.

5.2. Application of Explainable AI Models in Renewable Energy. ML models are widely utilized and have achieved outstanding performance in various sectors, but they are frequently regarded as black boxes, because it is difficult to comprehend how they work in practice. This lack of transparency poses a problem for experts in power systems, who are held accountable when making recommendations and decisions based on these test models. However, XAI approaches have been developed in recent years to solve this issue by improving the explainability of ML models, thereby allowing for a better comprehension of their outputs. Several researchers have applied XAI successfully in the domain of RE. Utama et al.[156] employed an XAI approach to extract information from an ANN/multilayer perceptron (MLP) framework for failure detection in PV systems. Their study evaluated Anchors, Diverse Counterfactual Explanations (DiCE), and SHAP. The researchers found that SHAP explanations were mainly in line with domain knowledge for a model with 99.11% precision. This demonstrates that SHAP explanations can provide meaningful insights into the behavior of a model and increase the level of user trust. Overall, the study emphasizes the importance of XAI approaches in explaining complex models such as MLPs and highlights their potential to improve user trust in AI systems. Wand et al.[143] suggested a novel neural network called a direct XAI neural network for predicting solar irradiance. It comprises two linear layers, an input layer, and a nonlinear layer with a ridge activation function, and the hyperparameters, weights, and

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Table 3. Application of XAI Techniques to Different Renewable Energy Domains

Renewable energy domain	XAI methods	Main outcomes	Ref
Solar energy	SHAP, DiCE, MLP	Accuracy of 99.11% achieved with SHAP	156
Solar energy	Direct explainable neural network	A value of R^2 = 0.8659 was achieved	143
Solar energy	LIME	Improved knowledge of fault sources for PV panels	187
Wind energy	Variational autoencoder	41% reduction in CO_2 emission	146
Wind energy	Deep residual recurrent neural network	The model predicted high efficiency	188
Wind energy	Base neural network	Low RMSE in the range 0.263−0.361 m/s	189
Geothermal energy	Geothermal operational Optimization with machine learning	A novel ML model was proposed specifically for geothermal energy	120
Wheat-based biomass	Gradient boosting regression and random forest	A value of R^2 > 0.85 was achieved	190
Solid biofuel	Physics-informed neural network	The model effectively analyzed the Bratu problem	191
Biofuels	Physics-informed neural network	Cetane numbers of fuel could be predicted with a mean absolute error of 0.8 cetane number units	192

biases were optimized by using a two-layer training framework. It outperformed traditional methods, with a high training efficiency (R^2 = 0.8659), a small model size, and a short training time. Sairam et al.[187] developed an XAI-based fault detection system for incipient failures in PV panels. To detect defects from the data streams for the PV panels, the fault classifier leveraged an XGBoost classifier.

Irradiance-based three-diode model (IB3DM) and XGBoost lack the explainability needed for field employees to grasp the sources of defects. IB3DM and XGBoost formed the basis for an XAI application built with the LIME framework, where an XGBoost-based classifier was used to provide explanations to field experts via edge device user interfaces. The explainability aided field engineers in understanding the sources of defects, allowing for human system augmentation. Heo et al.[146] developed a generative model based on XAI to produce stochastic possibilities for offshore wind power in a power system. In comparison to offshore wind power for 2022, the predicted XAI-driven net-zero carbon roadmap revealed that with carbon capture and storage, the total cost of power production and fossil fuel expenses could be reduced by 4% and 42%, respectively, with a 41% reduction in CO_2 emissions. In the domain of wind energy, Heo et al.[146] implemented a variational encoder-based XAI-based ML model to simulate a wind energy system, which yielded excellent outcomes and interpretability. Several researchers have recently used XAI techniques in the domain of RE, as summarized in Table 3.

6. POTENTIAL AND CHALLENGES OF EXPLAINABLE AI APPLICATION IN RENEWABLE ENERGY

Renewable energy (RE) sources such as solar, wind, and hydropower have gained in popularity in recent years due to their environmental advantages, low cost, and potential to ensure energy security. However, integrating RE sources into the current energy infrastructure can be difficult as they are intermittent and variable, which can lead to grid instability and collapse. XAI can help in this regard, as a collection of approaches and technologies that make AI systems visible, explainable, and trustworthy.[143,151] By enhancing the predictability and dependability of renewable energy sources, XAI can assist in overcoming some of the issues associated with renewable energy integration. XAI models can optimize wind turbine performance by appropriately forecasting wind patterns and modifying their settings and can maximize the usage of energy storage devices, such as batteries, by forecasting the supply and demand for energy and by adjusting storage capacity. Furthermore, by optimization of the design and operation of RE systems, XAI models can be used to improve their efficiency and efficacy. XAI methods may be used to create and validate various RE models and scenarios, such as the effects of the location of a solar panel or the orientation of a wind turbine. XAI can also be used to monitor and diagnose the operation of RE systems and to identify any problems or flaws that may occur. This can aid in maintenance and decrease downtime, resulting in considerable cost savings and increased energy output. However, there are several obstacles associated with integrating RE with XAI. One major concern is that AI systems may grow to be too sophisticated and difficult to understand, leading to a lack of transparency and accountability. This can make it challenging for stakeholders, such as energy regulators, to evaluate and control the performance and safety of AI-enabled RE systems. Furthermore, there is a possibility that AI systems will be biased or prejudiced, leading to inequity and unfairness in the energy industry. In summary, RE and XAI have enormous and far-reaching potential impacts and repercussions. Although the use of XAI with RE sources can assist in addressing some of the difficulties related to energy production and use, several possible hazards and obstacles must be addressed. As a result, it is essential to continue studying and developing innovative ideas and technologies that can aid in the promotion of a sustainable, equitable, and transparent energy system for all.

The application of XAI in the RE domain has enormous potential to change how people live and work. The use of RE technology is becoming increasingly vital as the world transitions toward more sustainable and ecologically acceptable energy sources. The increasing use of RE is also making the RE-generating systems larger and more complex. The application of AI & ML in this domain is enormously useful in modeling and optimization. However, their black-box nature is challenging for the stakeholders. Hence, the advancements in XAI systems are enabling the creation of more dependable and trustworthy AI applications.

The development of more efficient and cost-effective solar technology is essential for future RE research. This involves refining the design of solar panels to catch more sunlight and discovering new materials to convert sunlight into power more effectively. Other areas of study include the development of energy storage technology to handle the intermittent nature of solar and wind power and improvements in the efficiency of wind turbines. Another important area of investigation is the incorporation of RE into current energy systems. This will include the development of new forms of infrastructure and technology to enable the effective transmission and dissemination of RE and remove regulatory and governmental

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obstacles to the adoption of RE. Future research prospects in the field of XAI include the development of new approaches and strategies for explaining the judgments of AI systems. This will involve the creation of algorithms that offer more extensive and clearer explanations of how an AI system reached a particular choice as well as the design of new algorithms. There is also a need for the development of tools and frameworks to assess the quality of these explanations. Other areas of focus include the creation of more interpretable ML models, which can give insights into how these models make predictions and the development of novel methods of human-AI interaction that can help humans better understand and engage with AI systems. Finally, a deeper study of the ethical and societal consequences of RE and XAI is required. This will involve investigating the environmental effects of RE technology and the possibility of unforeseen repercussions from XAI. It will also entail defining laws and procedures to guarantee that these technologies are created and used in an ethical, transparent, and societally acceptable manner. Overall, the future for RE and XAI, in which a more sustainable and trustworthy future can be created for everyone by investing in research and development in these areas, seems promising.

7. CONCLUSIONS

This current work has focused on the intersection of two rapidly developing fields, RE and XAI. We have carried out a comprehensive assessment of the role of XAI in RE, and we have presented an examination of the challenges and prospects associated with using XAI in renewable energy systems.

- The use of XAI is essential to foster trust and openness in AI systems, especially in safety-critical areas such as energy systems. We have provided an overview of the current state of RE systems and have highlighted their complexity and the challenges associated with integrating them into traditional energy systems.
- The study has explored the specific applications of XAI in RE systems, focusing on three major areas: energy forecasting, energy system optimization, and energy grid management. We have investigated the benefits and drawbacks of implementing XAI in each of these disciplines and have described existing research and applications.
- In the section on energy forecasting, we analyzed how XAI could be utilized to improve the accuracy of energy demand and supply projections. Numerous strategies for the development of XAI models were reviewed, such as rule-based systems and ML models, and how these techniques have been used in RE systems were described.
- The study also addressed ethical concerns related to the use of XAI in RE systems. We found that XAI models must be built to protect individuals' and communities' privacy and liberty, while also addressing concerns about prejudice and discrimination. We stressed the importance of including stakeholders in the design and implementation of XAI systems to ensure alignment with social and environmental goals.

In addition, we have put forward numerous recommendations for future research and development in this field. More interdisciplinary collaborations between RE experts and XAI experts are required, as is the development of standardized data sets and evaluation metrics. More research into the ethical and social implications of using XAI in RE systems is recommended. Overall, this work makes a significant and timely contribution to the field of XAI-enabled RE and emphasizes the potential of XAI to assist in tackling the challenges associated with integrating RE sources into traditional energy systems.

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