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Review Article

Machine learning in solar energy systems: Methods, applications, and future directions

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Abstract. In the present era, the ever-growing need for energy and the greenhouse gas emissions from fossil fuel burning have become a real challenge. Solar energy is an attractive option among various options available in renewable energy domain. Solar energy systems are rapidly expanding, and that growth brings real challenges as they need to face challenges such as unpredictable output, constant changes, and complex operations. To handle these challenges and for smoother operation, Machine Learning (ML) can be useful as it can handle a large amount of data and keep everything running smoothly. In this review, a comprehensive overview of applying ML to solar energy is presented. The review will explore the working of existing ML techniques, covering both conventional as well as modern approaches. The key application areas are identified, ranging from forecasting and optimization to fault detection and energy management in integrated grids. It also discusses some important barriers like data inconsistency, the black-box nature of conventional ML models, and the difficulty in scaling up to real-world settings. On the brighter side, the review points to some exciting new directions like explainable AI, physics-informed learning, and real-time analytics. It is observed that it is a rapidly evolving field with marked shifting toward ML tools that are more flexible, explainable, and can be tuned into the bigger system. Overall, this review provides a combined and forward-looking perspective, offering actionable insights for the development of robust, scalable, and practically deployable ML solutions in solar energy systems.

Keywords: Machine Learning; Solar Energy System; Optimization; Sustainability; Explainable Artificial Intelligence

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1. Introduction

The global conversation surrounding climate change and sustainable development has intensified significantly, driven by growing awareness of the pressing need for transformative measures to reduce environmental damage while fostering economic growth (Huynh *et al.*, 2025; Solangi and Magazzino, 2025; Tat Quyen *et al.*, 2025). The use of fossil fuels for energy generation, transportation, and daily life was found to produce greenhouse gas and CO_2 emissions that accelerate global warming (X. P. Nguyen *et al.*, 2025a; Zeńczak and Łuszczynski, 2025). As a result, this contributes to a range of consequences, including increasingly frequent and intense extreme weather events, sea-level rise, and challenges affecting agriculture and water availability (Nunes, 2023). Indeed, rising demands for energy consumption, increased environmental concerns, and the exhaustion of fossil fuels results in a tendency towards adopting renewable sources of energy (Hoang *et al.*, 2021b; IEA, 2021; IRENA, 2024a). Modern power systems have started to incorporate various renewable resources, such as wind (Dinata *et al.*, 2025; Tanoto *et al.*, 2026), hydropower, geothermal (X. P. Nguyen *et al.*, 2025b; Zhang *et al.*, 2023), biomass (Nguyen *et al.*, 2025, 2024a), biofuels (Ahmed *et al.*, 2023a; Sirohi *et al.*, 2023), tidal (Abd Rahim *et al.*, 2023; Kurniawan *et al.*, 2024), and solar energy (Ahmed *et al.*, 2023b; Khan *et al.*, 2024). Wind power is known for to its low cost of operation and its ability to generate electricity on a large scale, but its intermittent operation and reliance on wind speed fluctuations are major challenges (Amarzaya and Ko, 2025; Chen *et al.*, 2021). Hydropower plays a significant role in global electricity production, but is limited by geographical constraints and ecological impacts (Bachtiar *et al.*, 2023). Biomass energy can use agricultural and organic wastes for producing biofuel, bioenergy, heat, and power (Escalante *et al.*, 2022; Hoang *et al.*, 2021a; Nguyen *et al.*, 2021); however, land use, feedstock availability, and emissions remain a concern. Likewise,

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geothermal energy and tidal energy have limitations due to site-specific needs and high installation expenses (Llanos and Blessent, 2025). Among these energy sources, solar energy has attracted more attention because of its availability, sustainable nature, and ability to produce large amounts of electricity and green fuels (Al-Ali *et al.*, 2025; Liu *et al.*, 2019). The photovoltaic (PV) system, which is able to convert solar radiation directly to electricity, has been an integral part of modern energy systems (Mamodiya *et al.*, 2025b). In addition, solar could be used to produce green hydrogen (Hoang *et al.*, 2023; Nguyen *et al.*, 2025). Nevertheless, solar energy applications face problems associated with the dependency of this source on environmental conditions (Yalama *et al.*, 2022; Zeńczak and Zapałowicz, 2024). Unpredictable weather conditions, the presence of various atmospheric disturbances, and seasonal changes pose uncertainties when generating solar power. Classical modeling and forecasting approaches are unable to account for these nonlinearities effectively (Salman *et al.*, 2024; Sehrawat *et al.*, 2023).

Issues related to energy, energy security, and global warming are increasingly being debated worldwide, leading many countries to introduce policies and regulations in response. One of the most influential initiatives in this area was introduced by the United Nations, which established 17 Sustainable Development Goals (SDGs) to guide global sustainable development efforts by 2030. The seventh goal focuses on ensuring universal access to affordable, reliable, modern, and sustainable energy. In this context, renewable energy has been recognized as a key driver of sustainable development (Güney, 2019). The connections between renewable energy development and global sustainability transitions are illustrated in Figure 1 in three subfigures. The link between renewable energy and several of the United Nations Sustainable Development Goals (SDGs) is shown in Figure 1a. Affordable and clean energy (SDG 7) is depicted as the enabling force for clean water (SDG 6), sustainable cities (SDG 11), responsible consumption and production (SDG 12), and climate action (SDG 13), and indirectly helps to achieve health (SDG 3), innovation (SDG 9), and ecosystem protection (SDG 15). As shown in Figure 1b, the capacity of renewables has grown globally from 2010 to 2021. Hydropower continued to dominate over the period, as did solar photovoltaic and wind energy, which grew rapidly, reflecting increased investment and technological development in renewable electricity generation. The circular chart also shows capacity additions in 2021 for renewables, which were dominated by solar PV and

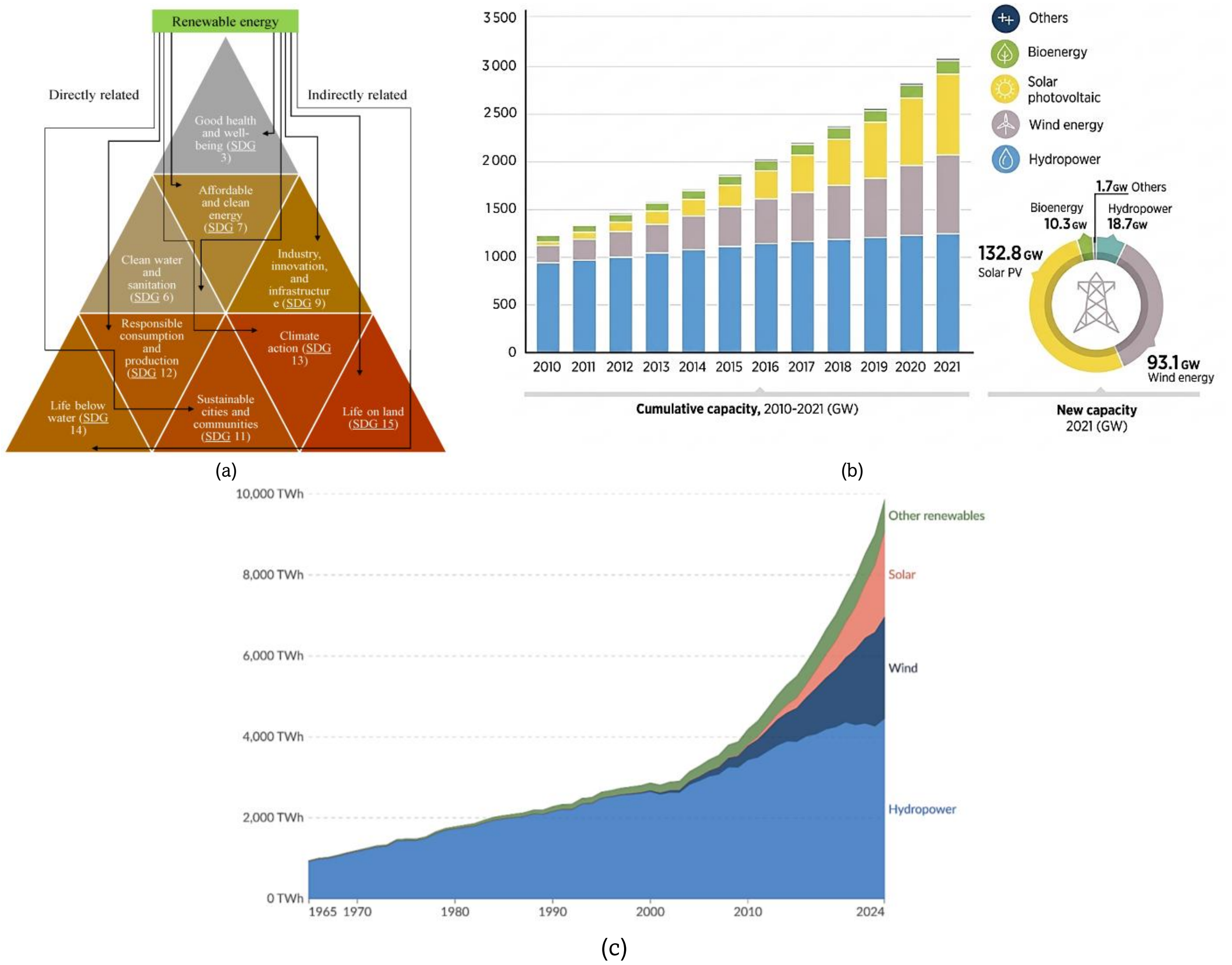

Fig 1. (a) depicts the SDG related to renewable energy (Reproduced from Ref. (Guchhait and Sarkar, 2023) under the Creative Commons CC BY 4.0 license), (b) illustrates the growth in renewable capacity (Reproduced from Ref. (IEA, 2022) under the Creative Commons CC BY 4.0 license), (c) highlights the expansion of renewable electricity generation, particularly solar energy (Reproduced from Ref. (Ritchie *et al.*, n.d.) under the Creative Commons CC BY 4.0 license).

wind energy. The data shown in Figure 1c illustrates the evolution of the global electricity generation from traditional generation to renewable energy generation over the long term, especially the significant increase in solar and wind power since 2010.

The fast-paced shift towards energy systems with minimal carbon emissions has made solar energy one of the most important elements in the global decarbonization process. The swift growth of PV energy capacity around the world is not just due to technical innovations and price declines, but also to increased efforts at developing sustainable energy structures (IRENA, 2024b; REN21, 2024). As shown in Figure 2, the cost of solar PV systems has declined substantially across major markets, which has significantly contributed to the rapid adoption and scalability of solar energy technologies.

Solar energy is expected to be a key element because of its ability to scale up, adaptability to different locations, and potential for minimizing environmental impacts (Okumuş *et al.*, 2021; Zeńczak and Zapałowicz, 2022). Though,its large-scale implementation brings many operational difficulties that emanate from the technology's intrinsic reliance on environmental factors (Al-Habaibeh *et al.*, 2023; Wang *et al.*, 2019). Solar irradiance, which is the main source of power generation for PV, is subject to considerable spatial and temporal variations because of cloud movement, atmospheric changes, and seasonal effects. These variations are transmitted throughout the PV system, leading to high levels of nonlinearity and nonstationarity in the energy output (Kumar Dhaked *et al.*, 2025; Voyant *et al.*, 2017). As illustrated in Figure 3, global energy systems are undergoing a structural transition from fossil fuel dependence toward RE sources, with solar and other clean technologies expected to dominate future energy supply under net-zero scenarios.

Traditional modeling, like using physics-based or statistical methods, has helped us get a handle on how PV systems work. Still, these approaches often rely on simplifying assumptions, such as linear relationships or complete system knowledge, which limit their applicability in real-world scenarios. They struggle to work across different climates or to keep up when environmental conditions shift quickly (Abduljabbar *et al.*, 2026; Nguyen *et al.*, 2026). As more solar gets added to the grid, those weaknesses become more challenging, so forecasts become poor. This leads to poor energy dispatch, thus leaning harder on backup reserves (Al-Habaibeh *et al.*, 2023; Kumar Dhaked *et al.*, 2025). As a result, ML is gaining attention in solar energy research as an alternative to conventional modeling approaches. Over the past few years, machine learning (ML) has been developed as an effective method for tackling such problems (Raaflie Caesar Putra Hadi *et al.*, 2026; Sharma *et al.*, 2022). The ML algorithms play a vital role in various fields,

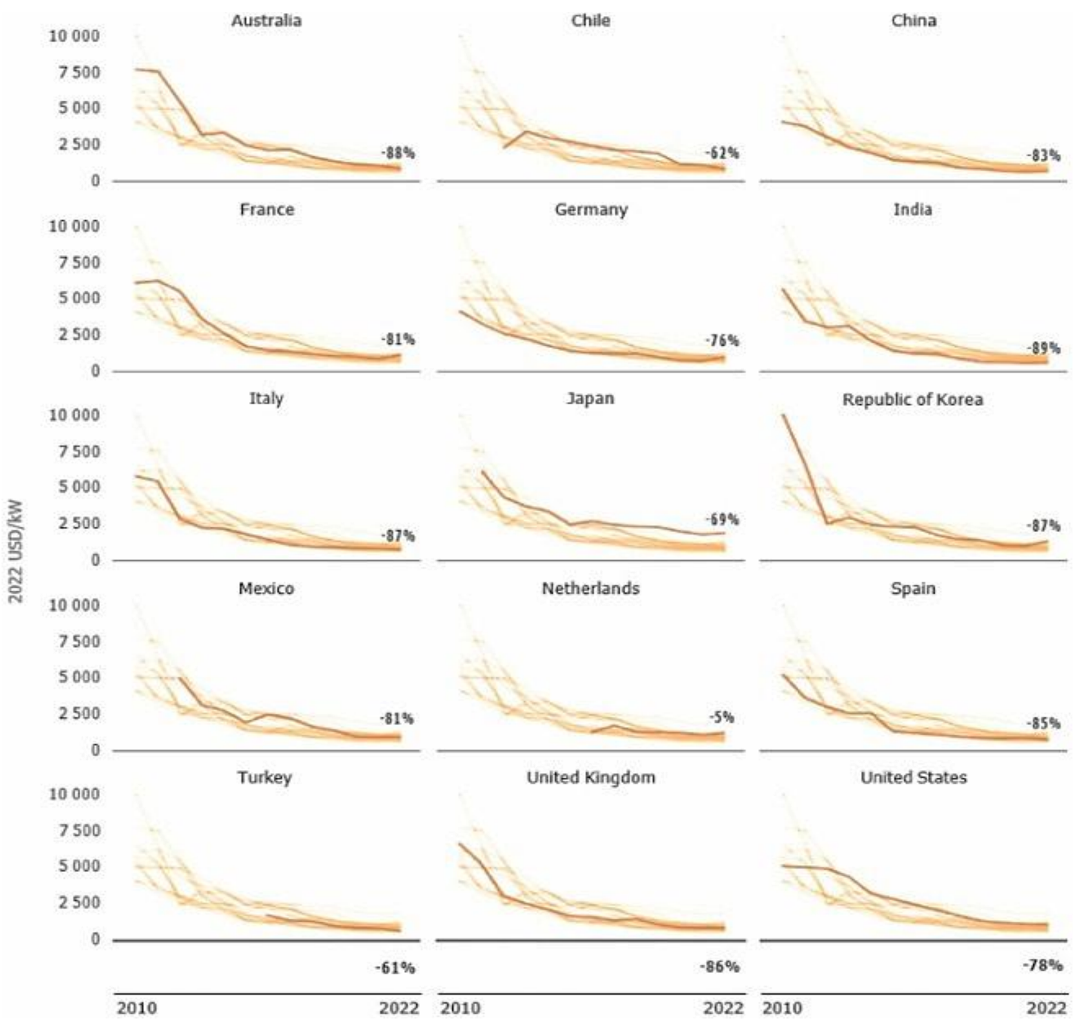

Fig 2. Trends in total installed costs of PV projects across major global markets from 2010 to 2022, illustrating the significant reduction in deployment costs and improved economic competitiveness of solar energy (Pourasl *et al.*, 2023)

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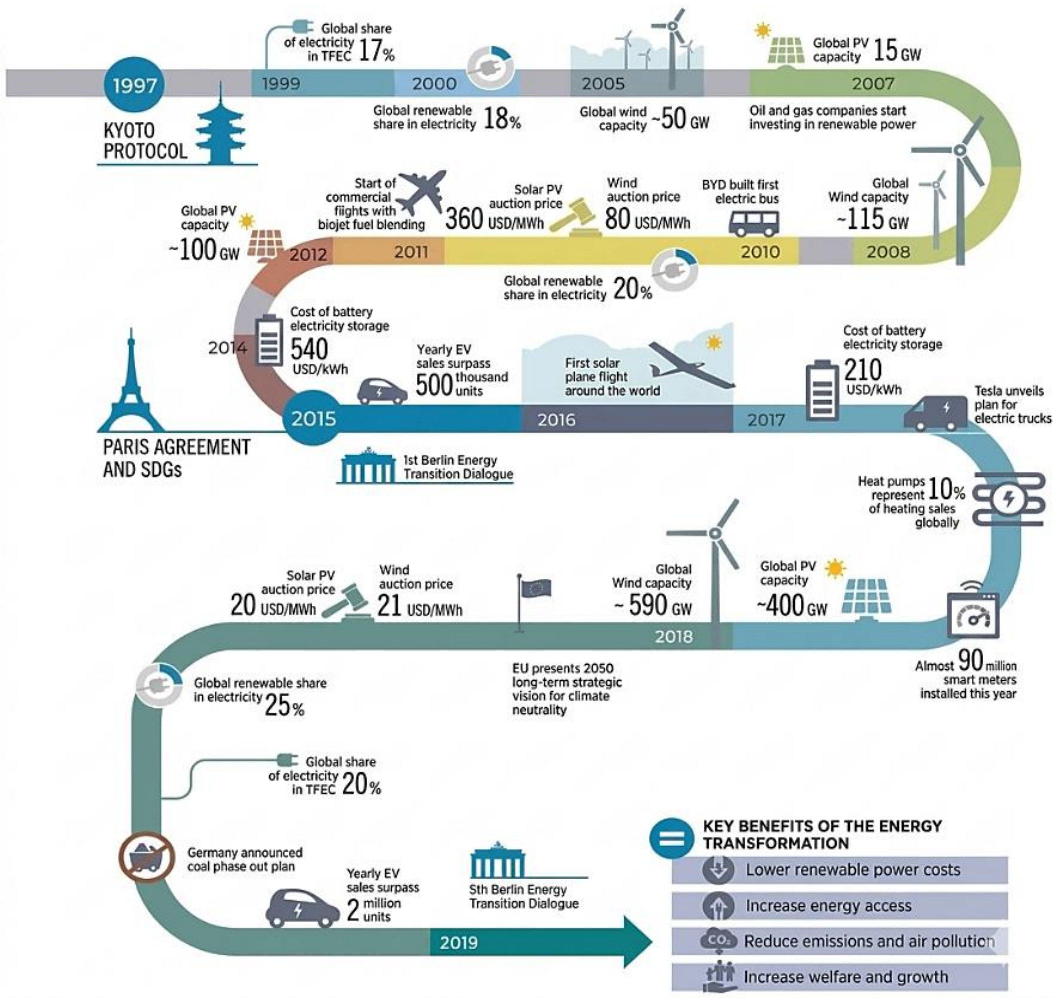


Fig 3. Changing roadmap of global energy supply by source (Reproduced from Ref. (Güneş *et al.*, 2023) under the Creative Commons CC BY 4.0 license)

including healthcare, finance, energy, and environmental management, by improving accuracy, efficiency, and automation. In recent years, the growing availability of large datasets and advanced computing power has significantly accelerated the development and application of ML techniques across industries. ML algorithms, through their utilization of massive data sets and sophisticated computation methods, are capable of improving the precision of predictions, enhancing the performance of the systems, and managing energy intelligently (Chen *et al.*, 2022; Hoang *et al.*, 2026; Le *et al.*, 2023; D. Pham *et al.*, 2025). As a result, ML in solar energy systems has attracted much interest and has been successfully utilized in many aspects (Al-Ghezi *et al.*, 2022; Bouakkaz *et al.*, 2025). Unlike traditional methods that rely on predefined equations and simplifying assumptions, ML techniques leverage data-driven learning to capture complex and nonlinear relationships inherent in solar energy systems (Kandagatla *et al.*, 2024). Numerous studies have demonstrated that ML algorithms can outperform classical methods in solar irradiance forecasting, PV power prediction, and system optimization, particularly when large and high-resolution datasets are available. The ML models exhibit strong adaptability to changing data patterns, making them well-suited for dynamic and uncertain energy environments (Gaboitaolelwe *et al.*, 2023; Mamodiya *et al.*, 2025a).

Availability of heterogeneous data sets makes ML even more valuable for solar systems. The information provided by sensors on the ground, satellite observations, and numerical weather predictions gives a multi-dimensional representation of environmental and system states. If used efficiently, such data sets allow building powerful predictive models able to capture not only temporal dependencies but also spatial relationships. Modern learning algorithms, specifically deep learning, have shown great results in feature extraction and temporal pattern recognition based on solar data (Effendi *et al.*, 2026; Le *et al.*, 2024). On the other hand, although the potential of ML-based methods seems quite promising, there are still several crucial drawbacks that have not yet been adequately investigated in the relevant literature. First, a number of methods strongly rely on the quality and accessibility of data, which means that they are prone to errors, missing data, and domain differences depending on the geographic location. Second, the problem of complexity versus interpretability is a significant barrier for practical implementation, especially in cases when the application is connected to critical infrastructure such as energy systems. Third, most investigations concentrate on specific applications, including forecasting or fault detection, without offering a comprehensive view of integrating various methods into solar energy systems (Mukund Deshpande *et al.*, 2022; Zhang *et al.*, 2025).

Modern Power systems have become increasingly complex, and soon, mere prediction capabilities would no longer be sufficient. In such cases, adaptable solutions become an essential aspect to consider, and when coupled with innovative technologies, they give rise to numerous exciting applications in the industry. The use of ML in combination with IoT-based monitoring systems, smart grids, and energy storage makes it possible to take proactive decisions, handle maintenance issues, and make optimal use of energy resources (Ahmed *et al*., 2026; Obakhume and Opatola, 2025). By doing so, the technology contributes to creating highly adaptive energy grids, cost savings, and seamless operation in RE-based environments (Hassan *et al*., 2023; Zhang *et al*., 2025). That is why it is crucial to shift from discussing model performance to identifying its limitations, scalability, implementation capabilities, etc.

The scientific community has invested plenty of time in researching individual components, from the forecast of radiation to the selection of the most efficient algorithm for the task at hand, but none have yet come to an attempt to unite all the efforts under a common roof. And this is precisely the objective of this review. This begins by reviewing different types of ML approaches in general terms, including traditional algorithms, artificial neural networks, and hybrid approaches combining ML with domain knowledge. This review will not only analyze the architecture of each model but also consider its functionality, advantages, and drawbacks when applied to solar energy problems. The following part of our review will focus on the particular applications of ML models in solar energy. These include, but are not limited to, solar irradiance forecast, optimization of solar systems, fault detection, and energy management. Fourthly, there is the technical aspect of the implementation of this technology, which entails dealing with difficult data, ensuring that models perform well in practice, scale up, and integrate into actual energy systems. In summary, this review attempts to draw from both theoretical and practical aspects of ML in solar energy systems. This ensures an integrated approach rather than fragmented research areas. The real strength of this work comes from how it pulls together existing research, not just to compare performance, but to point out key gaps in current methods. It dives into big challenges: getting models to generalize across different climates, dealing with how much data quality matters, and figuring out what's actually happening inside complex learning systems. Instead of looking at ML as just some stand-alone set of tools, it shows how these techniques fit into the bigger picture, like monitoring, control, and decision-making in energy systems. This way of looking at things makes it clear: to boost reliability and efficiency, predictive models need to be built directly into real-time operations.

The review highlights emerging research trends that are likely to shape the future of intelligent solar energy systems. This involves the use of explainable AI approaches to increase transparency, including physics-aware constraints for increasing robustness, and lightweight adaptive models for edge computing. The discussion on emerging trends is provided in connection with current challenges, which helps provide future directions for research.The primary contributions of this review can be summarized as follows:

- The structured classification of ML methods, from traditional to deep learning and mixed-methods approaches, highlighting their relative strengths and weaknesses.
- Based on application needs, defining the connections between different models and the critical areas of solar energy technology, e.g., prediction, optimization, and diagnosis.
- The critical review of the problems associated with each approach from both methodological and practical viewpoints, for instance, data availability, generalizability, interpretation, etc.
- The identification of research voids and priorities that will lead to the further improvement of existing ML technologies.

Overall, this review presents a systematic and reflective framework for scholars and professionals, facilitating the creation, assessment, and implementation of sophisticated ML approaches in solar power generation systems. The flowchart depicting the review is depicted in Figure 4.

2. Key challenges in solar energy

The extensive use of solar energy systems presents a series of complicated issues that go beyond the problem of variability. These problems emerge due to the inherent nature of solar energy, the inadequacies of current models, and the implementation factors associated with the real world. Solving them is important for making sure that solar energy is

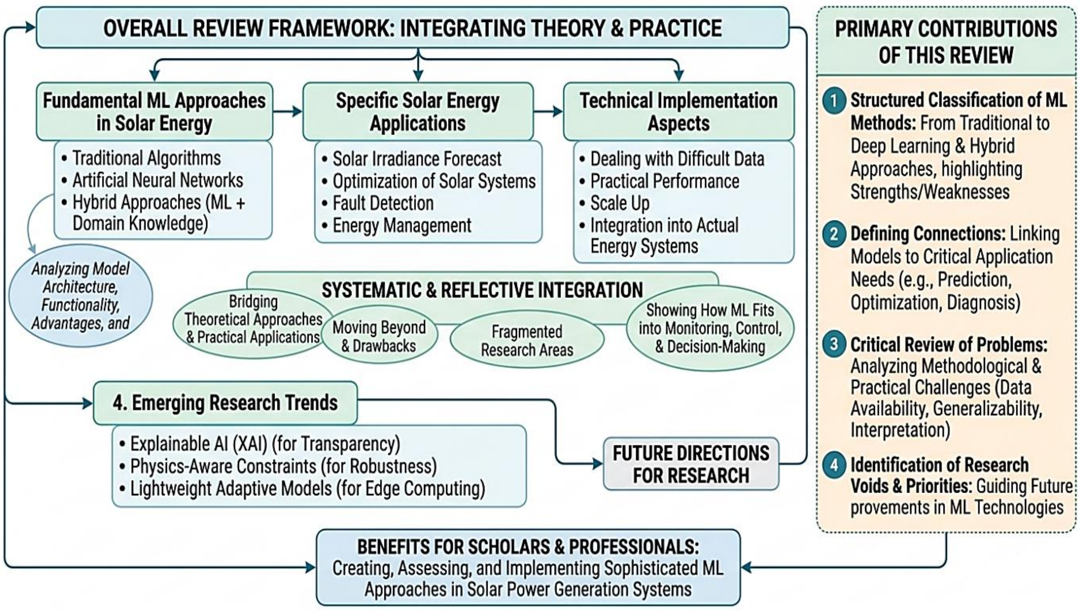


Fig. 4 Review flow chart

effectively integrated into the current power grid (Khalid, 2024). One of the key issues is the random and nonstationary behavior of solar irradiance, which has a direct impact on the generation of PV power. The production from the sun is very dependent on changes in the atmosphere, such as cloud motion, aerosols, and seasonal variations. This can happen at different timescales, and uncertainty is high. According to current research, variability is one of the leading causes of errors in predictions, especially in short-term predictions, because of the quick changes in irradiance levels (Mauceri *et al*., 2019; Voyant *et al*., 2017).

Another significant challenge arises from the high-dimensional and complex interactions among variables within PV systems. PV performance is influenced by a combination of meteorological conditions, system design parameters, and local environmental factors, all of which interact simultaneously. These interdependencies result in highly nonlinear and intricate input–output relationships, making accurate modelling and prediction particularly difficult for conventional approaches (Ahmed *et al*., 2020). Although ML techniques are designed to address complex and nonlinear relationships in solar energy systems, their effectiveness is highly dependent on the quality and representativeness of training data. In practice, models trained in one geographic or climatic region often exhibit limited generalization when applied to different environments, highlighting persistent challenges in cross-regional transferability. Additionally, data quality issues remain a significant concern, as solar datasets collected from distributed sensor networks frequently contain missing values, noise, and measurement errors due to communication failures or hardware limitations. While preprocessing techniques such as filtering, imputation, and normalization are commonly employed to improve data reliability, there is currently no standardized framework for solar data preparation. As a result, inconsistencies in data handling can adversely affect model performance, hinder reproducibility, and complicate the comparison of results across different studies (Labed and Lorenzo, 2004; Singh *et al*., 2024).

In terms of energy systems, where any decision influences not only financial but also technical issues, a lack of interpretability can be problematic when applying models to practice (Hoang *et al*., 2021c). Current research trends highlight the importance of building an interpretable and explainable model, although there is still no effective solution (Aslam *et al*., 2025). Finally, from the viewpoint of the entire system, incorporation into power networks raises other issues. Solar energy has high volatility and, thus, requires efficient solutions for fast decision-making on generation, storage, and demand (Shadvar and Rahman, 2024). Although modern forecasting models based on ML provide high levels of accuracy, their incorporation into real-time applications faces such limitations as computational speed, communication network infrastructure, and compatibility with current systems. According to recent studies, there is a gap between ML forecasts and control policies, which negatively affects the application of the former to practice (Borrego-Díaz and Galán Páez, 2022; Samek *et al*., 2019).

A further limitation of current research lies in its fragmented nature, where most studies focus on narrowly defined tasks such as forecasting, fault detection, or optimization without

Table 1
Comprehensive analysis of challenges, failure modes, and future research directions in ML-based solar energy systems (Benti *et al*., 2023; Hassan *et al*., 2023; Q. Wang *et al*., 2025; Zhang *et al*., 2025)

Challenge domain	Underlying cause	Failure mode in ML systems	Impact on evaluation & deployment	Mitigation strategies	Open research directions
Data quality degradation	Sensor errors, missing records, and environmental interference	Learned patterns become noisy or biased	Inflated training performance, poor real-world reliability	Data cleaning, imputation, anomaly filtering	Self-supervised learning for noisy environments
Data heterogeneity	Variability across locations, climates, and system setups	Model overfits local patterns	Weak cross-site performance	Data normalization, domain alignment	Domain adaptation and meta-learning frameworks
Non-stationary Dynamics	Rapid temporal changes in irradiance and weather conditions	Model fails to track evolving patterns	Performance drift over time	Time-aware modeling, adaptive retraining	Continual learning and drift detection methods
Limited labeled data	Scarcity of annotated fault or rare-event data	Poor classification and detection accuracy	Reduced reliability in critical applications	Semi-supervised and transfer learning	Few-shot and self-supervised learning approaches
Model overfitting	High model complexity vs limited data diversity	Excellent training results but poor generalization	Misleading evaluation metrics	Regularization, cross-validation	Robust generalization frameworks under distribution shift
Lack of interpretability	Use of deep and complex architectures	Inability to explain model decisions	Low trust in operational deployment	Explainable AI (XAI) techniques	Causality-aware and inherently interpretable models
Computational constraints	High model complexity and data volume	Slow inference and high energy consumption	Limits real-time and edge deployment	Model compression, pruning	Hardware-aware ML and efficient architectures
Uncertainty ignorance	Deterministic modeling assumptions	Overconfident predictions	Risk in decision-making systems	Probabilistic modeling, ensembles	Uncertainty-aware and risk-sensitive ML frameworks
System integration complexity	Interaction with grid, storage, and control systems	Incompatibility with existing infrastructure	Deployment delays and instability	Modular architectures, API integration	Standardized interoperable ML-energy frameworks
Scalability limitations	Differences in system size and operational conditions	Performance inconsistency across installations	Difficult large-scale deployment	Distributed learning and cloud-edge integration	Federated learning and scalable ML pipelines

considering their integration within a unified system framework. This task-specific approach restricts the development of holistic solutions capable of addressing the full lifecycle of solar energy systems. Recent studies increasingly emphasize the need for integrated frameworks that combine prediction, diagnostics, and control to fully exploit the capabilities of intelligent solar energy systems. In addition, the practical deployment of ML models remains constrained by scalability challenges. Many high-performing models are computationally intensive, limiting their applicability in resource-constrained environments such as distributed or edge-based solar installations. This gap between high-accuracy laboratory models and real-world deployment highlights the need for lightweight and efficient algorithms. The evolving nature of climate patterns introduces additional uncertainty, as nonstationary environmental conditions can degrade the performance of data-driven models over time. These factors collectively underscore the importance of developing adaptive, scalable, and integrated ML solutions for solar energy systems (Dubey *et al.*, 2026; Li *et al.*, 2024; Vandrangi, 2025).

Over time, such variability can degrade model performance, a phenomenon commonly referred to as concept drift. Most existing models lack the flexibility to adapt to these evolving data distributions in real time, highlighting the need for adaptive and continuously learning approaches. These challenges collectively indicate that conventional methodologies are insufficient for addressing the dynamic nature of solar energy systems (Alma'asfa *et al.*, 2024; Okumuş *et al.*, 2021). There is a growing need for solutions that are robust, interpretable, and capable of real-time adaptation under changing environmental conditions. Achieving this requires not only advances in ML techniques but also their integration with domain knowledge and system-level considerations. The following sections, therefore, examine various modelling strategies and application domains, providing a critical evaluation of their effectiveness and limitations (Gama *et al.*, 2014; Lu *et al.*, 2018). Table 1 breaks down the key challenges for ML in solar energy systems, with details on where things fail and where the research should head next.

3. Solar energy systems and data characteristics

The success of ML approaches used in solar energy depends largely on the physical properties of PV systems and the features of the data used for describing such systems. According to various reviews published recently, the increase in prediction accuracy and optimization does not solely depend on algorithm advancement; there is also an increased focus on gaining knowledge regarding the processes occurring in the systems and proper data handling. The main challenge here lies in dealing with the interaction between environmental factors and the elements of PV systems, which creates non-linear patterns (Dazhi, 2014; Luo *et al.*, 2025). Further, past studies

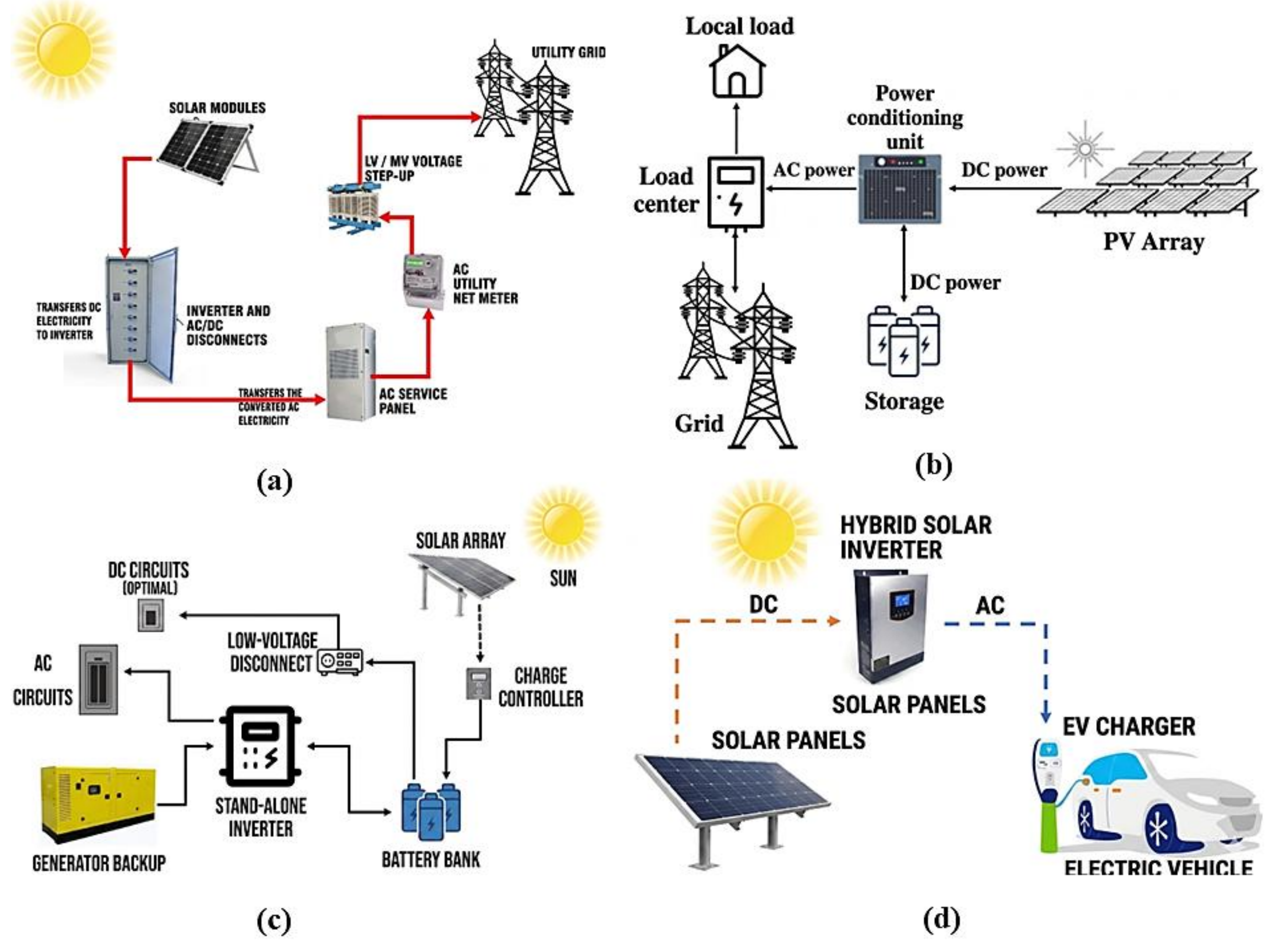


Fig 5. Solar energy (a) plant description (Reproduced from Ref. (Obaideen *et al.*, 2023) under the Creative Commons CC BY 4.0 license); (b) on a grid system (Reproduced from Ref. (Obaideen *et al.*, 2023) under the Creative Commons CC BY 4.0 license); (c) rooftop system (Reproduced from Ref. (Obaideen *et al.*, 2023) under the Creative Commons CC BY 4.0 license); (d) charging station for EVs (Reproduced from Ref. (Obaideen *et al.*, 2023) under the Creative Commons CC BY 4.0 license)

emphasize that solar energy systems are intrinsically data-rich and depend on multiple inputs, including measurements of irradiance, meteorology, and historical electrical production. With the abundance of high-resolution datasets collected by ground-based sensors, satellites, and numerical weather prediction simulations, the domain has witnessed an exponential growth in the application of data-centric methods. Nevertheless, these datasets typically suffer from noise and inconsistencies due to differences in resolution, which may impact the accuracy of the models trained if not handled appropriately (Luo *et al*., 2025). Moreover, from previous literature on this subject, it can be inferred that the effectiveness of ML algorithms in their application to solar energy depends to a large extent on how well the physics behind the systems are captured by the data. In other words, changes in solar radiation and temperature not only impact the efficiency of power production but also the stability and accuracy of the predictions made by the models in question (Tina *et al*., 2021).

3.1 Photovoltaic system fundamentals

Photovoltaics (PV) refer to the essential technology used in the transformation of solar energy into electricity using the properties of semiconductors. The transformation is facilitated through the phenomenon referred to as PVs, which involves the generation of electrons and holes within the semiconductor material as a result of the presence of photons. Modern PV consist of modular arrays, inverters, mounting systems, and control systems (Green, 1982; Skoplaki and Palyvos, 2009). Figure 5 depicts the solar energy plant (Figure 5a), roof top power plant (Figure 5b), on grid solar power plant (Figure 5c), and a solar powered EV charging plant (Figure 5d).

In terms of operations, the performance of a PV system depends on a variety of factors from both the environment and the PV system itself. The amount of solar irradiance can be considered the main factor that determines the level of energy produced, but temperature, angle of the panel, shading, and material properties greatly affect the efficiency of energy conversion. It has been shown that higher irradiance does not necessarily produce proportionate levels of energy due to temperature-related efficiencies and other non-linear characteristics (Arun *et al*., 2024; Shaker *et al*., 2024). Moreover, PV systems exhibit dynamic and time-varying behaviour, influenced not only by fluctuations in environmental conditions but also by long-term degradation processes. Factors such as material aging and soiling accumulation contribute to gradual efficiency losses and increase uncertainty in system performance over time. In addition, partial shading introduces mismatch losses within PV arrays, significantly reducing energy yield and further complicating system behaviour. These effects collectively highlight the need for robust modelling approaches capable of capturing both short-term variability and long-term degradation dynamics (Bou-Rabee *et al*., 2026; Nguyen *et al*., 2024b).

Traditional PV modeling techniques such as equivalent circuits modeling and physics-based modeling have been extensively used to model PV systems. Although these modeling techniques offer significant theoretical benefits, they come with various limitations. These include the making of certain assumptions in order for modeling to take place and the need for precise knowledge of the model parameters, which might not always be easy to get. The ability to adjust themselves to different climatic conditions and different types of systems is also quite difficult for these models (Bui *et al*., 2022; Munusamy *et al*., 2023). Considering all these constraints, recent research has been inclined towards data-driven modeling methodologies that make use of operational data to represent the intricacies of the system behavior. The presence of monitoring systems in the installed PV systems has allowed researchers to gather accurate datasets, including electric parameters and environmental factors. Such a database can serve as an ideal base for the application of advanced techniques and algorithms to optimize system operations and enhance its performance. Several studies confirm the superiority of such approaches to be more flexible and effective, especially in varying conditions (Pedram *et al*., 2025; Praveen Kumar *et al*., 2024).

The other crucial component in PV systems is their integration into larger energy systems. In the case of the grid-connected PV systems, PV arrays need to work in harmony with electricity grids by satisfying voltage levels, frequencies, and stability. In this regard, various control mechanisms, such as MPPT, inverters, and synchronizations, need to be employed (Le *et al*., 2021). Moreover, the rising popularity of distributed PV systems has also resulted in the emergence of decentralized energy frameworks, wherein several smaller units together perform the function of generating power for the grid (Gandhi *et al*., 2022). Such an approach creates new difficulties in terms of coordination, management, and control, especially when high percentages of RE are involved. As previous research indicates, distributed systems necessitate sophisticated analysis and control measures for efficient management and maintenance of the system's integrity (Hu and Cheng, 2017; Khalid, 2024).

In summary, PV systems exhibit dynamic, nonlinear, and data-intensive characteristics that are strongly influenced by environmental conditions and system configurations. Although conventional model-based approaches provide fundamental insights into system behaviour, their limitations in addressing real-world complexities have motivated the adoption of advanced data-driven methodologies. A thorough understanding of PV system fundamentals is therefore essential for the development of robust and reliable analytical models. The subsequent sections of this paper present a comprehensive discussion of ML techniques applied to PV system analysis, with a focus on their capabilities, limitations, and practical relevance (Benti *et al*., 2023; Luo *et al*., 2025).

3.2 Solar irradiance and performance metrics

Solar Irradiance is a measure of the energy available at the PV panel, and therefore, an important determinant of output variability from such devices. It is usually broken down into three main categories of irradiance, namely, global horizontal irradiance, direct normal irradiance, and diffuse horizontal irradiance. All these are measures of different mechanisms through which solar irradiance reaches the Earth's surface and have different weightages dependent on atmospheric conditions, solar geometry, and environmental variables (Herrando et al., 2023; Polo and Kaskaoutis, 2023; Wang et al., 2025). The temporal pattern of irradiance is evident with clear diurnal variation as well as periodic variations due to the orbital behavior of the Earth around the sun. There are also non-periodic variations attributed to weather-related variables such as clouds and aerosols. From past studies, there is evidence of non-linearities introduced in the process of irradiance measurements due to irregular atmospheric disturbances, especially when partial clouds cause shadowing effects. These non-linear effects would be especially evident in high-resolution data (Fariz and Basha, 2024; Herrando *et al*., 2023).

In addition to temporal variability, solar irradiance also

Table 2
Overview of solar irradiance components and performance metrics used for evaluating PV systems and forecasting models (Abdulla *et al.*, 2024; Buonanno *et al.*, 2024; Çerçi, 2025; Pinson and Girard, 2012)

Category	Element	Definition/Role	Key characteristics	Advantages	Limitations	Impact on analysis/modeling
Irradiance components	Global Horizontal Irradiance (GHI)	Total solar radiation on a horizontal surface	Combination of direct and diffuse radiation	Represents overall available solar energy	Does not isolate beam/diffuse effects	Primary input for PV power estimation
	Direct Normal Irradiance (DNI)	Solar radiation received directly from the sun	High intensity under clear-sky conditions	Essential for concentrating solar systems	Highly sensitive to cloud cover	Influences peak generation modeling
	Diffuse Horizontal Irradiance (DHI)	Scattered radiation due to atmospheric interactions	Dominant under cloudy conditions	Captures non-direct radiation contributions	Lower intensity compared to DNI	Important for accurate irradiance decomposition
Variability factors	Temporal Variability	Changes over time (diurnal, seasonal)	Predictable patterns short-term fluctuations	Enables periodic modeling	Sudden changes under cloud cover	Affects forecasting accuracy
	Spatial Variability	Differences across geographic locations	Influenced by climate and terrain	Supports regional analysis	Requires spatial data alignment	Impacts model generalization
	Atmospheric Effects	Cloud cover, aerosols, humidity	Introduces irregular fluctuations	Reflects real environmental conditions	Difficult to model precisely	Major source of uncertainty
Performance metrics (System)	Performance Ratio (PR)	Ratio of actual output to theoretical output	Normalized efficiency indicator	Accounts for system losses	Sensitive to environmental variations	Evaluates system efficiency
	Capacity Utilization Factor (CUF)	Ratio of actual energy to maximum possible energy	Long-term performance indicator	Useful for system benchmarking	Does not capture short-term dynamics	Assesses energy utilization
Performance metrics (Model)	Mean Absolute Error (MAE)	Average absolute difference between predicted and actual values	Linear error measurement	Easy interpretation	Does not penalize large errors	Measures average prediction accuracy
	Root Mean Square Error (RMSE)	Square root of mean squared error	Emphasizes larger deviations	Sensitive to outliers	Can over-penalize extreme errors	Highlights large prediction errors
	Mean Absolute Percentage Error (MAPE)	Percentage-based error metric	Scale-independent comparison	Easy cross-dataset comparison	Undefined when actual values are near zero	Useful for relative error analysis
Advanced evaluation	Multi-Metric Evaluation	Use of multiple error metrics	Comprehensive assessment	Captures different error aspects	Increases evaluation complexity	Improves model comparison reliability
	Probabilistic Metrics	Prediction intervals, uncertainty estimation	Quantifies prediction confidence	Supports risk-aware decisions	Requires advanced modeling	Enhances reliability assessment

exhibits significant spatial heterogeneity due to differences in geographic location, altitude, and local climatic conditions. These factors influence the intensity and distribution of solar radiation, resulting in distinct statistical characteristics across different sites. Consequently, irradiance measurements collected from different regions are not directly comparable without appropriate normalization or domain adaptation techniques, which have important implications for model transferability and generalization in solar energy applications (Sevgin, 2025). A few key metrics are used to measure the performance of the solar energy systems with regard to different irradiance levels. Among those is the Performance Ratio (PR), which compares the measured power output of the systems to the theoretical output based on standard conditions. The Performance Ratio automatically takes into consideration all losses, such as heat, inverters, and climatic conditions in its calculations. The Capacity Utilization Factor (CUF), on the other hand, measures the ratio of the actual generated power to the theoretical maximum over a given time frame (Çerçi, 2025; Abdulla *et al.*, 2024). Statistical error metrics play a central role in evaluating model performance from both predictive accuracy and analytical perspectives. Commonly used indicators include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Each metric emphasizes different aspects of prediction error: RMSE is more sensitive to large deviations due to its quadratic formulation, MAE reflects the average magnitude of errors, and MAPE enables scale-independent comparison across datasets. The selection of an appropriate evaluation metric is therefore highly context-dependent, as different metrics may yield varying interpretations of model performance depending on the application and data characteristics (Makridakis *et al.*, 2018a). A recent trend in the scientific literature is recognizing the limitations of using a single performance metric, especially in highly variable contexts. Multi-metric evaluation systems have become increasingly popular as a way to evaluate all aspects of the model's predictive capability. Also, noteworthy is the importance of analyzing model output under various operating conditions, such as cloudless and cloudy environments (Buonanno *et al.*, 2024).

There are other types of measurements that have also gained increasing interest lately, and these include the metrics pertaining to uncertainty and reliability. The use of probabilistic evaluation methods like prediction intervals and distribution-based measurements adds another layer of analysis in addition to the deterministic metrics. It is worth noting that this type of measurement is especially useful in situations where there is uncertainty involved in the decision-making process. To conclude, it is evident that the solar irradiance data presents both order and unpredictability, which require proper consideration. Metrics for performance and error are vital when it comes to measuring system efficiency and predictions. This makes it very important to understand them before any model results are interpreted (Bańbura and Bobeica, 2023; Buonanno et al., 2024; Hong *et al*., 2016; Makridakis *et al*., 2018a; Pinson and Girard, 2012). Table 2 shows some of the metrics for solar irradiance and performance.

3.3 Data sources and preprocessing techniques

Accurate assessment of solar energy systems not only relies on the type of models but is also influenced by the quantity and quality of the data provided as inputs. In recent years, there has been a considerable increase in the number of solar datasets available for use, providing more opportunities for modeling. There are various issues associated with these data, which need to be resolved through proper preprocessing (Harrou *et al*., 2023). There are three main types of sources to obtain solar datasets. First, ground-based measurement systems provide very frequent data on irradiance, temperature, and electricity production in a particular area, having good temporal accuracy but poor spatial extent. Second, satellite measurements give wide-area irradiance estimates, allowing for regional and global analysis, but with possible low temporal accuracy and possible biases in estimation due to complex atmospheric behavior. The third type of data is numerical weather predictions, producing forecasts of meteorological data and extensively used in forward analysis. Review papers indicate that by merging multiple data sources, one can get better descriptions of both local variations and atmospheric phenomena (Allal *et al*., 2024; Attya *et al*., 2025; Ghodusinejad *et al*., 2026; Harrou *et al*., 2023). Nevertheless, initial solar datasets might have many missing data points, noise, or inconsistent information caused by malfunctioning sensors, communication failures, or environmental effects. Therefore,

Table 3
Overview of data sources, preprocessing methods, and their influence on ML performance in solar energy systems (Çerçi, 2025; Huld *et al*., 2012; Zhang *et al.,* 2025)

Category	**Type/Technique**	**Description**	**Advantages**	**Limitations**	**Impact on modeling performance**
Data sources	Ground-Based Measurements	Sensor-based local data (irradiance, temperature, power output)	High temporal resolution; accurate local representation	Limited spatial coverage; sensor errors	Improves short-term forecasting accuracy
	Satellite Data	Remote sensing-based irradiance estimation	Wide spatial coverage; useful for regional/global analysis	Lower temporal resolution; estimation uncertainty	Enhances spatial generalization
	Numerical Weather Prediction (NWP)	Model-based meteorological forecasts	Provides future weather inputs; useful for forecasting tasks	Model bias; computational complexity	Improves medium/long-term predictions
Data quality issues	Missing Data	Gaps due to sensor failure or transmission issues		Reduces data reliability	Causes model instability if unhandled
	Noise & Outliers	Measurement errors or environmental disturbances		Distorts learning patterns	Degrades model accuracy
	Data Inconsistency	Variability in sampling rates or formats		Requires alignment	Introduces bias if not corrected
Preprocessing techniques	Data Cleaning	Removal of outliers and erroneous values	Improves data reliability	May remove useful extreme cases	Enhances model robustness
	Missing Value Imputation	Interpolation, mean/median filling, ML-based imputation	Preserves dataset completeness	Risk of introducing bias	Stabilizes training process
	Normalization / Scaling	Min–max scaling, standardization	Ensures uniform feature range	May distort distribution if misapplied	Improves model convergence
Feature engineering	Feature Selection	Correlation analysis, importance ranking	Reduces dimensionality	Risk of losing relevant features	Improves model efficiency
	Feature Transformation	Log, polynomial, encoding methods	Captures nonlinear patterns	Requires domain knowledge	Enhances predictive performance
	Time-Series Decomposition	Trend, seasonal, residual separation	Reduces noise; clarifies patterns	Additional preprocessing complexity	Improves forecasting accuracy
Data integration	Multi-Source Fusion	Combining sensor, satellite, and NWP data	Comprehensive representation	Data alignment challenges	Improves generalization
	Temporal Alignment	Resampling and synchronization	Ensures consistency	May introduce interpolation errors	Enables reliable modeling
Advanced processing	Real-Time Data Processing	Streaming data handling	Enables adaptive modeling	Requires infrastructure support	Supports real-time decision-making
	Automated Pipelines	End-to-end preprocessing workflows	Improves scalability and consistency	Implementation complexity	Enhances reproducibility

such problems can negatively impact further data processing and lead to incorrect results. Thus, data preprocessing becomes an essential stage to prepare the data for analysis. There are several techniques for data preprocessing, including outlier removal, missing value imputation, and normalization. Earlier research shows that preprocessing data increases the reliability of models and prevents wrong analysis results (Allal *et al.*, 2024; Jaber *et al.*, 2022; Voyant *et al.*, 2017). The step of feature engineering involves generating informative variables through the manipulation of raw inputs to uncover latent relationships. Methods such as correlation-based selection, feature selection, and dimensionality reduction, among others, have been commonly used for this purpose. When it comes to time series data, decomposition techniques like wavelet transform or filter-based approaches may be utilized to remove noise and distinguish between useful signal components within input data (Mushtaq *et al.*, 2019). This becomes especially critical when dealing with the high variance of irradiance, which may be prone to noise interference (Phiri *et al.*, 2023; Shedbalkar and More, 2024; Xiang *et al.*, 2025).

One more point to consider concerns multi-source input data synchronization. The problem arises because of differences in terms of temporal resolution, sampling frequency, and even spatial scale. Therefore, synchronization of different data sources becomes necessary prior to analysis. An example of the problem may include resampling or interpolation of satellite and ground-based data to a unified time scale. Ignoring this issue might lead to the appearance of systematic errors. Modern studies emphasize the necessity of employing integrated data fusion approaches (Shata *et al.*, 2025; Sultana and Tsutsumida, 2025; Xiang *et al.*, 2025). Also, sensor networks and digital monitoring tools have led to an increase in continuous data sources that need to be effectively processed. Such systems necessitate scalable data preprocessing strategies that are able to handle large quantities of data, while also preserving data integrity. It is noted that automation of the data preprocessing process, alongside real-time validation, has become critical to achieving reliable data quality within such systems (El Husseini *et al.*, 2025; Jiang *et al.*, 2026). Despite recent advancements, the development of a standardized framework for data preprocessing in solar energy research remains a significant challenge. Variations in data management practices, feature extraction methodologies, and transformation techniques lead to inconsistencies across studies, making it difficult to perform fair comparisons and reproducibility assessments. This lack of standardization has been widely recognized as a critical limitation in the current literature, as it hinders the establishment of unified benchmarks and the reliable evaluation of model performance across different datasets and application contexts (Buonanno *et al.*, 2024; Huynh *et al.*, 2020).

To conclude, it should be mentioned that the sources of information regarding solar energy have their specific peculiarities, and proper data preprocessing is needed to achieve reliable results. Not only does good data processing increase the quality of calculations performed by analysts, but it also allows making comparisons between various studies and situations. These issues are important as they serve as the starting point for developing further models that are based on such data. The following table illustrates sources of data used when working with solar energy issues (Çerçi, 2025; Huld *et al.*, 2012).

4. Machine learning methods for solar applications

The increasing availability of high-resolution solar energy data, along with the rising complexities associated with PV systems operations, has made ML a pivotal methodology for modeling and analysis within the field of solar energy. Unlike deterministic and rule-based models, which cannot capture the behavior of systems through data, ML provides a means of capturing the behaviors through pattern extraction from massive heterogeneous data sets. Such an advantage makes ML ideal in fields such as solar energy, where the input/output relationships between systems are governed by complex interactions among several variables with high levels of time variation (Di Leo *et al.*, 2025; Sebastianelli *et al.*, 2024). Figure 6 depicts the ML framework for application in solar energy.

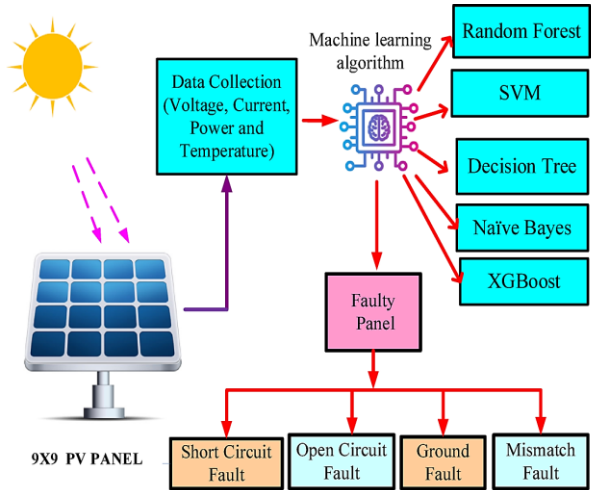


Fig 6. ML framework for application in solar energy (Reproduced from Ref. (Khandeparkar *et al.*, 2025)under the Creative Commons CC BY 4.0 license).

The latest studies reveal that the efficiency of ML algorithms for solar applications depends on how well their properties match the problem's nature. For example, when dealing with structured datasets containing a small number of features, classical ML algorithms can be used. However, when faced with problems featuring sequential dependencies or high-dimensional input data, the use of deep learning models becomes more appropriate. In addition, the recent tendency toward incorporating multiple data sources, including meteorological parameters, past power generation statistics, and geographical factors, increases the versatility of ML methods, allowing for more accurate modeling of solar installations (Liu *et al.*, 2023; Mellit and Kalogirou, 2008; Saadati and Barutcu, 2025). Moreover, besides model selection, the success of ML techniques depends on issues like data representation, feature extraction, and even training approach. According to research, proper feature engineering and input transformation have been shown to play a vital role in improving ML models' performance, especially when the input data present noisy or random features. Besides, it is also crucial that the training methodology be well-chosen to guarantee a robust model and better generalization capability (Salazar-Achig *et al.*, 2025; Tercha *et al.*, 2024).

Another critical issue highlighted in the literature concerns the trade-off between model complexity and practical applicability. Deep learning models, while capable of achieving high predictive performance, typically require substantial computational resources and large volumes of training data, which can limit their feasibility in real-world applications. In contrast, simpler ML models are generally more computationally efficient and offer greater interpretability, making them easier to deploy and analyse. However, these models often struggle to capture complex nonlinear relationships and may exhibit limited generalization capability when dealing with high-dimensional and dynamic solar energy data. Consequently, selecting an appropriate modelling approach requires balancing predictive accuracy, computational efficiency, and interpretability based on the specific requirements of the application (LeCun *et al.*, 2015; Mellit *et al.*, 2021). In an attempt to solve some of the aforementioned issues, modern research has examined hybrid/ensemble methods where several learning paradigms are used at once. In essence, such techniques seek to capitalize on the strengths of multiple models, thereby making it easier to manage various types of data as well as operations. That said, current trends in the scientific community include an increasing number of efforts dedicated to developing methods that are both transparent and adaptable, especially in case of energy systems (AlKandari and Ahmad, 2024; Di Leo *et al.*, 2025). Considering the wide range of techniques and their applicability to various purposes, it becomes imperative to conduct a systematic comparative analysis of the roles played by all the techniques in solar energy systems. For this reason, the following section offers an organized overview of ML techniques divided into conventional approaches, neural networks, and hybrids/ensembles. In addition to theoretical frameworks, the discussion focuses on performance, weaknesses, and applications (Barhmi *et al.*, 2024; Gupta *et al.*, 2025).

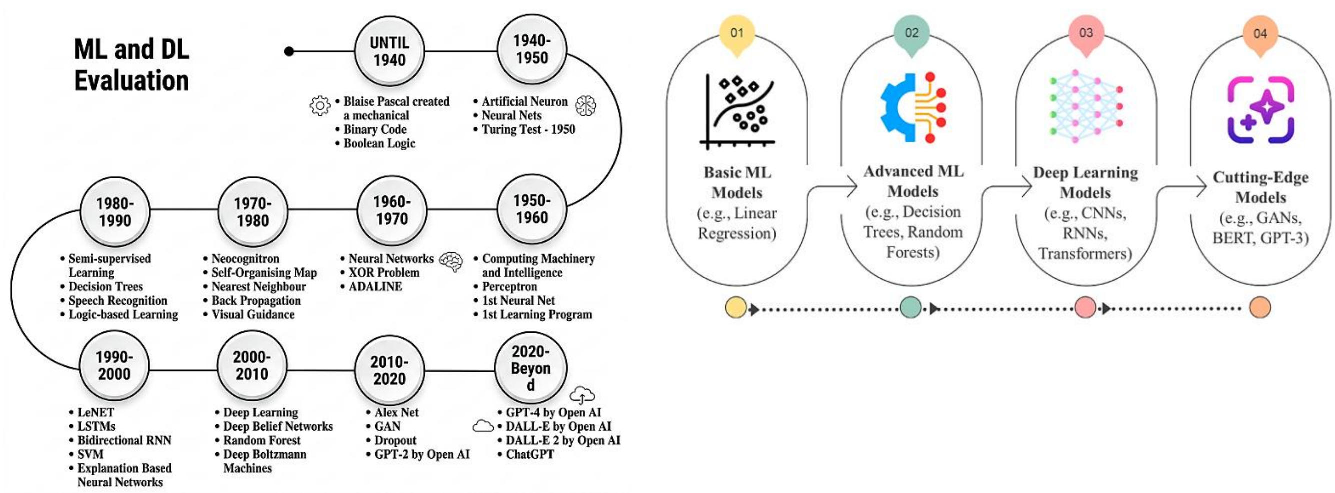
4.1 Conventional ML models

Traditional ML algorithms have served as key components in solar analytics, in particular in structured prediction problems where input features are determined on the basis of weather observations and past system outputs. Generally speaking, traditional algorithms are preferred in practice owing to an adequate combination of prediction accuracy, interpretability, and computing efficiency. According to literature review findings, traditional methods are still commonly used in solar irradiance modeling and PV power generation forecasting under conditions of moderate data volumes and complexities (Ahmed *et al.*, 2020; Khouili *et al.*, 2025; Tian *et al.*, 2023). Figure 7 depicts the progression of ML in recent years. Figure 7a depicts the chronological overview of key milestones in ML. As it started with Boolean logic and mechanical computation to the emergence of ANNs, backpropagation, and modern architectures. Figure 7b depicts the categorization of ML models into four stages as basic models (LR), advanced models (DT and RF), deep learning models (CNNs and RNNs), and cutting-edge models like GANs, BERT, and GPT, showing increasing complexity and capability.

SVM models are common among traditional algorithms, owing to the rigorous mathematical background in statistical learning and flexible non-linear data transformation mechanisms based on kernel mappings (Dang *et al.*, 2025). The use of SVMs is justified by their ability to identify complex relationships within input data without overfitting even with small amounts of training samples, which makes them applicable for local solar forecasting in data-limited situations. Nevertheless, the performance of the model greatly depends on kernel function and hyperparameter settings and grows substantially in terms of computational costs with an increase in the amount of training samples (Ahmed *et al.*, 2020; Tian *et al.*, 2023).

However, Random Forest (RF) algorithms overcome some of the challenges discussed above through ensemble methods. Through building a set of decision trees using random sampling techniques and combining their results, RF decreases the variance without significantly increasing bias. Such characteristics improve RF's resilience to noise and missing data in solar data due to faulty sensors and other sources of interference. Also, RF algorithms offer native measures of feature importance that help understand the relevance of input parameters. Nevertheless, one drawback of RF algorithms is that they do not have built-in techniques for modeling temporal relationships, which might hinder their effectiveness in time-series forecasting tasks (Esen *et al.*, 2025; Gupta *et al.*, 2025; Hasan and Horvat, 2024).

Gradient boosting approaches, in particular Extreme Gradient Boosting (XGBoost), have proven effective by providing accuracy in combination with efficiency (D. T. Pham



(a) (b)

Fig. 7. Evolution of ML and Deep Learning (a) Historical Timeline of ML and DL Development (Reproduced from Ref. (Jawad *et al.*, 2026) under the Creative Commons CC BY 4.0 license); (b) Progression of ML Model Complexity (Reproduced from Ref. (Razzaq and Shah, 2025) under the Creative Commons CC BY 4.0 license)

et al., 2025; Tuan Anh, 2025). In contrast to RF, which trains trees separately from one another, boosting approaches build models sequentially, where at each step, an emphasis is placed on minimizing the error of the preceding models. Such approaches allow lowering the bias and increasing the ability of XGBoost to generalize. Studies demonstrate a superior performance of boosting algorithms in predicting solar energy production compared to many other algorithms, provided that inputs have been properly selected, and algorithm parameters have been tuned. At the same time, boosting methods are sensitive to noise and require a significant amount of parameter tuning (Chen and Guestrin, 2016; Gupta and Singh, 2025; Tahir *et al.*, 2024).

Conventional approaches, such as k-Nearest Neighbors (k-NN) and linear regression-based algorithms, may be used as benchmarking methods. Although instance-based learning allows capturing patterns within a dataset using k-NN, high-dimensional datasets suffer from the curse of dimensionality, reducing the effectiveness of this approach. Linear regression-based algorithms are usually unable to capture the nonlinearities of real-world data. Thus, they might only be useful for benchmarking purposes (Ahmed *et al.*, 2020; Hastie *et al.*, 2009). While SVMs are characterized by low variance and complexity, which makes them suitable for small data sets, RF algorithms decrease variance through averaging of ensembles. On the other hand, the goal of XGBoost is to reduce the bias through an error correction process, which results in better accuracy in cases when there is enough training data (Ahmed *et al.*, 2020; Meenal *et al.*, 2021; Tripathi *et al.*, 2024). Nevertheless, conventional ML models are faced with a number of restrictions despite the variety of benefits. Firstly, the dependence on feature engineering is an essential drawback of such methods, as this step demands careful selection of variables. The second major disadvantage is that the ML models cannot capture long-term dependencies, thus limiting their efficiency in time series prediction tasks. In regard to solar power generation systems, it becomes critical due to the dependence on temporal continuity (Gupta *et al.*, 2025; Wang *et al.*, 2026). Moreover, the problem of achieving generalization through diverse environmental settings is still relevant. The ability of ML algorithms that are developed with datasets for certain locations to work effectively in different settings highlights their dependence on the data distribution changes. Hence, there is a need for a more flexible modeling approach that will be capable of achieving similar results despite the changes in environmental settings (Ukoba *et al.*, 2024; Yao *et al.*, 2022). To conclude, the traditional ML models serve as a good starting point for solving issues related to the use of ML technology for solar energy purposes, as these models feature numerous advantages related to their interpretability and effectiveness. Nonetheless, the increasing challenge of conventional ML algorithms to deal with multidimensional data and time-related dependencies served as the basis for shifting to a new modeling paradigm, which is discussed further in the next subsection (Gupta *et al.*, 2025; Mazher and Azmat, 2024). Table 4 provides a detailed comparative analysis of the traditional ML models.

4.2 Deep Learning approaches

Deep learning techniques have gained popularity in modeling solar applications, especially in cases where there is sequential data and high-dimensional features. Deep learning

Table 4
Advanced comparative analysis of conventional ML models for solar energy applications (Benitez and Singh, 2025; Gupta *et al.*, 2025; Mazher and Azmat, 2024; Wang *et al.*, 2026; Yao *et al.*, 2022)

Model	Core learning principle	Scalability	Feature dependency	Temporal modeling capability	Interpretability	Robustness to noise	Key limitations	Representative applications
SVM	Kernel-based margin maximization in high-dimensional space	Limited for large datasets ($O(n^3)$ training)	High (requires well-engineered features)	Weak (no inherent sequence modeling)	Moderate (depends on kernel)	Moderate	Sensitive to kernel choice; computationally intensive at scale	Local irradiance estimation; small-dataset PV forecasting
RF	Bagging-based ensemble of decision trees	High (parallelizable)	Moderate (handles raw features reasonably well)	Weak (no explicit temporal structure)	Moderate (feature importance available)	High	Cannot capture long-range temporal dependencies; large model size	PV output prediction; feature importance analysis
XGBoost	Gradient boosting with regularization and shrinkage	High (optimized and parallelizable)	High (benefits from engineered features)	Weak–Moderate (via lag features)	Low–Moderate	Moderate (sensitive if poorly regularized)	Requires careful hyperparameter tuning; can overfit noisy data	Short-term forecasting; structured regression tasks
kNN	Instance-based learning using distance metrics	Poor (slow inference with large n)	High (distance metric sensitive)	Weak	High (intuitive)	Low–Moderate	Curse of dimensionality; sensitive to scaling and noise	Baselines: simple regression/classification
LR	Linear mapping via least squares optimization	Very high (computationally efficient)	High (assumes linear relationships)	Weak	High (fully interpretable)	Low (sensitive to outliers)	Cannot capture nonlinear relationships; oversimplifies complex systems	Baseline modeling, trend analysis, and simple PV output estimation

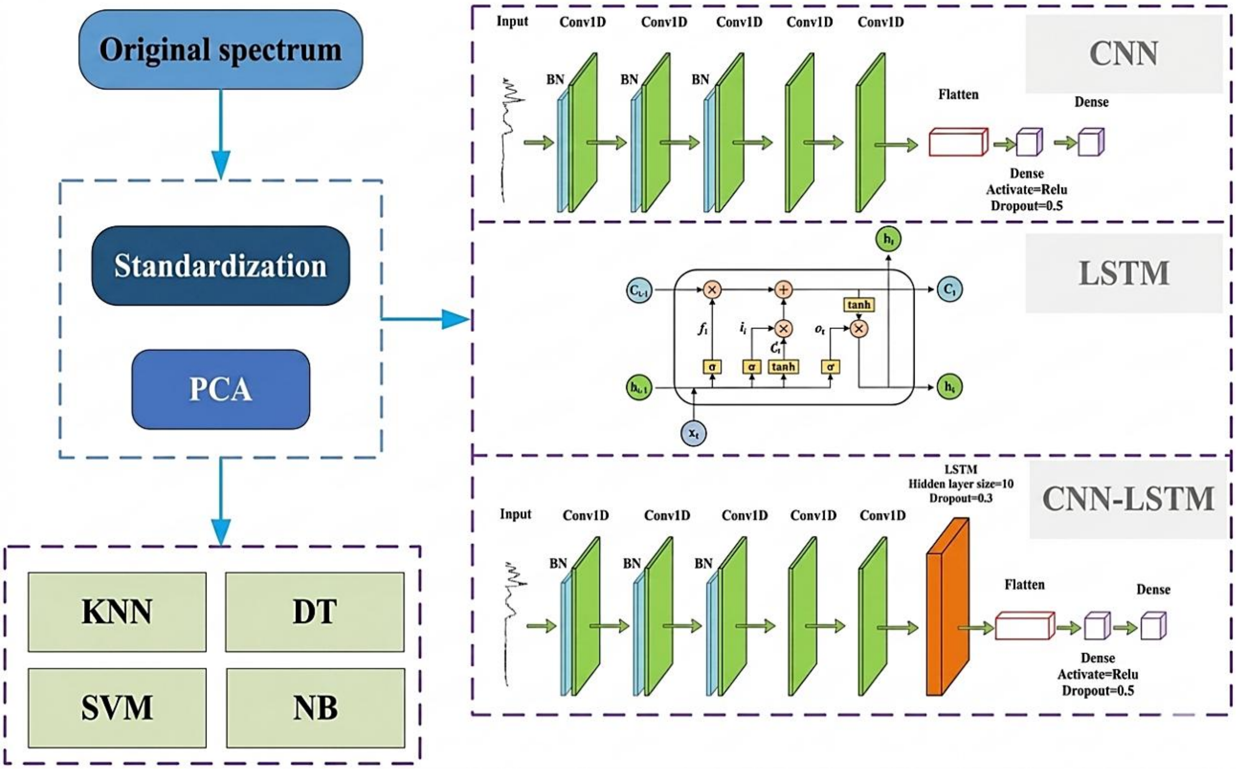


Fig. 8. CNN-LSTM framework (Reproduced from Ref. (Sun *et al.*, 2023) under the Creative Commons CC BY 4.0 license)

methods can automatically learn features from the raw data, unlike traditional ML models, where there was extensive use of manually constructed features in training the models. Deep learning models have hierarchical feature learning capabilities and can thus capture complex representations from the data in cases where the data are complex temporally (Benitez and Singh, 2025; Parsa, 2025). One of the deep learning models that has found wide application in modeling solar systems is the Long Short-Term Memory network. The LSTM networks are similar to the traditional recurrent neural network models, but with additional components such as the memory cell and gates, including the input gate, forget gate, and output gate. These components enable the network to capture important information and drop unimportant features in the data. This helps in addressing the vanishing gradients issue that affects normal RNNs. LSTM models are suitable for modeling time-dependent data in applications such as solar power systems because they can model the data over long time steps. Studies conducted have shown that the LSTM models are more accurate in capturing temporal variability than the traditional models (Deng *et al.*, 2025; Khouili *et al.*, 2025).

In order to benefit from the unique strength of the two architecture designs mentioned above, the hybrid version of the deep learning algorithms has been developed, incorporating the layers of CNN and LSTM into one framework, as depicted in Figure 8. The models such as CNN–LSTM use convolutional layers for feature extraction and follow them up with recurrent layers to capture temporal behavior. The proposed architectures thus allow addressing spatial and temporal correlations at once, becoming an appropriate choice for cases when multiple input sources are used. Hybrid algorithms are reported to outperform single architecture designs due to more comprehensive data representations they provide (Camacho *et al.*, 2025; Ghennioui *et al.*, 2026; Khan *et al.*, 2025; Rajasundrapandiyanleebanon *et al.*, 2023). Gated Recurrent Units (GRUs) provide an improved option as compared to LSTM, as GRU integrates the capabilities of both input and forget gates in one single gate. Thus, there is less complexity in terms of design structure, which means fewer parameters to train, making GRU training much faster. GRU networks require less computation than LSTM. However, the drawback of GRUs is that they may not be as efficient at modeling complex data, but according to research, they have shown to perform almost as well as LSTMs (Deng *et al.*, 2025; Elmousaid *et al.*, 2024; Rajagukguk *et al.*, 2020). Unlike recurrent neural networks, Convolutional Neural Networks concentrate on capturing spatial patterns through the use of convolution. Despite the fact that CNNs were initially created for processing images, CNNs have proven to be useful in dealing with problems related to solar energy due to the fact that there is spatial information involved when using satellite images or weather maps. Through convolution, CNNs are able to find local and hierarchical features that are efficient in terms of representing spatial patterns. Furthermore, one-dimensional CNNs can be used to process time series data by detecting short-range dependencies (Rajasundrapandiyanleebanon *et al.*, 2023; Saad *et al.*, 2024).

The second challenge relates to the vulnerability of deep learning models to distribution changes. If the changes occur due to any changes in the environment, the performance of the models will deteriorate, necessitating careful adaptation. Transfer learning and domain adaptation are some techniques that researchers have considered increasingly to make the models more robust to distribution changes (Aslam *et al.*, 2021; Camacho *et al.*, 2025; Khan *et al.*, 2025; Saberironaghi *et al.*, 2025). In conclusion, the use of deep learning techniques makes it possible to effectively model the patterns that exist within the data on solar energy. Deep learning models are very useful in

Table 5
Comparison of ML models for solar energy applications (Assaf *et al*., 2023; Gupta and Singh, 2025; Khouili *et al*., 2025; Q. Wang *et al*., 2025).

Model	Model	Strengths	Limitations	Typical applications
Conventional ML	Support Vector Machine (SVM)	Strong generalization; effective with small datasets	Sensitive to kernel selection; high computational cost for large data	Solar irradiance prediction, small-scale PV forecasting
	Random Forest (RF)	Robust to noise; reduces overfitting; feature importance	Cannot model temporal dependencies explicitly	PV power prediction, performance analysis
	XGBoost	High accuracy; efficient; handles structured data well	Requires tuning; sensitive to noise if not regularized	Short-term forecasting, regression tasks
	k-NN	Simple; no training phase	Poor performance in high dimensions; slow inference	Baseline comparison
Deep learning	LSTM	Captures long-term temporal dependencies	High computational cost; requires large datasets	Time-series forecasting, multi-step prediction
	GRU	Faster training; fewer parameters than LSTM	Slightly lower capacity in complex scenarios	Real-time forecasting
	CNN	Efficient spatial feature learning; parallel computation	Limited long-term temporal modeling	Satellite-based solar prediction
Hybrid models	CNN-LSTM	Handles spatiotemporal data effectively	Complex architecture; high computation	Multi-source data forecasting
	Decomposition + ML	Reduces noise; improves prediction accuracy	Requires preprocessing design	Irradiance forecasting
Ensemble Methods	Bagging/ Boosting/ Stacking	Improved stability and accuracy	Increased complexity; less interpretable	High-accuracy forecasting systems

the analysis of high-dimensional datasets, especially because they can learn complicated dependencies from such data. Nevertheless, their success depends on certain considerations, such as data availability and computing costs, as discussed above. More so, the lack of interpretability poses additional problems for the application of deep learning models. The following subsection discusses the solutions to these challenges, including the use of hybrid techniques. Table 5 presents a comparative analysis of various deep learning architectures (Benti *et al*., 2023; Khouili *et al*., 2025).

4.3 Hybrid and ensemble techniques

The main driver behind hybrid and ensemble approaches used for solar energy prediction is to combine multiple sources of data or modeling methodologies into one coherent predictive framework. The goal is not necessarily to enhance the capability of the model per se but rather to leverage a combination of multiple data representation mechanisms to better handle the heterogeneity of different variations (Shedrack Onwusinkwue *et al*., 2024; Ukoba *et al*., 2024).

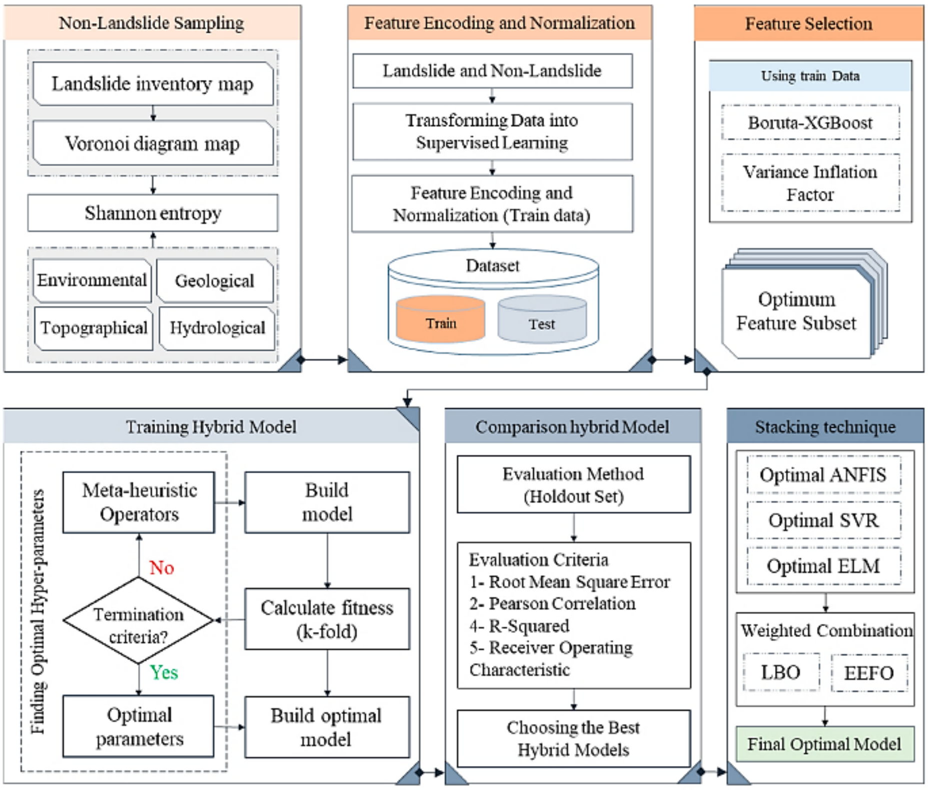


Fig 9. Stacked ensemble ML framework (Reproduced from Ref. (Yousefi *et al*., 2024) under the Creative Commons CC BY 4.0 license)

One key principle that underlies many hybrid approaches is that of a modular framework in which different processes are handled by different modules. Thus, for example, in such a framework, input data could first be transformed or segmented based on different behavior characteristics, and then a specific model would be applied to each of the resulting subsets of the data. In this way, different processes can be handled by different components of the framework while retaining consistency within the entire framework, without having to rely on one single model capturing all possible behavior aspects (Coya *et al.*, 2024; Ye *et al.*, 2026). The other significant consideration of hybrid modeling relates to data fusion, which is essentially a process of merging information gathered from several sources through various stages of the modeling procedure. There are three basic types of data fusion – early, intermediate, and late fusion, each having advantages and disadvantages regarding information preservation and the level of complexity required. While early fusion allows joint modeling of data from different sources, it increases the risk of noise in the case of incompatible sources. On the other hand, late fusion makes it possible to preserve model independence, but does not provide sufficient information interaction (Alaerjan *et al.*, 2024; Dou *et al.*, 2025; Ma and Li, 2026).

Ensemble models, by contrast, represent an attempt to aggregate predictions obtained from various models in order to achieve greater accuracy and reduced uncertainty. An ensemble approach is effective to the degree that the base models used in it are sufficiently diverse. Indeed, if models are too similar to each other, their outputs are unlikely to differ substantially, and thus there will be little benefit in using the entire ensemble rather than just one of its models (Sehrawat *et al.*, 2023; Wang *et al.*, 2023).

A final factor to consider when designing ensemble systems is how weighting and selection are performed. In static weighting, a constant level of importance is assigned to each classifier, while in dynamic weighting, the degree of

Table 6
Overview of hybrid and ensemble modelling strategies, data fusion techniques, and aggregation mechanisms for advanced solar energy applications (Ali *et al.*, 2026; Lafuente-Cacho *et al.*, 2025; Liu *et al.*, 2025; Miraki *et al.*, 2025; Sakib *et al.*, 2025; Zhang *et al.*, 2020).

Category	Approach/ Strategy	Core concept	Key design considerations	Advantages	Limitations	Application relevance
Hybrid modeling	Modular Pipeline Design	Sequential processing with specialized components	Selection of stages; compatibility between modules	Improves representation of complex data patterns	Increased system complexity	Multi-stage solar forecasting frameworks
	Signal Decomposition Integration	Splitting data into trend/seasonal/residual components	Choice of decomposition method; reconstruction accuracy	Reduces noise; stabilizes learning	Preprocessing overhead	High-variability irradiance prediction
	Spatial–Temporal Integration	Combining spatial and temporal processing blocks	Data structure alignment; feature consistency	Captures multi-dimensional dependencies	Complex architecture design	Multi-source solar data analysis
Data fusion techniques	Early Fusion (Input-Level)	Combining multiple data sources before modeling	Data normalization; compatibility of sources	Enables joint feature learning	Sensitive to noisy inputs	Multi-sensor solar datasets
	Intermediate Fusion (Feature-Level)	Merging extracted features from different models	Feature alignment; dimensional consistency	Balanced information integration	Requires feature engineering	Hybrid feature-based modeling
	Late Fusion (Decision-Level)	Combining outputs from separate models	Selection of aggregation rule	Maintains model independence	Limited cross-feature interaction	Ensemble forecasting systems
Ensemble methods	Bagging	Training models on different data subsets	Sampling strategy; number of models	Reduces variance; improves stability	Limited bias reduction	Robust solar prediction systems
	Boosting	Sequential correction of model errors	Learning rate; iteration control	Improves accuracy; reduces bias	Sensitive to noise	High-precision forecasting
	Stacking	Meta-model combining base predictions	Meta-learner selection; diversity of models	Flexible and adaptive combination	Higher complexity	Multi-model solar forecasting
Aggregation strategies	Static Weighting	Fixed weights assigned to models	Weight selection method	Simple implementation	Not adaptive to changing conditions	Stable environments
	Dynamic Weighting	Adaptive weights based on performance	Real-time evaluation; update rules	Improves adaptability	Requires monitoring mechanism	Variable weather conditions
	Meta-Learning	Learning optimal combination using a secondary model	Training data for meta-model	High flexibility; improved accuracy	Increased training complexity	Advanced ensemble frameworks
Uncertainty handling	Probabilistic Ensembles	Using model diversity to estimate uncertainty	Distribution modeling; confidence intervals	Provides reliability assessment	Computational overhead	Risk-aware decision-making
	Confidence Interval Estimation	Quantifying prediction spread	Statistical assumptions	Enhances interpretability of results	May require large datasets	Grid operation planning

contribution is adjusted according to the performance of the model in certain situations. Higher-level systems use meta-learning strategies to decide how to best combine models for maximum effect, which enables the system to respond dynamically to evolving datasets (Hanif *et al.*, 2025; Huang *et al.*, 2023). A flow chart of the stacked ensemble ML method is depicted in Figure 9.

In addition to these benefits, the use of hybrid and ensemble models presents new possibilities for uncertain prediction, since multiple predictions can be employed to establish levels of certainty or probabilities. This feature becomes especially useful for decision making scenarios where risk assessment is needed, since this information allows decision-makers to evaluate the likelihood of certain outcomes occurring (Miraki *et al.*, 2025; Sakib *et al.*, 2025). These approaches have their own drawbacks, however, which need to be considered in terms of design choices. The integration of several components results in higher complexity in both computational and implementation terms, which requires coordinated work between various components. Besides, the compatibility of these components can become a problem especially for hybrid models when the data representation is very different from one another. Another drawback that is worth noting is the loss of transparency that comes from combining several models, as it becomes increasingly hard to interpret the output as the complexity grows (Ali *et al.*, 2026; Lafuente-Cacho *et al.*, 2025).

From the systems approach, hybridization and ensemble modeling can be seen as part of the shift towards composite model building, where high performance comes not from a single model but from the coordinated action of several interacting components. In conclusion, hybridization and ensemble are approaches that go beyond the boundaries of individual models. They rely on the principles of integration, diversity, and adaptation and require careful work in terms of design choices and implementation. The data flow, model interactions, and aggregation process are crucial aspects for the success of these modeling strategies (Ceylan and Yumurtacı, 2025; Liu *et al.*, 2025; Zhang *et al.*, 2020). In general, hybrid and ensemble modelling strategies, data fusion techniques, and aggregation mechanisms for advanced solar energy applications are given in Table 6.

5. Applications of ML in solar energy

ML algorithms have developed to become fundamental elements of contemporary solar power systems, being involved in performing a variety of functions ranging from simple predictions to complex decisions made on the basis of various datasets. Besides, ML methods are utilized for more than just making forecasts; they play an important role in planning, controlling, and analyzing the performance of a whole system (Abualigah *et al.*, 2022; Mamodiya *et al.*, 2025b). The following section is devoted to an overview of several important application fields.

5.1 Solar irradiance and power forecasting

Predictive precision with respect to solar radiation and electricity production is of crucial significance in fulfilling the requirements and supplying the required generation. Models that employ ML can be used to predict data on various time scales, contingent upon the requirements on each scale (Vanlalchhuanawmi *et al.*, 2025).

Intra-minute time scales may be considered when the forecast model needs to operate on a very short horizon. In such cases, grid balancing is a significant application, where instantaneous corrections are required whenever there is an unforeseen change in electricity generation. On the other hand, day-ahead or intra-day time scales may be considered for short-horizon forecast models. These forecast models require prediction data for energy scheduling and trading purposes in the energy markets. Another development in this regard includes scenario-based and probabilistic forecasts, whereby several forecasts are generated as opposed to having a single prediction. This provides decision-makers with an idea about various possible states that could arise in the future. Furthermore, forecasting tools now integrate contextual inputs, including local climate patterns and site attributes (Chatterjee *et al.*, 2024; Gupta *et al.*, 2025; Lari *et al.*, 2025).

5.2 PV system performance optimization

ML becomes an important factor in improving the efficiency of operation in PV devices because it provides possibilities for adaptive optimization approaches. Specifically, such applications are aimed at the maximum energy gain and reduced losses in the face of changing conditions. First, ML technologies are applicable for the improvement of power generation control strategies. Namely, ML algorithms become helpful to find the optimal operating point in terms of current and voltage of the system. Unlike classical methods, this approach allows for taking into account various changes since ML algorithms rely upon data. Second, ML algorithms can be applied for optimizing operations in PV cells in regard to their operational parameters, depending on various factors such as exposure to the environment or other specifics of usage (Chandola *et al.*, 2026; Lari *et al.*, 2025; Naser *et al.*, 2025). ML techniques are also being applied to energy loss analysis, whereby they help determine inefficiencies caused by either environmental or operating conditions. The identification of such contributing factors enables efficient measures for boosting system efficiency (Chatterjee *et al.*, 2024).

5.3 Fault detection and predictive maintenance

The reliable operation of solar energy generation systems necessitates consistent monitoring and timely fault detection to ensure their proper functioning. ML offers advanced fault diagnosis through recognizing certain patterns related to system wear and tear and malfunctioning. ML led fault detection solutions use ML algorithms to separate regular operation from abnormal states. They can detect a variety of problems ranging from equipment degradation and electric faults to the impact of the environment on the system. Unlike traditional monitoring techniques based on a set of fixed rules, ML methods are capable of adapting to changing conditions and discovering subtle deviations. Prediction of remaining useful life (RUL) and potential failure in predictive maintenance builds upon the above approach, allowing for proactive planning of repair operations. It helps avoid unplanned downtimes caused by sudden equipment breakdowns and saves money on reactive maintenance. Such applications are especially relevant to large-scale solar facilities where manual inspection is impossible. A third application area that is beginning to emerge is root cause analysis, where ML models can be leveraged to identify the reasons for observed anomalies. This will facilitate effective problem-solving in the maintenance process (Ahmed *et al.*, 2020; Mellit *et al.*, 2021; Zhang *et al.*, 2020).

5.4 Energy management and grid integration

The incorporation of solar energy into the energy grid brings about substantial difficulties concerning variation, intermittence, and balancing with other sources of energy. ML offers means by which the challenges can be controlled through energy management systems. In distributed energy systems, ML helps in balancing power generation, storage, and usage to maximize efficiency in energy usage. The ML models assist in making decisions such as load shifting, storage allocation, and demand response to balance the supply and demand (Arévalo and Jurado, 2024; Mellit *et al.*, 2021; Yang *et al.*, 2018; Zhao, 2025).

In interconnected energy systems, ML is useful in stabilizing the system through prediction and control of system parameters. This is achieved in voltage control, frequency control, and congestion management (Mellit *et al.*, 2021). ML algorithms can be utilized in energy market optimization where prediction models assist in making bidding and price-related decisions. The applications allow solar energy systems to become more competitive when dealing with energy markets. Also, as solar energy systems integrate with smart grids, ML finds its applications in real-time monitoring and management through using ongoing data streams. This application allows for adjusting to changes in circumstances (Chandola *et al.*, 2026).

5.5 Emerging application areas

In addition to the traditional fields, ML has started to find applications in various new sectors that help enhance the functioning of solar energy systems. These include location and resource selection, which entails the use of models based on geographical and environmental data to determine the ideal locations for installing the solar panels. ML also finds application in policy formulation and planning, where it helps make predictions about future energy trends. Another area where ML can be employed concerns the use of solar energy in conjunction with hybrid energy systems that incorporate multiple forms of energy generation, including wind power, energy storage systems, and other traditional forms of energy generation (Das *et al.*, 2024; Matos *et al.*, 2024). Table 7 presents a detailed comparison of different types of ML applications in solar energy systems. It identifies the aims, data needs, benefits, and system-related aspects of these applications.

6. Model evaluation, challenges, and limitations

Rigorous evaluation of ML models in solar energy systems requires a multidimensional framework that accounts for prediction accuracy, robustness under variability, and operational feasibility. Review literature consistently highlights that many reported performance gains are highly dependent on experimental design choices, including dataset selection, preprocessing pipelines, and validation strategies. Consequently, a critical assessment of evaluation practices, data-related uncertainties, and deployment constraints is essential to ensure that ML models provide reliable and transferable performance in real-world conditions (Hyndman and Athanasopoulos, 2021).

6.1 Performance metrics and validation strategies

The evaluation of performance in solar energy systems goes further than simply reducing errors since context-specific assessment of the model is essential. Although mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) are among the key metrics, research articles highlight that these error terms only assess some dimensions of prediction performance, especially under extreme conditions. Models with similar errors on average

Table 7
Comparative analysis of major ML application domains in solar energy, emphasizing functional roles, data characteristics, and operational impact (Arévalo and Jurado, 2024; Das *et al.*, 2024; Khan *et al.*, 2025; Kiasari *et al.*, 2024)

Applications	Operational objective	Role of ML	Input Data characteristics	Key advantages	Primary challenges	System-level impact
Solar Irradiance & power forecasting	Predict future solar generation across different time horizons	Time-series prediction, probabilistic forecasting, scenario generation	High-frequency temporal data, meteorological inputs, historical generation data	Improves grid stability; supports energy scheduling and trading	Sensitivity to weather variability; uncertainty in extreme conditions	Enables reliable dispatch planning and grid balancing
PV performance modeling & optimization	Maximize energy output and system efficiency	Pattern learning, parameter optimization, adaptive control	Operational system data, environmental conditions, performance logs	Enhances energy yield; reduces operational losses	Requires continuous data monitoring; model recalibration needed	Improves long-term system efficiency and cost-effectiveness
Fault detection & predictive Maintenance	Identify anomalies and predict system failures	Anomaly detection, classification, remaining useful life estimation	Sensor data, electrical measurements, system diagnostics	Reduces downtime; enables proactive maintenance	Limited labeled fault data; false alarm risk	Increases system reliability and reduces maintenance costs
Maximum power point tracking	Optimize real-time power extraction under varying conditions	Real-time decision-making, adaptive control strategies	Instantaneous voltage, current, irradiance data	Faster response to environmental changes; improved power output	Real-time computation constraints; sensitivity to noise	Enhances instantaneous energy harvesting efficiency
Energy management & grid integration	Balance supply-demand and optimize resource allocation	Optimization, load forecasting, decision support systems	Multi-source data (generation, load demand, storage status)	Enables efficient energy distribution; supports smart grid operation	Complexity in multi-system coordination; data integration challenges	Improves grid stability and energy utilization efficiency
Emerging applications (site selection, hybrid systems)	Optimize system planning and integration	Spatial analysis, multi-objective optimization	Geographic, climatic, and infrastructure data	Supports strategic planning; improves deployment efficiency	Data heterogeneity; uncertainty in long-term predictions	Facilitates scalable and sustainable energy expansion

might show very different performances when confronted with rapid decreases in irradiance levels, affecting grid stability significantly. As an alternative solution, multi-dimensional evaluation criteria become widely employed as they integrate error metrics into a larger evaluation process, including bias, variance, distribution error, and other indices. Specifically, error asymmetry and tail error assessment metrics are crucial for applications requiring worst-case scenarios (Bessa *et al.*, 2015; Hyndman, 2014; Makridakis *et al.*, 2018b).

The methodology used for model validation is equally important. Review papers advise against random sampling as a validation technique because of the problem of temporal leakage – information from the future becomes included in training data. Therefore, techniques like rolling horizon and blocked cross-validation, which are appropriate for modeling in time series, should be considered. Cross-domain and cross-seasonal validation techniques can also be considered as another advanced feature in model evaluation. This kind of validation method is used to see whether the model performs well in terms of its ability to handle environmental variability. Recent research suggests using evaluation techniques based on probabilistic forecasting, such as prediction interval coverage probability and continuous ranked probability score (Hyndman, 2014; Purwanto *et al.,* 2024). Though such advancements have been made, however, one of the primary drawbacks associated with this field is that there is no standardization with respect to benchmarking methods, making comparisons between various research studies difficult. The use of different data sets, pre-processing techniques, and evaluation methods makes the process of determining model superiority impossible (Gupta *et al.*, 2025; Wang *et al.*, 2026).

6.2 Data quality, uncertainty, and generalization

Data quality is a fundamental determinant of model reliability, yet solar energy datasets are frequently affected by

Table 8
Advanced overview of model evaluation strategies, data-related challenges, and deployment limitations in ML-based solar energy applications (Ahmed *et al.*, 2020; Kiasari *et al.*, 2024; Matos *et al.*, 2024; Song *et al.*, 2025).

Aspect	Category	Key elements	Technical implications	Challenges	Recommended directions
Performance evaluation	Error Metrics	MAE, RMSE, MAPE	Quantifies prediction deviation under different error sensitivities	Single-metric evaluation may misrepresent performance	Use multi-metric evaluation frameworks
	Distributional Metrics	Bias, variance, error distribution	Captures model consistency and error spread	Difficulty in interpreting multiple metrics	Integrate statistical and probabilistic measures
	Probabilistic Metrics	Prediction intervals, CRPS	Evaluates uncertainty and confidence in predictions	Increased computational complexity	Adopt uncertainty-aware evaluation models
Validation strategies	Temporal Validation	Rolling window, time-series split	Preserves temporal structure for realistic evaluation	Computational overhead	Standardize time-aware validation protocols
	Cross-Domain Validation	Cross-site, cross-season testing	Evaluates generalization across environments	Data availability limitations	Develop benchmark multi-region datasets
	Benchmarking Practices	Standard datasets and pipelines	Enables reproducibility and fair comparison	Lack of unified standards	Establish open benchmarking frameworks
Data-Related challenges	Data Quality Issues	Missing values, noise, inconsistencies	Affects model stability and learning accuracy	Difficult preprocessing and cleaning	Develop robust data preprocessing pipelines
	Data Heterogeneity	Multi-source variability	Impacts model consistency across datasets	Integration complexity	Use standardized data fusion strategies
Uncertainty	Environmental Uncertainty	Weather variability, atmospheric effects	Introduces inherent unpredictability	Hard to model deterministically	Use probabilistic and ensemble approaches
	Model Uncertainty	Approximation and training limitations	Affects prediction reliability	Overconfidence in outputs	Apply Bayesian and ensemble-based methods
Generalization	Distribution Shift	Changes in climate, location, system setup	Reduces model transferability	Performance degradation in new environments	Use transfer learning and domain adaptation
	Scalability Issues	Application across large systems	Affects deployment feasibility	Computational and data constraints	Develop scalable and adaptive models
Interpretability	Model Transparency	Feature importance, explainability methods	Enables understanding of predictions	Limited interpretability in complex models	Use explainable AI techniques (XAI)
	Trustworthiness	Reliability and consistency	Builds confidence in decision-making	Black-box behavior	Combine interpretable and high-performance models
Deployment constraints	Computational Cost	Training and inference complexity	Limits real-time application	High resource requirements	Develop lightweight and efficient models
	System Integration	Compatibility with existing infrastructure	Affects practical deployment	Integration complexity	Use modular and interoperable frameworks
	Model Lifecycle	Monitoring, retraining, updating	Ensures long-term performance	Model drift over time	Implement continuous learning pipelines

systematic and stochastic imperfections. Review papers report that measurement errors, sensor calibration drift, and communication failures introduce inconsistencies that can distort learned relationships. These issues are particularly pronounced in long-term datasets, where gradual degradation in data quality may remain undetected (Ohtake *et al.*, 2022). Aside from inaccuracies inherent in the collected data, uncertainties stem from various factors like environmental variations, model deficiencies, and the preprocessing stage of the data itself. Environmental uncertainty comes from atmospheric phenomena that have predictable behavior as well as random variations, whereas model uncertainty is caused by the problems with the learning process, including approximations and sensitivity to the data. According to reviews, the lack of modeling of these types of uncertainties may cause overconfidence in models, which in turn might influence decision-making negatively (Lunche Wang *et al.*, 2024; Wang *et al.*, 2026).

Recently, research efforts were made in developing modeling techniques that are uncertainty-aware, for instance, using ensembles to estimate variance, applying Bayesian inference, or estimating quantiles. Such approaches allow predicting not only point estimates, but intervals and distributions, giving a possibility to make better decisions. Nevertheless, such approaches introduce new challenges in terms of complexity and calibration (Gneiting and Raftery, 2007). Generalization under varied conditions has been recognized as one of the major obstacles in applying ML approaches for solar energy forecasting. The models trained on regional data usually experience a distribution shift in application to different regions, resulting in lower prediction accuracy. Review papers have discussed several reasons for this problem, including discrepancies in climatic conditions, system architecture, and data acquisition strategies (Pandžić and Capuder, 2023). A recently raised challenge pertains to the relationship between data pre-processing and model performance, with data normalization, transformation, and treatment of missing data having a significant effect on the results. According to reviews, data pre-processing is supposed to be considered an important part of the model-building process, rather than a separate procedure (Ahmed *et al.*, 2020).

6.3 Interpretability and deployment constraints

The growing popularity of complex ML algorithms has raised significant issues of interpretability, robustness, and practical implementation. According to review articles, many advanced algorithms often prove to be insufficiently transparent, hindering understanding of how the input features affect the outcomes. Such models become especially inconvenient when explanations of their decisions are necessary, for example, in cases related to system control and maintenance or regulatory compliance (Rudin, 2019). Various solutions have been offered as a response to the problem of interpretable algorithms, with such techniques as feature attribution methods, sensitivity analysis, and surrogate modeling being some examples. These solutions seek to shed light on algorithmic decisions without adversely affecting prediction quality. Finding an optimal solution that would combine interpretability with efficiency proves to be quite a challenge (Weller, 2019). Lastly, the use of ML algorithms in solar energy systems involves considerations that relate to reliability and trustworthiness, especially for mission-critical purposes. The need for ensuring reliability through performance consistency across varying scenarios and means of detecting faults is vital for gaining confidence in the system. Table 8 offers a detailed discussion of the approaches adopted for evaluating ML algorithms, issues encountered, and future research directions in relation to solar energy systems (Visser *et al.*, 2024).

7. Explainable AI and physics-informed ML

ML for solar energy systems will evolve from the current state of performance-focused modeling to the creation of robust, adaptable, and integrated intelligent systems. Although present systems have shown considerable progress in terms of accuracy and efficiency, they can only go so far because of the shortcomings of robustness, transferability, interpretability, and integration into the physical world. Future work should aim to incorporate ML algorithms into dynamic energy systems as integrated parts (Fathollahi, 2025; Villano *et al.*, 2024). One key step toward this goal is to shift from fixed and data-set-specific ML models to ones that are aware of the context and constantly adapting to the changing environment.

7.1 Explainable AI and physics-informed ML

Explainable Artificial Intelligence (XAI) refers to a set of methods and techniques designed to make the decisions and predictions of artificial intelligence systems more transparent, interpretable, and understandable to humans. As AI models become increasingly complex, particularly with the use of deep learning and ensemble methods, understanding how these models generate outputs has become a major challenge. XAI aims to address this issue by providing clear explanations of model behavior, thereby improving trust, accountability, and fairness in AI-driven systems. The lack of causal interpretability is one of the most notable shortcomings of current ML applications in the field of PV, where the learned association does not necessarily reflect a physically significant relationship. The future of research in such application domains should focus on the creation of causality-based ML approaches that would allow models to understand whether two variables are associated by coincidence or by a physical relationship (Fathollahi, 2025; Raja Sekhar *et al.*, 2025; Verdone *et al.*, 2025). The idea of Explainable Artificial Intelligence (XAI) will develop towards decision consistency when model predictions are explained according to domain-specific reasoning. This will require the introduction of hierarchical explanation algorithms that work on several layers, including feature, model, and systems-level (Buschmeier *et al.*, 2025). In the context of solar application of ML, PIML will become an interesting avenue for research in the field. One of the major problems of current solutions is static formulation of physical relationships in the system. Future developments should focus on adaptive approaches that adjust system constraints according to data distribution and other parameters. Another promising research direction involves incorporating hybrid symbolic-neural methods that incorporate explicit representations of physical laws alongside learned representations. These models might have the advantage of improving interpretability and generalizability, especially when there is little or dirty data available (Buschmeier *et al.*, 2025; Moosavi *et al.*, 2024; Zhang *et al.*, 2022).

7.2 Real-time and edge-based solar analytics

Growing decentralization in solar power generation calls for an approach towards intelligent decision-making in real-time. In the future, models developed by ML techniques need to function with stringent latency, energy, and computation requirements, calling for the design of models that are both accurate and resource-efficient. One key area of research is the co-design of algorithms and hardware, wherein different models are designed based on particular devices. This entails the development of neural architectures that make use of certain computational properties of hardware (Han *et al.*, 2016; Sze *et al.*, 2020).

The move towards real-time decision-making calls for models that can continually adapt without starting off afresh in their training process. In other words, there needs to be a model that can learn new patterns of behavior but also retain its existing knowledge. A promising line of research is the creation of event-driven learning systems that update their models only when significant changes are detected in the input data. Such a system would not require constant computation and can be applied effectively to settings where variability occurs intermittently. The convergence of all these methods will result in the development of solar systems that regulate themselves and operate autonomously (Liyuan Wang *et al.*, 2024; Zhou *et al.*, 2024).

7.3 Integration with smart grids and storage

The future systems will be operating as an integral part of an ecosystem-like energy system, involving decision-making and optimization at all levels, ranging from production through storage to utilization. This calls for the development of ML capabilities that can operate on several levels. A particularly promising area here lies in the development of ML based on distributed or multi-agent models, where each of the parts of the system will serve as an independent decision-making agent. In doing so, they have to coordinate their actions by common goals under conditions of limited information and communications capacity. The inclusion of energy storage in the process adds even more complexity, owing to multiple criteria, such as efficiency, wear, costs, and dependability of energy sources involved (Matos *et al.*, 2024; Pandey *et al.*, 2023; Zhou *et al.*, 2024).

The next crucial issue is managing the propagation of uncertainties among interdependent systems, whereby uncertainties in RE production influence other elements of the power system, like energy storage units and grid stability. This calls for developing uncertainty-aware system-level models, which will account for the interdependence between different subsystems. Another essential aspect is the creation of an architecture that will facilitate the incorporation of ML models in existing systems, thus facilitating large-scale adoption. This will involve designing a modular system that allows for the substitution of one element without affecting other parts of the system (Chien, 2025; Matos *et al.*, 2024; Pandey *et al.*, 2023; Pinson, 2013).

8. Conclusion

This review provides a comprehensive synthesis of the application of ML techniques in solar energy systems, bridging the gap between methodological advances and practical deployment considerations. The analysis points out that while data-driven approaches are significantly improving the intelligence, efficiency, and operational performance of solar energy systems, there are still several critical challenges. These include limitations in data quality and availability, inconsistencies in model evaluation practices, lack of interpretability and constraints associated with large scale deployment. The results highlight that future advances in this field cannot be achieved solely through improvements in predictive accuracy. Instead, there is an increasing demand for building strong, transparent, and adaptable learning structures that can function under real-world conditions. Such frameworks must handle the inherent variability and complexity of solar energy systems while ensuring reliability and scalability. In the future, the combination of ML with the physical processes behind solar energy generation and the grid operation is one of the main research directions. This requires the development of tightly coupled systems, integrating learning algorithms with system dynamics and control mechanisms to facilitate more effective and coordinated energy management. Such a high level of integration is required to allow for large-scale and practical deployment. ML is overall poised to be a game-changer in the development of the next generation of solar energy systems for greater resilience, efficiency, and sustainability. The insights presented in this review can provide a basis for future work, underscoring the need for developing interpretable, adaptive, and deployable models to tackle the complexity of real-world energy systems.

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