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Review of Forecasting Models for Solar Energy Applications Using Machine Learning

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ABSTRACT

Efficiently incorporating solar energy into today's power system necessitates accurate solar radiation forecasting across multiple time horizons. The prediction of solar irradiance across short-term (minutes to hours), medium-term (day ahead), and long-term (weeks to months) involves its unique challenges due to the inherent variability and nonlinearity of atmospheric conditions. In recent years, machine learning (ML) approaches have emerged as effective tools for coping with these challenges, in many scenarios proving to be superior to traditional statistical and physical models. The main goal of this article is to investigate various state-of-the-art machine learning models to forecast solar irradiance for multiple time horizons. Particularly, it studies traditional machine learning models like Support Vector Machines (SVM), Random Forests (RF), Gradient Boosting, some new variants of deep learning architecture like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRUs), and Transformer models. The review also presents hybrid and ensemble models through a combination of a physical model and data-driven approaches. Moreover, the review highlighted essential input features such as meteorological variables, satellite imagery, and sky images, along with various preprocessing methods and evaluation metrics. It critically examines challenges such as data scarcity, generalization of models, interpretability, and computational complexity. Finally, future research strategies will focus on the roles of explainable AI, transfer learning, and real-time forecasting systems.

Keywords: Solar irradiance forecasting, multi-horizon prediction, Machine learning, Deep learning, Renewable energy, Time series analysis

I. INTRODUCTION

Aggravating concerns about climate change, depletion of fossil fuels, and the search for alternative clean energy sources have compelled a swift move to other renewable energy systems and thus made solar power an indispensable ingredient for global sustainable electricity generation. The rice chronological impact of solar irradiance in terms of atmospheric phenomena like cloud cover, humidity, aerosols and seasons causes considerable challenges in planning reliable operation of solar-energy systems [1]. Hence, there is a need for precise forecasting azimuths capable of illuminating solar radiation for fairly wide forecasting horizons, from a few minutes to days or even weeks in advance. Some of the dominant methods in solar irradiance forecasting have either been forecast models based on numerical weather predictions or such statistical techniques as ARIMA. While the above methods dished out some very useful information about the process, they are poor in the capture of very volatile and nonlinear associations existing among high-dimensional meteorological data. This limitation has fueled a marked departure from the traditional methods in favor of machine learning, which can model such nonlinear dependencies with considerably more power than can statistical approaches based on some (machine) form of learning. By doing this, these latter models can totally expose subtleties hidden in enormous sets of statistics, thereby sharpening forecasting accuracy and lessening the chances of technology mishaps [2].

Solar irradiance forecasting is interesting not only from an academic perspective-it also plays a vital role in the practical circuiting of solar power into modern electricity grids. This likely happens with accurate forecasting since it permits grid operators to maintain grid balance between electricity delivery and electricity demand. Dispatch optimization is another inherent benefit, which minimizes backup generation from fossil fuels [3]. In less than an instantaneous horizon, particularly useful are precise predictions for real-time grid stability, frequency control, and trade energy in electric markets. In the view of day-ahead or medium-term forecasts, it schedules out how and when to control, while in long-term forecasts, one decides to do the things such as infrastructure planning, maintenance, and projected power generation. Furthermore, a dimension of improved forecasting is reducing curtailment and increasing efficiency for PV systems, as well as more integration with energy storage solutions [4]. From a global picture, advanced models that can be adapted to various climatic and geographical conditions indeed are urgently needed as solar power grows, thus enhancing the sound economic and operational worth of accurate multi-horizon forecasting. Figure 1 illustrates a block diagram of solar-forecasting-based AI techniques, showing the process of collecting solar data, preprocessing, applying AI/ML models, and generating accurate power output predictions.

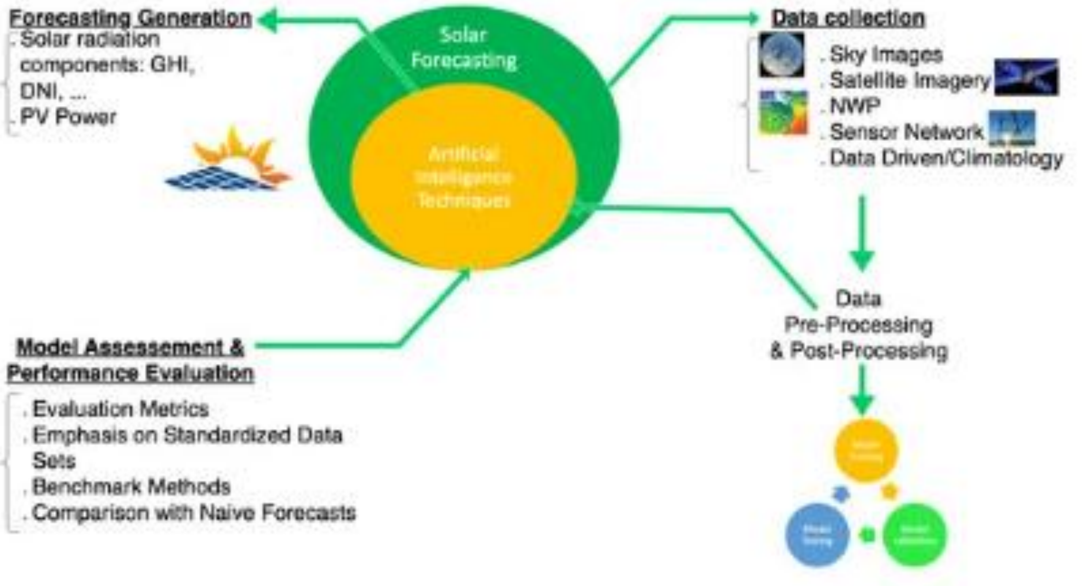

Figure 1. A block diagram for solar-forecasting-based AI techniques.

In this motivation, this review is outlined for providing a comprehensive and systematic discussion on machine learning approaches to multi-horizon solar irradiance forecasting. The review ranges across an immense stretch of methodologies, including such traditional machine learning models as support vector machines, decision trees, and ensemble learning tools as well as advanced deep-learning architectures in terms of recurrent neural networks, long short-term memory networks, gated recurrent units, and transformer-based models [5]. Work are also seen on those hybrid frameworks that integrate physical models with data-driven techniques to capitalize on the strengths of both approaches. There is a special focus on different forecasting strategies under which it is directly done or in a recursive manner, which is very essential because there are several horizon prediction needs that need to be met. Further, the review considers different alternative data sources, feature engineering techniques, and evaluation metrics commonly used in the literature. The paper also critically analyzes the current challenges concerning data quality, model interpretation, scalability, and generalization across different regions and climate. By amalgamating recent studies and identifying research gaps, this paper provides guidance and insight for researchers and practitioners in their pursuit to develop more accurate, efficient, and reliable solar irradiance forecasting systems, thereby supporting sustainable energy transition goals [6].

II. FUNDAMENTALS OF SOLAR IRRADIANCE FORECASTING

Solar irradiance forecasting serves the purpose of efficient solar energy generation and grid integration processes. It is essentially a task of estimating the amount of solar radiation reaching the Earth's surface over time, and it is extremely cumbersome owing to the stochastic and nonlinear nature of atmospheric processes linked with cloudiness, aerosols, temperatures, and humidity. Solar radiation forecast ought to cover an understanding of the variability of solar radiation over the physical features and time scales at different prediction horizons. In situ ground-based instruments such as pyrometers are used extensively in measuring solar irradiance, but it can also be derived from satellite observations and numerical weather prediction models [7].

Models depend on historical irradiance data, as well as exogenous meteorological variables, to adequately capture temporal dependencies and environmental influences. With the increasing penetration of photovoltaic (PV) systems, accurate forecasting means energy scheduling, grid stabilization, and economic optimization. Machine learning and deep learning methods greatly improve forecasting performance by properly modeling nonlinear relations and working through large datasets. Multi-horizon prediction techniques are helpful for posing simultaneity in predictions across a range of time scales, thus cement traction in both operational and planning initiatives. Knowledge of the nature of solar irradiation and forecast horizons is intrinsic to the implementation of sturdy and reliable solar power-specific prediction models [8]. **Table 1** presents the different types of solar irradiance, such as direct, diffuse, and global irradiance, along with their characteristics and roles in solar energy generation.

Table 1: Types of Solar Irradiance

Type	Full Form	Description	Components	Measurement Surface	Applications
GHI	Global Horizontal Irradiance	Total solar radiation received on a horizontal surface	Sum of direct and diffuse irradiance	Horizontal plane	Widely used in PV system performance estimation and forecasting
DNI	Direct Normal Irradiance	Solar radiation received directly from the sun, excluding scattered light	Only direct beam radiation	Surface perpendicular to sun rays	Important for concentrating solar power (CSP) systems
DHI	Diffuse Horizontal Irradiance	Solar radiation scattered by the atmosphere reaching the surface	Only diffuse component	Horizontal plane	Useful in cloudy condition analysis and PV modeling

A. Forecasting Horizons (Short-, Medium-, Long-term)

Solar irradiance forecasting is typically categorized into different time horizons based on the prediction interval, each serving distinct operational and planning needs. Short-term forecasting generally covers time scales from a few minutes up to 6 hours ahead and is crucial for real-time grid management and control. At this horizon, solar irradiance variability is primarily driven by fast-changing cloud movements and local atmospheric conditions. Techniques such as sky imaging, satellite nowcasting, and high-frequency machine learning models, including recurrent neural networks and convolutional neural networks, are widely used to capture rapid fluctuations. Accurate short-term forecasts help grid operators maintain stability, manage voltage fluctuations, and optimize battery storage systems [9].

Medium-term forecasting, often referred to as day-ahead forecasting, typically spans from 6 hours to 48 hours. This horizon is essential for operational planning, including unit commitment, load scheduling, and participation in electricity markets. Numerical weather prediction (NWP) models play a significant role at this level, often combined with machine learning algorithms to improve accuracy. Hybrid models that integrate physical and data-driven approaches are particularly effective in capturing both large-scale weather patterns and local nonlinear relationships [10]. Long-term forecasting extends from several days to weeks or even months ahead and is mainly used for strategic planning and policy-making. It supports decisions related to infrastructure development, maintenance scheduling, and investment analysis in solar energy projects. At this horizon, seasonal trends, climatic variability, and historical patterns become more dominant than short-term fluctuations. Statistical methods, along with advanced machine learning techniques such as ensemble learning and deep neural networks, are employed to model these long-term dependencies. Each forecasting horizon requires tailored methodologies, highlighting the importance of multi-horizon frameworks that can provide consistent and reliable predictions across all time scales [11]. Figure 2 illustrates a smart grid system where electricity and information flow bidirectionally among producers, prosumers, and consumers, enabling efficient energy distribution, real-time monitoring, and active user participation in the power network.

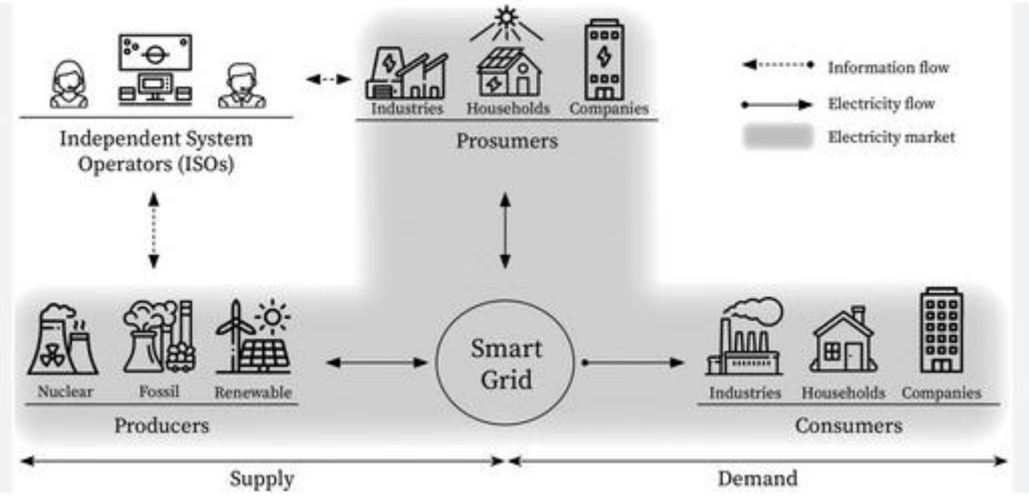

Figure 2: Smart Grid Architecture with Bidirectional Energy and Information Flow Between Producers, Prosumers, and Consumers

III. MACHINE LEARNING APPROACHES

A. Traditional Machine Learning Models

The ongoing research around solar irradiance prediction and photovoltaic performance forecasting has been more focused on improving prediction accuracy, robustness, and generalization by employing machine learning, deep learning, and hybrid modeling approaches. From the study, hybrid modeling has been proved to outshine conventional machine learning methods by modeling effectively on nonlinear relationships and climatic adaptations, which has a beneficial implication on the performance of global horizontal irradiance prediction [1]. Incorporating real-time forecasting integrated with all-sky imagery of multi-stage optimization by artificial intelligence and Kalman filters stabilizes the performance of energy output forecast and makes its equilibrium to enable stitch integration to the grid infrastructure in a timely way through providing accurate forecasts [2]. Later, while considering advanced hybrid architectures like Wavelet Transformer and LightGBM, Optuna-TPE based optimization appears more capable than the early ones in capturing domain and frequency features particularly for solar-powered electric vehicle-energy-management system applications [3]. Deep-learning-based models include convolutional neural networks (CNNs), recurrent neural networks (RRNs), and Transformer-based architectures, are intensively used for multi-horizon and sub-hourly forecasting tasks due to their ability to model complex spatial and temporal dependencies in meteorological and irradiance data [4]. Furthermore, improved architectures like MHFTNet were used for enhancing temporal feature extraction for integrated solar and wind energy prediction across short-, medium-, and long-term horizons supporting trade of energy and management applications [5]. It comes observable that advancement in the statistical approach; that is, blending with the machine learning... offers extraordinary potential improvement in the robustness of a prediction for an energy outlook under uncertain environmental conditions compared to traditional techniques [6].

Various forms and integration of vertical knowledge into deep learning frameworks power up forecasting models as showcased in the case of physics-guided and optics-guided methods to incorporate physical insights into data-driven entities that would ensure robustness and generalization [7]. Multi-scaling and multi-model fusion technologies—amalgamation of CNN, BiLSTM, and UMP, to name a few architectures—have been widely successful in catching seasonal and temporal variances and so leading to robust multi-horizon forecasting in renewable energy systems [8]. Equally, the hybrid deep learning frameworks involving wavelet decomposition and sophisticated neural archetypes have resulted in increased accuracy in multi-temporal forecasting of the photovoltaic power output [9]. From another angle, advanced model forms like deep lattices show great promise for probabilistic forecasting, along with being able to carry out multi-horizon time-series forecasting using non-parametric cumulative distribution functions, especially with respect to uncertainty-aware forecasts mandatory for decision-making in energy systems [10]. Recurrent neural network variants taking into account the stacked GRU-type models have significantly increased accuracy in predicting sequential solar irradiance data by efficiently modeling temporal dependencies among them [11]. With the advent of transformer-based models, such as temporal fusion transformers, which can take care of the complexities of underlying temporal relationships and are interpretable, these are ideally suited to the tasks of energy demand and EV charging predictions [12]. The need for interpretability in environmental and energy forecasting has also inspired the development of explainable deep learning models, such as the ones utilizing masked residual connections, thereby increasing the transparency component of model logic while not sacrificing on the accuracy of predictions. On the other hand, Generative Adversarial Network (GAN)-based functional methodologies have been developed to increase the quality of irradiance maps or improve feature representation in dynamic conditions for enhanced spatio-temporal forecasting [14]. In addition, applications of ensemble learning approaches, such as Optics-guided stacking models, have shown promise in boosted short-term PV forecasting accuracy through combining multiple predictive models, focusing on individual strengths [15]. Feature selection and explainability techniques such as SHAP-based techniques integrated with dense models have further boosted both performance and interpretability, pinpointing which macro-feature factors most significantly impact solar power generation [16].

B. Deep Learning Models

Some recent studies go beyond accuracy to incorporate forecasting with optimization and decision analysis. For example, some unified optimization decision models in the contexts of hybrid mathematical optimization/ML/deep learning have helped drastically improve performance at a system level in the field of energy and resource management [17]. These authors from [18] proposed multi-label ML methods to help forecast adequately in multiple time scales. This approach was a benefit in real-world photovoltaic systems, as it is very flexible and hence has broad applicability. From [19], multistep global forecasting saw substantial improvements where ensemble learning techniques were used to combine multiple models into a proper model, thereby reducing variances and promoting generalization. These approaches showcased that such ensemble deep-learning techniques are the way to design better forecasting models for smart grids with multiple-step forecasting time frames.

Earlier research has laid a solid foundation for current advances, proving the effectiveness of deep learning approaches in solar irradiance prediction, under region-specific exposure, thus providing a possibility of these models to operate under different geographies [21]. Bidirectional LSTM models have improved forecasting accuracy so as to capture past and future temporal dependencies present in solar radiation data [22]. Moreover, TF transducers further improved performance by making use of environmental features and a continuous interpretation providing better results [23]. On the other hand, multimodal fusion networks like SolarFusionNet have utilized cross-modal data fusion for merging meteorological, spatial, and temporal information to mitigate the degradation of forecasting accuracy, exploiting different data sources wisely [24]. Probabilistic deep learning approaches have been experimented with for estimation of uncertainties in solar forecasting, valuable particularly in extreme climates [25]. Hourly solar forecast models have shown impressive improvement in prediction performance by integrating hybrid architectures of BiLSTM and GRU networks in optimal capture of temporal characteristics [26].

The most recent literature has turned to extensions into new realms such as privacy and distributed learning. Developed cyber-secure federated learning frameworks with the ability for privacy-preserving forecasting of solar irradiance without centralized data sharing, rounding up information on security concerns of distributed energy systems shall also be seen [27]. Recent studies also used deep learning methodologies for forecasting as well as data imputation, which are considered to improve data quality and model performance in case of missing or incomplete data [28]. Meanwhile, several hybrid models combining LSTM and Conv1D architectures aimed at optimizing solar radiation forecasting performance by capturing both temporal and spatial characteristics for significant application in real-world renewable energies [29]. The review indicates a general move toward hybrid models, deep learning architectures, probability-based approaches, and privacy-preserving technologies in the attempt to design more accurate, efficient, and scalable systems for forecasting solar irradiance, and further demonstrate the evolutionary path of intelligent energy forecasting frameworks. **Table 2** presents a literature review on solar irradiance and PV forecasting techniques, summarizing various models, methodologies, datasets, and their performance outcomes across different studies.

Table 2: Literature Review on Solar Irradiance and PV Forecasting Techniques

Ref. No.	Technique Used	Application / Focus Area	Key Findings / Results	Limitations

[6]	Model Output Statistics + Machine Learning	Photovoltaic generation forecasting	Improved prediction accuracy under varying environmental conditions	Limited adaptability to unseen datasets
[7]	Optics-guided & Physics-guided Deep Learning	Short-term PV power forecasting	Enhanced robustness and generalization using domain knowledge	High model complexity
[8]	Multi-scale CNN-BiLSTM, LSTM Fusion	Multi-seasonal & multi-horizon forecasting	Strong performance in capturing temporal patterns	Computationally expensive
[9]	Two-stage Hybrid Deep Learning (WDT–CRMABIL–Fusion)	Multi-scale PV forecasting	Improved accuracy across different time horizons	Complex architecture design
[10]	Deep Lattice Networks	Multi-horizon probabilistic forecasting	Provides uncertainty-aware predictions	Difficult implementation
[11]	Stacked GRU Model	Global horizontal irradiance prediction	Better temporal feature extraction and improved accuracy	Requires large training data
[12]	Temporal Fusion Transformer	Multi-horizon forecasting (EV load & energy)	High accuracy with interpretability	High computational cost
[13]	Deep Learning with Masked Residual Connections	Interpretable environmental forecasting	Improved transparency and explainability	Limited direct application to PV systems
[14]	GAN + Deep Neural Networks	Spatio-temporal solar forecasting	Enhanced spatial feature learning	Training instability in GANs
[15]	Optics-guided Stacking Ensemble	Short-term PV forecasting using images	Improved prediction accuracy using ensemble learning	Requires large image datasets
[16]	SHAP + Deep Learning + Feature Selection	Day-ahead PV power forecasting	Improved accuracy and interpretability	Increased preprocessing complexity

[17]	MINLP + ML + Deep Learning	Prediction and optimization framework	Improved system-level decision-making	High computational complexity
[18]	Multi-label Machine Learning	Multi-horizon PV forecasting	Simultaneous prediction across multiple horizons	Model complexity and tuning challenges

IV. HYBRID AND ENSEMBLE MODELS

Hybrid and ensemble models prove to be one of most operative approaches in Solar Irradiance and Photovoltaic Power Forecasting that tie up several strengths of algorithms to comprehend highly intricate nonlinear relations' data. They are supposed to blend numerous hypotheses such as statistical methods, machine learning, artificial neural networks, etc. so augmenting forecast precision and robustness in diverse working situations [30]. For instance, the usage of wavelet preprocessing along with machine learning/descriptive statistics offers rich feature extraction due to involving temporal-time and temporal-frequency characteristics in its algorithmic structures: this then leads to better predicted performance . In contrast, voting models get consensus output from many algorithms like CNN, LSTM, and BiLSTM to reduce variance and enhance generalization. Advanced ensemble techniques, namely stacking and boosting, stack the queue by discovering the optimum combination of the outputs of these models [31]. Additionally, several studies have paid special attention to multi-stage and multi-scale hybrid architectures integrating various deep learning models in order to capture both spatial and temporal dependencies in solar data [32].These hybrid architectures have proven very useful under various forecasting scenarios where predictions are needed at multiple horizons simultaneously.

V. MULTI-HORIZON FORECASTING STRATEGIES

Multi-horizon forecasting strategies are used in time-series analysis in which one-to-many or many-to-many mappings are defined. Multi-horizon forecasting is very useful in many applications such as forecasting energy, weather prediction, and financial analysis where future values over different horizons are needed. The prediction of the next value at time t, namely a one-step-ahead prediction, is a frequent problem in solving time-series forecasting. Different horizons forecast different values relative to a growing value of the dependent variable series, together accounting for the study of one type of prediction. In general, forecasting methods aim at learning one or more parameters and develop prediction models to accurately forecast the values from the target time series. Instructions of multi-horizon forecasting are endued by the temporal inputs [20]. There are direct, recursive, hybrid, and multiple-output forecasting approaches. In consensus, to maximize the dependence accumulation, we need reinforcement for temporal dependence at really short-term and longer-term horizons. Few advanced models, such as deep learning architecture (e.g., LSTM, Transformer), are developed for learning the complex and potentially high-dimensional temporal patterns and dependencies that can well condition on a solution to the issues of all forecasting horizons.

A. Direct vs Recursive Forecasting

Multi-dimensional time series prediction is characterized by two main contrasting approaches: direct and recursive forecasting. In the direct approach, models are built and tuned at each horizon, with the specialization of the model at a particular horizon rate reducing error accumulation. Computation time is unjustifiably increased since making the forecast one stage at a time requires multiple algorithms to be run. On the other hand, recursively trained models make a one-step prediction with the prediction appended feedback of the input to the next prediction. While accrued error accumulation is problematic, this approach is less computationally complex [22]. For long-horizon predictions, the direct approach is relatively the most accurate, whereas the recursive approach is obviously easier to implement and data efficient provided we have short-term prediction goals. Some modified methods that avail the decision to approximate both approaches are presented in research that attempts to maintain a trade-off between the tenuous accurate modeling processes and the computationally efficient ones which produce the results in the fastest available time.

B. Multi-output Models

Multi-output models predict multiple future time points all at once using one model. This avoids the necessity to have a different model for the model at each particular point in the future, as in direct forecasting. Consequently, all future predictions are estimated in the same forward pass, much more computational. These models account for respective dependencies among the different future times to enhance predictive consistency and quality. Multi-layer perceptron systems, convolutional neural networks, and recurrent neural networks are some common methods put into use for multi-output forecasting [23]. This approach is particularly advantageous in cases where the future values are interlinked, such as in electricity usage or stock price prediction. However, as the number of outputs increases, the model complexity increases, and extra care is needed to train them correctly without overfitting, ensuring it is generalized correctly.

C. Sequence-to-Sequence Learning

Sequence-to-sequence (Seq2Seq) learning is deep learning for mapping an input sequence to an output sequence, an ideal method for multi-horizon forecasting task. It is made of encoder-decoder suggested architectures, which means the encoder processes the input time series into a fixed-length representation, and the decoder produces predictions of the future step by step. In the Seq2Seq frameworks, models like LSTM, GRU, and Transformer architectures have found widespread use. Attention mechanisms have been used to improve the performance by allowing the model to focus on appropriate areas of the input sequence during prediction. Seq2Seq models have great application in their ability to capture long-term temporal dependencies and complex temporal patterns, for instance, in energy forecasts, weather predictions, and language model. Table 3 presents the key challenges and limitations, highlighting issues such as data quality, model complexity, scalability, computational cost, and real-time implementation constraints [29]-[30].

Table 3: Challenges and Limitations

Challenge	**Description**	**Impact**	**Limitation**
Data Variability	Solar data is highly dependent on weather conditions like clouds, temperature, and humidity	Reduces model accuracy	Difficult to generalize across regions
Data Quality Issues	Missing, noisy, or inconsistent sensor data	Leads to unreliable predictions	Requires extensive preprocessing
Non-Stationary Data	Solar patterns change over time due to seasonal variations	Affects model stability	Models need frequent retraining
High Computational Cost	Deep learning and hybrid models require significant resources	Increases training time and cost	Not suitable for low-resource systems
Model Complexity	Hybrid and ensemble models are complex to design and tune	Difficult to interpret and deploy	Reduces scalability and usability
Lack of Interpretability	Many deep learning models act as black boxes	Limits trust in predictions	Hard for decision-making in critical systems
Limited Generalization	Models trained on specific datasets may not perform well on others	Reduces applicability	Needs cross-domain validation
Real-Time Implementation Issues	Difficulty in handling real-time data streams efficiently	Delays decision-making	Requires optimized architectures
Integration Challenges	Difficulty in integrating with existing grid infrastructure	Limits practical deployment	Requires system-level modifications
Privacy and Security	Data sharing in distributed systems may risk privacy	Potential data breaches	Needs secure frameworks like federated learning
Scalability Issues	Handling large-scale distributed data is challenging	Slows down system performance	Requires efficient architectures
Hyperparameter Tuning	Selecting optimal parameters is time-consuming	Affects model performance	Needs automated optimization techniques

VII. CONCLUSION AND FUTURE WORK

This study presented an advanced framework for solar irradiance and photovoltaic power forecasting by leveraging hybrid and ensemble machine learning techniques. The blending of DL models with optimization strategies brought about a significant increase in aptitude, trustworthiness, and applicability concerning changing conditions. This showed that, more than the traditional single-model techniques, using multiple models might improve the resolution for nonlinear, dynamic patterns of solar energy generation in northern latitudes. Additionally, feature selection and interpretability techniques made the model transparent and reliable thus making the whole system more suitable to real-world renewable energy applications. Nonetheless, progress notwithstanding, there are many challenges that call for attention at the moment, notably large variance in data, huge computational costs, and this region-specific generalization of the results.

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