Solar Irradiance Forecasting Approaches Based on Machine Learning: A Systematic Literature Review

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***Abstract*—The prediction of solar irradiance plays a crucial role in the design, performance, and stability of renewable energy sources, and especially photovoltaic (PV) power generation. Accurate forecasting helps in managing energy, grid stability, and integration of solar energy in contemporary power systems. The study is a Systematic Literature Review (SLR) of 37 recent (2019-2025) peer-reviewed papers on solar irradiance forecasting that apply Machine Learning (ML), Deep Learning (DL), and hybrid or ensemble modelling methods. The review is based on the Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA 2020) to make it transparent and reproducible. A thorough search of seven large databases, such as Google Scholar, IEEE Xplore, Web of Science, Springer Nature Link, ScienceDirect, MDPI and the ACM Digital Library, was conducted to find relevant studies. Based on a structured synthesis of the chosen literature, the findings suggest that there is a definite methodological change in the traditional ML methods to DL and hybrid modelling structures. Although the classical ML algorithms have low computational complexity and can be effectively used to make short-term predictions, DL architectures consistently outperform them in terms of capturing nonlinear temporal and spatial patterns in solar irradiance data. Moreover, hybrid models combining DL architectures with signal decomposition and feature fusion methods also improve predictive accuracy. Nevertheless, the review notes that there are a number of ongoing shortcomings, such as the lack of geographic generalizability because of single-site dominance, the lack of consistency in reporting computational efficiency, the inconsistency of evaluation metrics, the lack of robustness testing in dynamic weather conditions, and a strong bias towards short-term forecasting horizons. In order to fill these gaps, future studies need to focus on multi-site and cross-climatic validation, domain adaptation using transfer learning, designing lightweight models to deploy in real-time, standardised benchmarking guidelines, and broaden their scope to medium and long-term forecasting with enriched meteorological inputs. Overall, the results offer an evidence-based, systematic review of existing trends in methodology and emphasise the need to balance predictive accuracy with generalizability, efficiency, and practical application in solar energy forecasting systems.**

Keywords*—*Solar irradiance forecasting; Machine Learning; Deep Learning; hybrid models; Systematic Literature Review

I. Introduction

Solar power is a major renewable resource that can be used to reduce climate change and to supply the ever-growing global electricity demand. However, solar irradiance is very temporal and sensitive to meteorological conditions like cloud dynamics, atmospheric composition, temperature and humidity making it difficult to make precise predictions [1]. This natural intermittency presents an element of uncertainty in the operation of Photovoltaic (PV) power systems and electrical grids to the stability, reliability and economic performance of the system [2]. The inaccuracy of the forecasts can lead to power imbalances, poor dispatch choices, reserve overage, and operational expenses, which restrict the large-scale integration of solar energy [3]. Therefore, improving the accuracy and strength of solar irradiance forecasting is a focal point of research in the field of renewable energy and grid integration [4].

To address these issues, various forecasting strategies have been explored, including classical statistical models and physical models as well as data-driven Machine Learning (ML) models [5]. Though conventional models are based on pre-established assumptions and simplified physical relationships, they do not usually describe the nonlinear and stochastic interactions between solar irradiance and atmospheric variables [6]. ML-based methods have thus become popular because of their ability to acquire complicated patterns using historical irradiance and meteorological information. Earlier experiments have used regression models, tree-based algorithms, Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), and Deep Learning (DL) models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks to enhance the accuracy of forecasts. Ensemble and hybrid models have also been put forward in order to capitalise on complementary model strengths and to enhance performance under different climatic conditions [7].

Although they are said to be successful, in the real world of operation, ML-based forecasting models are usually limited. Issues with data quality, non-stationarity and distributional changes due to seasonal variability, climate anomalies, or sensor degradation can cause Model performance to degrade [8]. In addition, most studies based on site-specific data and controlled experimental design limit model extrapolation across geographical areas and time spans. More advanced methods like feature selection, hyperparameter optimisation and probabilistic forecasting have been proposed to enhance robustness and reliability. However, the quantification of uncertainty and operational resilience has not been investigated thoroughly in most of the literature [9, 10]. New methods such as transfer learning and federated learning have demonstrated the potential to deal with data scarcity, privacy issues and regional heterogeneity. Conversely, Explainable Artificial Intelligence (XAI) methods are becoming more popular to enhance the

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interpretability of models and enable trust in ML-driven prediction systems [11-13].

This Systematic Literature Review (SLR) critically analyses and synthesises recent advances in ML, DL and hybrid-based solar irradiance forecasting reported between 2019 and 2025. The review systematically finds and categorises available forecasting methods into ML, DL and hybrid architectures and compares their reported performance based on popular metrics. In addition to performance comparisons, the study will discuss the advantages and disadvantages of these techniques in practical implementation. The discussion identifies some common problems, such as inadequate generalisation of models across geographic and climatic boundaries, preponderance of short-term forecasting research, underreporting of operational and computational needs and weak performance in highly variable weather. Lastly, the review identifies several significant research gaps and future research directions. It also offers practical insights and methodological advice on developing reliable, scalable and application-oriented solar irradiance forecasting models for renewable energy systems.

This SLR makes the following contributions to the literature:

- Provides a comprehensive systematic review of ML, DL and hybrid methods for solar irradiance forecasting.
- Provide a structured classification of forecasting approaches into traditional ML, DL and hybrid/ensemble models used for solar irradiance prediction.
- Provide a comparative evaluation of forecasting performance across studies using commonly reported metrics such as RMSE, MAE, nRMSE and the coefficient of determination (R^2).
- Provide a critical analysis of ongoing limitations such as limited model generalizability across climatic regions, insufficient reporting of operational and computational metrics, the dominance of short-term forecasting studies and limited evaluation under highly variable weather conditions.
- Identification of key research opportunities such as the development of generalizable multi-site forecasting models, integration of NWP with DL for longer forecasting horizons, lightweight and efficient architectures for real-time deployment, probabilistic forecasting frameworks and the creation of standardised benchmark datasets.

The rest of this study will be organised in the following way: Section II will provide the background. Section III describes the methodology of the review according to the PRISMA framework. Section IV introduces the chosen studies to review and provides a comparative analysis of the forecasting models and their performance. Section V explains the major issues of research, limitations, and the practical deployment. Section VI points out the future research directions and methodological recommendations. Lastly, Section VII gives the limitations of this review and the conclusion of the work.

II. BACKGROUND

In order to contextualise the existing studies on solar irradiance forecasting, it is necessary to develop a clear vision of the inherent features of the variability of solar irradiance, the constraints of the traditional forecasting methods, and the increasing role of ML in renewable energy systems. This section examines these background concepts and systematically prepares the ground on which the detailed analysis in the following sections will be based.

A. Solar Irradiance Variability

The other important parameter that influences PV power production is solar irradiance. But solar irradiance is highly variable since it is affected greatly by the atmospheric and meteorological conditions [14]. Variables such as the concentration of aerosols, movement of clouds, humidity, temperatures, and geometry of the sun contribute to the variability of solar irradiance [15]. Fluctuation of solar irradiance presents a number of challenges to the management of power systems, particularly in the increased use of solar energy in modern electrical systems [15]. The issue is that, contrary to the traditional fuels, solar energy cannot be turned on and off according to the load needs [16]. Thus, it is important to forecast the amount of solar irradiance accurately to ensure stability and proper power load management, as well as participation in energy market activities. Short-term variability may bring about voltage fluctuations and frequency instability, whereas longer-term forecasting errors can be inefficient scheduling of backup generation and higher operating costs [17]. Consequently, the nature and cause of the variability of solar irradiance is the key area of concern in renewable energy studies.

B. Challenges in Solar Irradiance Forecasting

The prediction of solar irradiance remains a challenge because it is stochastic, nonlinear and dynamic in nature [18]. Although the radiation of the sun itself is deterministic, it interacts with a number of atmospheric variables, including clouds, aerosols, and water vapour, which make it stochastic [19]. Solar irradiance forecasting at the beginning was largely grounded on statistical and physics-based modelling with the use of Numerical Weather Predictions (NWP) [20]. Although these techniques are promising when studied at a greater time scale, they perform poorly in forecasting short-term variations in the solar irradiance [21]. The reason is that they are not effective in forecasting irradiance in partly cloudy skies. Moreover, the availability of data is another issue, as not all the data may have been available and there may be noise in sensors that capture irradiance measurements [22]. The lack of data and climatological differences between various geographical locations also make the predictive models training and deployment more difficult [23]. Such problems have inspired the creation of data-driven methods that can directly acquire complex patterns through historical observations.

C. Machine Learning for Solar Irradiance Forecasting

Machine Learning (ML) algorithms have proven to be quite effective in forecasting the performance of solar energy systems thanks to their ability to deal with non-linear relations and build complicated representations of varied inputs [24]. The ML algorithms have proven to be the best approaches in solar radiation forecasting in the short term as well as in day-ahead predictions [25]. This has been attributed to the fact that the algorithms have the capability to simulate very complex interactions of non-linear meteorological variables such as the solar irradiation, temperature, wind speed, and humidity [26]. ML algorithms do not require any assumption regarding physical processes, as opposed to other traditional methods, which require some physical properties. The algorithms are capable of making good use of historical irradiation and meteorological data to enhance their forecast effectiveness [27]. Solar irradiance forecasting has been performed with different ML methods, such as regression-based methods, Decision Trees (DTs), Support Vector Machines (SVMs), ensemble learning methods, such as Random Forests (RFs) and Gradient Boosting (GB), Deep Learning (DL), and hybrid methods that integrate data-driven methods with other methods [28, 29]. The techniques are highly appreciated due to their flexibility in modelling. The computation needs, however, differ significantly among model classes.

ML algorithms that are applied in predicting solar irradiance have three major classifications. They are unsupervised, hybrid and supervised [30]. Among all these types, the supervised ML algorithms have demonstrated excellent performance in the case of sufficiently good quality training data [31]. These algorithms mostly use handcrafted features extracted from historical solar irradiance data, weather parameters, and time indicators to obtain accurate predictions [32]. Nevertheless, their effectiveness is highly dependent on having plenty of data, being vulnerable to overfitting, and low generalisation abilities for unknown locations with different climates [33]. In order to overcome these issues, the DL algorithms have gained a great deal of interest in recent years due to their ability to directly obtain complex features based on raw data [34]. The most popular DL structures to use in modelling solar irradiance time series include Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory Networks (LSTM) [35, 36]. Particularly, LSTM algorithms have been effective in learning long-term dependencies in solar irradiance variations [37, 38].

Unlike supervised learning methods, unsupervised learning methods do not need labelled data and are mainly applied to the task of clustering, pattern discovery, and regime identification [39]. These methods are very useful in understanding the underlying structure of irradiance and meteorological data and can be used to aid forecasting by adaptive model selection or feature extraction [40]. But in contrast to the supervised methods, the unsupervised methods do not directly produce irradiance forecasts and are generally only feasible when combined with predictive models [41].

Hybrid forecasting methods are also increasingly being combined with supervised and unsupervised learning techniques using statistical or physical models. These kinds of hybrid models take advantage of complementary capabilities of different algorithms to enhance the accuracy and reliability of predictions in different weather conditions [42]. Hybrid Machine Learning models, especially, have gained quite a lot of attention in relation to predicting solar irradiance due to the nonlinear, non-stationary, and stochastic nature of solar energy [43]. The solar irradiance is also subject to a number of meteorological conditions, such as cloud cover, temperature, humidity, wind speed, and aerosol content; such factors cannot be well modelled using only one modelling method [44]. Hybrid models are able to give a more realistic account of these complex dynamics by combining complementary learning approaches.

Even though hybrid approaches tend to enhance predictive reliability, they can add complexity to the model, raise the cost of computation, and raise the design and tuning needs [45]. Hybrid ML models, in general, have better accuracy, flexibility, and generalizability of multiple forecasting horizons [46]. They are especially fit in real-world solar energy systems because they are able to combine spatial, temporal, and physical information, and accurate forecasting is important in grid stability, energy management, and to enable the successful integration of renewable energy resources [47].

Though significant progress has been made in this area, there is a tendency for ML, DL, and ML-DL forecasting algorithms to be ineffective in practice because of non-stationary processes, seasonality changes, and changes in the distribution of weather patterns [48]. In a bid to mitigate these challenges, ensemble learning techniques, probabilistic forecasting and hyperparameter optimisation approaches have been proposed. However, there are inconsistent uptakes of these methods in the literature. These difficulties prove the necessity of the systematic analysis and critical synthesis of the existing approaches.

This development of ML-based solar irradiance forecasting studies forms the basis of the SLR in this study, which seeks to synthesise existing knowledge, evaluate the methodological strengths and limitations, and uncover gaps and future research directions in the field of ML-based solar irradiance forecasting.

III. Methodology

The methodology of this SLR defines the structured approach adopted to identify, screen, and synthesise existing research on ML and DL-based solar irradiance forecasting. The review was conducted in accordance with the PRISMA 2020 guidelines to ensure transparency, methodological rigour, and reproducibility.

A. Review Protocol and Prisma Guidelines

The SLR in this study was conducted in accordance with the PRISMA framework, which provides a structured process for identifying, screening and selecting relevant studies. A predefined review protocol was established to guide the search strategy, inclusion and exclusion criteria, data extraction and synthesis process. This protocol was designed to minimise selection bias and ensure consistency throughout the review.

B. Research Questions

The SLR in this study was guided by the following Research Questions (RQs):

- RQ1: What types of predictive models are used for solar irradiance forecasting and what model architectures are commonly adopted?

- RQ2: What data sources, input features, feature selection methods and feature engineering techniques are utilised in these forecasting models?
- RQ3: What forecasting horizons are primarily addressed in the literature?
- RQ4: What model optimisation and tuning techniques, evaluation metrics, and validation methods are employed to assess forecasting performance?
- RQ5: What key findings, limitations, challenges and research gaps are reported in the literature regarding the development, generalizability and real-world deployment of solar irradiance forecasting models?

C. Research Objectives

To address these research questions, the following Research Objectives (ROs) were formulated:

- RO-1: To identify and analyse the types of predictive models, including ML, DL and hybrid approaches, used for solar irradiance forecasting and to examine their commonly adopted architectures.
- RO-2: To investigate the data sources, input features, feature selection methods and feature engineering techniques utilised in solar irradiance forecasting models.
- RO-3: To examine the forecasting horizons addressed in the literature, including short-term, medium-term and long-term solar irradiance prediction.
- RO-4: To analyse the optimisation and tuning techniques, evaluation metrics and validation methods used to assess and compare forecasting model performance.
- RO-5: To identify the key findings, limitations, challenges and research gaps reported in the literature regarding the generalizability and real-world deployment of solar irradiance forecasting models.

D. Search Strategy

A comprehensive search strategy was developed using combinations of relevant keywords and Boolean operators. These keywords were combined using logical operators (AND, OR) to retrieve relevant studies. The search was limited to peer-reviewed publications to ensure scientific quality. The primary search terms included:

("solar irradiance forecasting" OR "solar radiation prediction") AND

("machine learning" OR "deep learning" OR LSTM OR CNN OR GRU OR transformer OR "ensemble learning" OR "hybrid models" OR "sky images")

The literature search was limited to studies published between 2019 and 2025 to capture recent advances in ML and DL techniques for solar irradiance forecasting.

E. Data Source Material

A comprehensive literature search was conducted using seven major electronic databases widely recognised in the fields of renewable energy, power systems and artificial intelligence. These databases include Google Scholar, IEEE Xplore, Web of Science, SpringerLink, ScienceDirect, MDPI and ACM Digital Library. These databases were selected to ensure broad coverage of high-quality, peer-reviewed research.

F. Inclusion and Exclusion Criteria

Clear inclusion and exclusion criteria were established to maintain the rigour and relevance of the SLR. The journal or conference articles were included under the following strict conditions:

- They have been published between 2019 and 2025.
- They have been peer-reviewed and are accredited according to the latest Department of Higher Education and Training-accredited journal list.
- They focused on ML and DL based solar irradiance or solar radiation forecasting.
- They provided an empirical evaluation using quantitative performance metrics.

Studies were excluded if:

- They have been published before 2019.
- They have no empirical or experimental validation.
- The metric evaluation results are not explicitly discussed.
- They are written in other languages instead of English.
- They are tutorials, letters, editorials, review articles, opinion papers, and blogs.

These criteria ensured that the review captured recent, evidence-based research while excluding non-technical or outdated sources, thereby strengthening the reliability and relevance of the synthesised findings.

G. Study Selection Process

The study selection followed the PRISMA four-stage process:

- Identification: All records retrieved from databases were compiled, and duplicates were removed.
- Screening: Titles and abstracts were screened to exclude irrelevant studies.
- Eligibility: Full-text articles were assessed based on inclusion and exclusion criteria.
- Inclusion: Studies meeting all criteria were included in the final review.

A comprehensive literature search was conducted across relevant academic databases to identify studies on solar irradiance forecasting using ML techniques. A total of 162 records were initially identified through database searching.

Following identification, 66 duplicate records were removed, leaving 92 unique records for screening. The titles and abstracts of these records were screened to assess relevance to the research objectives. During this stage, 43 records were excluded for being irrelevant to solar irradiance forecasting or for lacking ML or DL methodologies.

The remaining 49 reports were sought for full-text retrieval; all were successfully obtained. These reports were then assessed for eligibility based on predefined inclusion and exclusion criteria. As a result of the full-text assessment, 12 reports were excluded for reasons including a lack of empirical or experimental validation and for not explicitly discussing metric evaluation results.

Ultimately, 37 studies met all inclusion criteria and were included in the final review. Each included study corresponded to a single report. The complete study selection process is illustrated in the PRISMA 2020 flow diagram shown in Fig. 1.

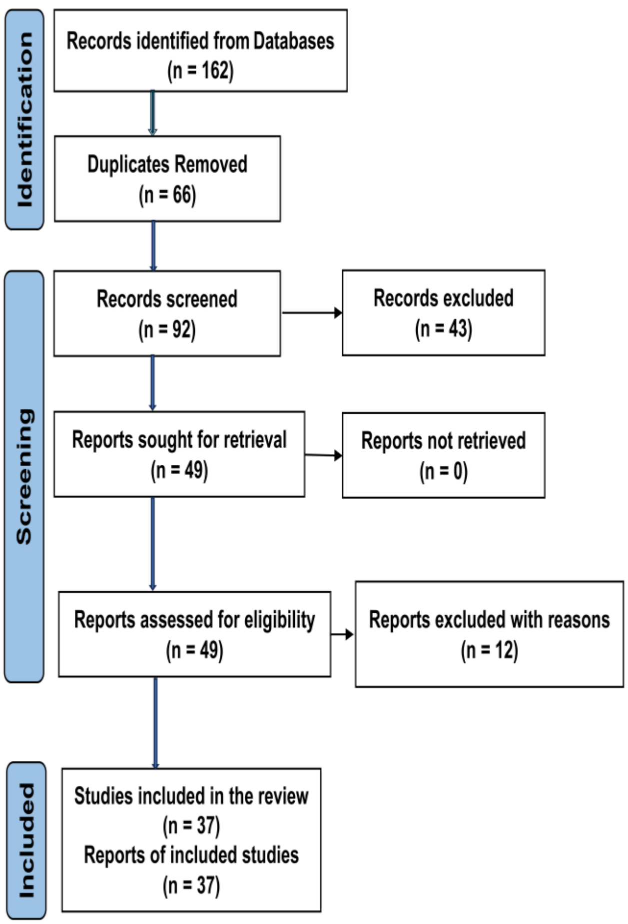

Fig. 1. PRISMA 2020 flow diagram of this study.

This systematic selection process ensures that only high-quality, relevant, and methodologically sound studies contribute to this review's findings.

H. Quality Assessment

The quality of the included studies was systematically assessed to determine the reliability and methodological rigour of the research in a simplified checklist-based framework. Instead of numeric scoring, the studies were graded according to four broad criteria that encompassed the quality of data, methodological rigour, the strategy of validation and clarity of reporting. Each of the criteria was assessed based on three possible outcomes, i.e., Yes, Partial or No (or not reported). The rating of "Yes" means that the criterion is completely met, the rating of "Partial" means that the criterion is met partially, and the rating of "No" means that the criterion is not met or not mentioned.

The following defines the assessment criteria: data quality evaluates whether the size, duration and source of the data are clearly described and adequate to the forecasting task; methodological rigour evaluates whether the model architecture, hyperparameter tuning and methodological decisions are clearly explained and reproducible; validation strategy evaluates whether suitable validation methods, such as time-based splitting or cross-validation, are employed to avoid data leakage and guarantee robustness; reporting clarity evaluates A Partial rating is also used to prevent subjectivity when a criterion is covered, but not detailed or comprehensive enough. Examples include a mention of a dataset source, but its size or duration is not completely stated, or validation is mentioned, but an unsuitable or imprecisely described method is employed.

Based on these criteria, each study was classified using a rule-based approach where high quality means that all four criteria were rated as "Yes", medium quality means that at least two criteria were rated as "Yes" and no criterion was rated as "No" (i.e., only "Partial" allowed otherwise), and low quality means any criterion was rated as "No". The final synthesis has filtered out studies that are of low quality in order to have a review that is grounded on solid and methodologically sound evidence. Table I includes the quality assessment criteria and checklist, and Table II includes the summary of the assessment results of all included studies. The findings show that none of the chosen studies were of low quality according to the established criteria; all of them are of high and middle quality. This implies that all of the included studies have a minimum level of methodological rigour and reporting adequacy. The most frequent restrictions found in medium-quality studies are associated with missing reporting of validation processes and transparency of hyperparameter tuning. This systematic but streamlined evaluation system enhances transparency, minimises subjectivity, and provides uniformity in assessing the quality of the methodology of the reviewed literature.

TABLE I. QUALITY ASSESSMENT CRITERIA AND CHECKLIST

Criterion	Description	Yes	Partial	No
Data Quality	Dataset source, size, duration, and type are clearly described and sufficient for the forecasting task	Clearly specified dataset (source, duration, resolution, inputs)	Partially described dataset (missing size/duration/type details)	Datasets unclear or not reported

Methodological Rigour	Model architecture, feature engineering, and hyperparameter tuning are clearly justified and reproducible	Full model description + tuning/justification provided	Model described but limited tuning/justification	Model unclear or not reproducible
Validation Strategy	Use of appropriate validation (chronological split, CV, walk-forward), preventing leakage	Clearly defined robust validation method	Validation mentioned but unclear/incomplete	No validation strategy reported
Reporting Clarity	Metrics clearly reported (RMSE, MAE, R², etc.) with transparency	Clear metrics and results reported	Metrics reported but incomplete/inconsistent	Metrics unclear or missing

TABLE II. QUALITY ASSESSMENT RESULTS FOR INCLUDED STUDIES

Ref	Data Quality	Methodological Rigour	Validation Strategy	Reporting Clarity	Quality
[49]	Yes	Yes	Yes	Yes	High
[50]	Yes	Yes	Yes	Yes	High
[51]	Yes	Yes	Yes	Yes	High
[52]	Partial	Yes	Partial	Yes	Medium
[53]	Partial	Yes	Partial	Yes	Medium
[54]	Yes	Yes	Yes	Yes	High
[55]	Yes	Yes	Yes	Yes	High
[56]	Yes	Yes	Yes	Yes	High
[57]	Yes	Yes	Partial	Yes	Medium
[58]	Yes	Yes	Yes	Yes	High
[59]	Yes	Yes	Yes	Yes	High
[60]	Yes	Yes	Partial	Yes	Medium
[61]	Yes	Yes	Yes	Yes	High
[62]	Yes	Yes	Yes	Yes	High
[63]	Yes	Yes	Yes	Yes	High
[64]	Partial	Yes	Partial	Yes	Medium
[65]	Yes	Yes	Yes	Yes	High
[66]	Yes	Yes	Yes	Yes	High
[67]	Yes	Yes	Yes	Yes	High
[68]	Yes	Yes	Partial	Yes	Medium
[69]	Yes	Yes	Yes	Yes	High
[70]	Yes	Yes	Yes	Yes	High
[71]	Yes	Yes	Yes	Yes	High
[72]	Yes	Yes	Yes	Yes	High
[73]	Yes	Yes	Yes	Yes	High
[74]	Yes	Yes	Yes	Yes	High
[75]	Yes	Yes	Yes	Yes	High
[76]	Yes	Yes	Yes	Yes	High
[77]	Partial	Yes	Partial	Yes	Medium
[78]	Yes	Yes	Yes	Yes	High
[79]	Yes	Yes	Yes	Yes	High
[80]	Yes	Yes	Yes	Yes	High
[81]	Yes	Yes	Yes	Yes	High
[82]	Yes	Yes	Yes	Yes	High
[83]	Yes	Yes	Partial	Yes	Medium
[84]	Yes	Yes	Yes	Yes	High
[85]	Yes	Yes	Yes	Yes	High

I. Data Extraction and Synthesis

For each included study, relevant technical details were systematically extracted, including the type of predictive model, forecasting horizon, data sources, model architecture, feature selection techniques, feature engineering techniques, tuning techniques, evaluation metrics, validation methods, key findings, and reported limitations. Due to variations in datasets and experimental settings, a descriptive qualitative synthesis was employed instead of a quantitative meta-analysis.

J. Classification Framework

The selected studies were organised according to their primary methodological approach into three categories: ML, DL, and Hybrid/Ensemble models. Each study was classified based on its principal contribution or best-performing model, rather than on all models included in the comparative evaluation. This methodological categorisation enables a structured comparison across studies, despite variations in objectives, datasets, and performance metrics, thereby facilitating the identification of methodological trends, research gaps, and potential directions for future work.

IV. Review of Selected Studies

In this section, 37 studies on ML, DL and Hybrid/Ensemble solar irradiance forecasting published between 2019 and 2025 are reviewed. The summaries of these studies are presented in Table III to Table V. Each research is evaluated in terms of the purpose, research methodologies, findings, and limitations found. The Goal dimension reflects the main research aim of every research, whereas the Method dimension explains the models or techniques applied. The outcome dimension will summarise the key results or findings of the performance, and the limitations dimension will identify the limitations or challenges that are reported by the authors. This is a summary of previous work that used ML, DL, and Hybrid/Ensemble in predicting solar irradiance. The methods go all the way from classical regression and tree models to DL structures, such as CNNs, RNNs, LSTMs, and hybrid/ensemble models. The works explore both the short-term (minutes to hours) and long-term predictions, using various input characteristics such as historical irradiance, meteorological variables, time indicators, sky images, and satellite-based data. Other works examine the probabilistic forecasting and quantification of uncertainty to aid in decision-making with regard to grid operations.

TABLE III. Summary of Selected ML Studies on Solar Irradiance Forecasting

Reference	Goal	Method	Outcome	Limitations
[49]	To evaluate whether linear ML algorithms can provide accurate short-term solar irradiance forecasting using sky images while maintaining low computational complexity.	Applied linear ML, including Lasso Regression, Ridge Regression (RR), Bayesian Ridge (BR), Stochastic Gradient Descent (SGD), LR, Generalized Linear Model (GLM), and RANSAC using three years (2014-2016) 1-minute resolution sky images (1536×1536 RGB) and solar irradiance data collected at the Energy Ville campus, Belgium. Used evaluation metrics including RMSE, Forecast Skill (FS), RMSE of Ramp Rate (RR), and Execution time (seconds) and used a chronological train/test split for model validation. Used Fisheye correction for feature engineering.	The Lasso achieved the highest accuracy for 5-10 min ahead forecasts, with RMSE of 0.05-0.062 W/m². SGD performed best for 15-30 min ahead with RMSE of 0.067-0.076 W/m². BR and RR consistently ranked among the top-performing models across all horizons. All models except RANSAC outperformed the smart persistence benchmark, demonstrating that simple linear models can rival more complex approaches for short-term forecasting.	Forecasting horizons are limited to 30 minutes due to the spatial constraints of sky imagers. The study is based on a single geographic location, limiting generalizability. Model performance depends strongly on image quality, reducing its applicability in regions lacking imaging infrastructure.
[50]	To develop a computationally efficient method for short-term and ahead-of-time solar irradiance forecasting from sky images while maintaining competitive accuracy.	The kNN and RF were employed for nowcasting and forecasting solar irradiance up to 4 hours ahead using two single-location sky image datasets (TSI-880 and ASI-16) covering 15 years in 10-minute resolutions, paired with GHI measurements from Golden, Colorado, USA. Used Latent Semantic Analysis (LSA) and Singular Value Decomposition (SVD) for future extraction. Used evaluation metrics, including Normalized MAPE (nMAPE) RMSE, Normalized RMSE (nRMSE) and used a chronological train/test split for model validation.	The proposed kNN model achieved competitive hourly forecasting accuracy, with nMAPE of 14.9% for TSI-880 and 14.7% for ASI-16; RMSE of 122.2 and 116.7 W/m²; and nRMSE of 7.7% and 8.9%, respectively, while reducing computational complexity by about 30% compared to state-of-the-art CNN/LSTM-based DL models.	The model's performance relies heavily on the availability and quality of sky camera images, limiting its applicability in regions lacking such infrastructure. Evaluation was conducted at a single site, limiting assessment of generalizability to other climates, camera setups, or large-scale deployment.
[51]	To forecast daily solar radiation in Riyadh, Saudi Arabia, using ML techniques and compare their predictive performance.	The study applied three ML models: ANN, RF, and LR, using historical meteorological data to predict daily GHI, obtained from the King Abdullah City for Atomic and Renewable Energy (KACARE). Used evaluation metrics including RMSE, MAE and direction accuracy and used a hold-out train/test split for model validation.	The RF model achieved the best performance, with a direction accuracy of 92.8571%, MAE of 13.6747 and an RMSE of 10.3157, outperforming the ANN and LR models. The results demonstrate that ensemble tree-based methods provide more accurate solar radiation predictions than traditional regression and neural	The study used data from a single location, limiting the generalizability of the results to other regions. Additionally, the comparison involved only three ML models, and more advanced DL approaches were not investigated. The study also focused on daily forecasting, without evaluating multi-step

			network approaches for the dataset studied.	or short-term high-resolution predictions.
[52]	To evaluate solar power forecasting performance using statistical, ML, and DL approaches.	Multiple algorithms were tested, including statistical models (Moving Average, Exponential Smoothing, ARIMA, SARIMA), ML models (RF, DT, LR, SVR, GB), and DL models (ANN, RNN, CNN, LSTM), using a dataset containing weather variables and generated solar power, for a 3-hour ahead forecasting horizon. Used Correlation-based feature selection. Feature extraction via transformations. Used evaluation metrics, including RMSE and MAE, and used a hold-out train/test split for model validation. Used adaptive feature selection	The RF model achieved the best forecasting performance with an RMSE of 4.04 kW and an MAE of 2.54 kW, outperforming all other models. DL models showed moderate performance due to the limited dataset size, and statistical models produced the highest errors, indicating poor capability to capture nonlinear patterns in solar power data.	The dataset used in the study was relatively small, limiting the performance of DL models, which typically require large datasets. The study also focused on single-dataset evaluation, meaning the results may not generalise to other geographic regions or datasets. Additionally, hybrid forecasting models were not explored, which could potentially improve prediction accuracy by combining multiple algorithms.
[53]	To improve the accuracy and reliability of solar power forecasting by evaluating different ML and DL models and identifying the most effective approach.	Four models were implemented and compared: LR, Polynomial Regression (PR), ANN, and RF, using historical solar power, meteorological, and environmental data for forecasting horizons of 1-10 days. Random Forest Regression (RFR) was used for future selection. Used evaluation metrics, including RMSE and R^2, and used a chronological train/test split for model validation. Correlation matrix used for feature selection. Grid search CV used for tuning.	The RF model achieved the best forecasting performance, with the lowest RMSE of 1.72 and the highest R^2 of 97.5% for up to 10-day-ahead forecasting. ANN also performed well but was slightly less accurate than RF. LR and PR produced higher prediction errors. The results demonstrate that ensemble learning methods, such as Random Forests, are highly effective at capturing nonlinear relationships in solar power data.	Forecasting accuracy decreases as the prediction horizon increases, especially for long-term forecasts such as 10 days ahead, due to increased weather uncertainty. The study evaluated only four models, and hybrid or ensemble combinations beyond RF were not explored. Additionally, the study does not clearly discuss dataset diversity or multiple geographic locations, which may limit the generalizability of the results.

TABLE IV. SUMMARY OF SELECTED DL STUDIES ON SOLAR IRRADIANCE FORECASTING

Reference	Goal	Method	Outcome	Limitations
[54]	To develop and evaluate DL based models for daily solar irradiance forecasting using single-site and multi-site data.	Evaluates DL models, including LSTM, GRU, CNN, Bidirectional LSTM (Bi-LSTM), and Attention-based LSTM, using multi-location and single-location solar irradiance data spanning 36 years. Pearson correlation, Spearman correlation, and XGB feature importance were used for feature selection. Used evaluation metrics including MSE, RMSE, and R^2 and used a rolling window validation method.	Demonstrated that bi-LSTM and at-LSTM models provide accurate daily solar irradiance forecasts, with R^2 values of 0.68-0.70 in the first location and R^2 values of 0.72-0.73 in the second location. This study shows that incorporating multi-site historical data improves prediction accuracy and reliability compared to single-site univariate models.	Performance gains depend on long-term, multi-site data, potentially limiting applicability in regions with sparse measurement infrastructure. Computational costs and DL model complexity were not assessed, restricting insights into efficiency, scalability, and real-world deployment.
[55]	To evaluate and compare DL and ML models for long-term solar radiation forecasting to support microgrid planning and photovoltaic energy potential assessment.	Applies multiple DL and ML models, including GRU, LSTM, RNN, FFNN, and SVR, RF on 17 years of hourly and daily solar irradiance data (2000-2017) from two regions in Korea. Used Pearson correlation analysis for feature selection. Used only RMSE evaluation metrics and used validation methods, including chronological train-test split and sliding-window method.	Demonstrated that GRU outperformed the other DL and ML models, with RMSE of between 0.3909 W/m^2 and 0.4582 W/m^2 for the hourly solar radiation data and 5.3315 W/m^2 and 6.2672 W/m^2 for the daily solar radiation data, demonstrating its effectiveness for 1-year-ahead long-term solar radiation forecasting.	The study focuses on long-term horizons, limiting applicability to short-term forecasting. Computational costs and DL model complexity versus ML models were not examined, restricting insights into efficiency, scalability, and real-world deployment.
[56]	To develop a sky image-based DL model for short-term 1-hour-ahead GHI forecasting without relying on numerical meteorological inputs across different weather conditions.	Develops a deep CNN SolarNet and compares it to the Persistence model (classic), Persistence of Cloudiness, SVR, and ANN, trained on six years of sky images and corresponding GHI data from a single site. Used nRMSE and FS evaluation metrics, and used a chronological train-test split validation method	The SolarNet model demonstrated robust performance, outperforming the other models, achieving an nRMSE of 8.85% and a forecasting skill score of 25.14%.	Evaluation was limited to a single site, raising concerns about generalizability. The approach relies solely on image-based inputs, excluding numerical meteorological variables. The high computational complexity of the deep CNN architecture may limit its applicability in regions without sky-image infrastructure.

[57]	To compare the predictive performance of ML and DL models for Global Solar Radiation (GSR) and Diffuse Solar Radiation (DSR) prediction across multiple locations.	Evaluates and compares several ML and DL models, including SVR, RF, Polynomial Regression (PR), ANN, CNN, and RNN, using 12 years of hourly solar irradiance data (2005-2016) from four locations in Nigeria. Used evaluation metrics including *r*, RMSE, MAE, NMBE and used a chronological train-test split validation method	The DL models outperformed the ML models for GSR and DSR prediction, with the RNN achieving the best overall performance in Yobe, yielding *r* of 0.9546, RMSE of 82.22 W/m², and MAE of 36.52 W/m². ML models had the lowest computation costs.	Computational costs and DL model complexity relative to ML models were not examined, limiting understanding of their efficiency, scalability, and real-world applicability.
[58]	To compare statistical, ML, and DL models for short-term and long-term forecasting of GHI using high-quality measured data from Islamabad, Pakistan.	Compares multiple forecasting models, including Seasonal ARIMAX, Facebook Prophet (FBP) for longer horizons, and ML and DL models such as ANN, CNN, and LSTM on 4.75 years of hourly GHI data (2017-2021) from Islamabad, Pakistan. Used evaluation metrics including R², MAE, MSE, RMSE and used a time-ordered train-test split validation method. Used Pearson correlation for feature selection.	The DL models performed best for short-term GHI forecasts, achieving R2 scores of 0.987, 0.977, and 0.984, while statistical models were more efficient for long-term forecasts, with R^2 scores above 0.90.	The study is limited to a single geographic location, restricting generalizability to other climates. Computational costs and DL model complexity relative to ML models were not assessed, limiting insights into efficiency, scalability, and real-world deployment.
[59]	To develop a multi-modal fusion network for short-term solar irradiance micro-forecasting using both infrared images and past irradiance data, addressing intermittent and nonlinear patterns during cloudy periods.	Proposes a CNN-L and Multiple-Image CNN-LSTM fusion network (MICNN-L) that integrates infrared sky/cloud images and historical irradiance time-series and is evaluated against benchmark models, including Linear SVM, Nonlinear SVM, Linear GP, Nonlinear GP, DNN, RNN, GRU, and LSTM using 15-second infrared sky images and solar irradiance data from the University of New Mexico, Albuquerque, USA. Used evaluation metrics, including MAPE, and used a time-ordered train-test split validation method.	MICNN-L showed 46.42% improvement in MAPE, and CNN-L showed 42.02% improvement in MAPE compared to benchmark ML/DL models. Cloudy day classification achieved 99.23% accuracy. Proposed models effectively captured nonlinear spatio-temporal variations and improved short-term forecasts.	Evaluation is based on single-site, high-frequency (15 s) data, with dataset duration and calendar years unspecified. Reliance on infrared sky imagery increases computational complexity and limits applicability in regions without sky-image infrastructure.
[60]	To compare ML and DL algorithms for solar irradiance forecasting and identify the most effective model.	Evaluated several ML models, including DT, kNN, RF, SVM, XGB, Stacking, Light GBM, Boosting, CatBoost, MLP, and LSTM, on three years (2017-2020) of hourly and 15-minute solar irradiance data for multiple locations in Izmir, Turkey. Used evaluation metrics, including MAE, MSE, RMSE, and R^2 and used a chronological train-test split validation method. Tested LightGBM, Pearson, recursive elimination, chi-square, and LR for feature selection.	The MLP achieved the best performance with an RMSE of 0.79, demonstrating that neural networks can effectively capture nonlinear patterns in GHI forecasts and guiding solar panel deployment decisions.	The dataset is specific to the NSRDB and spatially restricted to a 4 km × 4 km area, limiting generalizability. In addition, computational cost and relative model complexity were not assessed, constraining insights into efficiency, scalability, and real-world deployment.
[61]	To accurately forecast solar electricity generation at a solar farm in Amherst for operational, technological, and financial planning.	Develops and compares several DL variants, including LSTM-V, Bi-LSTM, and GRU-II, as well as baseline regressors such as LASSO, Ridge, Elastic-Net, and SVR on four-year (2015-2019) 5-minute interval time-series meteorological and solar energy data from the Amherst weather station in Massachusetts, USA. Used evaluation metrics, including RMSE, MSE, MAE, and MAPE and used a hold-out train-test split validation method. Used a correlation heatmap for feature selection	The Bi-LSTM achieved the best performance, outperforming the other models, with an MAE of 0.0135, RMSE of 0.0315, MSE of 0.0012, and MAPE of 0.1205.	The dataset is restricted to a single location, limiting generalizability across different climatic conditions. Only five-minute interval predictions were evaluated; longer forecasting horizons were not assessed. Additionally, computational cost and relative model complexity were not examined, constraining insights into efficiency, scalability, and real-world deployment.
[62]	To accurately forecast short-term solar irradiance from historical sky image sequences while leveraging clear sky models for improved performance.	Employed a DL Vision Transformer-based network with auxiliary clear sky model input, benchmarked on two datasets spanning from 2004 to 2019 in 10-minute intervals. Used the evaluation metric normalised Mean Absolute Percentage (nMAP) and used a chronological train-test split validation method.	The DL Vision Transformer outperforms prior DL methods across two datasets, achieving reduced nMAP errors by 6.9% and 8% for nowcasting for the 2015 and 2016 datasets, and 5.4% and 8.8% reduction for 4-hour ahead prediction, and outperformed previous methods, especially for 3-	The study is limited to benchmark datasets (TSI880 and ASI16), with performance under diverse climatic conditions or alternative camera configurations not evaluated. The forecasting horizon is limited to 4 hours, and computational costs were

			and 4-hour forecasts under variable weather conditions.	not assessed, limiting insights into scalability and practical deployment.
[63]	To evaluate the impact of different forecasting time horizons on the accuracy of solar irradiance prediction using ML and DL models.	Compares eight models, including LR, CNN-LSTM, XGB, RF, CNN, BiLSTM, ConvLSTM, and MLP, on 2 years (2020-2021) of solar irradiance data at 60 min, 30 min, 15 min, 10 min, and 5 min intervals in Limpopo Province, South Africa. Used evaluation metrics, including RMSE, nRMSE, MAE, and R^2 and used a hold-out train-test split validation method.	The results showed that prediction accuracy generally decreases with increasing prediction horizon and that DL models outperformed conventional ML models overall. The ConvLSTM model achieved the best RMSE of 7.43 at a five-minute interval, and the MLP performed better than other models across most prediction intervals, with RMSE ranging from 18.87 to 75.52.	The dataset is restricted to a single location, limiting generalizability across different climatic conditions. Model performance for longer forecasting horizons (>1 hour) was not evaluated. Additionally, computational cost and relative model complexity were not assessed, constraining insights into efficiency, scalability, and real-world deployment.
[64]	To explore DL techniques for solar energy forecasting within microgrid systems.	Evaluates multiple ML and DL models for forecasting solar irradiance, including Baseline Regression, LR, Lasso, Ridge, Elastic-Net, RF, GB, XGB, LightGBM, RNN, GRU, and LSTM on 9.11 years of hourly solar irradiance data from a chosen location. Used the evaluation metric normalised RMSE and used a hold-out train-test split validation method.	The DL RNN outperformed the other models, with a testing RMSE of 0.00534, and the Traditional ML RF model also performed well, with a testing RMSE of 0.09.	Computational cost and relative model complexity were not evaluated, limiting insights into practical efficiency, scalability, and deployment feasibility. Additionally, the dataset is restricted to a single location, constraining generalizability across different climatic conditions.
[65]	To evaluate DL models for short-term 1-hour ahead solar irradiance forecasting.	Compares several DL models such as Temporal Convolutional Networks (TCN), ARIMAX, SVR, standard LSTM, LSTM with 32 convolution kernels, and SENet using 3 years (2013-2016) of hourly solar irradiance data from Bend, Oregon, USA (University of Oregon). Used the evaluation metric normalised RMSE, Training time per epoch, and GPU memory usage. Used a cross-year validation method.	LSTM achieved the highest forecasting accuracy, with an average RMSE of 0.069, while TCN significantly reduced training time and resource consumption, increasing only 6% to an average RMSE of 0.0738.	Evaluation was restricted to 1-hour-ahead forecasts, with performance for longer horizons or alternative datasets not assessed. Additionally, the dataset is limited to a single location, constraining generalizability across different climatic conditions.
[66]	To compare DL models for very short-term solar irradiance forecasting and identify the most accurate architecture for local PV applications.	Evaluates RNN, GRU, LSTM, and TCN architectures for one-step-ahead forecasting using 1-year (2019) 15-minute resolution solar irradiance data from Karachi, Pakistan, obtained from NSRDB. Used evaluation metrics, including RMSE, MAE, and R^2 and used a hold-out train-test split validation method.	The LSTM model outperformed other models, achieving the highest R^2 of 0.9934 and the lowest RMSE of 0.020051, demonstrating its effectiveness for highly accurate solar irradiance forecasting.	The dataset is limited to a single location, restricting generalizability across varying climatic conditions. Computational cost and model complexity were not assessed, limiting insights into efficiency, scalability, and real-world deployment. In addition, performance for longer forecasting horizons (>15 minutes) was not evaluated.
[67]	To develop a DL based approach for short-term solar irradiance forecasting using sky camera images.	The study indeed proposes an LSTM-based DL model compared against the Yoo model and the persistence model using 25 days of 1-minute-resolution sky images from a ground-based sky camera, combined with GHI measurements at Kookmin University in Seoul, South Korea. Used evaluation metrics, including MBD, RMSD, rMBD, rRMSD and UVI and used a hold-out train-test split validation method.	The proposed LSTM-based DL model achieves better 10-minute-ahead forecasting accuracy under partly cloudy conditions (UVI > 20), with RMSD of 199.75 W/m², rRMSD of 25.1%, MBD of -60.65 W/m², and rMBD of -12.70%, outperforming the persistence and Yoo models. For clear and overcast sky conditions (UVI < 5), the model's performance is comparable to that of the persistence model, reflecting the lower irradiance variability and simpler forecasting requirements in these cases.	The model's performance relies heavily on the availability and quality of sky camera images, limiting its applicability in regions lacking such infrastructure. Evaluation was conducted at a single site, limiting assessment of generalizability to other climates, camera setups, or large-scale deployment.
[68]	To investigate whether DL models can improve the accuracy of solar radiation forecasting for advanced building	Developed and compared an ANN model and an RNN model for solar radiation prediction, using a one-week dataset with different sampling frequencies (1-hour	The RNN significantly outperformed the ANN, achieving 47% improvement in NMBE and 26% in RMSE. Increasing data granularity (from 1 h to 10 min)	The study relied on a relatively short historical dataset, limiting the model's ability to capture long-term patterns and seasonal variability. The study did not

	control applications, such as model predictive control (MPC).	and 10-minute data) from a local weather station in Alabama for training. Used evaluation metrics, including RMSE CV(RMSE), and nMBE and used a hold-out train-test split validation method. Used Pearson correlation for feature selection.	reduced CV(RMSE) from 30.9% to 9.41% for ANN and from 9.83% to 7.64% for RNN. Implementing a moving-window algorithm further improved RNN nMBE from 0.9% to 0.2%. Cloud cover was identified as a significant influencing factor on prediction accuracy.	provide a quantitative evaluation of computational complexity, training time, or scalability, making it unclear how practical the models are for large-scale or real-time deployment. Validation was conducted under offline experimental settings without real-time analysis, so model performance under operational conditions remains untested.
[69]	To develop and evaluate a near-real-time solar irradiance forecasting model using only historical GSR time series in a data-scarce region of Vietnam.	Developed a standalone DL optimised LSTM network compared to ARIMA, DNN, MLP, and SVR, and evaluated across multiple short-term forecast horizons (1-30 min) using 1-min resolution GSR time series from Bac-Ninh, Vietnam. Used evaluation metrics, including *r*, RMSE, ENS, MAE, RRMSE, and MAPE and used a hold-out train-test split validation method. Used PACF-based lag feature selection. Used grid search for tuning.	The LSTM model consistently outperformed benchmark models across all horizons. At a 1-minute horizon, it achieved RMSE of 40.91 W/m², MAE of 21.64 W/m², R of 0.9920, WI of 0.9984, and ENS of 0.9831. Relative RMSE ranged from 10 to 15% across horizons.	The dataset is restricted to a single location, limiting generalizability across different climatic conditions. Computational cost and model complexity were not evaluated, constraining insights into efficiency, scalability, and practical deployment. Validation restricted to very short-term horizons
[70]	To improve solar irradiation forecasting accuracy using ML and DL models, and evaluate the effectiveness of the N-BEATS architecture for time-series solar radiation prediction.	Evaluated SARIMA, LSTM, and N-BEATS (Neural Basis Expansion Analysis for Time Series Forecasting) to predict clear-sky GHI, DHI, and DNI using daily aggregated meteorological data from the NSRDB for four regions in Bangladesh (Khulna, Chittagong, Sylhet, and Rajshahi). Used evaluation metrics, including MAE, RMSE, R^2, and MAPE and used a hold-out train-test split validation method. Used XGB feature importance for feature selection.	The N-BEATS model achieved the highest forecasting accuracy, with RMSE values of 29.03-35.77 for clear-sky GHI and MAPE values of 2.34-3.29%, outperforming SARIMA and LSTM. N-BEATS effectively captured solar radiation patterns, while LSTM performed the worst.	The study was limited to four regions within Bangladesh, which restricts the generalisability of the findings to other climatic conditions. Additionally, the dataset was aggregated to daily values, potentially overlooking short-term variability in higher-resolution solar radiation data. The study also evaluated a limited number of forecasting models, and hybrid or ensemble approaches were not explored.
[71]	To conduct a comparative analysis of ML and DL strategies for solar irradiation forecasting.	The study evaluated 9 ML and DL models, including LR, MLP, ELM, Kernel Ridge Regression (KRR), SVR, Gaussian Process Regression (GPR), CNN, LSTM, and Bi-directional LSTM (Bi-LSTM), using historical solar irradiation data from 2000-2005, obtained from the Batna meteorological station in Algeria. Used evaluation metrics, including MAE, RMSE, and R, and used a chronological train-test split validation method.	Among ML models, ELM with 16 features achieved the best performance, with RMSE of 4.004, MAE of 2.918, and R of 0.849. Among DL models, Bi-LSTM achieved the best overall performance for 1-day-ahead forecasts, with RMSE of 1.392, MAE of 1.021, and R of 0.989 using 25 features. The results demonstrate that DL models, particularly Bi-LSTM, significantly outperform traditional ML methods for solar irradiation forecasting.	The study used data from only one location, which limits the generalisability of the results to other climatic regions. Additionally, the study focused on individual ML and DL models, rather than hybrid or ensemble approaches, which could further improve forecasting accuracy.

TABLE V. SUMMARY OF SELECTED HYBRID/ENSEMBLE STUDIES ON SOLAR IRRADIANCE FORECASTING

Reference	Goal	Method	Outcome	Limitations
[72]	To compare the performance of common ML and DL algorithms for short-term solar irradiance forecasting and improve prediction accuracy under irradiance variability.	Evaluates ML models, including SVR, kNN, RF, and DL models such as ANN, CNN, LSTM, GRU, and a hybrid CNN-LSTM model, using grid-search hyperparameter optimisation on five years of hourly solar irradiance data (2015-2019) from a single site in Islamabad. Used evaluation metrics including adjusted R^2, NRMSE, MAD, MAE, and MSE. Used a 5-fold grid search cross-validation method for tuning.	Demonstrated that the CNN-LSTM hybrid model achieved the best performance among the other models with an adjusted R^2 of 0.984.	The study is based on a single geographic location and a fixed historical dataset, raising concerns about its generalizability to other regions.
[73]	To develop a robust and accurate ensemble model for hourly GHI forecasting to support reliable solar energy	Develops an XGBF-DNN hybrid ensemble model and compares it to Smart Persistence (SP) and other ML models, including SVR, RF, XGB, and DNN, on 10 years of hourly solar irradiance data (2005-2014) across three different climatic regions in India. Used evaluation metrics including FS,	Demonstrated that the proposed XGBF-DNN model outperformed the other models for a 1-hour ahead forecast, with RMSE values	The study focuses on long-term horizons, limiting applicability to short-term forecasting. Computational costs and DL model complexity relative to ML

	system planning and operation.	RMSE, and MAE. Used a Clear-sky index and temporal encoding feature engineering.	of 56.68 W/m^2, 53.78 W/m^2 and 91.86 W/m^2 for all three locations, with 33-40% improvement in FS.	models were not assessed, restricting insights into efficiency, scalability, and real-world deployment.
[74]	To improve 1-hour-ahead solar irradiance forecasting accuracy by incorporating multivariate inputs and a multi-branch hybrid DL structure.	Develops a hybrid WPD-CNN-LSTM-MLP model using a multi-branch architecture and compares it to BP, RNN, LSTM, SVM, BP-MLP, RNN-MLP, LSTM-MLP, and CNN-LSTM-MLP on 3 years of hourly solar irradiance data (2012-2016) across three sites in the USA: Denver, Clark, and Folsom. Used evaluation metrics including RMSE, MAE, MBE, FS and R². Used WPD decomposition feature engineering.	Demonstrated that the proposed WPD-CNN-LSTM-MLP model achieved superior prediction accuracy compared to other models, with MAE of 14.3523-20.3853, RMSE of 32.1006-46.1336, nRMSE of 15.4795-23.9178%, and R values of 0.9858-0.9940 across the three locations. WPD further reduced errors and improved correlation.	The study focuses on short-term horizons, limiting applicability to long-term forecasting. Computational costs and DL model complexity relative to ML models were not assessed, restricting insights into efficiency, scalability, and real-world deployment.
[75]	To develop an accurate and robust short-term hourly GHI forecasting model for reliable grid integration and energy market participation.	Develops a hybrid LSTM-CNN DL model and compares it to SP, SVM, ANN, CNN, LSTM, and CNN-LSTM on 1 year of hourly solar irradiance data (2019) across 23 locations. Used evaluation metrics including RMSE, MAE, R² and computational time.	The hybrid LSTM-CNN model improved prediction and outperformed standalone models for 1-hour-ahead forecasts, with MAE of 27.38-37.02, RMSE of 42.89-58.12, R of 0.9673-0.9853, and FS of 37%-45% across all the locations.	The study focuses on short-term horizons, limiting applicability to long-term forecasting. Computational costs of the hybrid DL model relative to ML models had high computational times, restricting efficiency, scalability, and deployment in computational resource-constrained locations.
[76]	To develop a hybrid short-term solar irradiance forecasting model for both GHI and Plane of Array (POA) irradiance with high predictive accuracy.	Develops a modified multi-step CNN-stacked LSTM network with dropout and compares it to CNN and LSTM on one month of solar irradiance data (2019) at a single site from Sweihan Photovoltaic Independent Power Project, Abu Dhabi, UAE. Used evaluation metrics including RMSE, MAE, MAPE, R², MSE, and NRMSE. Used a hold-out train-test split validation method.	The proposed hybrid model outperformed other ML and DL models for 1-hour-ahead forecasts, achieving an RMSE of 0.36, an R² of 0.98 for GHI, an MAPE of 61.24, and an R² of 0.96 for POA irradiance, demonstrating improved accuracy for short-term solar irradiance prediction.	The study is limited to a single location, affecting generalizability, and the computational costs and complexity of DL models versus ML models were not assessed, limiting insights into efficiency, scalability, and real-world deployment.
[77]	To develop a hybrid intelligent model for accurate short-term solar irradiance/power forecasting using wavelet decomposition and Generative Adversarial Networks (GANs) with evolutionary optimisation for two regions.	Proposes a Wavelet Transform Package (WTP)-GAN, optimised using a modified Dragonfly Algorithm (DA), and compared to ARMA, ANN, CNN, GAN, SVR, Fuzzy method, and RNN using 1 year of hourly solar irradiance data (2019) from two locations. Used evaluation metrics including RMSE and MAPE. Used a Wavelet decomposition feature engineering. Used dragonfly algorithm plus modified 3-phase DA for hyperparameter tuning.	The hybrid WTP-GAN with modified DA outperformed other models across multiple horizons of 1-6 hours ahead, with MAPE of 0.0282 & 0.0262, and RMSE of 0.0473 & 0.0479 for 1-pace forecast, and MAPE of 0.0531 & 0.0631, and RMSE of 0.0895 & 0.0946 for 6-pace forecast:	The study relies on a single year of data, limiting seasonal and multi-year generalizability. Moreover, computational cost and model complexity were not assessed, restricting insights into efficiency, scalability, and practical deployment.
[78]	To develop a heterogeneous ensemble dynamic selection (HetDS) model for solar irradiance forecasting, improving performance over single models.	Proposes a HetDS model that chooses the best forecasting model for each test pattern from a pool of seven methods, which include ARIMA, SVR, ANN, Extreme Learning Machine (ELM), Deep Belief Network (DBN), RF, and GB, using 1 year (2020) hourly solar irradiance data from four locations in Brazil. Used evaluation metrics including RMSE, MAPE, and MAE. Used a time-lag windowing and feature engineering. Used full Grid Search for hyperparameter tuning. Used a chronological train/test split validation.	The HetDS models performed better than the other models for 1-hour-ahead forecasts, with RMSE ranging from 0.0600 to 0.1762, MAPE ranging from 10.57% to 55.85%, and MAE ranging from 0.0426 to 0.1169 across all four cities.	The study is based on one year of data, limiting seasonal and multi-year generalizability. Additionally, computational cost and relative model complexity were not evaluated, constraining insights into efficiency, scalability, and real-world deployment.
[79]	To develop a hybrid decomposition-integration DL framework for short-term solar irradiance forecasting that better captures nonlinear and non-stationary patterns in irradiance data.	Develops a Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN)-Wasserstein GAN-LSTM hybrid model and compares to benchmark models evaluated, including RNN, GRU, Transformer, LSTM, WGAN, CEEMDAN-LSTM, CEEMDAN-WGAN, CEEMDAN-LSTM-WGAN variants using one year (2018), 5-minute resolution	The proposed CEEMDAN -WGAN-LSTM model outperformed all benchmark models across four seasonal test sets. Compared to sub-optimal benchmarks, its errors were reduced by 3.51% for MAE, 6.11% for MAPE, and 2.25%	The model was evaluated using one year of data from a single location, limiting generalizability across different climatic regions and multi-site settings. In addition, computational cost and relative model complexity were not assessed, constraining

		GHI data from NSRDB measured in Texas, USA. Used evaluation metrics including MAE, MAPE, RMSE, and R^2. Used a CEEMDAN-based decomposition for feature engineering and feature selection. Used a chronological train/test split validation.	for RMSE, and it showed the lowest errors with the highest R^2 values among the evaluated methods across seasons.	insights into efficiency, scalability, and real-world deployment.
[80]	To improve mean hourly GHI forecasting by providing accurate probabilistic predictions for grid stability and PV integration.	Develops a hybrid CNN-LSTM model combined with quantile regression and compares it with ANN, CNN, LSTM, and persistence models using one year (2019-2020) of hourly solar irradiance data, including sky images down-sampled to 64×64 pixels collected at the University of French Polynesia, Tahiti. Used evaluation metrics including MAE, RMSE, MSE, R^2, nMAP (deterministic); PICP, PINAW, CWC (probabilistic). Used a Sky image down-sampling for feature engineering. Used a chronological train/test split validation.	The CNN-LSTM hybrid model achieved the best deterministic and probabilistic performance for 1-h-ahead forecasts, with an RMSE of 100.58 W/m², an MAE of 66.09 W/m² and an R^2 of 0.85 on test data. For probabilistic forecasting, it obtained the lowest CWC values across multiple prediction intervals: 8.54 at PI (38%), 17.04 at PI (68%), 33.37 at PI (95%), 47.98 at PI (99%), demonstrating superior uncertainty quantification.	The dataset is restricted to a single location, limiting generalizability across different climatic conditions. Computational cost and model complexity were not evaluated, constraining insights into efficiency, scalability, and practical deployment. In addition, reliance on satellite imagery reduces applicability in regions without imaging infrastructure.
[81]	To improve 24-hour-ahead solar GHI forecasting accuracy for reliable grid management using an ensemble DL approach.	Employed a hybrid Wavelet Transform (WT)-BiLSTM model and compared it with GRU, LSTM, and standalone BiLSTM models using a one-year monthly solar GHI dataset, using a one-month moving window mechanism for the location of Ahmedabad, Gujarat, India. Used evaluation metrics including MAPE, RMSE, FS, and R^2. Used a moving window mechanism validation.	The proposed WT-BiLSTM ensemble outperformed benchmark, LSTM, GRU, and standalone BiLSTM models for 1-day-ahead forecasts, with a reduced Monthly average RMSE of 26.04-58.89% vs benchmark and up to 57% vs LSTM. The MAPE reduced by 9-51.18% vs benchmark. The achieved R^2 is 0.94, and the forecast skill is 47%.	The dataset is restricted to a single location, limiting generalizability across different climatic conditions. Computational cost and model complexity were not evaluated, constraining insights into efficiency, scalability, and practical deployment.
[82]	To improve solar radiation forecasting accuracy in Indian cities by integrating advanced signal decomposition techniques with ML and DL models.	This study developed nine novel ensemble models integrating Variational Mode Decomposition (VMD) and Discrete Wavelet Transform (DWT) with five DL algorithms, including GRU, LSTM, BiLSTM, CNN, and DNN, along with two ML algorithms, ANN and SVR, using historical meteorological data from 2000 to 2012 in seven major Indian cities provided by the Indian Meteorological Department. Used evaluation metrics including RMSE, MAE, and R^2. Used a VMD & DWT signal decomposition for feature engineering.	VMD-based DL ensembles significantly outperformed DWT-based models. Among all configurations, the VMD-GRU model achieved the best performance across all cities for 1-step-ahead forecasts, with RMSE of 0.82-1.22, MAE of 0.54-1.02, and R^2 of 0.83-0.93. This superior performance is attributed to GRU's lower parameter count, reduced memory requirements, and faster training capability.	The study utilised a limited set of meteorological variables, excluding other potentially influential atmospheric parameters. The study did not provide quantitative evaluations of computational complexity, training time, or the scalability of the hybrid models. Validation was conducted in an offline experimental setting without real-time deployment analysis.
[83]	To enhance solar radiation forecasting accuracy by developing a hybrid intelligent DL framework that integrates signal decomposition and evolutionary optimisation techniques.	Proposes a hybrid OVMD-PACF-ISSA-DBN-OSELM hybrid model combining optimal VMD with an evolutionary DBN online sequential ELM (EDBN-OS-ELM); applies partial autocorrelation function (PACF) for input variable selection; improves the sparrow search algorithm (SSA) to optimise DL hyperparameters. The model was developed and validated using hourly solar radiation data from January, May, and October 2022, collected from a single station of the National Data Buoy Centre. Used evaluation metrics including RMSE, MAE and R. Used hold-out train/test split validation method. Used the Partial Autocorrelation Function for feature selection. Used OVMD (Optimal Variational Mode Decomposition) for feature engineering. Used the improved Sparrow Search Algorithm (ISSA) algorithm for hyperparameter tuning.	The proposed model achieved the best performance across the January, May, and October datasets. For January, the model obtained an RMSE of 23.153 W/m², an MAE of 13.225 W/m², and an R of 0.9923, while the model obtained an RMSE of 39.223 W/m², an MAE of 24.962 W/m², and an R of 0.9924 for May. The model significantly outperformed BP, ELM, LSTM, DBN-based variants, and SSA-based hybrids for 10-minute-ahead forecasts.	The experimental evaluation was conducted using data from only three months (January, May, and October 2022), which limits the assessment of seasonal robustness. Additionally, the dataset was obtained from a single NDBC station, restricting geographical generalizability. The study focused solely on single-step forecasting, and multi-step prediction scenarios were not investigated.
[84]	To develop a robust and accurate deep hybrid	Developed a hybrid CEEMDAN-AG-RE-ELM that combines CEEMDAN for signal decomposition,	The proposed model achieved strong forecasting accuracy	The framework involves multiple complex stages

	framework for short-term GSR forecasting by combining signal decomposition, time-frequency analysis, deep feature extraction, and ML.	Continuous Wavelet Transform (CWT) to generate time-frequency scalogram images; cascade CNN (AlexNet + GoogLeNet) for deep feature extraction; RReliefF for feature selection; ELM for final forecasting using a two-year (2018-2019), hourly dataset from the Yulara Solar System, near Uluru (Ayers Rock). Used evaluation metrics including RMSE, MAE, and MAPE. Used a hold-out train/test split validation method. Used the RReliefF for feature selection. Used CEEMDAN decomposition for feature engineering. Used the 10-fold CV for hyperparameter tuning.	across multiple horizons of 1-, 2- and 3-hour ahead, with RMSE of 0.0642, MAE of 0.0241, MAPE of 0.1201 for 1-hour ahead and RMSE of 0.0686, MAE of 0.0285, MAPE of 0.1279 for 2-hour ahead and RMSE of 0.0724, MAE of 0.0315, and MAPE of 0.1317 for 3-hour ahead, outperforming conventional regression models; demonstrates superior robustness and accuracy.	(decomposition, image transformation, CNN feature extraction), which may increase computational cost. Performance was validated on a specific dataset; generalizability to other locations and longer horizons was not assessed.
[85]	To improve daily GSR prediction accuracy by developing a hybrid DL-ML framework that effectively extracts temporal features and enhances regression performance.	Proposed a hybrid CNN-SVR (CSVR) model and compared it to STM, DBN, RBF, BRF, MARS, WKNNR, GPML, and M5TREE models using Ground-measured daily GSR. Used evaluation metrics including RMSE, MAE, Willmott's d, NSE, and Legates-McCabe Index. Used a hold-out train/test split validation. Used Atom Search Optimisation (ASO) for feature selection. Used HyperOpt (Bayesian/TPE for hyperparameter tuning.	The proposed CSVR model consistently outperformed benchmark DL and ML models across six solar farms in Queensland, Australia. It achieved RMSE/MAE ranges of 2.172-3.305 MJ/m² and 1.624-2.370 MJ/m², respectively, compared to 2.514-3.879 MJ/m² and 1.939-2.866 MJ/m² from competing models. Higher correlation, Willmott's Index, Nash-Sutcliffe efficiency, and Legates-McCabe indices confirmed superior agreement between predicted and observed GSR.	Model complexity is relatively high due to multi-stage optimisation (feature selection, CNN, SVR, hyperparameter tuning). Evaluation was limited to daily forecasting and a specific geographical region, which may affect generalizability to other climates or shorter forecasting horizons.

Table VI summarises the quantitative findings of all 37 studies reviewed, indicating per reference, the model type, the best-performing model, forecast horizon, the type of input data used, the evaluation measure, and the best-reported score. This overview allows the direct cross-study comparison of the reported performance.

TABLE VI. SUMMARY OF SELECTED HYBRID/ENSEMBLE STUDIES ON SOLAR IRRADIANCE FORECASTING

Ref	Model Type	Best Model	Forecast Horizon	Input Dataset Type	Best Metric	Best Score
[49]	ML	Lasso Regression	5-30 min (Very short-term)	Numerical (irradiance + meteorological)	RMSE	0.050-0.076 W/m²
[50]	ML	kNN	4 h (Short-term)	Numerical (time series)	nRMSE	7.7-8.9%
[51]	ML	RF	1 day (Short-term)	Numerical (irradiance)	Directional Acc.	92.86%
[52]	ML	RF	3 h (Short-term)	Numerical	RMSE	4.04 kW
[53]	ML	RF	1-10 days (Medium-term)	Numerical	RMSE	1.72
[54]	DL	Bi-LSTM / Attention LSTM	1 day (Short-term)	Numerical (long-term time series)	R^2	0.68-0.73
[55]	DL	GRU	1 year (Long-term)	Numerical (hourly/daily)	RMSE	0.3909-0.4582
[56]	DL	SolarNet (CNN)	1 h (Very short-term)	Sky images	nRMSE	8.85%
[57]	DL	RNN	1 h (Short-term)	Numerical (multi-site)	RMSE	82.22 W/m²
[58]	DL	LSTM/CNN	1 h (Short-term)	Numerical (irradiance + meteorological)	R^2	0.987
[59]	DL	MICNN-L	15 sec (Very short-term)	Sky images	MAPE improvement	46.42%
[60]	DL	MLP	15 min-1 h (Very short-term)	Numerical (NSRDB)	RMSE	0.79
[61]	DL	Bi-LSTM	5 min (Very short-term)	Numerical	MAE	0.0135
[62]	DL	Vision Transformer	Now-4 h (Short-term)	Sky images + clear-sky model	nMAP	↓5.4-8.8%
[63]	DL	ConvLSTM	5-60 min (Very short-term)	Numerical	RMSE	7.43
[64]	DL	RNN	1 h (Short-term)	Numerical	nRMSE	0.00534

[65]	DL	LSTM	1 h (Short-term)	Numerical	nRMSE	0.069
[66]	DL	LSTM	15 min (Very short-term)	Numerical (NSRDB)	R^2	0.9934
[67]	DL	LSTM	10 min (Very short-term)	Numerical	RMSD	199.75 W/m²
[68]	DL	RNN	10 min-1 h (Very short-term)	Numerical	RMSE improvement	26%
[69]	DL	LSTM	1-30 min (Very short-term)	Numerical	RMSE	40.91 W/m²
[70]	DL	N-BEATS	1 day (Short-term)	Numerical (multi-region)	RMSE	29.03-35.77
[71]	DL	Bi-LSTM	1 day (Short-term)	Numerical (irradiance)	RMSE	1.392
[72]	Hybrid	CNN-LSTM	1 h (Short-term)	Numerical	Adjusted R^2	0.984
[73]	Hybrid	XGBF-DNN	1 h (Short-term)	Numerical (multi-region)	RMSE	53.78-91.86
[74]	Hybrid	WPD-CNN-LSTM-MLP	1 h (Short-term)	Numerical	RMSE	32.10-46.13
[75]	Hybrid	LSTM-CNN	1 h (Short-term)	Numerical (multi-site)	MAE	27.38-37.02
[76]	Hybrid	CNN-stacked LSTM	1 h (Short-term)	Numerical	RMSE	0.36
[77]	Hybrid	WTP-GAN + DA	1 h (Short-term)	Numerical	MAPE	0.0262-0.0282
[78]	Hybrid	HetDS	1 h (Short-term)	Numerical (multi-city)	RMSE	0.0600-0.1762
[79]	Hybrid	CEEMDAN-WGAN-LSTM	5 min (Very short-term)	Numerical (NSRDB)	MAE improvement	3.51%
[80]	Hybrid	CNN-LSTM + Quantile Reg.	1 h (Short-term)	Sky images + numerical	RMSE	100.58 W/m²
[81]	Hybrid	WT-BiLSTM	24 h (Short-term)	Numerical	RMSE reduction	26-59%
[82]	Hybrid	VMD-GRU	1 h (Short-term)	Numerical (multi-city)	RMSE	0.82-1.22
[83]	Hybrid	OVMD-ISSA-DBN-OSELM	1 h (Short-term)	Numerical	RMSE	23.15-39.22
[84]	Hybrid	CEEMDAN-AG-RE-ELM	1-3 h (Short-term)	Numerical + time-frequency	RMSE	0.0642-0.0724
[85]	Hybrid	CNN-SVR	1 day (Short-term)	Numerical	RMSE	2.17-3.31

V. Discussion

The review summarises 37 peer-reviewed publications published between 2019 and 2025, narratively summarised in Table III to Table V and quantitatively summarised in Table VI. Taken together, these studies provide a comprehensive overview of the state of the art in ML, DL and hybrid forecasting of solar irradiance. Despite the literature showing significant gains in predictive accuracy and methodological sophistication, a critical cross-analysis of the synthesised evidence reveals several key observations about current trends in methodological approach, limiting factors and important research gaps. The gaps need to be addressed to ensure operational preparedness and the generalizability of forecasting models for integrating renewable energy in the real world.

A. Key Findings and Empirical Observations

The initial important observation is that DL and hybrid models have evidently dominated the methodological approach to solar irradiance forecasting. A summary of the information in Table III, Table IV, and Table V, as shown in Fig. 2, indicates a significant shift towards complex neural network-based techniques. Fig. 2 reveals that 49% (n=18) of the studies employ DL models as reported in [54]-[71], 38% (n=14) use hybrid or ensemble approaches as reported in [72]-[85], and 14% (n=5) rely on traditional ML models as reported in [49]-[53]. Overall, this highlights a clear shift in the literature towards more data-intensive, architecture-rich forecasting approaches.

The second important observation concerns the relative performance of ML, DL, and hybrid models across various forecasting horizons and evaluation metrics. An overview of the findings in Table VI, which provides a cross-study comparative summary, shows that DL and hybrid models tend to be superior to traditional ML methods, especially for very short- and short-term forecasting. Table VI shows that the LSTM, CNN, and their variants are the best DL-based predictors across various datasets. For example, the RMSE values were as low as 7.43 [63] and 29.03-35.77 [70] when using DL models, while the coefficients of determination were as high as $R^2 = 0.987$ in [58] and $R^2 = 0.9934$ in [66]. On the same note, MAE as low as 0.0135 is reported in [61], indicating a high predictive accuracy for very short-term forecasts. Conversely, traditional ML models exhibit relatively low consistency in performance, with RMSE values of 4.04 kW [52] and 1.72 kW [53] for medium-term forecasting and nRMSE values between 7.7% and 8.9% [50]. Hybrid and ensemble models also improve predictive performance by integrating various learning paradigms or signal decomposition methods. As shown in Table VI, hybrid models frequently achieve competitive or superior results, with RMSE values of 0.36 [76], 0.0600-0.1762 [78], and 23.15-39.22 [83], as well as MAE values of 27.38-37.02 [75]. Moreover, other hybrid methods do not provide absolute values but enhanced performance, such as RMSE decreases of 2659% [81] and MAE increases of 3.51% [79] and are therefore effective in optimising the prediction accuracy. Additional examination of Table VI reveals that the performance edge of DL and hybrid models is the greatest at short-term forecasting horizons (0-24 hours), whereby high-frequency temporal patterns can be fruitfully represented. Conversely, comparative advantage is less stable in medium- and long-term forecasting. To discover more competitive RMSE values like 1.72 in [53] and 0.3909 -0.4582 in [55], simpler ML and simpler DL models can be used, because they need less data and are simpler to model.

The third important point is the excessive focus on very short-term and short-term forecasting horizons. As shown in Fig. 3, 95% (n = 35) of the studies focus on predictions with intervals up to 24 hours ahead, with a range of seconds. Very short-term forecasts of 15 seconds to 1 hour ahead account for 30% (n = 11) of the studies, including [49], [59]-[61], [63], [66]-[69], and [79]. Short-term forecasts of 1 to 24 hours ahead dominate the literature, comprising 65% (n = 24) of studies, including [50]-[52], [54], [56]-[58], [62], [64], [65], [70], [71], and the majority of hybrid studies [72]-[85]. Conversely, the medium- and long-term forecasting horizons are underrepresented, with only 5% (n = 2) of the studies, namely [53] and [55]. This distribution indicates that there is significant research interest in operational forecasting for real-time PV system management, but longer-term forecasting has not been fully explored.

The fourth important observation concerns the prevalence of accuracy-based evaluation measures, especially the RMSE. As shown in Fig. 4, RMSE is the most widely reported metric, appearing in 76% (n = 28) of the studies, including [49]-[54], [56]-[58], [60], [61], [63]-[66], [69]-[76], [78]-[85]. Mean Absolute Error (MAE) is reported in 54% (n = 20) of studies, including [51]-[53], [57], [60], [61], [66], [69], [71], [72], [74]-[76], [78]-[80], [82]-[85]. The coefficient of determination (R^2) appears in 38% (n = 14) of studies, including [53], [54], [58], [60], [63], [66], [70], [72], [74]-[76], [80]-[82]. Mean Absolute Percentage Error (MAPE) and its normalized variants are reported in 32% (n = 12) of studies, including [50], [59], [61], [62], [69], [70], [76]-[79], [81], and [84]. Forecast Skill (FS) is used in 16% (n = 6) of studies, including [49], [56], [73], [75], and [81]. Computational efficiency metrics such as execution time, training time, and resource utilisation are reported in only 11% (n = 4) of the studies, including [49], [50], [65], and [75]. This implies that a great focus is on predictive accuracy, minimal focus on computational performance, and scalability.

The fifth important finding is that there is a low use of multimodal input strategies that combine numerical and visual information. Numerical data, including historical irradiance and meteorological variables, is the most commonly used input type, appearing in 62% (n = 23) of the studies, including [51]-[53], [55], [58], [60], [61], [64], [66], [69]-[74], [76]-[78], [81]-[83] and [85]. A smaller proportion of studies (19%, n = 7) utilise sky or cloud imagery, including [49], [50], [56], [59], [62], [67], and [80]. But only 8% (n=3) of studies present both numeric and pictorial information in a multimodal format, namely, [59], [62], and [80]. This shows that although multimodal learning offers the potential to capture spatial and temporal dynamics, its use remains limited in the existing literature.

The sixth notable point is that comparatively less common is the systematic feature engineering and feature selection methodology. Signal decomposition techniques are used in only 14% (n=5) of the 37 studies and explicit feature selection methods are used in only 16% (n=6). Most research studies do not explicitly specify structured feature engineering pipelines and instead use raw or minimally processed input data. This demonstrates the lack of an opportunity to leverage data preprocessing techniques to improve model performance and interpretability.

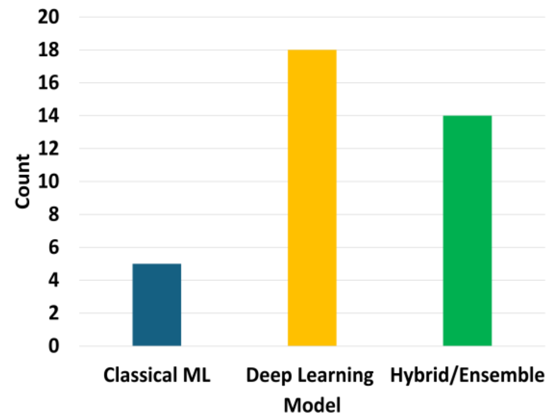

Fig. 2. Distribution of model families across the 37 reviewed studies.

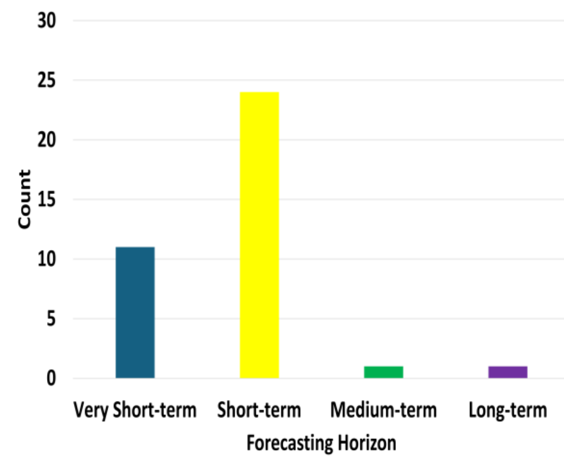

Fig. 3. Distribution of forecasting horizons across the 37 reviewed studies.

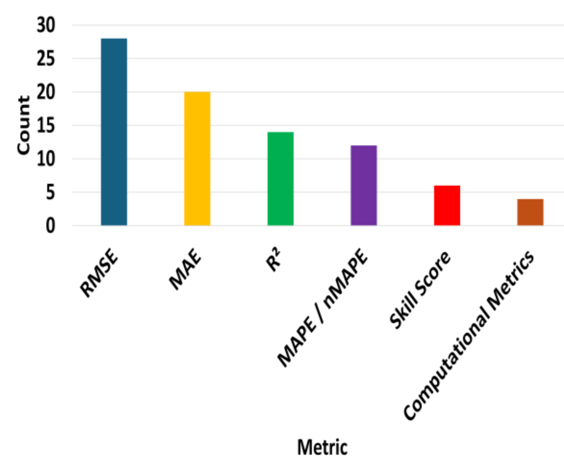

Fig. 4. Frequency of evaluation metrics reported across 37 reviewed studies.

The seventh significant observation is related to the evaluation settings, namely the distribution of single- and multi-location studies. The majority of the reviewed literature, approximately 65% (n = 24), relies on single-location datasets, including [49]-[53], [56], [58], [59], [61], [63]-[69], [72], [76], [79]-[81], [83], and [84]. In contrast, only 35% (n = 13) of the studies utilise multi-location datasets, such as [54], [55], [57], [60], [62], [70], [73]-[75], [77], [78], [82], and [85]. Even though multi-location studies tend to show better generalisation and model robustness across different climatic conditions, their relatively low use points to a significant gap in the literature. The continued dominance of single-site assessments highlights ongoing issues with data availability and the lack of focus on creating geographically transferable models. Therefore, the applicability of most proposed forecasting methods is questionable, especially across a range of environmental and operating conditions.

All these important observations point to several serious limitations in the existing body of literature, which inform the research gaps considered in the next section.

B. Persistent Limitations and Identified Research Gaps

Although the methodology improved, the overall presentation of the tables shows that there are several crucial and enduring limitations to the successful application and the generalizability of these models.

The first critical gap is the narrowness of the medium-term and long-term forecasting horizons. The literature reviewed is highly biased towards very short and short-term predictions, with 95% (n = 35) of the studies considering forecasting periods of less than 24 hours. Conversely, very few studies 5% (n = 2) discuss the medium- and long-term forecasting. This reveals a major research gap on how to come up with models that can make reliable predictions over a period of days, seasons and over a long period of time, which are crucial in strategic energy planning, grid expansion and policy making.

The second critical gap is that there exists no standardised benchmarking and fair comparison of forecasting models. Even though the DL and hybrid models tend to perform better than traditional ML methods, comparisons are often inconsistent due to differences in datasets, forecasting horizons, input features and evaluation metrics. This complicates the process of coming up with conclusive findings on the most effective models in various circumstances.

The third serious gap is the excessive focus on accuracy-based evaluation measures, with little attention to computational efficiency. Whereas RMSE 76% (n = 28), MAE 54% (n = 20), and R^2 38% (n = 14) appear to be common measures, only 11% (n = 4) of studies report on computational measures such as execution time, training time, and resource utilisation. This means that little attention has been given to model scalability, efficiency, and real-time deployment, especially in resource-limited settings.

The fourth critical gap is the underutilisation of multimodal data integration practices. Even though numerical data dominates in the literature with 62% (n = 23) and only 8% (n = 3) of the studies have both numerical inputs and visual data, like images of the sky. This implies that little attention has been given to the potential of multimodal learning to capture temporal and spatial variations in solar irradiance.

The fifth critical gap is the little use of systematic feature engineering and feature selection methods. Signal decomposition techniques like VMD, CEEMDAN, and wavelet-based signal decomposition techniques are used only in 14% (n = 5) studies, whereas formal feature selection techniques are used in 16% (n = 6) studies. Most studies use raw or minimally processed input data, meaning they do not fully leverage preprocessing strategies that can enhance model performance, robustness and interpretability.

The sixth critical gap is the lack of generalizability as the majority of studies still use datasets from a single location. Even though 59% (n = 22) of the studies use multi-location data, a significant number of 41% (n = 15) of studies remain single-site assessments. This calls into question the strength and applicability of models across other climatic regions and the necessity of more extensive cross-regional validation systems.

The seventh critical gap is the growing sophistication of models with no consideration of interpretability and deployment feasibility. In the literature, there is an increasing tendency to the use of complex DL and hybrid models, such as CNN-LSTM, GAN-based, and transformer models. Nevertheless, these models are seldom tested for their interpretability, computational cost, or practical implementation. This implies that there is a lack of equilibrium between model accuracy, explainability, efficiency and usability in practice.

Overall, the review indicates that the field has made significant progress and has an unmistakably consistent trend towards the more complex hybrid and ensemble deep learning models. This development has, however, also led to an increase in the disparity between methodological innovation and practical applicability. The deep emphasis on gradual advances in predictive accuracy has, in numerous instances, been at the cost of dealing with the underlying issues of real-world implementation. Specifically, poor model generalizability, the lack of adequate focus on computational efficiency and operational constraints, and the continued focus on short-term forecasting horizons are among the barriers. To address these issues, it is necessary to make sure that the models of solar irradiance forecasting have the required operational reliability and practicality in the renewable energy systems.

VI. RECOMMENDATIONS

Based on the critical analysis of the 37 studies and the identified research gaps, several key recommendations are proposed to guide future work toward more robust, generalizable, and deployment-ready solar irradiance forecasting systems.

The high dependence on single-location datasets is one of the significant weaknesses that limit the generalizability of the model to different climatic conditions. Although multi-location studies such as [54], [57], [73], [75], and [82] demonstrate improved robustness, they remain in the minority. Multi-site assessment frameworks based on publicly available data sets like NSRDB, BSRN, ERA5, and NASA POWER should be used in future studies. Specifically, it is suggested to use leave-one-location-out cross-validation to evaluate the spatial robustness. Moreover, domain adaptation methods like feature alignments and adversarial learning can enhance the transferability of models across climatic regions.

Most analyses focus on predictive accuracy based on measures of RMSE, MAE and R^2, and while computational efficiency is rarely considered, as it is reported in only a small subset of studies, such as [50] and [65]. Future work ought to then take a dual evaluation approach, which takes into account both predictive accuracy and operational performance, such as latency, memory footprint, model size, and energy consumption. This is especially critical with hybrid and DL models, which might not be suitable in real-time or even edge deployment due to the computational bottlenecks.

The growing sophistication of DL and hybrid models requires the implementation of model compression and model optimisation strategies. Pruning, quantisation and knowledge distillation are techniques that can be used to reduce the complexity of models whilst maintaining performance. Moreover, frameworks based on deployment, especially edge-optimised inference pipelines, are to be considered to evaluate the feasibility of microgrid controllers and embedded systems in practice. This is particularly applicable to highly complex models like those reported in studies such as [74], [77] and [83], where deployment feasibility has not been sufficiently addressed.

Literature is extremely biased in regard to very short-term and short-term forecasting horizons, whereas medium-term and long-term forecasting is under-researched. Studies such as [53], [55] and [70] show deterioration in performance with increasing forecasting horizons, and illustrate the challenging nature of long-term prediction in the presence of atmospheric uncertainty. Future studies ought to expand the forecasting horizons to day-ahead and week-ahead by including NWP data, including ERA5 reanalysis data. It is suggested to implement hybrid architectures with CNNs, RNNs, and Transformer-based models to more effectively represent long-range temporal correlations and large-scale weather patterns.

The majority of current research tests models in average conditions without taking into account the variability in atmospheric conditions. Few studies, including [67], evaluate performance under varying conditions of clouds. Future work must then embrace scenario-based evaluation models, in which models are evaluated under clear-sky, partly cloudy, rapidly changing and extreme weather conditions. This stratified assessment is essential to real-world grid integration, where resilience to different conditions is more significant than a mean performance.

There is also a high level of inconsistency in the evaluation methods used in the literature, such as differences in data splitting strategies, normalisation methods, and reported metrics. In spite of the popularity of RMSE in the literature [49]-[85], other similar measures like MAPE, nRMSE, and skill scores are not always reported. Standardisation of benchmarking protocols, such as standard train-validation-test splits, rolling-window or walk-forward validation, and reporting standardised and normalised metrics should be implemented in future studies to increase the reproducibility and comparability of results across different studies.

Lack of standardised benchmark datasets is a significant limiting factor in the field. The available research is based on piecemeal data and does not allow reproducibility and equal comparison. Further work should be done on unified multi-modal benchmark datasets that involve ground-based irradiance measurements, meteorological measurements and satellite or sky-imaging measurements. Partitions of standardised datasets using popular sources (NSRDB, ERA5) should be created, and open benchmarking platforms with leaderboards should be created to speed up the methodological development.

Although the field of DL and hybrid models is improving, there is still a gap between theoretical growth and practical implementation. This is mainly because generalizability, computational efficiency and operational constraints have not been given much consideration. The deployment-conscious model design should thus be the focus of future research where the enhancement in predictive accuracy is matched with scalability, robustness, and computational feasibility.

Overall, the recommendations indicate that the development of models should be no longer based on the predictive accuracy but should be generalizable, operationally robust, and computationally efficient. These gaps need to be solved to bridge the gap between advanced forecasting models in the academic prototyping and their application in real-world energy systems.

VII. LIMITATIONS OF THIS SLR

Although this SLR followed PRISMA guidelines, certain limitations remain. The analysis was restricted to English-language publications and selected databases, potentially introducing publication bias. Additionally, the exclusion of grey literature may limit coverage of emerging current, on-the-ground research and industrial practices.

AUTHORS' CONTRIBUTION

ST Leholo conceptualised the study, developed the methodology, implemented the models, collected and curated the data, performed the formal analysis, and drafted the original manuscript. C Du and T.E Mathonsi contributed to supervision, reviewing and improving the manuscript through proofreading and editorial suggestions. All authors have read and agreed to the published version of the manuscript.

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