Energy Strategy Reviews 59 (2025) 101735

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

Review

Evaluating the impact of deep learning approaches on solar and photovoltaic power forecasting: A systematic review

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ARTICLE INFO

Keywords:
Deep learning
PV power forecasting
Solar radiation forecasting
Systematic review

ABSTRACT

Accurate solar and photovoltaic (PV) power forecasting is essential for optimizing grid integration, managing energy storage, and maximizing the efficiency of solar power systems. Deep learning (DL) models have shown promise in this area due to their ability to learn complex, non-linear relationships within large datasets. This study presents a systematic literature review (SLR) of deep learning applications for solar PV forecasting, addressing a gap in the existing literature, which often focuses on traditional ML or broader renewable energy applications. This review specifically aims to identify the DL architectures employed, preprocessing and feature engineering techniques used, the input features leveraged, evaluation metrics applied, and the persistent challenges in this field. Through a rigorous analysis of 26 selected papers from an initial set of 155 articles retrieved from the Web of Science database, we found that Long Short-Term Memory (LSTM) networks were the most frequently used algorithm (appearing in 32.69% of the papers), closely followed by Convolutional Neural Networks (CNNs) at 28.85%. Furthermore, Wavelet Transform (WT) was found to be the most prominent data decomposition technique, while Pearson Correlation was the most used for feature selection. We also found that ambient temperature, pressure, and humidity are the most common input features. Our systematic evaluation provides critical insights into state-of-the-art DL-based solar forecasting and identifies key areas for upcoming research. Future research should prioritize the development of more robust and interpretable models, as well as explore the integration of multi-source data to further enhance forecasting accuracy. Such advancements are crucial for the effective integration of solar energy into future power grids.

Contents

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https://doi.org/10.1016/j.esr.2025.101735
Received 17 September 2024; Received in revised form 2 April 2025; Accepted 18 April 2025
Available online 6 May 2025

1. Introduction

Precise and reliable prediction of solar photovoltaic (PV) power production is a critical challenge for the effective integration of solar energy into modern power grids. While traditional machine learning (ML) methods, a subfield of artificial intelligence (AI) that has highlighted revolutionary potential across different industries [1–3], have been used for this task, they generally struggle to detect the complex, non-linear relationships and temporal dependencies inherent in solar irradiance data. Deep learning (DL) algorithms, with their advanced abilities for handling large datasets and learning intricate patterns [4–6], offer a promising solution, especially given their capacity to improve with larger datasets [7]. However, there is a notable gap in the literature: a systematic understanding of the specific DL architectures, preprocessing techniques, and feature engineering methods that are most effective for solar PV forecasting. This lack of a comprehensive overview hinders further development and application of DL in this crucial area.

Renewable energy has recently seen a significant increase. The amount of electricity generated globally using variable renewable energy sources (VRE), a subset of renewable energy resources (RES) that includes solar photovoltaics (PV) and wind, raised from 1.857 TWh to 32 TWh between 2000 and 2019 [8]. By the end of 2030, hydro, solar, bioenergy, and wind energy will account for about 40% of the world's power supply, based on the 2020 report from the International Energy Agency (IEA) [9]. The fast evolution of RES in recent years has created significant issues for energy system management. Power systems must quickly change to make accessible this new mix of energy generation. Since most RES depend on solar irradiation or wind speed, it is challenging to anticipate their power generation due to their fluctuation and intermittency. Because of these characteristics, maintaining the normal operation and reliability of power systems demands more flexibility, which makes administration and maintenance more difficult [10]. Particularly solar PV as one of the most crucial RES, that the yearly solar energy incident on the earth's surface is roughly 1.5×1018 kW h/year, or 10,000 times larger than the world's actual annual electricity usage [11]. Risks resulting from PV power's unpredictable nature rise in line with solar PV capacity increase. Such dangers might be reduced by energy storage, but the costs of installation and maintenance are high. Nonetheless, solar irradiance prediction provides a quick, low-cost fix that works well for microgrid operation optimization issues including peak shaving, reducing the effect of uncertainty, and solving the power system's economic dispatch issue [12].

Many PV power forecasting techniques have been established; these methods may be categorized into four groups according to the prediction horizon [13]: very short-term, short-time "48–72 h ahead of time", medium-term, and long-term. Applications for each category include microgrid management, PV system control, and power market management. Every forecasting horizon has a particular application. For instance, Medium and long-term horizons are utilized for PV plant maintenance and planning, whereas short-term horizons are used for unit commitment, economic dispatch, and power system operations. One-step-ahead and multi-step-ahead forecasters appear in another classification; the latter are more often used. Whereas the multi-input multi-output method, the recursive approach, and the direct approach are the three primary methods for multi-step forecasting [14].

The accuracy of forecasters' predictions of PV plant power generation depends on several elements [15], including time-horizon, meteorological conditions, geographic location, and data accessibility. These factors may be utilized to select different forecasters, for instance, satellite pictures [16] can be used for local models, and numerical weather prediction (NWP) models [17,18] for physical methods. While NWP models are frequently employed to predict weather conditions up to 15 days ahead [19], their use is challenging because of the pricey equipment required and the unavailability of early-hours forecasts. For predicting short-term future up to a day ahead, statistical and probabilistic techniques such regression models [20], exponential smoothing, autoregressive models, ARIMA [21], time series ensemble [22], and probabilistic methods [23–25] are appropriate. Additionally, advanced techniques based on ML and AI [26], such as support vector machines (SVM), k nearest neighbor (kNN), extreme learning machine (ELM), and artificial neural networks (ANNs), are employed for short-term applications [27]. High forecasting accuracy may be achieved by combining sophisticated techniques with physical or statistical methodologies through hybrid systems [28,29]. On the other hand, DL models [30] present the potential to outperform the statistical models and the ML-based algorithms due to their capacity to handle sequential or time-series data which is the fundamental basis for solar forecasting. The successful application of advanced DL techniques in other areas of power systems highlights the potential for similar advancements in solar forecasting. These methods are gaining popularity in domains such as power plant control and optimization due to their ability to handle complex, non-linear, and time-varying data. By presenting a deep reinforcement learning-based framework for dynamic combustion optimization in a pulverized coal boiler, combining wall temperature limitations, [31] demonstrates the promise of reinforcement learning in difficult control issues. For instance, [32] proposes a prediction model for NOx emissions in flexible power generation that makes use of a channel equalization convolutional neural network, a complex DL architecture designed to manage time-varying delays. These examples demonstrate the effectiveness of DL in resolving significant problems in traditional power systems. These advancements greatly increase the appeal of the potential of state-of-the-art DL techniques to enhance the accuracy and robustness of solar PV forecasting. Specifically, the ability of advanced DL architectures to learn from complex, non-linear, time-series data, is crucial for addressing the challenges of intermittent and variable renewable energy generation. Moreover, DL's role in optimizing energy systems extends beyond single-source forecasting. For example, [33] examines the optimal operational strategy of a hybrid PV/wind renewable energy system using HOMER, demonstrating the importance of integrated modeling approaches for renewable energy management. This paper, however, focuses on system design and control strategies, lacking a deep dive into advanced DL techniques for individual resource forecasting, which is a critical component in this type of work. Although the use of DL continues to increase in various sectors, some studies focus on its utility in other domains, such as network security. For example, [34] presents a network intrusion detection system using a hybrid multilayer deep learning model; this highlights the broad application of DL and the need for specialized DL models tailored for the complexities of power system forecasting. Existing reviews of DL in renewable energy systems often focus on the broader application of machine learning (ML) in solar forecasting, or the general use of DL in VRE integration, but do not provide a comprehensive systematic analysis of specific DL techniques for solar PV forecasting. This highlights a gap that our work aims to fill, by conducting a systematic review that concentrates specifically on the application of deep learning methodologies for solar PV forecasting, using a rigorous and objective approach.

A systematic literature review (SLR) was carried out to understand the impact of deep learning on solar photovoltaic forecasts. Conducting an SLR is crucial as it may serve as a beneficial foundation for future research endeavors [35]. SLR identifies research gaps and guides future studies using papers retrieved and combined from electronic databases following an objective and transparent methodology to address well-defined research questions [36]. SLR studies generate new insights and help novice researchers grasp the state-of-the-art in the research area. Therefore, the current study aims to survey DL architectures applied to solar PV forecasting, evaluate their performance, and discuss their use from various aspects.

This SLR addresses the limitations of previous reviews by giving a comprehensive and detailed analysis of DL approaches specifically for solar PV forecasting. Unlike [37], which primarily focused on traditional ML algorithms, this work offers an in-depth evaluation of various deep learning architectures, including CNNs, RNNs, and their hybrid combinations. Furthermore, unlike [38], which centered on ANNs, this SLR examines the role of feature engineering and data preprocessing techniques (data clustering, data augmentation, and data decomposition), showcasing the importance of Wavelet Transform for data decomposition, K-means for data clustering, and GANs for data augmentation. Finally, this review identifies and discusses the challenges linked to the generalization, interpretability, and operating efficiency of DL models, GIVING valuable guidance for upcoming research in this domain. This systematic approach, using the Kitchenham methodology [36], guarantees an objective and rigorous analysis, resulting in a comprehensive understanding of the state-of-the-art and future directions of deep learning in solar PV forecasting.

The rest of the document is structured as follows. Section 2 gives an explanation of the relevant works and the study's motivation. Section 3 discusses the process. In Section 4, the SLR findings are displayed. Section 5 describes the deep learning methodology and preprocessing methods used in solar photovoltaic forecasts. Section 6 provides the discussion, while Section 7 ends the study.

2. Related works and motivation

The effective use of solar energy and its smooth integration into the electrical grid depends heavily on solar forecasting. Predicting future solar photovoltaic (PV) system output entails taking into account several variables, including weather, solar irradiance, cloud cover, and other environmental elements. The reliability and cost-effectiveness of solar power are eventually enhanced by accurate solar forecasting, which makes it possible to manage energy generation, grid stability, and energy trading effectively.

DL, a subfield of ML, holds the potential for enhancing the accuracy of solar forecasting. Because it can automatically recognize hierarchical representations of data, it can capture complex patterns and correlations that traditional modeling methods would miss. DL algorithms handle tremendous amounts of data, nonlinear correlations, and temporal dependencies that come with weather and solar irradiance patterns in the context of solar forecasting.

There have been reviews on topics pertaining to solar photovoltaic power generation forecasting. Some literature reviews have addressed all well-known forecasting approaches, including physical, statistical, and AI-based models. Iheanetu reviews the advancements in solar PV power forecasting methods, focusing on data-driven processes [39]. The findings indicate that each model has its advantages and disadvantages, and AI and ML methods are growingly being employed to forecast solar PV output power because of their accuracy and learning abilities from new historical data. The author anticipates that AI and big data will keep improving solar PV output energy prediction. An extensive analysis of advancements in the area of forecasting solar photovoltaic power is conducted by Sobri et al. [40]. Their goal is to examine and contrast different approaches to solar photovoltaic power prediction with respect to their features and efficacy. Their results are largely in line with the previous review, and they also note that ensemble methods were created by researchers in order to better forecast model performances by identifying the distinctive qualities of individual models. In contrast to using separate models, this combination yields accurate results. In the same context, Sudharshan et al. reviewed a variety of models for estimating solar power and irradiance [41] and came to the conclusion that hybrid and ensemble models offered better predictions with a time horizon of minutes to many days.

Several reviews have examined the application of ML and ANNs to solar forecasting. Basaran et al. [37] delivered a broad overview of ML algorithms, but their work predates the widespread adoption of deep learning techniques, thus failing to analyze the performance of deep neural networks such as CNNs and (RNNs). Qazi et al. [38] focused specifically on artificial neural networks (ANNs), particularly multilayer perceptrons (MLPs), neglecting recent advancements in RNNs and CNNs, which have shown promise in capturing temporal and spatial dependencies in solar data. Klaiber and van Dinther [42] examined the broader implications of deep learning in variable VRE systems, including solar, wind, and hydro, but lacked a detailed analysis of the specific DL architectures, features, and evaluation metrics used in the narrower field of solar PV forecasting. These reviews also fail to discuss data augmentation and data clustering, which is important for solar forecasting. In particular, none of the mentioned research provides a comprehensive and systematic evaluation of these aspects, leading to an incomplete and inconsistent insight into the application of deep learning in solar PV forecasting. Other reviews focused just on the adoption of AI-based methodologies for solar forecasting. For instance, Wang et al. conducted a taxonomy analysis of the current AI-based solar power forecasting techniques [43]. They also discussed the difficulties and possible avenues for future research in this area. With a particular focus on ML, DL, and hybrid models, Mellit et al. seeks to offer a comprehensive and analytical analysis of the most recent uses of AI approaches applied to Photovoltaic Output Power Forecasting [44]. They conclude that even though there has been an extensive study on the design of forecasters based on ML, they observed there has not been much done with deep learning to estimate PV power thus far. Therefore a few reviews have been done on examining the employment of DL algorithms for solar power prediction. Thus, the review [45] by Rial et al. focused on convolutional neural network-LSTM (CNN–LSTM), long short-term memory (LSTM), gated recurrent unit (GRU), and recurrent neural network (RNN) as DL algorithms for processing time-series data to estimate solar radiation and photovoltaic (PV) power. While these studies provide valuable insights, it is also essential to consider the specific research being conducted within the local context. For example, a comparative study by Ledmaoui et al. [46] evaluated various ML algorithms for forecasting solar energy production in Morocco. This research provides a useful local perspective and highlights the practical importance of accurate solar forecasting in the Moroccan energy sector. Although their study focuses on traditional ML rather than deep learning, it offers a valuable benchmark and underscores the growing body of work in this critical area.

It is important to remember that these papers are all narrative reviews, which may be more susceptible to bias and lack methodological rigor. A systematic review about the exclusive use of DL algorithms in solar forecasting does not exist in the literature, therefore there are systematic reviews that either focus on ML and ANNs for solar forecasting or the use of DL models for VRE in general. And that is the motivation for conducting this systematic and comprehensive literature review, focusing on the employment of DL approaches for solar photovoltaic forecasting. A brief comparison is provided here. Table 1 provides a comprehensive comparison between our and previous SLR.

We acknowledge that solar PV power prediction is a well-established research area with numerous existing studies. While various narrative reviews have explored PV forecasting methods, including those based on traditional ML and AI, this paper fills a critical gap

Table 1
Related work vs. current study.

Ref.	Review type	Database	Time span	Dataset	Research questions	Key findings
[37]	Systematic review	Scopus	2010–2020	49	RQ1 categorizes studies based on PV cell materials, standalone and grid-connected systems, and considers installation methods (ground-mounted or rooftop) and location. RQ2 looks at datasets from the evaluated research, covering things like wind speed, cloud cover, solar irradiance, and numerical weather forecasting. RQ3 identifies forecasting approaches in SLR studies, focusing on ML approaches due to insufficient statistical methods for complex sample feature relationships.	Polycrystalline PV panel technologies are the primary focus of studies due to their cost-effectiveness and wider light spectrum operation. Current forecasting methods use factors like historical power data, temperature, relative humidity, solar radiation, daytime duration, and cloud coverage to predict power. Some feature selection is used to determine forecasting accuracy. Most PV power forecasting studies use direct approaches, with machine learning methods like the k nearest neighbor, Support Vector Machine, random forest, and artificial neural network. Hybrid approaches combine multiple prediction models for more accurate forecasting results.
[38]	Systematic review	ACM, IEEE, ScienceDirect, Springer, Wiley, and ISI web of knowledge	2006–2013	24	RQ1: Which solar energy forecast methods are scholars focusing on, and how are their studies divided among these methods? RQ2: What is the field-level effectiveness of ANN modeling?	ANN models are highly accurate in predicting solar radiation in various climatic conditions due to their ability to accept multiple input parameters. This makes them more reliable than empirical models and makes them more demanding in renewable energy resource prediction, such as solar radiation predication and solar system design. Adaptive neuro-fuzzy inference systems, neural networks, and multilayer perceptrons enhance prediction accuracy in monthly and hourly solar radiation predictions. ANN models outperform statistical, conventional, linear, non-linear, and fuzzy logic models.
[47]	Systematic review	Web of Science, Science Direct, IEEE and Google Scholar	2013–2017	38	RQ1: Where, why, and by whom have researches been conducted? RQ2: What role do machine learning models play in addressing the forecasting issue? RQ3: What sort of data is being utilized? RQ4: How does the global adoption of renewable energy relate to predicting knowledge development?	A study of 38 papers published by 134 researchers on solar power forecasting reveals that the majority of these papers focus on computer science, information technology, and knowledge engineering. The study also highlights the potential of machine learning algorithms like ELM, ANN, and SVM to improve forecasting accuracy. However, less than 20% of the papers used electricity-related data for solar power forecasting and there was a lack of focus on data quality initiatives. The majority of the papers focused on solar radiation, with 73% combining solar irradiance data with meteorological data parameters. Most papers used machine learning algorithms, with data collected ranging from 5 to 15 years. Further research is needed to improve forecasting accuracy and address data quality issues in this sector.
[42]	Systematic review	Web of Science	1990–2019	136	How can DL be used to approach VRE integration difficulties as a solution facilitator and speed up its widespread integration in electrical systems?	Solution I: By improving solar and wind power forecasts, DL can reduce the uncertainty around the generation of VREs. Subsequent solution attempts are frequently based on advanced DL-forecasting models. Solution II: To improve the flexibility of electrical systems, DL can help with system scheduling, optimize it, and enable real-time grid management. Solution III: To maintain grid security and boost the effectiveness and dependability of VRE sources, DL can enhance intelligent condition monitoring.

(continued on next page)

Table 1 (*continued*).

Ref.	Review type	Database	Time span	Dataset	Research questions	Key findings
This Study	Systematic review	Web of Science	2015–2024	155	RQ1: Which deep learning techniques have been applied to solar forecasting in the literature?; RQ2: what different data preprocessing techniques and feature engineering approaches are used with DL algorithms for solar forecasting in literature?; RQ3: Which features have been employed in DL-based solar forecasting in the literature?; RQ4: Which evaluation metrics and approaches have been employed in solar forecasting in the literature?; RQ5: What are the obstacles in deep learning-based solar forecasting?	The finding mentioned that LSTM and CNN, and their combination the most used algorithms for solar forecasting. The Pearson correlation, Wavelet Transform, K-Means, and Generative Adversarial Networks are the most feature engineering techniques used. Ambient Temperature, Pressure, and humidity are the most input features used.

by providing a systematic review focused exclusively on the application of deep learning techniques for solar PV forecasting. Existing systematic reviews in this area often focus on traditional ML [37, 38] or broader variable renewable energy (VRE) applications using DL [42] but lack an in-depth analysis of DL's specific role in solar PV forecasting. Furthermore, other reviews that tackle DL algorithms, are narrative reviews [45], with potential bias and lack methodological rigor, so our paper aims at filling this void by rigorously analyzing the employment of DL techniques in solar PV forecasting, employing the well-known Kitchenham SLR methodology, thus setting the ground for deep analysis.

The main contributions of this work lie in its systematic and comprehensive evaluation of DL-based solar PV power forecasting, a specific focus not previously addressed in existing literature reviews. This specialization distinguishes it from previous reviews that are either narrative [42], focus on ML broadly [37], center on ANNs [38], or examine deep learning's implications within the wider context of general VRE applications [47]. Specifically, Basaran et al. [37] provide a wide-ranging overview of ML algorithms, but their research predates the surge in deep learning adoption, leading to a lack of analysis concerning deep neural network performance in solar forecasting. While Qazi et al. [38] concentrate primarily on ANNs, they omit discussion regarding the rise of RNNs and CNNs, which have demonstrated promise in capturing temporal and spatial dependencies in solar data. Similarly, although Klaiber and van Dinther [47] offer insights into DL within VRE systems, their analysis lacks a detailed examination of the specific DL architectures, feature engineering techniques, and evaluation metrics applied within the narrower domain of solar photovoltaic (PV) forecasting. Furthermore, these existing reviews offer only a limited overview of the data pre-processing techniques. Using the well-known Kitchenham protocol [36], our systematic approach ensures an objective and rigorous analysis of the chosen research domain. We identify and analyze the various DL architectures applied (RQ1), systematically categorize and evaluate the diverse feature engineering and data pre-processing techniques employed (RQ2), outline the commonly used features for DL-based solar forecasting (RQ3), assess the evaluation metrics (RQ4), and address the challenges and opportunities for future research in this field (RQ5). Specifically, our review reveals the most common DL models, such as LSTM and CNN, and their hybrid combinations. It also identifies key pre-processing techniques such as Wavelet Transform, K-Means, and GAN and their variants, and highlights the frequently used features like temperature, pressure, and humidity. Furthermore, our discussion of the challenges and opportunities for future research (RQ5) provides valuable guidance for researchers and practitioners working in this area. By offering a systematic, comprehensive, and focused examination of deep learning for solar photovoltaic power forecasting, this research contributes to a clearer understanding of the state-of-the-art and offers a rigorous foundation for future development in this field.

3. Research methodology

3.1. Protocol

Prior to conducting the SLR, a review protocol is developed. The review was conducted following Kitchenham's well-known review process [36]. The research questions are first formulated. Once research questions are established, pertinent studies are chosen using databases. Web of Science is the database that was employed for this investigation due to its comprehensive and highly reputable index of scholarly publications, covering a vast range of disciplines, which is particularly valuable for systematic reviews requiring broad coverage. Furthermore, its sophisticated search functionality and citation analysis tools facilitate efficient and precise identification of relevant research literature. Following the selection of pertinent research through applying a series of quality and exclusion criteria-based filters and assessments. In order to address the research issues, the pertinent data from the chosen studies were eventually retrieved and synthesized. Three components comprise our methodology: planning, conducting, and reporting as illustrated in Fig. 1.

The review's planning phase is the initial step. Research questions are determined at this stage, followed by the development of a procedure and, ultimately, its validation to determine the feasibility of the approach. Along with the research topics, article venues, primary searching words, and paper selection criteria are developed. Once all of that information has been defined, the procedure is reviewed again to determine whether it reflects an appropriate review procedure.

Carrying out the review is the second step. By searching within all of the chosen records, the included papers were chosen at this point. After the data was gathered, additional information about the research topics as well as details about the authors, year and kind of publication, and other aspects of the data were saved. After obtaining all the necessary data precisely, the data was aggregated to offer an overview of the relevant studies that have been published to date.

Recording the results and answering the research questions were the final steps in the evaluation process.

3.2. Research questions

The purpose of this SLR is to gather information about released research in the domain of DL and solar photovoltaic forecasting. Papers have been examined from a variety of angles to gain knowledge about the area of interest. For this SLR study, the five research questions (RQs) listed below have been developed.

- RQ1: Which DL models have been applied to solar forecasting in the literature?;
- RQ2: what different data preprocessing techniques and feature engineering approaches are used with DL algorithms for solar forecasting in literature?;

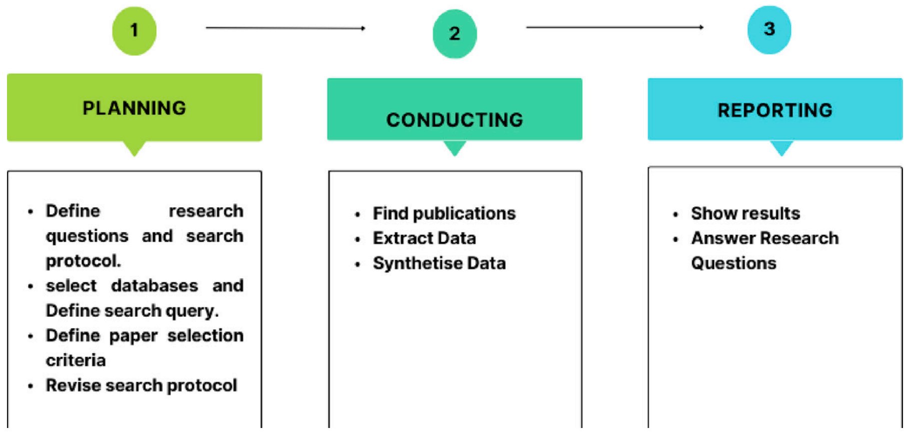

Fig. 1. The research methodology.

Table 2
Search query applied to topic fields.

Search query	Papers extracted
(“Data Augmentation” OR “data processing” OR “feature extraction” OR “Data Preprocessing” OR “Data Mining” OR “Data Analysis” OR “Data Clustering” OR “Feature Engineering” OR “Wavelet Transform” OR “Statistical Features” OR “Feature Selection”) AND (“Neural Networks” OR “ Deep Neural Networks” OR “Deep Learning Models” OR “Convolutional Neural Networks” OR “Recurrent Neural Networks” OR “Long Short-Term Memory” OR “Gated Recurrent Unit” OR “Autoencoders” OR “Stacked AutoEncoder” OR “Generative Adversarial Networks” OR “Transfer Learning” OR “Feedforward Neural Network” OR “Deep Reinforcement Learning” OR “Variational Autoencoder” OR “Generative Adversarial Network” OR “Deep Belief Network” OR “Radial Basis Function Network” OR “Hopfield Network” OR “Artificial Neural Network” OR “Reinforcement Learning” OR “Multilayer Perceptron” OR “Residual Network” OR “Capsule Networks” OR “Deep Boltzmann Machines” OR “DL” OR “FNN” OR “MLP” OR “CNN” OR “RNN” OR “LSTM” OR “GRU” OR “VAE” OR “GAN” OR “DBN” OR “RBFN” OR “ANN” OR “SAE”) AND (“solar forecasting” OR “Solar Energy Forecasting” OR “Solar power Forecasting” OR “Solar radiation Forecasting” OR “solar irradiation forecasting” OR “solar output forecasting” OR “Photovoltaic Forecasting” OR “Photovoltaic energy Forecasting” OR “Photovoltaic power Forecasting” OR “Photovoltaic output Forecasting” OR “PV forecasting” OR “PV energy Forecasting” OR “PV power Forecasting” OR “PV output Forecasting”)	preliminary research query. (155 papers)
(“Data Augmentation” or “data processing” or “feature extraction” or “Data Preprocessing” or “Data Mining” or “Data Analysis” or “Data Clustering” or “Statistical Features” or “Wavelet Transform” or “Feature Selection”) and (“Neural Networks” or “Deep Learning Models” or “Convolutional Neural Network” or “Long Short Term Memory” or “Generative Adversarial Networks” or “Generative Adversarial Network” or “Reinforcement Learning” or “Artificial Neural Network” or “Multilayer Perceptron” or “DL” or “LSTM” or “ANN”) and (“solar forecasting” or “Solar Energy Forecasting” or “Solar power Forecasting” or “Solar radiation Forecasting” or “solar irradiation forecasting” or “solar output forecasting” or “Photovoltaic power Forecasting” or “PV forecasting” or “PV power Forecasting” or “PV output Forecasting”)	After pilot test query (155 papers.)

- RQ3: Which features have been employed in DL-based solar forecasting in the literature? ;
- RQ4: Which evaluation metrics and approaches have been employed in solar forecasting in the literature? ;
- RQ5: What are the obstacles in deep learning-based solar forecasting?

3.3. Search strategy

The search is carried out by establishing all the possible keywords related to the two fields of interest, deep learning and solar photovoltaic forecasting, and their synonyms and acronyms, then a set of keywords was added pertaining to the data processing and feature engineering techniques to keep in line with the scope of the study, and to highlight the relevant studies to the previous mentioned research questions. The resulting search string is illustrated in Table 2:

After many pilot tests and the elimination of terms that did not have an impact on the number of generated papers, the final selection after applying this search string on the author keywords, abstract, title, and Keywords Plus attributes was 155 papers. The search execution was on 13th June 2024.

3.4. Inclusion and exclusion criteria

Considering the inclusion and exclusion criteria, the papers were evaluated and graded in order to capture the limits of the SLR and exclude irrelevant research. Table 3 lists all the inclusion and exclusion criteria used.

Table 3
Search query applied to topic fields.

Inclusion criteria	Exclusion criteria
Paper published between 2015 and 2024	Paper is a review or survey study
Paper written in English	Paper is a conference proceeding article
Paper is a research article	Paper without abstract

After the application of the exclusion and inclusion criteria, only 121 papers remained for further quality evaluation. To refine the search results by focusing on articles where the terms are closely related conceptually, rather than simply appearing in the same document, the proximity operator NEAR/50 was applied. The paper’s number was reduced to 28, and after the abstract screening and full-text availability check, the final number of papers was 26, forming the extracted and synthesized data to answer the research questions. Fig. 2 demonstrates the selection process.

4. Results

To more thoroughly assess the state of deep learning in solar forecasting currently. The amount of studies released annually over the previous ten years is displayed in Fig. 3. This graph shows that there have been more articles published on solar power forecasts recently.

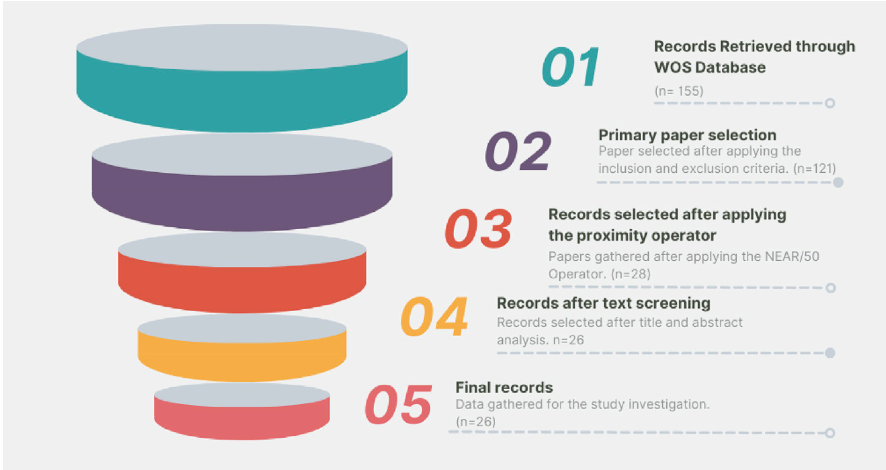

Fig. 2. The procedure for selecting studies.

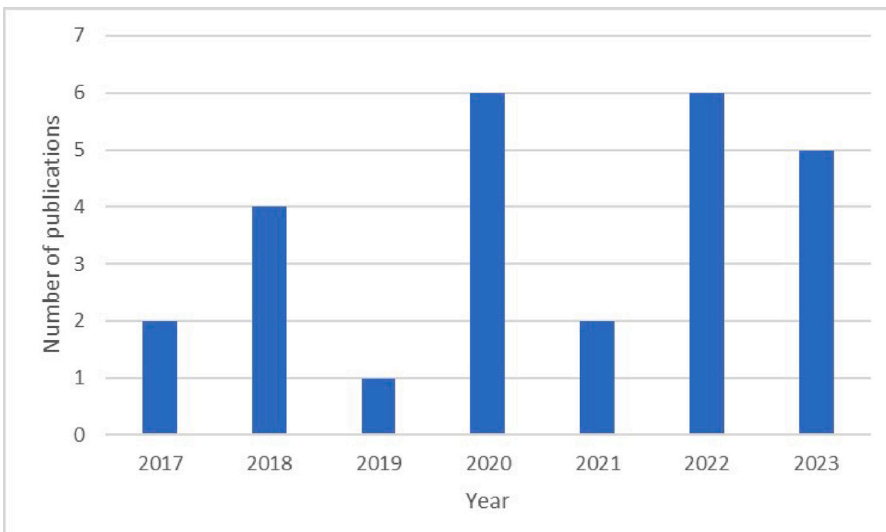

Fig. 3. Annual distribution of selected publications.

This enormous increase in research on deep learning in solar forecasting indicates a considerably higher level of interest in the topic. In 2015 and 2016, there were no studies on deep learning in solar forecasting because of the inclusion and exclusion criteria of this study.

Table 4 displays the selected publications where publication year, title, and algorithms employed are shown. DL models were reviewed and summarized in order to respond to the initial research question (RQ1). Table 5 enumerates the often-utilized models. The two most commonly utilized algorithms are LSTM and CNN, followed by ANN as the table illustrates. Additionally, Table 5 shows that RNN and GRU are frequently utilized. Finally, deep neural networks (DNN), and Elman neural network (ELM) come last with one occurrence time. Note that the algorithm can be used either as a proposed model or as a benchmark and that it can be utilized as a standalone model or integrated into a hybrid model. For instance, several studies [51,63] used LSTM for short-term photovoltaic power prediction, others such [65] used LTSM for one day a head solar power forecasting, while others like [72] used CNN to extract features from sky images for solar radiation forecasting. These are common applications of deep learning for solar energy.

Fig. 4 illustrates all the hybrid models used and enhanced variants of the basis models. The most common hybrid model used is CNN-LSTM with 5 times of occurrences followed by CNN-GRU with 2 times of occurrences. All the other hybrid and enhanced models "Deep CNN (DCNN), Dilated CNN (DCNN*), Quad-kernel Deep CNN (QK-CNN), BiLSTM, Autoencoder (AE) combined LSTM (AE-LSTM), DNN, Generalized Neural Network (GNN), Dilated CNN combined with BILSTM (DCNN-BILSTM), Convolutional Neural Network combined with BILSTM (CNN-BILSTM), CNN integrated with LSTM (CNN-LSTM), LSTM integrated with a CNN (LSTM-CNN), CNN integrated with GRU (CNN-GRU), GRU integrated with a CNN (GRU-CNN), ELM integrated with LSTM (ELM-LSTM), RNN combined with LSTM (RNN-LSTM)" were used once. In addition a set of popular convolutional neural network (CNN) architectures like ResNet, DenseNet, AlexNet, GoogLeNet, ShuffleNet SqueezeNet was used one time.

The quantitative analysis of the deep learning algorithms based on their performance evaluation metrics across our selected publications, indicates a number of trends. For example, in [48], the authors investigated nine ensemble models for solar radiation forecasting in seven Indian cities, finding that VMD-integrated GRU generally performed best with the following approximate RMSE ranges: Delhi (0.82), Chennai (0.83), Hyderabad (0.85), Nagpur (0.89), Patna (1.15), Trivandrum (0.95), and Bhubaneshwar (1.22). In comparison, other models produced varying RMSE values depending on the city and signal processing technique used, for example, VMD-integrated LSTM exhibited R2 scores between (0.41 and 0.74); VMD-integrated BiLSTM had R2 scores between (0.11 and 0.9); VMD-integrated CNN had R2 scores

Table 4
Selected papers.

Ref	Key	Deep learning algorithm(s) used	Year
[48]	P1	Gated Recurrent Units (GRU), Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Convolutional Neural Network (CNN), Deep Neural Network (DNN), and Artificial Neural Network (ANN)	2023
[49]	P2	Deep CNN DCNN), Back-propagation Neural Network (BPNN)	2017
[50]	P3	Generalized Neural Network (GNN) and ANN	2017
[51]	P4	LSTM	2021
[52]	P5	CNN and GRU	2022
[53]	P6	Quad-Kernel Deep Convolutional Neural Network (QK-CNN), LSTM, and Convolutional LSTM (ConvLSTM)	2022
[54]	P7	CNN, Support Vector Regression (SVR), ANN, LSTM, and Hybrid CNN-LSTM, LSTM-CNN	2023
[55]	P8	Hybrid CNN and Extreme Learning Machine CNN-ELM	2022
[56]	P9	GRU, LSTM, and CNN	2023
[57]	P10	CNN, BILSTM, hybrid CNN-BILSTM	2023
[58]	P11	Auto-Encoder (AE), LSTM, and hybrid AE-LSTM	2020
[59]	P12	Backpropagation Neural Networks (BPNN) and Elman Neural Networks (ENN)	2018
[60]	P13	ANN, Extreme Learning Machine (ELM), Deep Belief Network (DBN), Restricted Boltzmann Machine (RBM), CNN-LSTM, CNN-GRU, LSTM-CNN, GRU-CNN	2022
[61]	P14	ANN, CNN, LSTM, CNN-LSTM	2018
[62]	P15	CNN(ResNet, DenseNet) and ANN	2020
[63]	P16	LSTM, ELM, and LSTM-ELX	2023
[64]	P17	CNN	2020
[65]	P18	ANN, LSTM	2021
[66]	P19	Dilated Convolutional Neural Network (DCNN), CNN, LSTM, BILSTM, and DCNN-BILSTM	2022
[67]	P20	ANN	2017
[68]	P21	ANN, LSTM, and CNN	2022
[69]	P22	Feed Forward Neural Network (FFNN) ANN	2019
[70]	P23	ANN	2020
[71]	P24	Recurrent Neural Network (RNN), LSTM, Deep Belief Network (DBN), ANN	2018
[72]	P25	ANN, CNN, LSTM, CNN-LSTM, CNN-ANN	2020
[73]	P26	ANN	2020

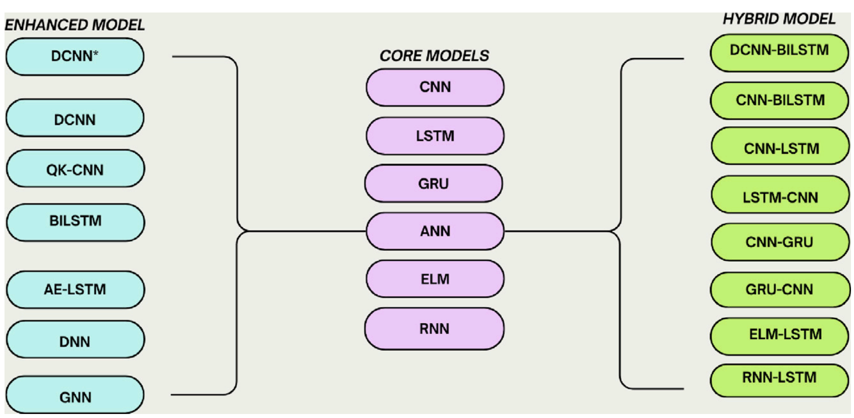

Fig. 4. The derived deep learning models.

Table 5
The most deep learning algorithms used.

Deep learning algorithms	Times of occurrence	Percentage (%)
LSTM	17	32.69
CNN	15	28.85
ANN	9	17.31
GRU	6	11.54
RNN	2	3.84
DNN	1	1.92
ELM	1	1.92
DBN	1	1.92

between (0.44 and 0.65); VMD-integrated DNN had R2 scores between (0.3 and 0.63), VMD-integrated ANN had R2 scores between (0.18 and 0.56), and VMD-integrated SVR variants (RBF, POLY, and LINEAR) R2 scores were generally between (0.03 to 0.48). DWT-integrated models had a generally lower R2 value for the same models, across all cities. In [53], the authors proposed a Quad-Kernel CNN (QK-CNN) model for intra-hour photovoltaic (PV) power forecasting, which demonstrated superior performance, yielding a better RMSE score of 3.11% compared to LSTM (4.31%) and ConvLSTM (3.57%). Furthermore, the QK-CNN model consistently outperformed single-kernel CNN and CNN-LSTM models across different forecast horizons and data resolutions (5, 10, and 15 min), and was able to explain 96% to 98% of the total variation in the forecasted PV power. In [56], the authors explored a dual-dimensional Time-GGAN data augmentation method for PV power forecasting and found that models trained on the augmented datasets achieved an average RMSE of 3.44%, compared to a higher average RMSE of 5.44% when using non-augmented datasets. Furthermore, they observed a 3.1% improvement in accuracy for LSTM models and a 2.3% improvement for CNN models when using their proposed data augmentation technique. As we can see there is no single model that outperforms all of the other ones, the selection is context-specific, and usually hybrid models tend to outperform the basic ones and are becoming popular. Also, there is a direct correlation between the quality of the data and the model performance, so, the preprocessing and the feature engineering step are of significant importance, which is why the research is trending toward hybrid models that combine decomposition, data clustering, data augmentation, and feature selection techniques.

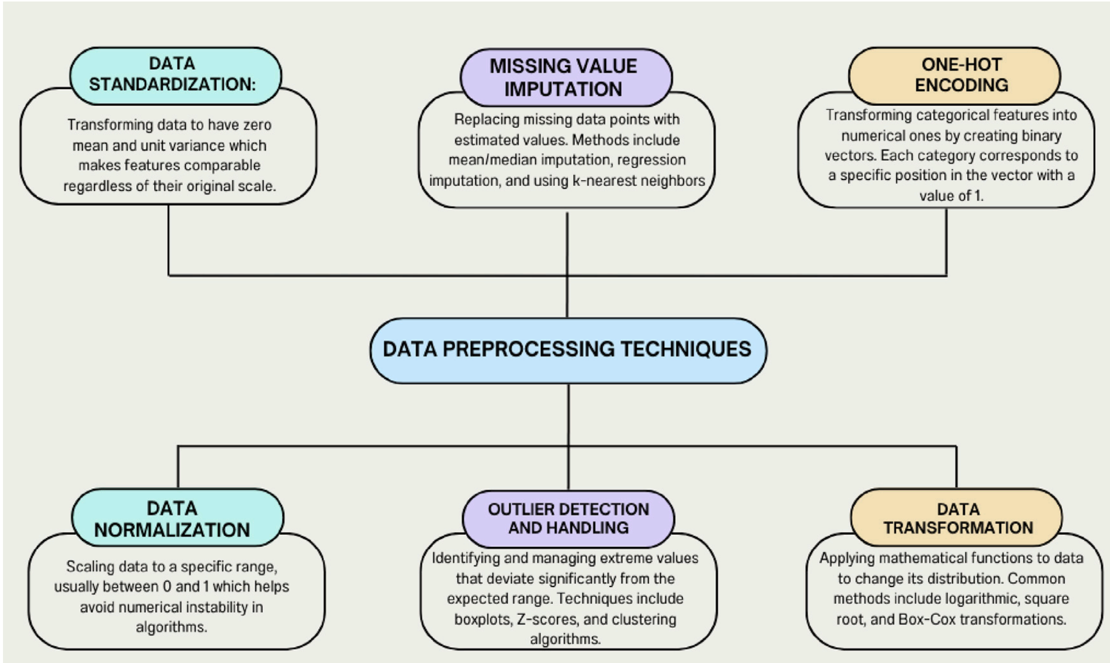

Fig. 5. Data preprocessing methods used.

While the following examples provide precise performance metrics, it is beneficial to consider each model type's overall strengths and weaknesses. LSTMs excel at learning temporal dependencies and suit time-series forecasting where long-term trends are strong. They are computationally heavy, however, and may not be suitable for high-dimensional data. CNNs are well-suited to learning spatial features and can be less computationally heavy than LSTMs. They are not necessarily superior at pulling out long-term temporal relationships, however. Hybrid models, such as CNN-LSTMs, attempt to combine the strengths of both, but their added complexity renders them more difficult to train and interpret. Furthermore, the model architecture must be chosen depending on the particular properties of the data and the forecast horizon. For short-term prediction, simpler models like CNNs or GRUs can suffice, while long-term prediction might require more sophisticated models like LSTMs or hybrid models. Essentially, the choice of the best model is always a compromise between accuracy, computational cost, interpretability, and the specific requirements of the application.

The meaning of data preprocessing and feature engineering might be confusing because they may refer to the same thing. Data preprocessing refers to the pretreatment done to the data before gets fed into the models, and feature engineering refers to the techniques done to decompose, group, and create new features based on the original data. Different data preprocessing techniques and feature engineering approaches used with DL algorithms for solar forecasting applied in studies were investigated and summarized, to address research question two (RQ2). Table 6 and Fig. 5 display every data preprocessing method and feature engineering strategy we were able to extract.

Table 6
Feature engineering techniques used.

Task	Feature engineering techniques
Data decomposition	Wavelet Transform (WT) Variational mode decomposition (VMD) Maximal Overlap Discrete Wavelet Transform (MODWT)
	Complementary ensemble empirical mode decomposition (CEEMD)
	Empirical Wavelet Transform (EWT) Empirical mode decomposition (EMD) Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN)
Data clustering	K-Means Soft-DTW-Based K-medoids Fuzzy C-means (FCM)
Data augmentation	Time Generative Adversarial Networks (TimeGAN) Generative Adversarial Networks (GAN) Conditional Time-Series Generative Adversarial Networks (CTGAN)
Feature selection	PEARSON Correlation RReliefF Feature Selection Maximum Relevance Interaction Gain (MRIG) SPEARMAN Correlation Mutual information analysis Principal Component Analysis (PCA) XGB feature importance Random forest feature importance

As illustrated in Table 6, the most data decomposition used is Wavelet Transform (WT) with its two types Discrete Wavelet Transform (DWT) and continuous Wavelet Transform (CWT), followed by Variational mode decomposition (VMD). For data clustering K-means method is the most employed in our sample, followed by the Fuzzy C-means (FCM) algorithm. For data augmentation, GANs and their variants are the most suited for this purpose. Finally, the Pearson correlation and RReliefF Feature Selection are the most used for the feature selection process.

Wavelet Transform (WT) and Variational Mode Decomposition (VMD) are great decomposition techniques used to analyze solar irradiance data by breaking it down into frequency components to reveal underlying patterns across multiple time scales. WT is particularly effective for time series data with transient or non-stationary characteristics, enabling the extraction of both low-frequency components (representing general trends) and high-frequency components (capturing rapid changes), which enhances forecasting model accuracy. Conversely, VMD excels at handling non-linear and non-stationary signals by decomposing them into distinct intrinsic mode functions (IMFs) with varying frequencies. While these methods give advantages like detailed time–frequency analysis, suitability for non-stationary data, and noise reduction, they also come with limitations. WT may require computationally expensive parameter adjusting, and VMD requires predefining the number of modes, which can be challenging. These techniques are particularly useful in scenarios where time series reveal complex characteristics, including both high-frequency fluctuations and long-term trends, and are often implemented for noise reduction by isolating and removing high-frequency components.

K-Means Clustering and Fuzzy C-Means (FCM) are unsupervised learning models widely employed for clustering solar radiation data into distinct categories. K-Means partitions data into clusters based on the proximity of data points to centroids, offering computational efficiency and straightforward implementation. In contrast, FCM allows data points to belong to multiple clusters, making it more suitable for datasets with gradual transitions between categories. Both methods stand out in identifying patterns, reducing data complexity, and facilitating analysis by grouping similar data points. But, they also face challenges. K-Means may struggle with high-dimensional data, assume spherical clusters, and are sensitive to initialization parameters, while FCM is computationally more expensive. These clustering techniques are great in scenarios requiring the identification of distinct patterns, such as differentiating between sunny and cloudy days. Generative Adversarial Networks (GANs) and their variants, including TimeGAN and CTGAN, are emerging as powerful tools for generating synthetic data that keep the statistical properties of original datasets. TimeGAN is particularly adept at capturing time-series dependencies, while CT-GAN considers additional parameters, such as weather conditions, to produce robust datasets. The main advantages of GANs include overcoming data scarcity, enhancing model generalization, and decreasing overfitting. However, training GANs can be computationally intensive, prone to bias in generated data, and challenging to optimize. These models are particularly useful in scenarios involving limited historical data, unbalanced datasets, or situations requiring synthetic yet realistic data to improve model performance. Pearson Correlation and ReliefF are widely used feature selection techniques in solar energy forecasting. Pearson Correlation quantifies the linear association between two variables, offering insight into the significance of each feature for model development. ReliefF, on the other hand, evaluates feature relevance based on how much a model's performance is affected when a feature is removed. These methods are computationally efficient, easy to interpret, and effective in reducing dimensionality, which accelerates model training. However, Pearson Correlation can be highly sensitive to outliers, and ReliefF may struggle with highly correlated features or non-linear relationships. These techniques are particularly valuable in scenarios requiring dimensionality reduction and the identification of the most meaningful features for model input. In the Appendix section, Tables A.10, A.11, and A.12 give more details about these techniques, and the papers where they appear.

The data preprocessing techniques used for most papers in our selection are the following:

- Data normalization is a data preprocessing method that converts data values to a common range, generally ranging from 0 to 1. This operation ensures that features with vastly different scales do not disproportionately impact the model's training, improving the stability and efficiency of the algorithm. Normalization is especially advantageous when data has a wide range of values, such as solar irradiance data, where outliers can significantly impact the model's accuracy. Common normalization methods include Min–Max Scaling and Max–Min Normalization, both of which rescale values to the desired range;
- Data standardization, on the other hand, centers data around zero and scales it to unit variance (standard deviation equal 1). This ensures that the variables are on a similar scale, preventing certain features from overtaking the learning process. Standardization is especially helpful when the data exhibit a Gaussian distribution, as it helps to normalize the data's shape. It is also beneficial for models that are sensitive to feature scales, such as linear regression and ANN. A common method for standardization is the Z-score, which removes the mean and divides it by the standard deviation;
- Missing value imputation and handling are critical aspects of solar forecasting, especially when working on real-world data that generally have missing data points due to equipment failure or other factors. Common techniques include mean/median imputation, linear interpolation, K-Nearest Neighbors (KNN) imputation, and more sophisticated approaches like multivariate imputation models. Some papers specifically employ mean imputation, linear interpolation, or KNN interpolation to fill in missing values, while others suggest resampling or removing entire days with significant missing data. The kind of data, the amount of missing data, and the intended prediction model accuracy all influence the method selection. Beyond imputation, papers often emphasize the need for outlier detection and handling, as well as basic data cleaning and preparation steps prior to applying forecasting algorithms. eventually, handling missing values effectively is vital for guarantying the reliability and accuracy of solar forecasting models;
- Outlier detection and handling are crucial aspects of solar forecasting using ML and DL models. Outliers, which are unrealistic measurements often caused by sensor errors, system failures, or extreme weather events, can significantly impact model accuracy. Techniques used for outlier detection include statistical methods like the 3σ rule, domain-specific filtering based on physical constraints, and data transformations such as log transformations. Additionally, visual methods like box plots and the interquartile range (IQR) can aid detect outliers. Once detected, outliers are often removed or corrected using methods like interpolation, KNN regression, or by leveraging the inherent outlier resistance of models like Support Vector Regression. Some papers specifically handle outlier removal by eliminating data points with zero radiation intensity or those caused by system shutdowns. Advanced approaches utilize copula theory to model dependencies between variables, allowing for the detection of outliers deviating from expected connections. The choice of outlier detection and handling techniques depends on the specific dataset, model, and research objectives;
- One-hot encoding is a technique used in solar forecasting models to represent weather types based on the ratio of diffuse horizontal radiation (DHR) and global horizontal radiation (GHR), classifying days as Sunny, Partially Cloudy, or Overcast/Rainy. Each weather kind is assigned a unique 3-bit binary code (one-hot vector), creating three separate feature maps for each category. This process is applied to both historical and day-ahead predicted weather data. This method provides a straightforward and interpretable way to incorporate weather information into solar forecasting models. While simple and efficient, it may oversimplify the complex relationship between weather types and solar irradiance and neglect nuances within each category. More sophisticated encoding schemes or alternative representation methods might be needed to ameliorate the accuracy and interpretability of solar forecasting algorithms;
- Solar forecasting models rely on careful data preparation to reach high accuracy. Data Transformation techniques like log or power transformations normalize skewed data distributions, improving model performance. Diurnal Data Extraction focuses on relevant daylight hours, eliminating irrelevant nighttime data and refining the model's focus on solar generation patterns. Furthermore, time series data frequently undergoes transformation, such as aggregating 5-min resolution data into hourly averages. This aggregation serves also as feature engineering, reducing data volume and potentially highlighting larger-scale patterns. Finally, Data Splitting, a standard practice in ML, consists of dividing the data into training and testing sets (typically 80:20). This ensures the model learns from the training data and can generalize to unseen data, preventing overfitting and promoting robust prediction capabilities. The creation of precise and trustworthy solar forecasting models is greatly aided by the combined use of these techniques.

Table 7
Features used for PV power forecasting.

Feature	Number of times used
Ambient temperature	11
Humidity	10
Historical PV power	10
Global Solar irradiance	6
Wind speed	6
Global horizontal irradiance (GHI)	5
Diffuse horizontal radiation (DHR)	3
Wind direction	3
Rainfall	2
Cell temperature	2
Current Phase average	1
UV index	1

Table 8
Features used for solar radiation forecasting.

Feature	Number of times used
Ambient temperature	5
Pressure	4
Wind speed	4
Humidity	3
Historical Global horizontal irradiance (GHI)	3
Wind direction	2
precipitation	1
Bright sunshine hours	1

Table 9
Full evaluation metrics used.

Key	Evaluation metric	Number of times used
RMSE	Root Mean Square Error	25
MAE	Mean Absolute Error	22
MAPE	Mean Absolute Percentage Error	8
R2	Coefficient of Determination	7
R	Correlation Coefficient	5
MBE	Mean Bias Error	2
FS	Forecast Skill	1
MSE	Mean Squared Error	1
MSLE	Mean Squared Logarithmic Error	1
MASE	Mean Absolute Scaled Error	1
NIA	Negative Index of Agreement	1
U1	Theil U-statistic 1	1
U2	Theil U-statistic 2	1
MHE	Mean Huber Error	1
SCC	Squared correlation coefficient	1

Research question three (RQ3) was addressed by examining and summarizing features utilized in the deep learning algorithms used in the publications. Tables 7 and 8 display all of the features used for PV power forecasting and Solar radiation forecasting respectively that we were able to retrieve.

Table 8 indicates that the most frequently employed features for forecasting solar radiation as a “dependent variable” are temperature, pressure, wind speed, and humidity. Other independent variables that are used for forecasting solar radiation include global horizontal irradiance (GHI), wind direction, precipitation, and bright sunshine hours.

The most popular features for PV power forecasts are shown in Table 7. The most often used features include ambient temperature, humidity, historical PV power, wind direction, global horizontal radiation (DHR), global solar irradiance, wind speed, and global horizontal irradiance (GHI). Other, less often used independent features include rainfall and UV index. PV power forecasting also took into account additional panel-related factors, such as cell temperature and current phase average, in addition to climatic variables.

In order to address the fourth research question (RQ4), evaluation metrics were determined. Table 9 lists all of the evaluation metrics that were used along with how often they were used.

According to Table 9, the most frequently employed metrics in the papers are RMSE, MAE, MAPE, and R2. In the appendix section, Table A.13 provides more details about these metrics.

Table 9 shows the parameters used for the papers that deal with deterministic forecasting, for the other studies interested in probabilistic forecasting, the metrics used are the following:

- **Average Coverage Error (ACE)**: Evaluates how well the forecasting quantiles, representing uncertainty, match the observed values;
- **Interval Sharpness (IS)**: Assesses the sharpness of the prediction interval (PI), indicating the degree of uncertainty quantified by the model;
- **Continuous Ranked Probability Score (CRPS)**: Provides an overall measure of probabilistic forecasting performance, encompassing both accuracy (ACE) and sharpness (IS);
- **Theil Inequality Coefficient (TIC)**: This measures the ratio of the variance of the prediction errors to the sum of the variance of the predicted values and the variance of the real values. Values closer to zero indicate better accuracy;
- **Prediction interval coverage probability (PICP)**: Measures the reliability of the predicted intervals by estimating the probability that the actual PV power falls within the predicted intervals;
- **Prediction interval normalized average width (PINAW)**: deter mines the width of the predicted intervals.

Several validation techniques were employed in addition to the evaluation metrics. Common techniques include hold-out validation, where data is divided into training and testing sets, and k-fold cross-validation, where the data is divided into multiple folds for training and testing. Some papers also utilize sliding window validation and multiple-stage validation, allowing for more robust assessments. Several papers use a combination of training, validation, and test sets, allowing for hyperparameter tuning and unbiased evaluation of unseen data. This systematic approach guarantees that the models generalize well to unseen data and provides a comprehensive assessment of their accuracy and effectiveness in forecasting solar radiation and PV system energy production.

To investigate the fifth research question (RQ5), the papers were investigated to determine whether they mentioned any limitations or suggestions for future approaches. While deep learning shows promise for solar forecasting, several limitations hinder its widespread adoption. The generalizability of models is often limited by the specific locations and datasets used in their development. Limited data availability, particularly for extreme weather events, and inconsistencies in data quality can impact model accuracy. Complex models, while powerful, can be computationally expensive and difficult to interpret. Moreover, hyperparameter tuning remains a challenge, often relying on trial-and-error methods. Many studies focus on forecasting accuracy without considering practical integration into grid and energy management systems. Future research should prioritize the development of models that are generalizable, data-efficient, computationally efficient, and readily integrated into real-world applications. Further exploration of signal processing techniques and multi-objective optimization approaches could also significantly enhance solar forecasting accuracy and effectiveness.

5. Deep learning-based solar forecasting

In this section, all deep learning models used in solar forecasting are explained.

- **ANNs:** Computational algorithms motivated by the biological nervous system, consisting of interconnected neurons structured in layers. Each link has a weight, representing its strength. ANNs learn by adjusting the weights so that the difference between the network’s and the desired output can be minimized [74]. Deep

Neural Networks (DNNs) have many hidden layers, referred to as the depth of the network. DNNs are capable of learning complex patterns and features from data [75].

- **RNN**: Neural network designed for handling sequential data like text, audio, or time series. Its feedback connections are designed to influence the current output by allowing information from previous time steps [76]. The vanishing gradient problem is a challenge for traditional RNNs, which affects their ability to learn long-range dependencies during backpropagation.
- **LSTM**: A variant of RNN, particularly created to address the vanishing gradient issue by introducing internal memory cells and gating mechanisms. These gates control information flow, allowing LSTMs to store and access information over long periods. This makes them effective for learning long-range dependencies in sequential data and handling complex [77]. LSTMs are computationally more complex than traditional RNNs.
- **GRU**: Another well-known RNN type that addresses the vanishing gradient problem using gates to control information flow. It has fewer parameters than LSTMs, which makes GRU computationally less expensive and more efficient. They use a combination of reset and update gates to learn long-term dependencies [78].
- **ENN**: A type of RNN that utilizes a context layer to keep information from previous time steps. This hidden layer stores past information and outputs it to the next layer, making ENNs appropriate for tasks needed in temporal context, like time series prediction [76]. ENNs are simpler than LSTMs and GRUs but may not be as effective for learning long-range patterns in complex sequential data.
- **CNN**: CNNs are employed in solar prediction to extract spatial and temporal features from image-like data like satellite imagery or historical solar irradiance data. They can learn patterns related to cloud movements, atmospheric conditions, and other factors influencing solar irradiance, which allows for the prediction of future solar power generation. For example, study [72] implemented a CNN using satellite images to predict solar irradiance in an ultra-short-term frame. This type of use shows the abilities of CNNs to process structurally linked data and make accurate forecasts [79]. CNNs employ convolutional layers to put filters to the input data, capturing patterns such as edges, corners, and textures. Pooling layers downsample feature maps, decreasing the number of parameters and making the network more efficient [80].;
- **Deep CNN (DCNN)**: DCNNs with several convolutional layers excel in solar prediction by capturing complex relationships between various influencing factors. By stacking convolutional layers, DCNNs learn progressively more abstract and hierarchical features from the data, allowing them to model intricate dependencies between solar radiation and meteorological conditions [81]. DCNNs are almost identical to CNNs but with multiple convolutional layers stacked on top of each other. This allows them to learn more complex and abstract features from the data, improving the accuracy of solar forecasting models [82].;
- **Dilated CNN (DCNN*)**: DCNNs* are particularly great for solar forecasting due to their ability to detect long-range dependencies in time series data. By employing dilated convolutions, DCNN*s expand the receptive field of convolutional filters, allowing them to capture the impact of past meteorological events on current and future solar irradiance [83]. DCNNs use dilated convolutions, which insert gaps between the filter coefficients, effectively expanding the receptive domain of the filters. This grants DCNNs to detect long-range temporal dependencies in the data, making them to model the influence of past weather patterns on current and future solar radiation [84];
- **QK-CNN**: QK-CNNs can be particularly beneficial in solar prediction when using satellite imagery, as they can extract features at multiple scales. By merging convolutional filters of varying sizes, QK-CNNs determine features corresponding to different cloud formations and atmospheric conditions, improving the accuracy of solar irradiance predictions. QK-CNNs utilize convolutional layers with four different kernel sizes, allowing them to extract features at multiple scales. This enables them to capture features at different levels of detail, enhancing the accuracy of solar irradiance predictions [85];
- **Hybrid Networks**: The abilities of different DL algorithms can be combined. Many hybrid models are included in our selection, such as the following: ELM-LSTM, RNN-LSTM, CNN-GRU, LSTM-CNN, and CNN-GRU.

6. Discussion

- **General discussion**: Such research is vulnerable to validity risks, which include external, construct, and dependability threats [107]. This SLR study addresses the external validity and construct validity because the initial search string was broad and produced a sizable number of studies 155 publications in all. The entire range of the SLR was covered by the search query. Since the SLR procedure has been elucidated and is repeatable, the validity of the SLR can be deemed well-handled in terms of its reliability. Should this SLR be repeated, it would yield marginally different chosen papers; however, these variations would stem from varied subjective assessments. It is quite doubtful, therefore, that the final results would vary. In comparison to other systematic reviews in this domain, this study distinguishes itself by its exclusive focus on deep learning (DL) for solar photovoltaic (PV) forecasting, as opposed to broader reviews covering traditional ML, ANNs, or general variable renewable energy (VRE) applications [37,38,42]. For example, Basaran et al. [37] focused on ML, while Qazi et al. [38] extensively studied ANNs, and Klaiber and van Dinther [42] centered on the broader DL implications in VRE. Our findings corroborate the increasing popularity of hybrid DL models, a trend also observed in narrative reviews like [45], which identified the superior performance of CNN-LSTM and similar architectures. However, our systematic approach allows for a more rigorous analysis of which models are most frequently used and what data pre-processing techniques are used alongside them. While previous reviews have mentioned Wavelet Transform (WT) and its utility, our SLR identifies it as the predominant data decomposition technique. A limitation identified in this study, and echoed across the literature is the dependence on context-specific data, which limits the generalization capabilities of DL-based solar forecasting models. This issue needs to be tackled by creating more robust and versatile models in the future.
- **Search-related discussion**: There is a chance that some important publications were omitted. A higher time frame, more synonyms, and a more comprehensive search could have produced further research. Nonetheless, the search term produced a large number of papers, suggesting a sufficiently thorough search.
- **RQ1-related (models) discussion**: As indicated by Table 5, the most popular algorithms are LSTM, CNN, and ANN. ANN means Multi-Layer Perceptron which could be named Feedforward Neural Network, or Backpropagation Neural Networks according to our study selection. In most cases, they serve as benchmarking algorithms to assess whether the proposed algorithm performs better than them. Consequently, even though it appears in numerous studies, this does not imply that it is the best model. Because "most used" does not certainly mean the best-performing ones, Table 5 should be carefully read. In actuality, hybrid models like CNN-LSTM, CNN-GRU, DCNN-BILSTM, and (AE-LSTM) as well as improved DL models like (DCNN*), BILSTM, and QK-CNN yield better outcomes and show great potential. To prevent negative effects on the required computational time and resources, it is critical to consider how complicated the models are.

Table A.10
Data decomposition techniques used.

Ref	Key	Data decomposition method	Utility in solar forecasting	Used in
[86]	WT	A mathematical technique that transforms a signal into wavelets, localized in both time and frequency domains, enabling detailed analysis of signals with varying frequency content over time, unlike traditional Fourier analysis.	The WT process involves convolving a signal using wavelet functions, each representing a different frequency scale, to accurately capture transient and stationary aspects of a signal, including solar radiation or PV electricity.	P1, P2, P8, P10, P14, P16, P19, P23
[87]	MODWT	An extension of the Discrete WT that enhances signal analysis by introducing shifted versions of the wavelet filter, resulting in overlapping filter outputs, enhancing time–frequency resolution, reducing-edge effects, and improving adaptability.	MODWT is a powerful tool for analyzing time series data, including solar irradiance measurements. By decomposing the signal into different frequency components, it helps identify and separate short-term fluctuations from long-term trends, enabling more accurate solar forecasting.	P4
[88]	EMD	A data-driven technique that decomposes a signal into intrinsic mode functions (IMFs), representing specific oscillatory modes with varying frequencies and time scales. It works iteratively, extracting the most oscillatory component, and adapts to non-stationary signals, making it effective for complex signals.	EMD allows for a more detailed understanding of the complex, multi-scale variability in solar irradiance, leading to improved forecasting models that capture both short-term and long-term patterns.	P19
[89]	EWT	A hybrid method that uses WT and EMD to analyze a signal's power spectral density and identify dominant frequency bands. It then constructs tailored wavelets and decomposes the signal, providing a more accurate representation of complex, varying frequency content.	EWT enhances solar irradiance forecasts by adjusting the wavelet basis to the signal's unique characteristics, providing a more accurate representation compared to traditional methods.	P15
[90]	VMD	A new signal decomposition method that breaks a signal into intrinsic mode functions (IMFs) occupying specific frequency bands. It uses a variational framework to minimize cost functions, balancing bandwidth and signal similarity, through iterative updates.	VMD is a technique for analyzing non-stationary time series data like solar irradiance. It decomposes signals into modes, minimizing variational problems, and enabling precise identification of solar irradiance patterns and improved forecasting models.	P1, P15, P19, P24
[91]	CEEMD	An improvement to the Empirical Mode Decomposition (EMD) method, addressing mode mixing. It introduces a white noise ensemble, adds and subtracts it multiple times, and applies EMD to each noisy signal. This ensemble averaging reduces noise influence and improves decomposition stability.	CEEMD improves solar irradiance data decomposition by introducing multiple noise realizations and performing EMD on each realization, reducing mode mixing and resulting in more accurate forecasting models.	P19
[92]	CEEMDAN	An extension of CEEMD that incorporates adaptive noise, adjusting the noise level based on the signal's characteristics. This method preserves intrinsic modes and reduces mode mixing and noise artifacts, allowing for more accurate decomposition of complex signals.	CEEMDAN is an adaptive approach that aids in analyzing complex solar irradiance data, enabling the creation of more accurate and robust solar forecasting models by providing a deeper understanding of intricate patterns within the time series.	P8

- **RQ2-related (preprocessing methods) discussion**: based on our study, the preprocessing techniques are grouped into four parts, data Decomposition, data Clustering, data Augmentation, and feature Selection. Wavelet Transform (WT) and VMD are the most important for data decomposition. K-Means algorithm and Soft-DTW-Based K-medoids are the most used for data Clustering. Generative Adversarial Networks (GAN) and their variants are unique models used for data Augmentation. PEARSON Correlation is the most used for feature Selection. These techniques are vital to enhancing deep learning models' effectiveness in solar forecasting. These methods help to enhance data quality, reduce noise, reveal hidden patterns, and select relevant features, ultimately leading to more accurate and robust predictions. However, it is important to be aware of potential drawbacks, for instance, excessive decomposition can introduce artifacts, clustering techniques may struggle with high-dimensional data, data augmentation can introduce bias, and feature selection can lead to information loss. Choosing the right techniques and implementing them carefully is crucial for optimal model performance.
- **RQ3-related (features) discussion**: For both solar radiation forecasting and PV power forecasting, temperature, pressure, wind speed, and humidity are the most often employed features. Along with past data on solar radiation and PV. Not every type of data is utilized to create the most useful features. For instance, temperature is expressed as average temperature; however, additional parameters, such as maximum and lowest temperatures, are sometimes used. And solar cell-related characteristics like cell temperature and current phase average are also employed. In addition to these aspects, it should be noted that sky images were the main input feature used in [72]. Every pixel in the image serves as a numerical input for the DL model. More research should focus on this kind of data.
- **RQ4-related (evaluation metrics and validation approaches) discussion**: Nearly all studies used RMSE and MAE to evaluate the model's quality. MAPE, R2, and its variations, such as the correlation coefficient and squared correlation coefficient, are additional evaluation criteria. A number of parameters are variations of the previously listed ones like Normalized MAPE (NMAPE) and Normalized RMSE (NRMSE), which were utilized in particular investigations. In addition to less common assessment metrics like MSE, MSLE, and MASE. In addition to hold-out validation, researchers favored K-cross validation, particularly the 10-fold cross-validation methodology, as the evaluation approach.
- **RQ5-related (challenges) discussion**: On the basis of the articles' explicit declarations, challenges were reported. There might be other difficulties, though, that were not covered in the papers that were determined. The major obstacles lie in improving a functioning model in the context of inconsistent data quality and limited data availability. Much more may be stated about the model's accuracy as more data is collected for testing and training. The models' complexity presents additional computing challenges, as does their integration into grid and energy management systems.

In the future, a number of important areas need to be explored to improve the real-world applicability of DL-based solar PV forecasting. To begin with, more powerful models that can generalize well

Table A.11
Data clustering/augmentation techniques used.

Ref	Key	Data clustering/ augmentation Method	Utility in solar forecasting	Used in
[93]	K-Means Algorithm	An unsupervised learning method for clustering data points. It partitions n data points into k clusters, assigning each to the nearest cluster. The algorithm works iteratively, assigning data points and recalculating centroids until cluster assignments converge.	It improves solar forecasting accuracy by grouping similar weather and irradiance data points, identifying distinct weather conditions, and optimizing model parameters, thereby enhancing the understanding of the complex relationship between weather and solar energy production.	P22, P25
[94]	Soft-DTW-Based K-medoids	A clustering algorithm that combines K-medoids and Dynamic Time Warping (DTW) to measure similarity between time series data points. It uses a differentiable version of DTW distance for gradient-based optimization, making it suitable for deep learning models.	Soft-DTW-Based K-medoids designed for time series data, particularly solar irradiance data. It uses dynamic time warping to capture complex patterns, resulting in more accurate and nuanced clustering. This improves solar forecasting models by better representing real-world solar energy production variability.	P5
[95]	Fuzzy C-means (FCM)	A fuzzy clustering algorithm that allows data points to belong to multiple clusters with varying membership degrees, unlike traditional methods like K-means. It uses a membership function to quantify belongingness and minimizes squared distances between data points and cluster centroids.	Fuzzy C-means (FCM) allows data points to belong to multiple clusters simultaneously, making it ideal for analyzing solar irradiance data. It can identify subtle relationships and transitions, improving solar forecasting models.	P21
[96]	GANs	DL models consisting of a generator and a discriminator. The generator produces synthetic data, while the discriminator distinguishes between real and generated data. Both are trained adversarially, with the generator attempting to deceive the discriminator.	GANs can create synthetic solar forecasting data by replicating real solar irradiance distribution, enhancing model performance and generalizability, especially in limited real data-rich environments.	P7
[97]	TimeGAN	A GAN designed for time-series data, capturing temporal dependencies and patterns to generate realistic sequences. It consists of a time series generator and a time series discriminator.	TimeGAN generates synthetic solar irradiance data, capturing temporal correlations and seasonal variations. This enhances the training dataset, enabling the model to learn more robust patterns and handle temporal dependencies better.	P5, P9
[98]	CTGAN	a conditional extension of TimeGAN that incorporates additional information like weather conditions or geographical location during data generation, generating synthetic time-series data conditioned on these specific values.	CTGAN is a valuable tool for solar forecasting, as it generates synthetic irradiance data based on weather parameters like temperature, humidity, and cloud cover, enhancing the model's performance under diverse weather conditions.	P21

across various geographical regions and climatic conditions need to be developed. This could be done by investigating transfer learning methods or creating domain adaptation techniques that can utilize data from various sources to enhance model performance in data-poor areas. Second, computational challenges associated with DL complex models should be overcome with research, particularly real-time forecasting. This would involve exploring methodologies to compress the models, say, pruning or quantization, or designing better DL models in terms of reduced resource requirements while they can fit onto edge devices. Third, efforts should be made in follow-up research into incorporating DL solar PV forecasts in grid management systems, enabling wiser decision-making and optimization. This may involve the development of interfaces between grid control systems and predictive models, or exploring the use of DL in real-time grid stability analysis and control. Finally, there is a need for further research on the interpretability of DL models, particularly in situations where transparency and accountability are paramount. This could involve devising methods for visualizing DL model decision-making, or finding out how to use explainable AI (XAI) methods for determining the key factors underlying model predictions.

Probabilistic forecasting plays a crucial role in managing the inherent uncertainty in solar energy production, offering a significant advantage over deterministic forecasts, which provide only a single-point prediction of PV power output. By giving a distribution of possible future values through quantiles, probabilistic prediction allows grid operators to evaluate risks, plan for contingencies, and make robust decisions regarding energy dispatch, storage, and trading. Several techniques have been explored in the literature for producing probabilistic solar predictions. Quantile Regression (QR), for instance, directly estimates the quantiles of the predictive distribution, giving a flexible and non-parametric approach [108]. For instance, [109] used Quantile Regression Forests to generate probabilistic day-ahead solar forecasts, evaluating performance using the Continuous Ranked Probability Score (CRPS) and Average Coverage Error (ACE). Their finding indicated that QR forests demonstrated more reliable uncertainty estimates in comparison to traditional point forecasts, although performance was sensitive to hyperparameter tuning. Another popular technique is Gaussian Process Regression (GPR), which provides a full predictive distribution based on a Gaussian process prior [110]. GPR offers great uncertainty quantification abilities but can be computationally expensive for massive datasets, as shown by Sheng, Hanmin, et al. [111] in their study on short-term solar irradiance forecasting. Ensemble methods, such as bootstrap aggregating (bagging) and boosting, also offer a promising approach to probabilistic forecasting by combining the predictions of multiple models [112]. These approaches can enhance robustness and precision but require careful consideration of ensemble diversity. The efficiency of probabilistic forecasts is typically assessed by employing indicators like the CRPS, which determines the overall accuracy of the predictive distribution, the ACE, which assesses the calibration of the prediction intervals, and the Interval Sharpness (IS), which quantifies the width of the prediction intervals [113]. While probabilistic forecasting offers significant benefits, several challenges exist. These include the computational cost of some methods, the need for reliable historical data to train probabilistic models, and the lack of standardized evaluation indicators, making it tough to compare the performance of different approaches. Upcoming research should concentrate on creating more efficient and robust probabilistic forecasting models, enhancing the interpretability of probabilistic predictions, and developing standardized evaluation indicators to facilitate comparison and benchmarking.

7. Conclusion

In this systematic literature review (SLR), we applied the well-known Kitchenham methodology to evaluate the diversity of deep learning (DL) approaches in solar photovoltaic forecasting. Our analysis highlights the range of feature sets, forecasting horizons, and methodologies used in the selected publications. Although all studies

Table A.12
Features selection techniques used.

Ref	Key	Features selection method	Utility in solar forecasting	Used in
[99]	Pearson correlation	PPMC is a statistical tool used to quantify the linear relationship between two continuous variables. There are three possible values for this scale: −1 for a perfect negative correlation, 0 for no linear connection, and 1 for a perfect positive correlation.	It helps identify features that linearly influence solar irradiance, such as cloud cover, temperature, and humidity.	P3, P11, P21, P22
[100]	RReliefF Feature Selection	RReliefF evaluates feature relevance by comparing prediction errors when a feature is randomly perturbed. It samples two instances near and far from the target instance and assesses the change in prediction error. Features causing significant error changes are considered more relevant.	RReliefF aids in identifying key features that significantly influence solar irradiance predictions, thereby enhancing the model's capacity to capture intricate patterns and relationships in solar irradiance data.	P8
[101]	MRIG	A feature selection method that prioritizes features based on their individual relevance to the target variable and their ability to provide complementary information when combined, using mutual information to assess both relevance and interaction.	MRIG is a powerful tool in deep learning models for solar forecasting, identifying predictive power-enhancing feature combinations and identifying synergistic relationships between factors like cloud cover and wind speed.	P16
[102]	Spearman correlation	It measures the monotonic relationship between two variables, considering the order of values rather than actual values. It is less sensitive to outliers and can handle non-linear relationships, making it suitable for identifying features with strong monotonic relationships.	Spearman correlation is a useful tool for deep learning models to identify features with strong monotonic trends, capturing subtle non-linear relationships in data, which can enhance forecast accuracy by capturing non-linear relationships.	P21
[103]	Mutual information	It quantifies the dependency between two variables, measuring how much information one variable provides about the other. It can handle both linear and non-linear relationships.	it can identify significant features influencing solar irradiance, even if not easily captured by linear correlation measures. This information can be valuable for deep learning models, resulting in more accurate forecasts and robust predictions.	P21
[104]	PCA	A technique that reduces dimensionality by transforming correlated variables into principal components, which capture the most variance in the data. This reduces dimensionality while retaining most information, simplifying the model and improving computational efficiency.	PCA is a crucial preprocessing step for deep learning models in solar forecasting, especially in datasets with numerous features. It reduces data dimensionality, streamlines training, and enhances model performance without sacrificing significant information.	P26
[105]	XGB feature importance	A robust gradient boosting algorithm renowned for its accuracy and capacity to handle large datasets, assigning a feature importance score based on its contribution to model prediction.	XGBoost feature importance helps identify the most influential weather variables impacting solar irradiance, providing valuable insights for model development and improving forecasting accuracy by focusing on the most relevant features.	P21
[106]	Random forest feature importance	An ensemble learning technique that combines multiple decision trees, determining feature importance by the average decrease in accuracy when a feature is randomly permuted.	It helps determine the most important features for predicting solar irradiance within the context of a random forest model.	P26

in our review employed deep learning for solar forecasting, there was considerable variation in their choice of features, forecast horizons, and prediction approaches (deterministic vs. probabilistic, multi-step ahead vs. one-step ahead). These variations were primarily influenced by the specific research goals and the availability of relevant datasets, emphasizing the context-dependent nature of solar forecasting. Notably, our findings demonstrates that models with a higher feature count did not necessarily lead to superior prediction performance. Instead, feature engineering and data preprocessing emerged as critical factors for achieving optimal model outcomes, reinforcing the significance of data-driven methodologies in solar forecasting.

Our analysis revealed that certain DL structures are more often used in solar prediction than others, with GRUs, CNNs, ANNs, and LSTMs being particularly prevalent. Most studies rigorously evaluated several DL algorithms to identify the best-performing model and demonstrated that hybrid models, which combine the strengths of different models, often outperformed their single-model counterparts. This reinforces the idea that different models capture different patterns in the complex data, and combining them provides a more robust final output. This also shows that the best approach might depend on the specifics of the application and the available data.

Beyond these observations, our analysis gives key insights into the evolution of the solar prediction problem through the lens of deep learning. We identified a clear trend toward using more sophisticated DL architectures and hybrid techniques, indicating a shift away from more basic methods. The increasing complexity in the DL field, coupled with the need for improved prediction accuracy, shows the importance of continued research in this area. Furthermore, the wide variability in feature sets, datasets, and evaluation metrics makes the comparison of DL performance between papers quite challenging, suggesting a need for standardization within the field. This is especially crucial for aiding the development of more standardized and robust methods for performance assessment, helping meaningful comparisons across different models and application scenarios.

The increasing application of DL models in solar PV forecasting offers significant potential for enhancing renewable energy integration into power grids. Precise prediction is not merely a technical pursuit; it is vital for optimizing grid management, allowing better control of energy dispatch, reducing curtailment of green resources, and supporting the reliability and resilience of the power system, which is essential to achieving the world's energy transition goals. For example, precise day-ahead forecasting is essential for unit commitment and economic dispatch in power systems with high integration of solar energy. Based on the current limitations identified, upcoming studies need to concentrate on developing more robust, flexible, and interpretable DL architectures, which can better account for uncertainties, adapt to varying weather conditions, and integrate with real-time forecasting needs. In addition, upcoming research should explore the penetration of diverse data sources, such as satellite imagery, IoT-based weather sensor data, and potentially even past grid load information, to improve the accuracy and robustness of solar prediction models. In addition, a

Table A.13
Feature engineering techniques used.

Key	Metric definition	Formula
RMSE	Measurement of the typical size of a group of predictions' errors. Larger errors are given greater weight than lesser errors.	$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$
MAE	A measure of the typical size of a group of predictions' errors. Larger errors are given greater weight than lesser errors.	$\mathrm{MAE} = \frac{\sum_{i=1}^{n} \lvert y_i - \hat{y}_i \rvert}{n}$
MAPE	an evaluation of the typical percentage variation between the numbers that were expected and those that were recorded. It facilitates comparisons between various datasets or models by offering a relative estimate of inaccuracy.	$\mathrm{MAPE} = 100\% \times \frac{\sum_{i=1}^{n}\left(\frac{\lvert y_i - \hat{y}_i \rvert}{\lvert y_i \rvert}\right)}{n}$
R2	A metric indicating how well the data match the regression model. It shows the percentage of the dependent variable's variance that the independent variable accounts for.	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
R	A measure of the linear connection between the actual and projected values. Its values range from −1 to 1, where 0 denotes no correlation, −1 represents a perfect negative correlation, and 1 represents a perfect positive correlation.	$\mathrm{R} = \frac{\mathrm{Cov}(y,\hat{y})}{\sigma_y \cdot \sigma_{\hat{y}}} \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2$
MBE	A measure of the predictions' typical bias. It shows whether actual values are routinely underestimated or overestimated by the model.	$\mathrm{MBE} = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)}{n}$
FS	A measure of the improvement of the forecast compared to a baseline forecast (e.g., persistence forecast). It shows how much better the model performs than a simple prediction method.	$\mathrm{FS} = 1 - \frac{\mathrm{RMSE_{model}}}{\mathrm{RMSE_{baseline}}}$
MSE	A measure of the mean squared discrepancy between the actual and expected values. Greater penalties are applied to bigger mistakes than to smaller ones.	$\mathrm{MSE} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}$
MSLE	A measure of the mean squared logarithmic discrepancy between the actual and projected values. When working with data that has a large range of values, it is especially helpful.	$\mathrm{MSLE} = \frac{\sum_{i=1}^{n}\left(\log(y_i+1) - \log(\hat{y}_i+1)\right)^2}{n}$
MASE	An equation that takes the mean absolute error of the naive forecast and scales it by that of the prior value (predicting the previous value as the next). It makes it possible to compare models more thoroughly between various datasets.	$\mathrm{MASE} = \frac{\sum_{i=1}^{n} \lvert \hat{y}_i - y_i \rvert}{\frac{\sum_{i=2}^{n} \lvert y_i - y_{i-1} \rvert}{n-1}}$
NIA	a measurement of the degree of agreement between the actual and projected values. It has a range of −1 to 1, with 1 denoting perfect disagreement, 0 denoting no agreement, and 1 denoting perfect agreement.	$\mathrm{d} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(\lvert y_i - \bar{y}\rvert + \lvert \hat{y}_i - \bar{y}\rvert\right)^2}$
U1	A measure of the relative bias in the predictions. It indicates how much the model overstates or understates the real values compared to a simple average.	$\mathrm{U1} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$
U2	A measure of the relative inefficiency in the predictions. It indicates how much the model's predictions differ from the real values compared to a simple average.	$\mathrm{U2} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}}$
MHE	Robust loss function that combines the advantages of Mean Absolute Error and Mean Squared Error. Compared to MSE, it is less susceptible to outliers but more sensitive to small errors than MAE.	$\mathrm{MHE} = \frac{1}{n}\sum_{i=1}^{n}\delta(y_i - \hat{y}_i)$
SCC	The correlation coefficient squared (r). It shows the percentage of the dependent variable's variance that the independent variable accounts for.	$\mathrm{SCC} = \left(\frac{\mathrm{Cov}(y,\hat{y})}{\sigma_y \cdot \sigma_{\hat{y}}}\right)^2$

y_i is the actual value,
$\hat{y}_i$ is the predicted value,
$\bar{y}$ is the mean of the actual values,
σ_y is the standard deviation of the actual values,
$\sigma_{\hat{y}}$ is the standard deviation of the predicted values,
n is the number of data points.

stronger emphasis on explainable AI (XAI) would increase the trustworthiness and adoption of DL models in the solar energy sector, by providing insights into why a model made a certain prediction.

In conclusion, this SLR fills a critical gap in the literature by providing a comprehensive and systematic investigation of DL techniques for solar PV prediction. Unlike previous reviews that concentrated on broader ML approaches or specific ANN models, this study analyzed a wider range of DL models, including CNNs, RNNs, and hybrid architectures, highlighting the trend toward more complex and sophisticated architectures. Furthermore, it showed the importance of feature engineering and data preprocessing techniques, identifying key approaches such as Wavelet Transform and GANs that are vital for enhancing model performance. Finally, this SLR addressed the limitations related to generalization, interpretability, and operating efficiency, giving valuable insights for future research and development in this rapidly developing field. The findings of this review will guide researchers and practitioners in the development and deployment of more accurate, robust, and efficient deep learning-based solar forecasting systems, contributing to the integration of renewable energy into power grids.

Building on the results and the limitations identified in this review, our future work will focus on developing a DL-based solar forecasting system, with particular attention to incorporating more advanced hybrid techniques with traditional statistical approaches addressing uncertainty in predictions using probabilistic forecasting and developing explainable DL techniques. The field of DL-based solar forecasting is rapidly evolving, and this SLR will serve as a solid foundation to guide research in this important direction.

Funding

This research is funded by the European University of Atlantic.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

In A.10, the data decomposition methods used, their definitions, utility, and the paper used each method.

In A.11, the Data Clustering and augmentation techniques used, their definitions, utility, and the paper used each method.

In A.12, the features selection techniques used, their definitions, utility, and the paper used each method.

In A.13, the metrics used, their definition and formula.

Data availability

No data was used for the research described in the article.

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