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Systematic review of artificial intelligence applications in predicting solar photovoltaic power production efficiency

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ABSTRACT

The global energy crisis and climate change demand more accurate and efficient renewable energy forecasting methods. Solar photovoltaic (PV) systems offer abundant clean energy but their efficiency is highly affected by weather variability, requiring advanced predictive models. This systematic review of 69 studies published between 2020 and 2024 evaluates artificial intelligence (AI) and machine learning (ML) applications in PV forecasting, with a focus on hybrid algorithms such as convolutional neural network-long short-term memory (CNN-LSTM). Results demonstrate that hybrid models consistently outperform traditional statistical methods and standalone AI approaches by capturing spatiotemporal patterns more effectively, achieving significant error reductions and improving reliability. A notable gap identified is the limited integration of consumer behavior into forecasting models, despite evidence that incorporating demand-side patterns enhances accuracy. Challenges also remain in data availability, scalability across diverse climates, and computational requirements. This review contributes by synthesizing recent advances and emphasizing consumer integration as an underexplored but critical dimension for future research. The findings provide a foundation for developing more precise, resilient, and scalable PV forecasting models, supporting optimized energy management and accelerating the transition toward sustainable energy systems.

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1. INTRODUCTION

The escalating global energy crisis and evident climate change, driven by economic growth and rising fossil fuel consumption, call for more efficient and sustainable renewable energy solutions [1]. Among the various options, solar photovoltaic (PV) energy stands out as a pivotal clean energy source capable of meeting worldwide electricity demand, with approximately 1,367 W/m² of solar radiation reaching the Earth's surface each day [2]. However, the efficiency of PV systems remains highly sensitive to environmental variables such as solar irradiance, ambient temperature, humidity, and precipitation, making reliable forecasting essential [3].

Accurate forecasting of PV energy generation plays a critical role in effective energy management. Reliable predictions enable better estimation of PV yields, inform scheduling of appliance usage during peak irradiance, and support preventive maintenance to sustain panel efficiency [4]. At a system level, PV forecasting contributes to grid stability, enhances renewable energy integration, and improves energy dispatch strategies [5]–[12]. Thus, robust forecasting models are fundamental for achieving cost efficiency, energy security, and sustainable development targets.

Yet, PV generation is inherently intermittent due to cloud movements, seasonal changes, and weather variability [13]. Traditional statistical approaches, such as autoregressive integrated moving average (ARIMA), have been widely used [14], but they struggle to capture nonlinear relationships and complex dependencies between meteorological factors and PV outputs. In response, artificial intelligence (AI) and machine learning (ML) methods, including artificial neural networks (ANN), support vector regression (SVR), and deep learning (DL) models, have emerged as more powerful alternatives [15], [16].

A notable advancement is the adoption of hybrid learning strategies, particularly convolutional neural networks combined with long short-term memory networks (CNN–LSTM) [17], [18]. CNN layers extract spatial features (*e.g.*, cloud cover and irradiance distribution), while LSTM layers capture short-term and long-term temporal dynamics. Recent studies have demonstrated the effectiveness of hybrid models for PV forecasting [19], [20], consistently showing that CNN–LSTM outperforms standalone AI/ML methods in predictive accuracy. This positions CNN–LSTM as the state of the art in AI-driven PV forecasting.

Nevertheless, several challenges hinder wider deployment. A major limitation is the scarcity of high-resolution datasets combining meteorological and PV generation variables, which are essential for model training and validation [21], [22]. Furthermore, many AI frameworks struggle to generalize across diverse climatic conditions, suffer from overfitting when data is limited, and lack mechanisms for adapting to dynamic real-world environments [23]–[25]. Another persistent gap is the limited integration of consumer behavior and demand-side factors into forecasting models, an important aspect for energy management but largely overlooked in current CNN–LSTM studies [19]. These gaps lead to the central research questions of this review: i) how effective are hybrid CNN–LSTM models in forecasting PV production efficiency, and ii) to what extent has consumer behavior been integrated into forecasting frameworks?

In light of these challenges, this study conducts a systematic review of 69 peer-reviewed publications from 2020–2024 to assess recent advancements in AI-driven PV forecasting [25], with a specific emphasis on hybrid CNN–LSTM models and the emerging dimension of consumption integration. The review examines forecasting methods, data processing techniques, model architectures, performance metrics, and application contexts. The main contributions of this study are threefold: i) providing a structured synthesis of hybrid CNN–LSTM models applications for PV forecasting, ii) identifying research gaps, particularly regarding the incorporation of consumption data, and iii) outlining future directions for developing hybrid models that are more accurate, generalizable, and practical for real-world energy systems.

The novelty of this review lies in its dual contribution: first, it consolidates recent AI-based PV forecasting research through a taxonomy of 69 studies published between 2020 and 2024; second, it highlights the underexplored but crucial integration of consumer behavior into forecasting models, which is vital for aligning production with demand and ensuring sustainable energy management.

2. METHOD

This review applied a structured approach to assess AI methods in forecasting solar PV performance. The procedure was aligned with PRISMA 2020 to ensure transparency and reproducibility, while additional measures were introduced to reduce bias and strengthen the robustness of the synthesis. The following subsections outline the review design, source selection, and appraisal procedures in more detail.

2.1. Review design

Standard approach. We conducted a systematic review in accordance with PRISMA 2020 to ensure transparent identification, screening, eligibility assessment, and inclusion reporting [26]. PRISMA is the *de facto* standard for reproducible evidence synthesis and minimizes selection/reporting bias through structured flow reporting and a priori criteria.

Novel additions tailored to this topic.

a. Cross-domain source balancing. Early retrievals were skewed toward ScienceDirect (~62% of hits), risking domain bias toward energy journals. We broadened sources to include Web of Science, Google Scholar, and ACM Digital Library to capture high-impact interdisciplinary outlets and AI/ML venues. This improves coverage of measurement/control and computing communities, strengthening external validity [27]–[36].
b. Operational focus on hybrid CNN–LSTM models and consumption integration. Beyond generic AI/ML, we operationally defined what counts as hybrid CNN–LSTM models and as user consumption integration (subsection 2.7) so that studies are classified consistently. This responds to gaps noted in prior work and enables direct comparability.

c. Bias mitigation and reliability checks. Dual independent screening with consensus adjudication; we recorded reasons for exclusion at full-text, and computed inter-rater agreement (Cohen's κ) to document screening reliability [34], [36].
d. Quality and risk-of-bias appraisal. We adapted items from TRIPOD (reporting of predictive modeling studies) and PROBAST (risk-of-bias domains) to the PV-forecasting context (time-aware validation, leakage checks, baseline comparators). This underpins the validity of the qualitative synthesis.

Justification: These additions address known threats to validity in AI reviews—source bias, inconsistent model labeling, optimistic validation, and reviewer subjectivity—thereby strengthening construct validity, internal validity, and reproducibility.

2.2. Information sources

We queried six databases with comprehensive and complementary coverage: IEEE Xplore, ScienceDirect, Scopus, Web of Science, Google Scholar, and the ACM Digital Library [26]–[38]. This selection ensures broad coverage across electrical and power engineering, renewable energy systems, artificial intelligence and machine learning (AI/ML), and interdisciplinary research domains. The use of multiple databases also reduces selection bias and increases the robustness and reproducibility of the literature review.

2.3. Search strategy

We combined relevant keywords using Boolean operators to systematically retrieve studies related to AI-based photovoltaic systems. The base search expression, summarized in Table 1, was designed to capture variations in terminology related to effectiveness, performance, photovoltaic technologies, and artificial intelligence or machine learning approaches across multiple databases. A publication year filter (2020–2024) was applied at the query stage to ensure a focus on recent developments, resulting in an initial pool of 9,013 records collected from all selected sources.

Table 1. Search expression utilized in the systematic review

Database	Query	Year of publication
Scopus, ScienceDirect, IEEE Xplore, Web of Science, Google Scholar, ACM Digital Library	"(Effectiveness)" OR "(Performance)" AND "(solar panels)" OR "(photovoltaic)" AND "(Machine Learning)" OR "(Artificial Intelligence)"	2020-2024

2.4. Study selection

The initial database search yielded a total of 9,013 records across Scopus, ScienceDirect, IEEE Xplore, Web of Science, Google Scholar, and ACM Digital Library. After removing 300 duplicates, 8,713 records remained for title and abstract screening. Based on the predefined inclusion and exclusion criteria, 8,148 records were excluded, leaving 565 studies for full-text assessment. Following eligibility checks, 196 studies were excluded due to insufficient methodological rigor, irrelevance to the research scope, or lack of accessible full-text, resulting in 69 studies that were finally included in the systematic review.

2.5. Quality appraisal and risk-of-bias

The methodological quality of each study was assessed using an adapted TRIPOD and PROBAST framework, focusing on risks such as data leakage, limited temporal validation, lack of baseline comparators, overfitting in small datasets, and inadequate handling of missing values. Studies were rated as low, unclear, or high risk of bias, with sensitivity checks applied to down-weight or exclude high-risk cases. By combining PRISMA guidelines with TRIPOD/PROBAST appraisal, this review ensures transparency, rigor, and reproducibility, thereby strengthening confidence in the synthesized evidence.

2.6. Operational definitions

To ensure consistent coding and comparability across studies, we operationalized key terms as follows. *Forecasted outcome* refers to any supervised target related to PV performance, including PV power (W, kW, MW), energy (Wh, kWh), or module/plant efficiency (%). When studies used different units, values were normalized to common scales during extraction to allow side-by-side interpretation [36]–[39] *Forecast horizons* were categorized as nowcasting (≤1 h), intraday (1–24 h), day-ahead (24–48 h), and multi-day/week-ahead (>48 h), and *temporal resolution* captured sampling rates (*e.g.,* 1–5 min, 10–15 min, hourly, daily). *Meteorological inputs* encompassed irradiance terms—global horizontal irradiance (GHI), direct normal irradiance (DNI), and diffuse horizontal irradiance (DIF)—and ambient variables (temperature, humidity, wind speed/direction, and rainfall/precipitation), with optional exogenous signals such as clearness index or sky imagery/satellite features when provided.

A study was labeled hybrid CNN–LSTM when convolutional layers were employed to extract spatial/feature maps (from gridded weather, sky images, or engineered temporal patches) that fed a recurrent module (LSTM/variants) for temporal dynamics, trained end-to-end or in a staged feature → sequence pipeline [16]–[18]. Architectures using CNN without recurrent units, or LSTM/GRU without convolutional feature extraction, were not coded as CNN–LSTM hybrids. Consumption integration denoted explicit use of user load or demand patterns: i) as exogenous predictors for PV forecasting, ii) as joint/co-targets in multi-task settings (PV and load predicted simultaneously), or iii) as coupled models where consumption modifies PV forecasts via control/dispatch constraints.

Baselines included persistence/naïve models, autoregressive integrated moving average (ARIMA) or other classical statistical methods, and standard ML/DL comparators (*e.g.*, SVR, RF, standalone LSTM). Validation schemes were coded as time-aware holdout (train/validation/test in chronological order), rolling/recursive (walk-forward) evaluation, k-fold blocked cross validation, and cross-site or cross season generalization. A study was flagged for potential leakage if any step used future information in training or scaling (*e.g.,* global normalization on the full series, shuffling time series without preservation of order). Performance metrics followed author reports but were harmonized to root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and R^2 where available; metric definitions were retained as stated by the original studies, and any unit conversions were logged in the extraction sheet [37], [38].

2.7. Step-by-step procedure

The literature search was conducted across IEEE Xplore, ScienceDirect, Scopus, Web of Science, Google Scholar, and the ACM Digital Library from 28 February 2022, with an update in December 2024, using the predefined Boolean string described in Section 2.3 (with field tags adjusted per database) and a publication year filter of 2020–2024. Search results (title, abstract, keywords, and DOI) were exported in RIS and CSV formats, merged, and de-duplicated using DOI matching, exact-title matching, and fuzzy-title similarity (threshold ≈ 0.90), followed by manual verification, resulting in the removal of 300 duplicate records. Title and abstract screening were performed based on the predefined inclusion and exclusion criteria, yielding 565 records for full-text assessment; subsequently, 196 studies were excluded with documented reasons, including out-of-scope content, insufficient methodological reporting, or limited accessibility. The remaining 69 studies proceeded to data extraction using a standardized form (section 2.5), independently conducted by two reviewers, with disagreements resolved through consensus or consultation with a third reviewer when necessary. Each included study underwent quality assessment and risk-of-bias appraisal using a taxonomy-oriented evaluation framework commonly adopted in AI-based systematic reviews, focusing on time-aware validation, data leakage prevention, baseline comparators, overfitting risks, and missing data handling [34]. The overall review process followed PRISMA based reporting practices to ensure transparency and reproducibility [36]. All search queries, timestamps, PRISMA flow counts, extraction sheets, and appraisal forms were archived as supplementary materials to support full replication of the review.

3. RESULTS AND DISCUSSION

The systematic review analyzed 69 articles, which were selected from an initial pool of 9,013 records retrieved from ScienceDirect (40%), IEEE Xplore (20%), Scopus (15%), Web of Science (10%), Google Scholar (10%), and the ACM Digital Library (5%), after screening for duplicates, relevance, and accessibility, see Figures 1 to 4. The selected articles, published between 2020 and 2024, represent global research efforts spanning 30 countries, with China contributing the largest number of publications (19 articles), followed by the United States (4), and Iran, Morocco, South Korea, Australia, and the United Kingdom (3 articles each). The results indicate substantial progress in AI-driven solar photovoltaic forecasting, particularly through hybrid modeling approaches, which consistently outperform standalone ML and DL methods, in line with recent studies reported in 2023 and 2024. A structured analysis based on source index, authors' nationality, and primary methodological categories is presented and discussed in detail in subsection 3.1, with the results summarized in the corresponding figures.

3.1. Results by source indexes, nationality, and methodological categories

The study selection was conducted in accordance with the PRISMA framework to ensure transparency and methodological consistency. As shown in Figure 1, the initial database search identified 9,013 records, which were reduced to 8,713 after duplicate removal. Title and abstract screening yielded 565 potentially relevant studies, followed by full-text evaluation of 265 articles. After excluding 196 studies that did not meet the defined scope, a total of 69 articles were retained for the final analysis.

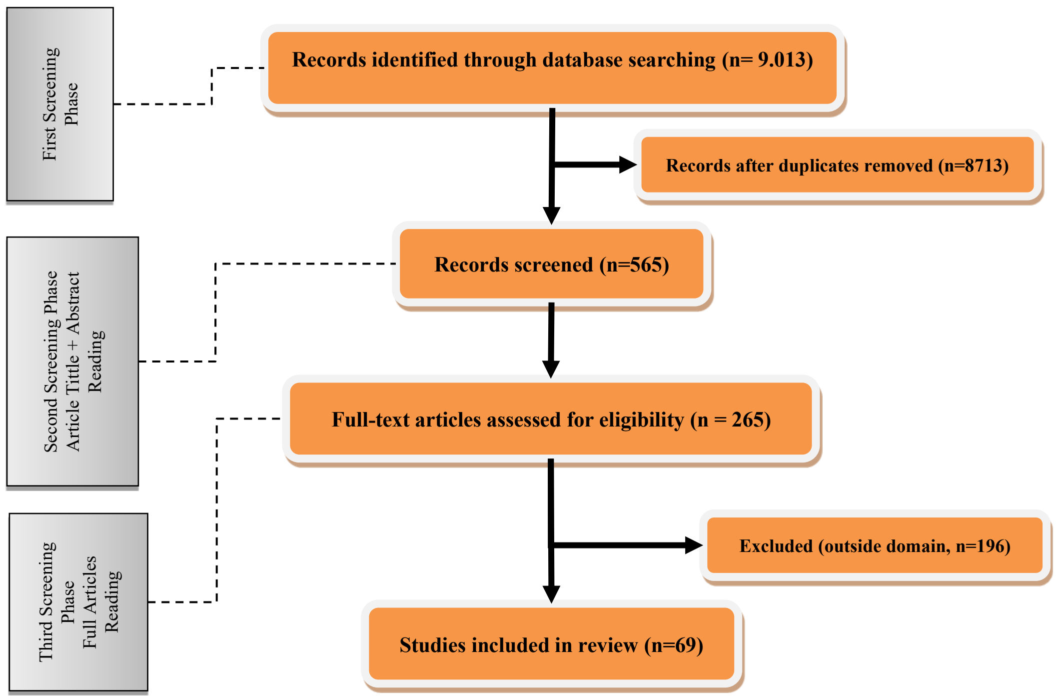

Figure 1. PRISMA flow diagram of study selection process

Figure 2 presents the distribution of the selected articles across databases. ScienceDirect contributed the largest proportion (40%), followed by IEEE Xplore (20%), Scopus (15%), Web of Science (10%), Google Scholar (10%), and ACM Digital Library (5%). This distribution reflects broad coverage across energy, engineering, artificial intelligence, and interdisciplinary research domains, with ScienceDirect showing a strong emphasis on energy-related journals

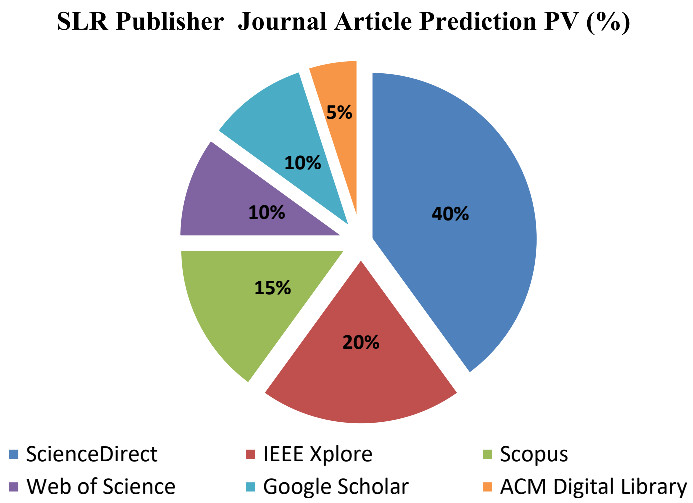

Figure 2. Distribution of PV-related journal articles by database

Figure 3 shows the distribution of articles based on the nationality of the authors. China contributed the highest number of publications, with a total of 19 articles. This was followed by the United States with four articles, while Iran and Morocco each accounted for three publications. Several other countries, including those from Europe, Asia, and Africa, contributed one or two articles each. Overall, the results indicate a geographically diverse set of contributions to the selected studies.

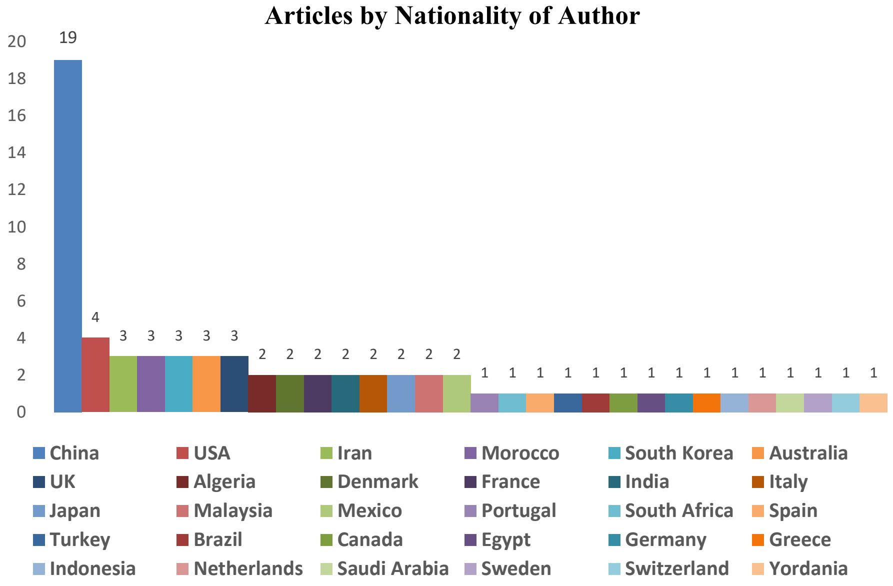

Figure 3. Articles by nationality of author

Figure 4 summarizes the methodological categories employed in the reviewed studies. Among the 69 articles, ML approaches were the most prevalent (43 articles), followed by DL and hybrid methods. ML techniques remain widely used due to their interpretability and relatively lower computational requirements. Hybrid models, although less frequently applied, demonstrated consistently strong performance across multiple studies, with reported improvements in error metrics such as RMSE and MAE [39], [40].

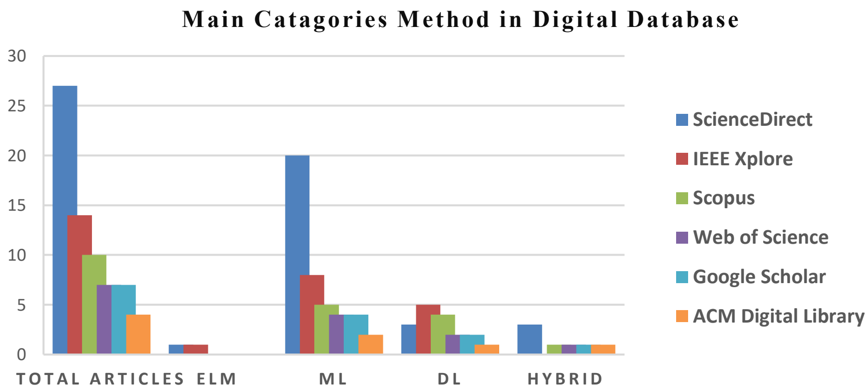

Figure 4. Main categories method in digital database

Recent studies published in 2023 further illustrate this trend. Ye *et al.* [41] reported that a LightGBM–XGBoost hybrid model outperformed conventional ML approaches across multi-seasonal datasets. Similarly, Sabareesh *et al.* [42] demonstrated improved forecasting accuracy using an LSTM–RNN hybrid model in PV systems incorporating incremental conductance maximum power point tracking (MPPT). These results indicate the growing relevance of hybrid approaches for PV forecasting under dynamic operating conditions.

3.2. Taxonomy-based solar PV prediction

A taxonomy of solar photovoltaic forecasting methods was developed based on the analysis of 69 selected articles. As shown in Figure 5, the reviewed studies are classified into three main categories: ML methods (*e.g.*, support vector regression and random forest), DL methods (*e.g.*, long short-term memory and convolutional neural networks), and hybrid models (*e.g.*, CNN–LSTM). ML approaches were the most frequently adopted, appearing in 43 articles, with a strong presence in ScienceDirect (20 articles), reflecting their relative simplicity and effectiveness for small to medium-sized datasets. DL methods were reported in 14 studies and demonstrated strong capabilities in capturing temporal dependencies (LSTM) and spatial features (CNN) when larger datasets were available. Hybrid models, which integrate the strengths of ML and DL, were identified in six articles and consistently outperformed standalone approaches. For example, studies [19] and [20] reported that CNN–LSTM models achieved up to 15% lower RMSE in PV power prediction compared with individual LSTM or CNN models by jointly learning spatial and temporal characteristics.

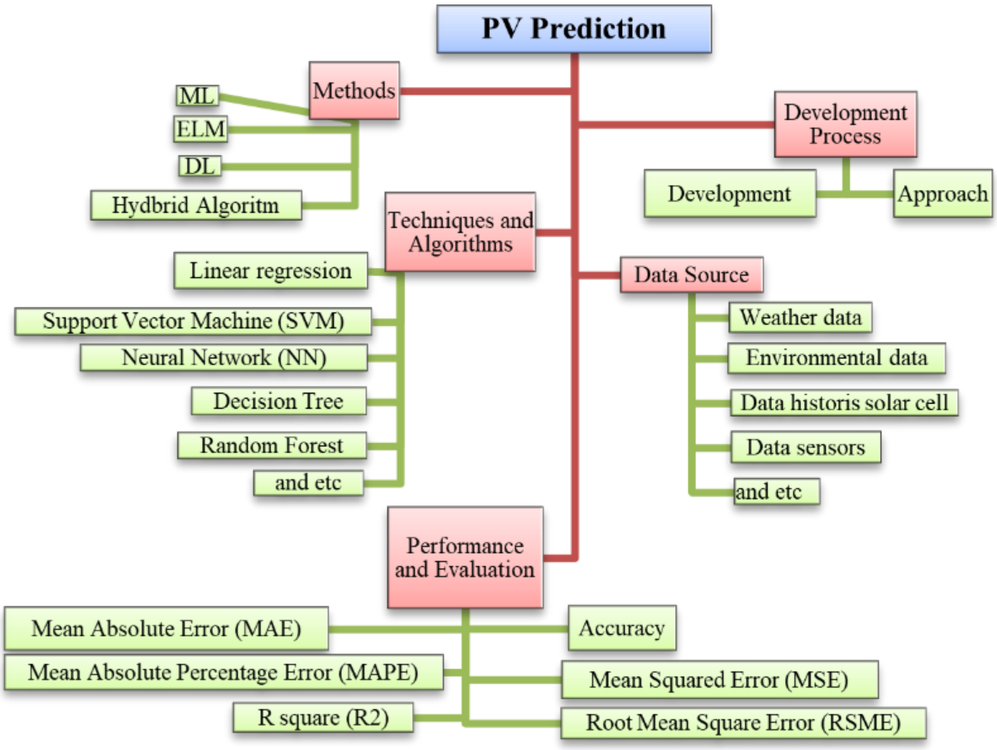

Figure 5. Taxonomy literature review of research PV prediction

Beyond structural classification, the developed taxonomy also highlights the temporal evolution of forecasting methods. Early studies (2020–2021) primarily relied on conventional machine learning techniques, due to their lower computational demands and stable performance on limited datasets [43]–[45]. From 2022 to 2024, research has increasingly shifted toward deep learning and hybrid architectures, driven by enhanced computational capabilities and the availability of higher-resolution meteorological and PV datasets. Hybrid models, such as CNN–LSTM and NARX-based approaches, have been widely adopted to overcome the limitations of standalone models in capturing nonlinear dynamics and complex temporal–spatial dependencies [19], [20], [46], [47]. This trend aligns with broader developments in AI-driven PV forecasting, where model integration has become a key strategy for improving both robustness and generalization performance [48]–[54]. In other words, combining multiple approaches is increasingly seen as more effective than relying on a single model.

3.3. Discussion of key findings

Our findings indicate that hybrid models, particularly CNN–LSTM architectures, consistently enhance PV forecasting accuracy by effectively capturing both spatial and temporal characteristics of solar power data. This observation aligns with the generalization analysis reported by Costa [55], who demonstrated the robustness of convolutional–LSTM networks for household PV forecasting, as well as with recent deep learning–based spatiotemporal approaches integrating frequency time representations and neural networks [40]. Hybrid architectures help address the limitations of traditional statistical models such as ARIMA, which struggle with nonlinear dynamics, and standalone artificial intelligence methods such as ANN, which may exhibit overfitting when applied to complex and high-dimensional PV datasets [14], [18], [23], [52].

The effectiveness of CNN–LSTM models primarily systems from their ability to jointly extract spatial features such as cloud movement patterns and irradiance distributions through convolutional layers, while simultaneously modeling temporal dependencies in PV output using LSTM units. Across multiple studies published between 2021 and 2024, this spatiotemporal learning capability resulted in consistent performance gains, with reported reductions of approximately 15% in RMSE compared to conventional machine learning baselines [19], [20], [24], [47], [49], [54]–[56]. For example, Souhaila and Mohamed [2] reported an R^2 value of approximately 97% using ensemble and hybrid learning strategies, underscoring the potential of such models for accurate energy planning and grid-level decision support.

The robustness of these findings is further supported by the diversity of databases considered in this review. By incorporating IEEE Xplore and the ACM Digital Library for AI-focused studies, Web of Science for interdisciplinary research, and Google Scholar for broader coverage of open-access publications, a wide range of methodological perspectives was captured. Nevertheless, potential selection bias remains due to the emphasis on English-language, peer-reviewed literature, which may limit the inclusion of relevant studies from underrepresented regions such as Latin America, Africa, and the Middle East.

To consolidate these observations, Table 2 provides a comparative summary of representative studies, outlining the applied methods and the best-performing algorithms reported in each case. The reviewed works encompass conventional machine learning, deep learning, and hybrid modeling strategies, evaluated using standard performance metrics including RMSE, MAE, MAPE, and the coefficient of determination (R^2). As summarized in Table 2, hybrid models particularly those integrating convolutional neural networks (CNN) with long short-term memory (LSTM) are most frequently identified as achieving superior forecasting performance [19], [20], [41], [47], [55], [56]. In addition, several studies report competitive results using advanced ensemble and gradient-boosting frameworks, such as combined LightGBM–XGBoost models [41], as well as graph-enhanced LSTM approaches incorporating multi-meteorological dependencies [38] Collectively, these findings reinforce the growing adoption of hybrid and enhanced deep learning models in photovoltaic power prediction.

Table 2. Summarizes representative studies on the best-performing hybrid PV forecasting models

Author and Year	Methods	Best algorithm
Agga *et al*. [19] (2022)	CNN, LSTM, CNN-LSTM	CNN–LSTM (superior spatiotemporal accuracy)
Cheng *et al*. [38] (2021)	Graph modeling with multi-meteorological factors, LSTM (MAE, RMSE)	Graph-based LSTM (enhanced time-series precision)
Ekinci [56] (2024)	LSTM-ED, Weather Data SVR, RMSE, MAE	Enhanced LSTM (≈8% error reduction with additional inputs)
Michael *et al*. [20] (2022)	LR, SVR, ANN, CNN, LSTM, Hybrid CNN–LSTM (RMSE, MSE)	CNN-LSTM (Lowest RMSE, MSE)
Ye *et al*. [41] (2023)	LightGBM, XGBoost, Weighted RMSE reciprocal	LightGBM-XGBoost (best metric performance)
Wang *et al*. [47] (2024)	CNN-LSTM, RMSE, MAPE	CNN-LSTM (4.2% MAPE in variable weather)

This review identifies a critical research gap in PV power forecasting related to the limited integration of consumer behavior and demand-side information. Among the 69 studies analyzed, only a small subset considered consumption patterns, primarily through indirect coupling with load forecasting frameworks, such as the CNN–LSTM-based approach reported by Agga *et al.* [19]. This limitation is significant, as user consumption behavior influences PV system efficiency and grid stability. Recent studies demonstrate that incorporating demand-side data can improve forecasting accuracy; for example, Ekinci [56] reported an error reduction of approximately 8% when household consumption patterns were integrated into LSTM-based PV forecasting models. Evidence from residential and microgrid energy studies further supports the importance of user behavior modeling as an underexplored yet impactful component of PV prediction research [7], [8].

The geographical distribution of PV forecasting studies reveals pronounced regional disparities. Research output is predominantly concentrated in developed regions, while contributions from developing countries remain limited due to challenges related to data availability and computational infrastructure. In regions with high climatic variability, such as monsoon-affected areas, forecasting models trained on data from more stable climates often exhibit reduced generalization performance [37], [46], [52]. Although broader database coverage enabled the inclusion of some studies from underrepresented regions, these findings highlight the need for improved international collaboration and data-sharing initiatives to enhance model robustness across diverse climatic conditions.

Despite their superior predictive accuracy, hybrid deep learning architectures particularly CNN–LSTM models present practical challenges associated with high computational complexity and resource requirements. Several studies emphasize the trade-off between accuracy and efficiency and suggest combining deep learning with physical modeling or optimization techniques to improve deploy ability in real-world energy systems [45], [49]. Consequently, future research should prioritize the development of lightweight hybrid architectures, model compression strategies, and decentralized learning frameworks capable of supporting real-time applications.

Overall, the findings confirm that hybrid deep learning models represent a substantial advancement in PV power forecasting by effectively capturing nonlinear and spatiotemporal dynamics. However, their broader adoption depends on addressing key challenges related to demand-side data integration, regional generalizability, and computational efficiency. Emerging approaches, including physics-informed learning [45], ensemble hybridization [48], and federated learning frameworks [21], offer promising directions for advancing accurate, scalable, and practical PV forecasting solutions.

3.4. Limitations of the review

While this review provides a structured synthesis of recent advances in hybrid deep learning models for solar PV generation and residential energy consumption forecasting, several limitations should be acknowledged. First, the literature search was limited to peer-reviewed journal articles published in English between 2020 and 2024. As a result, relevant grey literature, technical reports, and studies published in other languages may have been excluded, potentially introducing publication and language bias.

Second, substantial heterogeneity in methodological design and evaluation practices across the reviewed studies limited the ability to perform direct comparisons. Performance was reported using different metrics, including RMSE, MAE, MAPE, and R^2, while variations in temporal resolution (*e.g.*, hourly, daily, and monthly forecasting horizons) and geographical settings further constrained the generalizability of the findings across diverse climatic and socio-economic contexts.

Third, this review may be affected by publication bias, as studies reporting statistically significant or favorable predictive outcomes are more likely to appear in peer-reviewed journals, whereas negative or inconclusive results tend to be underreported. This imbalance may contribute to an optimistic representation of the performance of hybrid deep learning models in PV forecasting applications.

Finally, a formal meta-analysis was not conducted due to the lack of statistical homogeneity among the included studies. Instead, the results were synthesized using a narrative and thematic approach, which is suitable for identifying trends, methodological patterns, and research gaps, but does not allow for precise quantitative estimation of effect sizes. Future systematic reviews could address this limitation by adopting standardized evaluation protocols and harmonized datasets, thereby enabling more rigorous quantitative synthesis and comparative assessment.

3.5. Future research and practical implications

Future research in PV forecasting should prioritize the systematic integration of consumer behavior into AI-based prediction models, as most existing studies focus predominantly on production-side variables [57]. Evidence from recent works indicates that incorporating demand-side information improves the alignment between PV generation and actual electricity usage, particularly under high climatic variability and decentralized energy systems [56]. High-resolution smart meter data offer a practical foundation for this integration by capturing household consumption patterns at daily, weekly, and seasonal scales. These patterns can be transformed into structured features such as peak demand periods, load profiles, and long-term usage trends, which can be incorporated into hybrid forecasting models. In regions with limited data availability, agent-based or synthetic consumption modeling provides an alternative for enhancing model robustness and transferability [21].

Multi-input deep learning architectures, especially convolutional neural network-long short-term memory (CNN-LSTM) frameworks, are well suited to jointly model PV production and consumption dynamics. Prior studies demonstrate that enriching LSTM-based PV forecasting with user-level consumption data can reduce prediction errors by approximately 8% compared to production-only models [44], [56]. Graph-enhanced recurrent models further extend this capability by capturing interactions among distributed PV systems and residential loads in networked grid environments [38]. To address computational constraints, future work should emphasize feature selection, transfer learning, and efficiency-oriented model optimization strategies [45], [49].

From a practical and policy perspective, hybrid AI-based forecasting models can support grid stability, demand-side management, and large-scale PV integration. In Indonesia, achieving national renewable energy targets and the Net Zero Emission 2060 pathway requires predictive tools that account for both generation and consumption dynamics, in line with national energy planning frameworks and solar capacity targets [58], [59]. Overall, integrating consumer behavior represents a critical step toward more accurate, generalizable, and operationally relevant PV forecasting systems.

4. CONCLUSION

This systematic review examined 69 studies published between 2020 and 2024 to assess the application of artificial intelligence and machine learning in solar photovoltaic forecasting. The findings confirm that hybrid approaches, particularly CNN–LSTM architectures, consistently outperform traditional statistical models and standalone AI methods by effectively capturing nonlinear spatiotemporal patterns in meteorological and PV generation data. These improvements translate into notable error reductions and enhanced forecasting reliability, which are essential for efficient energy management and grid stability.

Despite these advances, the review identifies a significant research gap in the limited incorporation of consumer behavior and demand-side information into PV forecasting models. Most existing studies remain focused on production-side prediction, even though emerging evidence shows that integrating consumption patterns can further improve accuracy and system responsiveness. This imbalance highlights the need for unified forecasting frameworks that jointly consider generation and demand dynamics. Several challenges also persist, including constrained data availability in underrepresented regions, limited model generalizability across diverse climatic conditions, and the high computational cost of advanced deep learning architectures. Addressing these issues will require more inclusive datasets, scalable model designs, and efficiency-oriented implementations suitable for real-world deployment.

Overall, this review underscores hybrid AI-based models as the current state of the art in PV forecasting while emphasizing consumer behavior integration as a critical direction for future research. Advancing in this direction will support the development of more accurate, resilient, and scalable forecasting systems, contributing to optimized renewable energy integration and the global transition toward sustainable energy systems.

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AUTHOR CONTRIBUTIONS STATEMENT

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Liliana Swastina					✓			✓	✓	✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study. The findings are derived from the synthesis of 69 existing publications, and all relevant information supporting the results is available within the article.

REFERENCES

[1] J. Estévez, J. A. Bellido-Jiménez, X. Liu, and A. P. García-Marín, "Monthly precipitation forecasts using wavelet neural networks models in a semiarid environment," *Water*, vol. 12, no. 7, p. 1909, Jul. 2020, doi: 10.3390/w12071909.

[2] C. Souhaila and M. Mohamed, "Ensemble methods comparison to predict the power produced by photovoltaic panels," *Procedia Computer Science*, vol. 191, pp. 385–390, 2021, doi: 10.1016/j.procs.2021.07.049.

[3] C. A. F. Frederiksen and Z. Cai, "Novel machine learning approach for solar photovoltaic energy output forecast using extra-terrestrial solar irradiance," *Applied Energy*, vol. 306, p. 118152, 2022, doi: 10.1016/j.apenergy.2021.118152.

[4] R. Best, P. J. Burke, and S. Nishitateno, "Evaluating the effectiveness of Australia's small-scale renewable energy scheme for rooftop solar," *Energy Economics*, vol. 84, p. 104475, Oct. 2019, doi: 10.1016/j.eneco.2019.104475.

[5] Y. Tripanagnostopoulos, T. Nousia, M. Souliotis, and P. Yianoulis, "Hybrid photovoltaic/thermal solar systems," *Solar Energy*, vol. 72, no. 3, pp. 217–234, Mar. 2002, doi: 10.1016/S0038-092X(01)00096-2.

[6] G. Alkhayat and R. Mehmood, "A review and taxonomy of wind and solar energy forecasting methods based on deep learning," *Energy AI*, vol. 4, Jun. 2021, doi: 10.1016/j.egyai.2021.100060.

[7] Y. Lin, J. Liu, K. Gabriel, W. Yang, and C. Q. Li, "Data-driven based prediction of the energy consumption of residential buildings in Oshawa," *Buildings*, vol. 12, no. 11, Nov. 2022, doi: 10.3390/buildings12112039.

[8] M. Slowik and W. Urban, "Machine learning short-term energy consumption forecasting for microgrids in a manufacturing plant," *Energies*, vol. 15, no. 9, May 2022, doi: 10.3390/en15093382.

[9] T. Gunda and Others, "A machine learning evaluation of maintenance records for common failure modes in PV inverters," *IEEE Access*, vol. 8, pp. 211610–211620, 2020, doi: 10.1109/ACCESS.2020.3039182.

[10] A. Kaneko, Y. Hayashi, T. Anegawa, H. Hokazono, and Y. Kuwashita, "Evaluation of an optimal radial-loop configuration for a distribution network with PV systems to minimize power loss," *IEEE Access*, vol. 8, pp. 222341–222352, 2020, doi: 10.1109/ACCESS.2020.3043055.

[11] C. Srithapon, P. Fuangfoo, P. K. Ghosh, A. Siritaratiwat, and R. Chatthaworn, "Surrogate-assisted multi-objective probabilistic optimal power flow for distribution network with photovoltaic generation and electric vehicles," *IEEE Access*, vol. 9, pp. 34395–34414, 2021, doi: 10.1109/ACCESS.2021.3061471.

[12] B. Zazoum, "Solar photovoltaic power prediction using different machine learning methods," *Energy Reports*, vol. 8, pp. 19–25, Apr. 2022, doi: 10.1016/j.egyr.2021.11.183.

[13] Y.-J. Kim and Others, "Developing prediction models for solar photovoltaic energy generation using GBM," *Preprints*, 2023, doi: 10.20944/preprints202306.0679.v1.

[14] I. Ceylan, O. Erkaymaz, E. Gedik, and A. E. Gurel, "The prediction of photovoltaic module temperature with artificial neural networks," *Case Studies in Thermal Engineering*, vol. 3, pp. 11–20, 2014, doi: 10.1016/j.csite.2014.02.001.

[15] H. Chen and X. Chang, "Photovoltaic power prediction of LSTM model based on Pearson feature selection," *Energy Reports*, vol. 7, pp. 1047–1054, 2021, doi: 10.1016/j.egyr.2021.09.167.

[16] A. Saberian, H. Hizam, M. A. M. Radzi, M. Z. A. Ab Kadir, and M. Mirzaei, "Modelling and prediction of photovoltaic power output using artificial neural networks," *International Journal of Photoenergy*, vol. 2014, 2014, doi: 10.1155/2014/469701.

[17] E. Cebekhulu, A. J. Onumanyi, and S. J. Isaac, "Performance analysis of machine learning algorithms for energy demand–supply prediction in smart grids," *Sustainability*, vol. 14, no. 5, Mar. 2022, doi: 10.3390/su14052546.

[18] O. Turgut, S. Westgaard, and A. G. Cerit, "Time series forecasting of domestic shipping market: comparison of SARIMAX, ANN-based models and SARIMAX-ANN hybrid model," *Transportation Research Part E: Logistics and Transportation Review*, 2022.

[19] A. Agga, A. Abbou, M. Labbadi, Y. El Houm, and I. H. Ou Ali, "CNN-LSTM: An efficient hybrid deep learning architecture for predicting short-term photovoltaic power production," *Electric Power Systems Research*, vol. 208, p. 107908, Jul. 2022, doi: 10.1016/j.epsr.2022.107908.

[20] N. E. Michael, M. Mishra, S. Hasan, and A. Al-Durra, "Short-term solar power predicting model based on multi-step CNN stacked LSTM technique," *Energies*, vol. 15, no. 6, Mar. 2022, doi: 10.3390/en15062150.

[21] G. Wang, J. Yin, M. S. Hossain, and G. Muhammad, "Incentive mechanism for collaborative distributed learning in artificial intelligence of things," *Future Generation Computer Systems*, vol. 125, pp. 376–384, 2021, doi: 10.1016/j.future.2021.06.015.

[22] R. Belu, "Artificial intelligence techniques for solar energy and photovoltaic applications," in *Handbook of Research on Solar Energy Systems and Technologies*, IGI Global, 2012, pp. 376–436, doi: 10.4018/978-1-4666-1996-8.ch015.

[23] A. H. Assi, M. H. Al-Shamisi, H. A. N. Hejase, and A. Haddad, "Prediction of global solar radiation in UAE using artificial neural networks," in *Proceedings of the International Conference on Renewable Energy Research and Applications (ICRERA)*, 2013, pp. 196–200, doi: 10.1109/ICRERA.2013.6749750.

[24] M. N. Akhter and Others, "An hour-ahead PV power forecasting method based on an RNN-LSTM model for three different PV plants," *Energies*, vol. 15, no. 6, Mar. 2022, doi: 10.3390/en15062243.

[25] N. Zougagh, A. Charkaoui, and A. Echchatbi, "Artificial intelligence hybrid models for improving forecasting accuracy," *Procedia Computer Science*, vol. 184, pp. 817–822, 2021, doi: 10.1016/j.procs.2021.04.013.

[26] A. Sari, M. Modi Lakulu, and I. Y. Panessai, "Predicting premature birth during pregnancy using machine learning: A systematic review," *International Journal of Intelligent Systems and Applications in Engineering*, 2022.

[27] R. Topan, A. Rahman, M. M. Lakulu, and I. Y. Panessai, "Advancing preeclampsia prediction with machine learning: A comprehensive systematic literature review," *International Journal of Intelligent Systems and Applications in Engineering*, 2023.

[28] D. P. Sinambela, B. Rahmatullah, N. H. C. Lah, and A. W. Selamat, "Machine learning approaches for predicting postpartum

hemorrhage: a comprehensive systematic literature review," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 34, no. 3, pp. 2087–2095, Jun. 2024, doi: 10.11591/ijeecs.v34.i3.pp2087-2095.
[29] D. Rahmayani *et al.*, "Prediction of sexual violence against women (SVAW) using machine learning," *Journal of Hunan University Natural Sciences*, vol. 51, no. 3, 2024, doi: 10.55463/issn.1674-2974.51.3.3.
[30] L. Swastina, B. Rahmatullah, A. Saad, and H. Khan, "A systematic review on research trends, datasets, algorithms, and frameworks of children's nutritional status prediction," *International Journal of Artificial Intelligence*, vol. 13, no. 2, pp. 1866–1875, Jun. 2024, doi: 10.11591/ijai.v13.i2.pp1868-1877.
[31] W. A. Fazraningtyas, B. Rahmatullah, D. D. Salmarini, S. A. Ariffin, and A. Ismail, "Recent advancements in postpartum depression prediction through machine learning approaches: a systematic review," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 4, pp. 2729–2737, Aug. 2024, doi: 10.11591/eei.v13i4.7185.
[32] A. Shah, Suhailiezana, C. G. C. Kob, and M. Khairudin, "Effectiveness of m-learning applications for design and technology subject," *International Journal of Interactive Mobile Technologies*, vol. 13, no. 10, pp. 120–133, 2019, doi: 10.3991/ijim.v13i10.11324.
[33] A. Saad, S. Samuri, B. Rahmatullah, and M. C. Mustafa, "The trend of body mass index (BMI) changes among Malaysian children and the prediction at 48 months old," *Asia-Pacific Journal of Research in Early Childhood Education*, vol. 15, no. 2, pp. 187–206, May 2021, doi: 10.17206/apjrece.2021.15.2.187.
[34] O. S. Albahri and Others, "Systematic review of artificial intelligence techniques in the detection and classification of COVID-19 medical images in terms of evaluation and benchmarking: Taxonomy analysis, challenges, future solutions and methodological aspects," *Journal of Infection and Public Health*, vol. 13, no. 10, pp. 1381–1396, Oct. 2020, doi: 10.1016/j.jiph.2020.06.028.
[35] H. Pratama, M. N. A. Azman, G. K. Kassymova, and S. S. Duisenbayeva, "The trend in using online meeting applications for learning during the period of pandemic COVID-19: A literature review," *Journal of Innovation in Educational and Cultural Research*, vol. 1, no. 2, pp. 58–68, Dec. 2020, doi: 10.46843/jiecr.v1i2.15.
[36] C. Feng, "Studies on global remote interpreting: A PRISMA systematic review," *SHS Web of Conferences*, vol. 162, p. 1031, 2023, doi: 10.1051/shsconf/202316201031.
[37] M. Alaraj, A. Kumar, I. Alsaidan, M. Rizwan, and M. Jamil, "Energy production forecasting from solar photovoltaic plants based on meteorological parameters for Qassim region, Saudi Arabia," *IEEE Access*, vol. 9, pp. 83241–83251, 2021, doi: 10.1109/ACCESS.2021.3087345.
[38] L. Cheng, H. Zang, T. Ding, Z. Wei, and G. Sun, "Multi-meteorological-factor-based graph modeling for photovoltaic power forecasting," *IEEE Transactions on Sustainable Energy*, vol. 12, no. 3, pp. 1593–1603, 2021, doi: 10.1109/TSTE.2021.3057521.
[39] Y. Feng, W. Hao, H. Li, N. Cui, D. Gong, and L. Gao, "Machine learning models to quantify and map daily global solar radiation and photovoltaic power," *Renewable and Sustainable Energy Reviews*, vol. 118, p. 109393, 2020, doi: 10.1016/j.rser.2019.109393.
[40] C.-J. Huang and P.-H. Kuo, "Multiple-input deep convolutional neural network model for short-term photovoltaic power forecasting," *IEEE Access*, vol. 7, pp. 74822–74834, 2019, doi: 10.1109/access.2019.2921238.
[41] J. Ye, B. Zhao, and H. Deng, "Photovoltaic power prediction model using pre-train and fine-tune paradigm based on LightGBM and XGBoost," *Procedia Computer Science*, vol. 224, pp. 407–412, Jan. 2023, doi: 10.1016/j.procs.2023.09.056.
[42] S. U. Sabareesh, K. S. N. Aravind, K. B. Chowdary, S. Syama, and V. S. Kirthika Devi, "LSTM based 24 hours ahead forecasting of solar PV system for standalone household system," *Procedia Computer Science*, vol. 218, pp. 1304–1313, Jan. 2023, doi: 10.1016/j.procs.2023.01.109.
[43] M. Rana and A. Rahman, "Multiple steps ahead solar photovoltaic power forecasting based on univariate machine learning models and data re-sampling," *Sustainable Energy, Grids and Networks*, vol. 21, p. 100286, 2020, doi: 10.1016/j.segan.2019.100286.
[44] S. Theocharides, G. Makrides, A. Livera, M. Theristis, P. Kaimakis, and G. E. Georghiou, "Day-ahead photovoltaic power production forecasting methodology based on machine learning and statistical post-processing," *Applied Energy*, vol. 268, p. 115023, Apr. 2020, doi: 10.1016/j.apenergy.2020.115023.
[45] R. A. A. Ramadhan, Y. R. J. Heatubun, S. F. Tan, and H. J. Lee, "Comparison of physical and machine learning models for estimating solar irradiance and photovoltaic power," *Renewable Energy*, vol. 178, pp. 1006–1019, 2021, doi: 10.1016/j.renene.2021.06.079.
[46] E. Rangel-Heras, C. Angeles-Camacho, E. Cadenas-Calderón, and R. Campos-Amezcua, "Short-term forecasting of energy production for a photovoltaic system using a NARX-CVM hybrid model," *Energies*, vol. 15, no. 8, p. 2842, Apr. 2022, doi: 10.3390/en15082842.
[47] D. Wang, J. Liu, Y. Huang, B. Shi, and M. Jin, "Photovoltaic power prediction method combining solar radiation calculation and CNN-LSTM," *Taiyangneng Xuebao/Acta Energiae Solaris Sinica*, vol. 45, no. 2, pp. 443–450, 2024, doi: 10.19912/j.0254-0096.tynxb.2022-1542.
[48] X. Luo, D. Zhang, and X. Zhu, "Deep learning-based forecasting of photovoltaic power generation by incorporating domain knowledge," *Energy*, vol. 225, p. 120240, Sep. 2021, doi: 10.1016/j.energy.2021.120240.
[49] X. Wang, Y. Sun, D. Luo, and J. Peng, "Comparative study of machine learning approaches for predicting short-term photovoltaic power output based on weather type classification," *Energy*, vol. 240, p. 122733, Feb. 2022, doi: 10.1016/j.energy.2021.122733.
[50] F. Rodríguez, I. Azcárate, J. Vadillo, and A. Galarza, "Forecasting intra-hour solar photovoltaic energy by assembling wavelet-based time-frequency analysis with deep learning neural networks," *International Journal of Electrical Power & Energy Systems*, vol. 137, p. 107777, May 2022, doi: 10.1016/j.ijepes.2021.107777.
[51] I. Pervez, J. Shi, H. Ghazzai, and Y. Massoud, "NeuralPV: A neural network algorithm for PV power forecasting," *2023 IEEE International Symposium on Circuits and Systems (ISCAS)*, Monterey, CA, USA, 2023, pp. 1-5, doi: 10.1109/ISCAS46773.2023.10181648.
[52] L. Ramos, M. Colnago, and W. Casaca, "Data-driven analysis and machine learning for energy prediction in distributed photovoltaic generation plants: A case study in Queensland, Australia," *Energy Reports*, vol. 8, pp. 745–751, 2022, doi: 10.1016/j.egyr.2021.11.123.
[53] W. Khan, S. Walker, and W. Zeiler, "Improved solar photovoltaic energy generation forecast using deep learning-based ensemble stacking approach," *Energy*, vol. 240, Feb. 2022, doi: 10.1016/j.energy.2021.122812.
[54] J. Wang, Y. Zhou, and Z. Li, "Hour-ahead photovoltaic generation forecasting method based on machine learning and multi-objective optimization algorithm," *Applied Energy*, vol. 312, p. 118725, Mar. 2022, doi: 10.1016/j.apenergy.2022.118725.

[55] R. L. de C. Costa, "Convolutional-LSTM networks and generalization in forecasting of household photovoltaic generation," *Engineering Applications of Artificial Intelligence*, vol. 116, p. 105458, Nov. 2022, doi: 10.1016/j.engappai.2022.105458.
[56] E. Ekinci, "A comparative study of LSTM-ED architectures in forecasting day-ahead solar photovoltaic energy using weather data," *Computing*, vol. 106, no. 4, pp. 1611–1632, 2024, doi: 10.1007/s00607-024-01266-1.
[57] C. Xin, H. Zhao, and Y. Li, "Research on power user behavior analysis and prediction based on RFM-random forest algorithm," in *Proceedings of the 6th IEEE Conference on Energy Internet and Energy System Integration (EI2)*, 2022, pp. 1772–1778, doi: 10.1109/EI256261.2022.10117392.
[58] E. A. Setiawan, M. P. Sumarto, and M. Z. Hussin, "A lesson of solar energy development in Malaysia and Indonesia," *International Journal of Energy Economics and Policy*, vol. 14, no. 1, pp. 401–411, Jan. 2024, doi: 10.32479/ijeep.15258.
[59] A. P. Tampubolon and P. Simamora, "A call to revisit the existing national energy plan (RUEN)." Institute for Essential Services Reform (IESR), Oct. 2020.

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