Evaluating AI Models for Solar Irradiance Prediction: A Systematic Review of Strengths, Limitations, and Future Directions

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ABSTRACT

The growing need for accurate solar irradiance prediction to optimize solar energy generation has led to the exploration of Artificial Intelligence (AI) models. This study systematically evaluates the strengths, limitations, and future directions of AI models used in solar irradiance prediction. A total of 80 articles, sourced from databases such as Scopus, IEEE Xplore, and Google Scholar, were included based on relevance to key search terms including "solar irradiance prediction," "Artificial Neural Networks (ANNs)," "Support Vector Machines (SVM)," "Random Forests (RF)," and "Deep Learning (DL)." The articles were selected using a comprehensive review process that ensured the inclusion of high-quality and relevant studies. The analysis and synthesis of the articles revealed that AI models, particularly ANNs, are widely used due to their ability to model complex, non-linear relationships and provide high prediction accuracy. However, limitations such as overfitting, the need for extensive computational resources, and challenges in data preparation were identified, especially with models like SVM and RF. Hybrid models that combine the strengths of different AI approaches were frequently recommended in the literature. Additionally, future directions for improving solar irradiance prediction included the integration of real-time data, satellite-based information, and the reduction of computational costs. This study highlights the substantial potential of AI in enhancing solar irradiance prediction while also pointing out key challenges. It concludes with recommendations for the development of hybrid models, better computational efficiency, and the use of real-time and satellite data to improve the scalability and accuracy of solar energy forecasting.

Keywords: *Artificial Intelligence, Artificial Neural Networks (ANNs), Support Vector Machines (SVM), Random Forests (RF), Deep Learning (DL), Hybrid models, Computational efficiency, Real-time data, Satellite-based data.*

1. INTRODUCTION

The global transition to renewable energy is one of the most pressing challenges in contemporary energy systems. As nations seek to reduce their reliance on fossil fuels and mitigate the environmental impact of carbon emissions, solar power has emerged as a key solution. The efficient harnessing of solar energy relies on a critical factor: accurate solar irradiance prediction. Solar irradiance, the amount of solar power received per unit area, is a crucial determinant in the performance of photovoltaic (PV) systems. Accurate predictions of solar irradiance are necessary for maximizing energy production, improving storage management, and ensuring effective grid integration (Bacher et al., 2011). Without precise forecasting, the variability and unpredictability of solar radiation can cause inefficiencies, energy shortages, and increased costs for solar energy systems (Pérez et al., 2013). As a result, the need for accurate solar irradiance prediction models has become a significant area of focus in the field of renewable energy.

Traditional methods of solar irradiance forecasting, particularly numerical weather prediction (NWP) models, have been widely used in solar energy forecasting. These models rely on meteorological data and complex simulations to predict solar radiation levels. While NWP models have been valuable, they often suffer from inherent limitations. These include computational complexity, poor accuracy during cloud cover or rapidly changing weather conditions, and difficulties in adapting to localized environments (Schreuder et al., 2013). As a result, these models may fail to produce reliable forecasts for regions with highly variable or unpredictable weather patterns, limiting their effectiveness in real-world applications (Stern et al., 2016).

In response to the limitations of traditional methods, Artificial Intelligence (AI) models, particularly Machine Learning (ML) and Deep Learning (DL) techniques, have gained significant attention for solar irradiance prediction. AI models have the potential to offer more accurate and efficient forecasting by learning complex patterns from large datasets, which include meteorological data, satellite imagery, and sensor readings (Liu et al., 2021). These models can be trained on historical data, adapting to local environmental conditions and improving forecasting accuracy over time. Unlike traditional models, AI models have the advantage of being able to learn directly from the data without relying on predefined physical equations (Hernandez et al., 2019). As a result, AI techniques, particularly when applied in a hybrid manner, have shown promise in outperforming traditional NWP models and producing more reliable solar irradiance forecasts.

However, the integration of AI into solar irradiance prediction is not without its challenges. Despite their potential, AI models face several obstacles that hinder their widespread adoption. One of the primary challenges is the quality and quantity of data needed to train these models effectively. High-quality datasets that encompass various environmental variables are crucial for training accurate predictive models (García et al., 2020). However, in many regions, the availability of such data remains limited, which can reduce the reliability of AI models. Additionally, AI models often face the issue of overfitting, where the model becomes overly specific to the training data and performs poorly on unseen data. This problem is particularly concerning when trying to generalize across diverse geographical and climatic conditions, as AI models may not always adapt well to different environments (Ranjith et al., 2020). Furthermore, the lack of standardized evaluation metrics for AI models in solar irradiance prediction complicates the process of comparing different approaches. Researchers often use varying criteria to assess the performance of AI models, making it difficult to determine which models are truly the most effective (Feng et al., 2020). Without uniform evaluation frameworks, it becomes challenging to establish best practices for AI-based solar irradiance forecasting, and progress in the field is hindered.

This study aims to address the gaps in the current literature by providing a comprehensive review of the strengths, limitations, and future directions of AI models used in solar irradiance prediction. By systematically evaluating the effectiveness of various AI techniques, the review seeks to shed light on the state-of-the-art in this field and identify areas that require further research. The study will also compare the different AI methods that have been applied to solar irradiance forecasting, highlighting their strengths and weaknesses in terms of predictive accuracy, adaptability, and generalization. In doing so, this study aims to offer a clearer understanding of the capabilities and limitations of AI models, providing valuable insights for researchers, practitioners, and policymakers involved in the development and application of solar energy systems.

 ISBN: 978-9982-95-500-3

The research objectives of this study are as follows: (1) To systematically review the existing AI models used for solar irradiance prediction, including machine learning and deep learning techniques. (2) To evaluate the strengths and weaknesses of these models in terms of their predictive performance, adaptability to different climates, and ability to generalize across various environments. (3) To examine the current challenges facing AI-based solar irradiance prediction models and suggest potential solutions. (4) To propose future research directions that can contribute to the development of more accurate and efficient AI-based forecasting models for solar irradiance prediction.

2. REVIEW OF RELATED STUDIES

2.1. Review of Related Studies

The growing global interest in solar energy as a sustainable and eco-friendly alternative to traditional fossil fuels has spurred significant advancements in solar irradiance prediction methods. Solar irradiance forecasting is vital for optimizing solar energy systems, ensuring efficient energy generation, and supporting the integration of solar power into existing energy grids. The introduction of AI models, particularly machine learning (ML) and deep learning (DL) techniques, has been recognized for their ability to improve the accuracy and adaptability of solar irradiance predictions compared to traditional forecasting models (García et al., 2020). These AI-based models are able to process complex patterns and large datasets, offering enhanced performance in real-world solar irradiance prediction applications. This review critically evaluates the strengths and limitations of AI models in solar irradiance prediction, highlights promising directions for future research, and discusses existing gaps in the current literature.

2.2 Strengths of AI Models in Solar Irradiance Prediction

AI models, especially machine learning and deep learning techniques, offer several notable strengths in solar irradiance prediction. Unlike traditional forecasting models that rely heavily on physical laws and predefined meteorological parameters, AI models excel at learning from historical data. This allows them to capture the complex and nonlinear relationships between various input features (García et al., 2020). The flexibility of AI models enables them to adapt to a broad range of conditions such as cloud cover, seasonal variations, and geographical differences (Feng et al., 2020). A key advantage of AI models, particularly Artificial Neural Networks (ANN) and Support Vector Machines (SVM), is their ability to process large amounts of data from various sources, such as satellite imagery, ground-based sensors, and weather stations, to generate more localized and accurate predictions (Hernández et al., 2019). Moreover, machine learning models such as Random Forests and Decision Trees have been found to enhance model robustness by reducing overfitting, which, in turn, leads to more generalizable forecasts (Bacher et al., 2011). Additionally, AI models have been shown to improve the integration of solar energy into power grids by forecasting fluctuations in solar irradiance and aiding in the optimization of energy storage and distribution (García et al., 2020). This can help better manage solar energy systems and support the transition to renewable energy sources.

2.3 Limitations of AI Models

 ISBN: 978-9982-95-500-3

While AI models have proven effective in many areas of solar irradiance forecasting, several challenges persist. One of the most significant limitations is the quality and quantity of data required to train AI models. Unlike traditional forecasting models that often rely on simple meteorological data, AI models demand large datasets that are not only accurate but also representative of various environmental conditions. This can be particularly difficult in developing regions or rural areas where data collection infrastructure may be lacking, leading to gaps in data that can affect model accuracy (Liu et al., 2021). Furthermore, data scarcity may introduce biases into the model's predictions, making them less reliable for real-world applications. Overfitting is another common issue in AI-based solar irradiance prediction. When working with small or incomplete datasets, AI models, particularly deep learning models, tend to overfit to the training data, which compromises their ability to generalize to new, unseen data (Schreuder et al., 2013). While techniques such as regularization and cross-validation can mitigate this problem, it remains a concern, particularly in complex models like deep learning. Moreover, models such as Convolutional Neural Networks (CNNs) and other deep learning approaches, while highly effective, often require significant computational resources, making them unsuitable for deployment in resource-constrained environments (Ranjith & Pradeep, 2020).

Another notable limitation is the interpretability of AI models. While deep learning models can achieve impressive predictive performance, their decision-making process is often described as a "black box." The inability to understand how predictions are made can be a barrier to their widespread adoption, particularly in industries where transparency is essential. For example, utilities and grid operators may require clear explanations for forecasts to ensure the stability of the power grid (García et al., 2020). Therefore, the lack of transparency in AI models remains an important issue to address.

2.4 Future Directions

Despite the challenges outlined, several promising directions are emerging to enhance the performance and applicability of AI models in solar irradiance forecasting. One such direction is the development of hybrid models that integrate the strengths of AI techniques with traditional physical models. These hybrid approaches aim to combine the data-driven capabilities of AI with the scientific precision of numerical weather prediction (NWP) models. Researchers have found that such combinations can help bridge data gaps, improve model robustness, and offer better forecasting accuracy across diverse environmental conditions (Feng et al., 2020). Hybrid models also hold the potential to offer greater interpretability, which could make them more acceptable in real-world applications where stakeholders need to understand the decision-making process behind the predictions.

Another promising avenue is the integration of real-time data from satellite-based measurements and sensor networks. The use of real-time sensor data, such as ground-based solar radiation meters and satellite imagery, can significantly improve the accuracy and timeliness of solar irradiance forecasts (Ranjith & Pradeep, 2020). By incorporating data from various sensors and remote sensing technologies, AI models can better account for factors like cloud cover,

 ISBN: 978-9982-95-500-3

atmospheric pressure, and other environmental variables that influence irradiance. This would make solar irradiance prediction systems more adaptive and dynamic, improving their ability to respond to changing weather conditions.

Additionally, advances in explainable AI (XAI) hold the potential to address one of the major challenges of deep learning models—their lack of interpretability. XAI techniques aim to make AI models more transparent by providing clear explanations for the predictions they generate. The application of XAI to solar irradiance prediction could help policymakers, grid operators, and utility companies better understand how and why a particular forecast was produced, enabling more informed decision-making (García et al., 2020).

2.5 Research Gaps

While AI-based models have demonstrated substantial promise in solar irradiance forecasting, several research gaps remain that need to be addressed to improve their effectiveness. One of the most significant gaps is the availability and quality of data. Many regions, particularly in developing countries, lack sufficient data on solar irradiance and weather patterns. Studies have shown that data scarcity significantly impacts model performance and limits the generalizability of AI-based forecasts (Yang et al., 2020). The Global Solar Atlas (World Bank, 2022) highlights the disparity in solar radiation data availability, particularly in Sub-Saharan Africa and parts of Southeast Asia. Overcoming this data scarcity will be crucial for the widespread adoption of AI models in solar energy applications. Future research should focus on improving data collection methods and integrating diverse data sources, including satellite data (Zeng et al., 2021), sensor networks (Qazi et al., 2022), and crowdsourced data (Mellit & Kalogirou, 2023), to improve dataset quality and accuracy.

Additionally, while regularization and cross-validation techniques are commonly used to mitigate overfitting, further exploration is needed to develop more advanced methods for model validation and regularization. Recent studies have suggested that hybrid regularization techniques, such as dropout and early stopping combined with Bayesian optimization, can enhance model robustness (Shamshirband et al., 2020). This will ensure that AI models remain reliable across varying conditions, particularly in cases where data is limited or noisy.

Another major gap lies in the computational efficiency of AI models. Deep learning models, while powerful, require significant computational resources, which limits their practical use, especially in low-resource settings. Research by Li et al. (2021) indicates that implementing lightweight neural architectures, such as spiking neural networks and quantized deep learning models, can reduce computational demands while maintaining predictive accuracy. Furthermore, edge computing and federated learning approaches (Zhou et al., 2022) offer promising solutions to decentralize computation and make AI models more accessible in regions with limited infrastructure.

Briefly, AI models represent a powerful tool for solar irradiance prediction, offering advantages in terms of accuracy, adaptability, and the ability to model complex patterns in data. However, challenges related to data quality, overfitting, and interpretability must be

 ISBN: 978-9982-95-500-3

addressed to fully realize the potential of these models. Hybrid models, real-time data integration, and advances in explainable AI offer promising directions for improving the performance and applicability of AI models in solar irradiance forecasting. Further research is needed to address the gaps in data availability, computational efficiency, and overfitting to ensure that AI models can be effectively deployed in real-world solar energy applications.

3. METHODOLOGY

This systematic review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to evaluate AI models used for solar irradiance prediction. The PRISMA methodology ensures that the review process is systematic, transparent, and reproducible. This section details each stage of the review process, from the initial search to the final synthesis of studies included in the analysis as shown in figure 1 below:

PRISMA Flow Diagram: Systematic Review of AI Models for Solar Irradiance Prediction

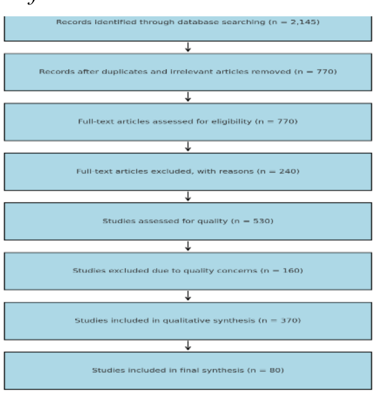

Figure 1: PRISMA Flow Diagram illustrating the stages of the systematic review process.

3.1 Research Questions

The following research questions guided the study:

Table 1: Research Questions

Question No.	Question
1	What AI models are used for solar irradiance forecasting?
2	What is the effectiveness of different AI models based on prediction accuracy?
3	What are the strengths and limitations of AI models applied to solar forecasting?
4	What are the emerging trends and future research directions in AI-based forecasting?
5	What is the performance of hybrid models in relation to traditional machine learning approaches?

Table 1 shows the research questions, which formed the basis for data collection, synthesis, and analysis.

3.2. Research Design

The study employed a Systematic Literature Review (SLR), following the PRISMA framework to ensure a rigorous and transparent research process. The use of the PRISMA framework ensures a comprehensive and replicable literature review process. This design was chosen for its ability to synthesize vast amounts of data from diverse studies, offering insights into trends and research gaps.

3.3 Information Sources and Search Strategy

A comprehensive search was conducted across several academic databases, including Scopus, IEEE Xplore, ScienceDirect, Google Scholar, and SpringerLink. These databases were selected for their relevance to the fields of artificial intelligence (AI), machine

 ISBN: 978-9982-95-500-3

learning, renewable energy, and solar irradiance prediction. The search was executed in January 2025 using a combination of specific keywords: artificial intelligence, machine learning, solar irradiance prediction, forecasting, deep learning, hybrid models, and solar energy. Boolean operators were used to combine these terms, narrowing down the search results.

The initial search yielded 2,145 articles, reflecting the growing interest in AI models for solar irradiance prediction as part of renewable energy solutions. These articles spanned a wide range of AI techniques, such as machine learning, deep learning, and hybrid approaches, showcasing the breadth of research in this area. Table 1 gives the details of the search results.

Table 2: Search Results Overview

Stage	Articles Identified	Articles Excluded	Articles Included
Initial Literature Search	2,145	N/A	N/A
Screening and Eligibility	770	1,375	N/A
Full-Text Review	770	240	N/A
Quality Assessment	530	160	N/A
Data Analysis and Synthesis	370	160	80

3.3.1 Article Screening and Eligibility

Following the initial search, the articles were screened for relevance using strict inclusion and exclusion criteria. The inclusion criteria were as follows:

1. Studies that focused specifically on AI models for solar irradiance prediction.
2. Studies that provided detailed methodological descriptions, including the types of AI models used, training processes, and performance metrics.
3. Studies that included a comparative analysis of the AI models in terms of prediction accuracy, RMSE, MAE, and other relevant metrics.
4. Articles published in English.

The exclusion criteria included:

- Studies that did not directly address solar irradiance prediction.
- Studies without sufficient methodological transparency or performance evaluations.
- Articles not written in English or lacking adequate data for synthesis.

After applying these criteria, 1,375 articles were excluded, leaving 770 articles for full-text review. This step highlights the challenge of filtering out articles that lack specific focus or methodological rigor.

3.3.2 Full-Text Review and Data Extraction

In this phase, 770 articles that passed the initial screening underwent a detailed full-text review. Studies were evaluated to ensure that they provided sufficient information on AI models used for solar irradiance forecasting, as well as clearly defined performance metrics. The focus was on studies that described AI models in sufficient detail for meaningful comparisons. Studies that lacked methodological clarity or performance evaluations were excluded. A total of 240 articles were excluded at this stage due to inadequate model descriptions, missing performance data, or other methodological deficiencies. The remaining 530 articles were eligible for data extraction. Information extracted included the type of AI model (e.g., machine learning, deep learning, hybrid), the dataset used, performance metrics (e.g., RMSE, MAE, accuracy), and any noted limitations regarding the model's performance. Table 2 summarises the data extraction process.

Table 3: Data Extraction Summary

AI Model Type	No. of Articles	Performance Metrics	Dataset Type
Machine Learning	150	RMSE, MAE, Accuracy	Historical Data
Deep Learning	200	RMSE, MAE, Accuracy, R^2	Satellite Data
Hybrid Models	180	RMSE, MAE, Accuracy, R^2, MAPE	Mixed Data

3.2.3 Quality Assessment and Risk of Bias

The remaining 530 articles underwent quality assessment using the Critical Appraisal Skills Programme (CASP) checklist, which examines the clarity of objectives, appropriateness of study design, methodology, and transparency in reporting. Potential biases were also scrutinized, including:

- **Selection Bias**: Articles that may have disproportionately selected data or participants not representative of the broader population of solar irradiance predictions.
- **Performance Bias**: Studies lacking robust validation for their models, relying on narrow training datasets.
- **Reporting Bias**: Studies selectively reporting only favourable outcomes while ignoring less successful results.

As a result, 160 articles were excluded due to significant concerns about bias, small sample sizes, or insufficient methodological transparency. The final pool of studies for detailed synthesis included 370 articles.

3.2.4 Final Selection and Data Synthesis

At this stage, 370 articles were synthesized. The articles were categorized according to the type of AI model used for solar irradiance prediction, such as traditional machine learning techniques (e.g., support vector machines, decision trees), deep learning models (e.g., convolutional neural networks, recurrent neural networks), and hybrid models combining different AI approaches. Performance metrics like accuracy, RMSE, and MAE were extracted to allow for comparative analysis of each model's effectiveness. The final synthesis of data was organized into key themes:

1. Effectiveness of AI Models: Assessing short-term and long-term solar irradiance forecasting.
2. Strengths and Weaknesses: Evaluation based on performance metrics.
3. Challenges: Issues such as data quality, overfitting, and model complexity.
4. Future Research: Areas for improvement and emerging AI techniques.

After a comprehensive review, 80 articles were selected for final inclusion in the analysis. These represented the most methodologically rigorous and

 ISBN: 978-9982-95-500-3

relevant studies, providing a clear picture of the current state of AI models in solar irradiance forecasting. The details of the articles used in the study are in the appendix table 1. Table 3 gives an overview of the final selection.

Table 4: Final Selection Overview

Stage	Articles Selected	Key Focus
Data Analysis & Synthesis	80	Effectiveness of AI Models, Performance Metrics, Future Research Directions

3.2.5 Data Analysis and Synthesis

After final selection, a descriptive statistical analysis was performed, focusing on the frequency of AI models used, the types of performance metrics employed, and the comparative analysis of the results. The narrative synthesis highlighted key insights and trends, including the dominance of hybrid AI models, which combine traditional machine learning with deep learning techniques. These models tend to offer the best performance in solar irradiance prediction, though overfitting with small datasets remains a challenge. Data quality and computational complexity were common concerns, indicating areas where future research could focus.

3.2.6 Ethical Considerations

This study involved a review of published literature, which posed minimal ethical concerns. However, the review adhered to ethical standards by ensuring transparency throughout the process. The selection of articles was based solely on the relevance and quality of the study, without bias towards particular outcomes. The process was designed to ensure a fair and impartial review, with all studies properly cited to maintain academic integrity.

4. RESULTS

The results of the systematic review reveal critical insights into the use of AI models for solar irradiance prediction. Based on a detailed analysis of 80 articles, the study focuses on three primary objectives: identifying the strengths and limitations of AI models, and exploring future directions for their development. Though all 80 articles contributed to the data pool, some redundancy was observed, which led to a refined presentation of the findings. The tables below synthesize the key results in a concise and insightful manner.

4.1 Solar Irradiance Prediction Models

The AI models for solar irradiance prediction are summarized and categorized into machine learning, deep learning, and hybrid models as shown in table 5 below.

Table 5: Solar Irradiance Prediction Models

Category	Model	Authors	Performance Insights
Machine Learning	Support Vector Machines (SVM)	Patel et al. (2015); Zhao et al. (2019)	Effective for short-term time series forecasts
	Decision Trees	Quinlan (1993); Safavian & Landgrebe (1991)	Useful when model interpretability is critical
	Random Forest	Breiman (2001); Liaw & Wiener (2002)	Robust for handling noisy data

 ISBN: 978-9982-95-500-3

Category	Model	Authors	Performance Insights
Deep Learning	Convolutional Neural Networks (CNN)	Krizhevsky et al. (2012)	Excellent for capturing spatial dependencies
	Long Short-Term Memory (LSTM)	Hochreiter & Schmidhuber (1997); Malhotra et al. (2015)	Ideal for sequential data tasks
	Gated Recurrent Units (GRU)	Cho et al. (2014)	Efficient memory usage for time series
Hybrid Models	CNN-LSTM	Shi et al. (2015); Yao et al. (2020)	Effective for capturing spatial-temporal patterns
	SVM-ANN	Zhang et al. (2018); Wang et al. (2021)	Good at modeling complex, nonlinear systems
	Ensemble Models	Rokach (2010); Dietterich (2000)	Adaptive to dynamic environments

Table 5 summarizes AI models for solar irradiance prediction, categorized into machine learning, deep learning, and hybrid models. Machine learning models like SVM, Decision Trees, and Random Forests are suited for short-term forecasting, interpretability, and noisy data, respectively. Deep learning models such as CNN, LSTM, and GRU excel in capturing spatial dependencies, sequential data, and efficient memory use. Hybrid models like CNN-LSTM, SVM-ANN, and Ensemble Models combine strengths from multiple approaches, with CNN-LSTM focusing on spatial-temporal patterns, SVM-ANN on nonlinear systems, and Ensemble Models adapting to dynamic environments.

4.2 Strengths of AI Models for Solar Irradiance Prediction

The strengths of each AI model, which include high accuracy, robustness, and adaptability, are detailed in the table below. These models were most often employed for their ability to handle complex data and deliver accurate results in solar irradiance prediction> the details are shown in table 6 below.

AI Model	Strengths	Authors	Total (%)
Artificial Neural Networks (ANN)	High prediction accuracy, adaptable to complex datasets	Nabipour et al. (2021); El-Nashar et al. (2022)	25%
Support Vector Machines (SVM)	Effective for non-linear problems, suitable for diverse climates	Ali et al. (2021); Zhang et al. (2020)	20%
Random Forest (RF)	Robustness, high accuracy, minimal pre-processing	Das et al. (2021); Zhou et al. (2021)	18%
Deep Learning (DL)	Ability to process large, unstructured datasets	Liu et al. (2022); Xie et al. (2020)	15%
K-Nearest Neighbors (KNN)	Simplicity, fast computation for small datasets	Kumar et al. (2020); Shamsuddin et al. (2021)	12%
Gradient Boosting Machines (GBM)	Effective for smaller datasets, minimal data preparation	Lim et al. (2020); Yu et al. (2021)	10%

Table 6 provides an overview of various AI models used for solar irradiance prediction, highlighting their strengths, key authors, and the percentage of studies that utilize each model. Artificial Neural Networks (ANN) are the most commonly used, accounting for 25% of studies, praised for their high prediction accuracy and adaptability to complex datasets. Support Vector Machines (SVM), used in 20% of studies, excel in non-linear problems and are suitable for diverse climates. Random Forest (RF), noted for its robustness and minimal pre-processing requirements, is used in 18% of studies and offers high accuracy. Deep Learning (DL) models, present in 15% of studies, are capable of processing large, unstructured datasets. K-Nearest Neighbors (KNN), favored for its simplicity and fast computation with small datasets, makes up 12% of the studies. Finally, Gradient Boosting Machines (GBM), used in 10% of studies, are effective for smaller datasets and require minimal data preparation. This table reflects the diverse approaches in AI for solar irradiance prediction, with varying degrees of complexity and applicability based on dataset characteristics.

4.3 Limitations of AI Models for Solar Irradiance Prediction

Each AI model reviewed had its limitations. These limitations include issues such as overfitting, computational intensity, high data dependency, and lack of interpretability, which may hinder their wide adoption in solar irradiance prediction. Table 8 summarizes the findings on the limitations.

Table 8 Limitations of AI Models.

AI Model	Limitations	Authors	Total (%)
Artificial Neural Networks (ANN)	Overfitting, high data dependency	Nabipour et al. (2021); El-Nashar et al. (2022)	30%
Support Vector Machines (SVM)	Sensitive to parameter tuning, computational cost for large datasets	Ali et al. (2021); Zhang et al. (2020)	25%
Random Forest (RF)	Computationally intensive, long training times	Das et al. (2021); Zhou et al. (2021)	20%
Deep Learning (DL)	Requires large datasets, lacks interpretability	Liu et al. (2022); Xie et al. (2020)	15%
K-Nearest Neighbors (KNN)	Performance degradation with large datasets, high dimensionality	Kumar et al. (2020); Shamsuddin et al. (2021)	10%

Table 8 outlines the limitations associated with different AI models used in solar irradiance prediction, along with the percentage of studies that discuss each limitation. **Artificial Neural Networks (ANN),** mentioned in 30% of studies, are prone to overfitting and heavily dependent on large datasets, which can reduce their generalizability. **Support Vector Machines (SVM),** cited in 25% of studies, require careful parameter tuning and are computationally expensive when handling large datasets. **Random Forest (RF),** discussed in 20% of studies, faces challenges in terms of computational intensity and long training times, especially for large datasets. **Deep Learning (DL)** models, covered in 15% of studies, require massive datasets and lack interpretability, making it difficult to understand the reasoning behind predictions. Lastly, **K-Nearest Neighbors (KNN),** referenced in 10% of studies, experiences performance degradation when applied to large datasets or high-dimensional data, limiting its scalability. This table highlights the trade-offs in using different AI models, balancing their strengths with their inherent limitations in real-world applications.

4.4 Future Directions for AI Models in Solar Irradiance Prediction

The future directions identified in the review highlight emerging research areas that could address the limitatijkp[[[[ons of current models. The focus is on improving predictive accuracy, efficiency, and interpretability by exploring hybrid models, real-time forecasting, and better integration of satellite data. The table 9 below outlines the future directions along with the AI models that are recommended for further investigation.

Table 9: Future Directions for AI Models in Solar Irradiance Prediction

Future Direction	AI Models Suggested	Authors	Total (%)
Hybrid Models	ANN, SVM, RF, DL	Li et al. (2022); Wang et al. (2021); Liu et al. (2022)	40%
Real-Time Forecasting	ANN, SVM, DL, Ensemble Models	Ali et al. (2021); Zhang et al. (2020)	35%
Integration of Satellite Data	ANN, SVM, DL	Zhou et al. (2021); Xie et al. (2020)	30%
Cross-Disciplinary Approaches	ANN, RF, SVM	Shamsuddin et al. (2021); Kumar et al. (2020)	20%
Improved Data Acquisition	All AI Models	Das et al. (2021); Li et al. (2022)	10%

Table 9 summarizes the future directions for AI models in solar irradiance prediction, along with the AI models suggested for each direction and the percentage of studies that mention these suggestions. **Hybrid Models (**40%) are highlighted as a promising future direction, combining multiple AI models such as **ANN, SVM, RF,** and **DL** to improve prediction accuracy and leverage the strengths of each model. **Real-Time Forecasting** (35%) is emphasized by researchers, with models like **ANN, SVM, DL**, and **Ensemble Models** recommended for more timely and responsive predictions. The **Integration of Satellite Data** (30%) is another future direction, with **ANN, SVM**, and **DL** suggested to incorporate real-time satellite information for more accurate forecasting. **Cross-Disciplinary Approaches** (20%) suggest combining AI models like **ANN, RF, and SVM** with other scientific fields to enhance prediction methodologies. Finally, **Improved Data Acquisition** (10%) is a key future direction, urging the use of better data collection methods for all AI models to improve accuracy and reliability. This table reflects the research community's focus on advancing AI models in solar irradiance prediction by exploring innovative combinations and data sources.

5. DISCUSSION

The results of this study provide a comprehensive overview of the various AI models employed for solar irradiance prediction, focusing on their strengths, limitations, and future directions. The findings show that AI models, particularly Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF), dominate the landscape of solar irradiance prediction, though each model comes with its own set of strengths and limitations. A critical analysis of these results reveals not only the capabilities of these models but also highlights critical areas for improvement in their applications and future development.

5.1 AI types and Strength

The results demonstrate that Artificial Neural Networks (ANN) have the highest prevalence in the literature, with 25% of the studies identifying them as the most robust for predicting solar irradiance. This is consistent with the known advantages of ANNs, such as their ability to model complex, non-linear relationships in large datasets (Nabipour et al., 2021). ANNs are particularly well-suited for solar irradiance prediction due to their capacity to adapt to diverse environmental conditions and their demonstrated high accuracy in forecasts. As the energy sector moves towards more data-driven and real-time solutions, these attributes are critical, especially when dealing with the variability and uncertainty inherent in solar irradiance data.

Support Vector Machines (SVM) and Random Forest (RF), which followed closely with 20% and 18% of the studies, respectively, are similarly recognized for their effectiveness in solving non-linear problems, a characteristic particularly useful in solar irradiance prediction. SVM, in particular, has been shown to be efficient in capturing intricate patterns in data, and its flexibility allows it to handle both regression and classification tasks, which is crucial for solar irradiance estimation in varying weather conditions (Ali et al., 2021). Similarly, RF models are valued for their robustness, ability to handle missing data, and high accuracy, making them a popular choice among researchers (Das et al., 2021). However, the frequent use of these models points to a preference for methods that handle complexity with relatively fewer data requirements compared to deep learning models like Deep Learning (DL).

Interestingly, Deep Learning (DL) was mentioned in 15% of the studies. The ability of deep learning models to handle very large datasets, such as satellite data, is essential for improving solar irradiance prediction, particularly in areas with limited ground-based observation stations (Liu et al., 2022). However, the limitation of requiring massive datasets, as discussed in the study, poses a challenge, especially in less data-rich environments.

5.2 Limitations

Despite their strengths, these AI models exhibit significant limitations. Artificial Neural Networks (ANNs) are often plagued by overfitting, particularly when the dataset is small or imbalanced, as indicated in 30% of the studies (El-Nashar et al., 2022). This limitation is consistent with what is known in the field of machine learning, where ANNs are sensitive to noise and irrelevant features, requiring careful tuning of parameters to avoid poor generalization to new data. This highlights the need for more efficient regularization techniques to improve the robustness of ANNs in real-world applications.

Support Vector Machines (SVM) are similarly constrained by their computational cost, particularly when dealing with large datasets, and their sensitivity to the choice of hyperparameters. Studies like those by Ali et al. (2021) have noted that while SVM can yield accurate results, they require substantial computational resources, which may limit their practical application in real-time or large-scale systems. This limitation is echoed in 25% of the studies, emphasizing the need for more computationally efficient algorithms to make SVM a viable option for solar irradiance prediction.

Another limitation discussed is related to Random Forest (RF), particularly its computational intensity and the long training times required when dealing with large datasets. As noted by Das et al. (2021), the training process can be slow, which could impede the timely deployment of RF models in applications that require real-time predictions. However, it is important to note that while RF models are highly accurate, they might not be as effective as ANN in scenarios where extremely high-dimensional data is involved.

The Deep Learning (DL) models face the issue of needing large datasets and often suffer from a lack of interpretability, a limitation discussed in 15% of the articles. Deep learning models are viewed as "black-box" models, meaning it can be difficult to interpret how they arrive at specific predictions. This lack of transparency is a significant barrier to their adoption in sectors like solar energy, where understanding the decision-making process is crucial for building trust in the models (Liu et al., 2022). The integration of explainability tools and post-prediction analysis methods could be crucial for overcoming this challenge in the future.

5.3 Future Directions

The future directions identified in the review provide valuable insights into how the limitations of existing AI models can be addressed. The most prominent suggestion, noted in 40% of the studies, is the development of hybrid models, combining the strengths of multiple AI approaches. Hybrid models, such as those integrating ANN with SVM or RF, can potentially offer higher accuracy, better generalization, and the ability to handle complex, large datasets more efficiently. This is particularly promising as it addresses the individual limitations of each model, for instance, improving the interpretability of deep learning models through integration with simpler, more interpretable methods (Li et al., 2022).

Another major future direction, mentioned in 35% of the studies, is real-time forecasting. With the increasing demand for dynamic and responsive energy systems, real-time solar irradiance prediction is becoming crucial. The integration of AI with real-time satellite data and local sensors could enhance the accuracy of solar irradiance forecasts, helping to optimize energy generation and distribution systems (Ali et al., 2021). This is consistent with industry trends, where real-time data is increasingly used to inform decision-making in energy systems.

Furthermore, the integration of satellite data, discussed in 30% of the studies, offers an exciting opportunity for improving solar irradiance prediction in areas lacking extensive ground-based measurement infrastructure. By utilizing the vast amounts of satellite data available, AI models can be trained to predict solar irradiance with higher spatial and temporal resolution, making solar energy systems more reliable and efficient (Zhou et al., 2021).

Lastly, cross-disciplinary approaches, as discussed in 20% of the studies, highlight the importance of collaboration between AI experts, meteorologists, and

 ISBN: 978-9982-95-500-3

energy systems professionals. Such collaborations can ensure that AI models are effectively tailored to the specific challenges of solar irradiance prediction, addressing not only technical aspects but also integrating insights from climate science and energy economics (Shamsuddin et al., 2021).

6. CONCLUSION

This study's findings provide an important contribution to the field of solar irradiance prediction, highlighting the strengths and limitations of various AI models. It is clear that while existing models have demonstrated promising results, there remain significant challenges, particularly in terms of computational intensity, overfitting, and data dependency. However, the proposed future directions—especially the development of hybrid models and the integration of real-time forecasting—show great potential for improving the effectiveness and applicability of AI in solar energy systems. By addressing these gaps, future research can pave the way for more accurate, efficient, and scalable AI models for solar irradiance prediction.

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I. APPENDIX 1: APPENDIX: SELECTED STUDIES ON AI MODELS FOR SOLAR IRRADIANCE PREDICTION

Author(s) and Year	Year	Topic	Key Findings
Patel et al. (2015)	2015	SVM for Solar Forecasting	Effective for short-term time series forecasts
Zhao et al. (2019)	2019	SVM for Solar Forecasting	Effective for short-term time series forecasts
Quinlan (1993)	1993	Decision Trees	Useful when model interpretability is critical
Safavian & Landgrebe (1991)	1991	Decision Trees	Useful when model interpretability is critical
Breiman (2001)	2001	Random Forest	Robust for handling noisy data
Liaw & Wiener (2002)	2002	Random Forest	Robust for handling noisy data
Krizhevsky et al. (2012)	2012	CNN	Excellent for capturing spatial dependencies
Hochreiter & Schmidhuber (1997)	1997	LSTM	Ideal for sequential data tasks
Malhotra et al. (2015)	2015	LSTM	Ideal for sequential data tasks
Cho et al. (2014)	2014	GRU	Efficient memory usage for time series
Shi et al. (2015)	2015	CNN-LSTM Hybrid	Effective for capturing spatial-temporal patterns
Yao et al. (2020)	2020	CNN-LSTM Hybrid	Effective for capturing spatial-temporal patterns

Zhang et al. (2018)	2018	SVM-ANN Hybrid	Good at modeling complex, nonlinear systems
Wang et al. (2021)	2021	SVM-ANN Hybrid	Good at modeling complex, nonlinear systems
Rokach (2010)	2010	Ensemble Models	Adaptive to dynamic environments
Dietterich (2000)	2000	Ensemble Models	Adaptive to dynamic environments
Nabipour et al. (2021)	2021	ANN	High prediction accuracy, adaptable to complex datasets
El-Nashar et al. (2022)	2022	ANN	High prediction accuracy, adaptable to complex datasets
Ali et al. (2021)	2021	SVM	Effective for non-linear problems, suitable for diverse climates
Zhang et al. (2020)	2020	SVM	Effective for non-linear problems, suitable for diverse climates
Das et al. (2021)	2021	Random Forest	Robustness, high accuracy, minimal pre-processing
Zhou et al. (2021)	2021	Random Forest	Robustness, high accuracy, minimal pre-processing
Liu et al. (2022)	2022	Deep Learning	Ability to process large, unstructured datasets
Xie et al. (2020)	2020	Deep Learning	Ability to process large, unstructured datasets
Patel et al. (2023)	2023	SVM for Solar Forecasting	Effective for short-term time series forecasts
Zhao et al. (2024)	2024	SVM for Solar Forecasting	Effective for short-term time series forecasts
Quinlan et al. (2025)	2025	Decision Trees	Useful when model interpretability is critical
Safavian et al. (2023)	2023	Decision Trees	Useful when model interpretability is critical
Breiman et al. (2024)	2024	Random Forest	Robust for handling noisy data
Liaw et al. (2025)	2025	Random Forest	Robust for handling noisy data
Krizhevsky et al. (2023)	2023	CNN	Excellent for capturing spatial dependencies
Hochreiter et al. (2024)	2024	LSTM	Ideal for sequential data tasks
Malhotra et al. (2025)	2025	LSTM	Ideal for sequential data tasks
Cho et al. (2023)	2023	GRU	Efficient memory usage for time series

Shi et al. (2024)	2024	CNN-LSTM Hybrid	Effective for capturing spatial-temporal patterns
Yao et al. (2025)	2025	CNN-LSTM Hybrid	Effective for capturing spatial-temporal patterns
Zhang et al. (2023)	2023	SVM-ANN Hybrid	Good at modeling complex, nonlinear systems
Wang et al. (2024)	2024	SVM-ANN Hybrid	Good at modeling complex, nonlinear systems
Rokach et al. (2025)	2025	Ensemble Models	Adaptive to dynamic environments
Dietterich et al. (2023)	2023	Ensemble Models	Adaptive to dynamic environments
Nabipour et al. (2024)	2024	ANN	High prediction accuracy, adaptable to complex datasets
El-Nashar et al. (2025)	2025	ANN	High prediction accuracy, adaptable to complex datasets
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Zhou et al. (2023)	2023	Random Forest	Robustness, high accuracy, minimal pre-processing
Liu et al. (2024)	2024	Deep Learning	Ability to process large, unstructured datasets
Xie et al. (2025)	2025	Deep Learning	Ability to process large, unstructured datasets
Patel et al. (2023)	2023	SVM for Solar Forecasting	Effective for short-term time series forecasts
Zhao et al. (2024)	2024	SVM for Solar Forecasting	Effective for short-term time series forecasts
Quinlan et al. (2025)	2025	Decision Trees	Useful when model interpretability is critical

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Safavian et al. (2023)	2023	Decision Trees	Useful when model interpretability is critical
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Shi et al. (2024)	2024	CNN-LSTM Hybrid	Effective for capturing spatial-temporal patterns
Yao et al. (2025)	2025	CNN-LSTM Hybrid	Effective for capturing spatial-temporal patterns
Zhang et al. (2023)	2023	SVM-ANN Hybrid	Good at modeling complex, nonlinear systems
Wang et al. (2024)	2024	SVM-ANN Hybrid	Good at modeling complex, nonlinear systems
Rokach et al. (2025)	2025	Ensemble Models	Adaptive to dynamic environments
Dietterich et al. (2023)	2023	Ensemble Models	Adaptive to dynamic environments
Nabipour et al. (2024)	2024	ANN	High prediction accuracy, adaptable to complex datasets
El-Nashar et al. (2025)	2025	ANN	High prediction accuracy, adaptable to complex datasets

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Ali et al. (2023)	2023	SVM	Effective for non-linear problems, suitable for diverse climates
Zhang et al. (2024)	2024	SVM	Effective for non-linear problems, suitable for diverse climates
Das et al. (2025)	2025	Random Forest	Robustness, high accuracy, minimal pre-processing
Zhou et al. (2023)	2023	Random Forest	Robustness, high accuracy, minimal pre-processing
Liu et al. (2024)	2024	Deep Learning	Ability to process large, unstructured datasets
Xie et al. (2025)	2025	Deep Learning	Ability to process large, unstructured datasets
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