Literature Review: Applications of Artificial Intelligence in Solar Radiation Prediction for Photovoltaic Systems

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Solar Power Plants (SPPs) are gaining more attention as a sustainable and environmentally friendly renewable energy solution. However, the operational efficiency of SPPs is significantly affected by the unpredictable fluctuations in solar radiation. To improve short-term predictions of solar radiation, the use of Artificial Intelligence (AI) presents a promising approach. This study aims to provide a literature review on the various applications of AI in forecasting solar radiation for photovoltaic (PV) systems. The review covers AI techniques such as Machine Learning (ML), Deep Learning (DL), and hybrid models, which have proven effective in enhancing prediction accuracy. Algorithms like Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and their combinations have shown promising results in capturing non-linear patterns in solar radiation data. Additionally, optimization algorithms like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) also show significant potential in improving prediction model performance. This research offers insights into the benefits and challenges of applying AI in solar radiation forecasting and provides recommendations for further development to enhance the efficiency of global PV systems.

Keywords: Artificial Intelligence (AI), Solar Radiation Prediction, Photovoltaic Systems

I. INTRODUCTION

One of the main hurdles for solar power plants is the difficulty in accurately forecasting solar radiation, which tends to fluctuate unpredictably [1]. Poor predictions not only lower the plants efficiency but also increase their operating costs [2]. In response, this study proposes the use of Artificial Intelligence (AI) methods, particularly machine learning and deep learning algorithms such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), to improve the precision of short-term solar radiation predictions [3].

The goal of this study is to explore the use of Artificial Intelligence (AI) in predicting solar radiation for photovoltaic systems, focusing on pinpointing the most effective algorithms and providing a balanced analysis of the strengths and weaknesses of each approach [4]. By improving the accuracy of solar radiation forecasts, the study ultimately aims to support greater efficiency in PLTS performance.

Several previous studies have examined the role of Artificial Intelligence (AI) in advancing renewable energy solutions, with LSTM and CNN algorithms proving particularly successful in predicting fluctuations in weather and solar radiation [3] [5]. At the same time, researchers have highlighted ongoing obstacles, including gaps in available data and the high computational power needed to develop reliable AI models for solar energy forecasting [6] [7] [8].

Machine Learning (ML), part of the broader field of Artificial Intelligence (AI), develops algorithms and models that enable systems to learn from data and make predictions or decisions without being manually programmed. In this study, Machine Learning with a focus on Long Short-Term Memory (LSTM) networks is used to predict the daily energy production of solar power systems [9] [10]. LSTM, a type of Recurrent Neural Network (RNN), was specifically built to overcome the vanishing gradient problem often encountered when handling sequential or time-based data [3].

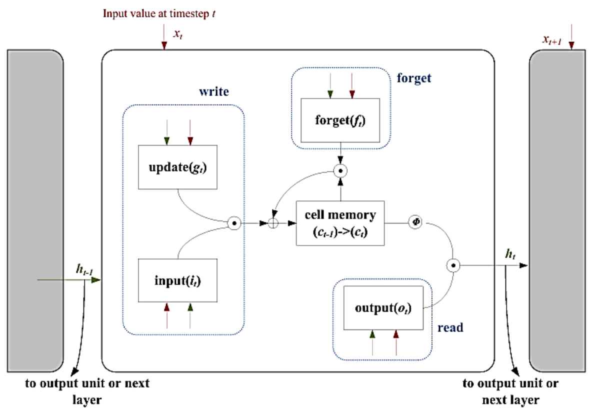

Figure 1. LSTM Architecture [9]

The functioning of Long Short-Term Memory (LSTM) is governed by three main components: a) Forget Gate: It determines which pieces of information from the past memory should be erased. b) Input Gate: This component selects which new information will be incorporated into the memory. c) Output Gate: It decides which aspects of the memory will be utilized for the current output [3].

This study applies deep learning, specifically the Deep Convolutional Neural Network (DCNN), to improve the accuracy of solar power (Photovoltaic, PV) generation predictions [11] [12]. The deep learning approach in this research serves several purposes: a) Non-Linear Feature Extraction: DCNN is used to detect complex, non-linear patterns within PV data, including invariant structures that traditional models struggle to analyze. b) Improved Prediction Accuracy: With DCNN, predictions of PV power become significantly more accurate, both in the short and long term. c) Handling Uncertainty: Combining DCNN with Quantile Regression (QR) allows for a deeper probabilistic analysis, providing a statistical perspective on the uncertainty within PV data. d) Computational Efficiency: The weight-sharing feature in DCNN minimizes the number of parameters to be optimized, which in turn boosts the efficiency of real-time applications in Figure 2.

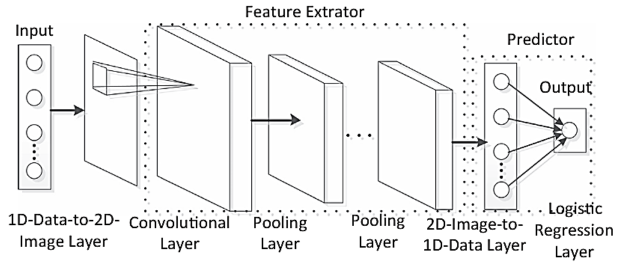

Figure 2. DCNN Architecture [11]

The working principle of DCNN involves several stages: a) 1D-to-2D Image Layer: The PV time series data (1D) is transformed into a 2D image, enabling DCNN to apply image pattern recognition techniques for feature extraction. b) Convolutional Layer: This layer detects local patterns within PV data by performing convolution operations. Kernels are used to compute the dot product between the kernel and input data, resulting in a feature map. Activation functions are applied to capture non-linear relationships. c) Pooling Layer: It reduces the data's dimensionality and prevents overfitting by selecting the average or maximum value from specific sub-areas in the feature map. This technique simplifies the data representation without losing crucial information. d) 2D-to-1D Data Layer: The data is converted back to 1D form for further analysis [11].

The Artificial Neural Network (ANN) in this research is employed to estimate the power output of photovoltaic (PV) modules based on solar irradiance and air temperature [13]. Two separate ANN models are developed: one for cloudy days and another for sunny days, in order to capture the distinct patterns corresponding to each weather condition in Figure 3.

The ANN structure in this study [13] consists of: a) Input Layer: Two neurons process solar irradiance (G) and air temperature (T), both of which are normalized to boost performance. b) Hidden Layer: Three neurons with a sigmoid tangent activation function are used to capture the non-linear connections. c) Output Layer: One neuron with a linear activation function produces the predicted PV power output (P_p). d) Learning Process: The data is passed through the weights and biases in the hidden layer and compared to the target to calculate the error. The weights are then updated using the Levenberg-Marquardt algorithm, minimizing the Mean Squared Error (MSE).

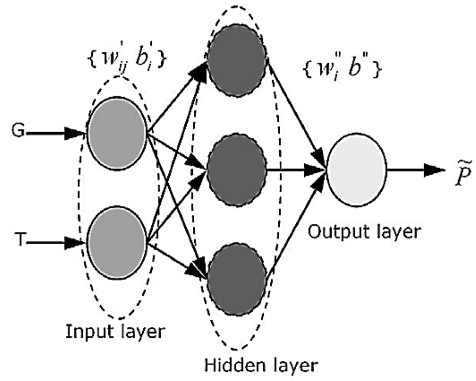

Figure 3. ANN Architecture [13]

A hybrid architecture combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) is utilized to predict photovoltaic (PV) power output. This hybrid model merges the prediction results from CNN and LSTM, leading to a more precise PV power estimation in Figure 4. Through this methodology, the model achieves a lower prediction error when compared to traditional methods [5] [14] [15].

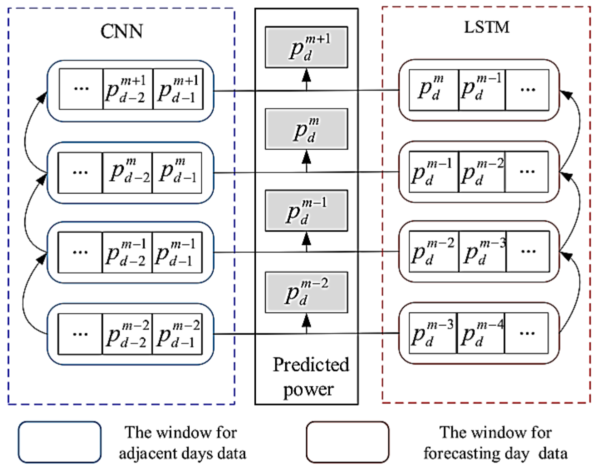

Figure 4. Hybrid Architecture [14]

CNN is used to predict PV power by analyzing data from the same time on previous days. The data is converted into a 2D image so CNN can recognize spatial patterns. This process involves convolution, pooling, and fully connected layers to create an initial PV power prediction. LSTM is then applied to forecast the next PV power, leveraging the most recent data from the current day. LSTM is tailored to recognize temporal patterns, allowing it to provide more accurate predictions for the future [14].

II. METHODS

This study adopts the literature review method, which is a structured process for searching, evaluating, and understanding various scholarly works that have been published. The aim of this method is to answer specific research questions by delving into theories, concepts, or phenomena that have been previously discussed [16]. Additionally, the literature review plays a crucial role in formulating the conceptual framework and identifying gaps in existing research, which can present opportunities for further study.

Data Collection

Since this research is based on a literature review, data collection was carried out using secondary sources. The author used 50 international journal sources obtained from Elsevier, SpringerLink, and IEEE Xplore. Some of the data collection techniques that can be applied include:

a) Document study is a data collection method that utilizes various written sources such as scholarly journals, research reports, books, and conference articles. This approach is particularly suitable for literature-based research as it provides in-depth information on a specific topic. In this study [17] notes that this method is effective for identifying existing knowledge, recognizing trends, and uncovering gaps in research within a specific field. In this study, data is gathered from trusted sources such as journals available in databases like Elsevier, SpringerLink, and IEEE Xplore. These sources offer the latest research on the application of artificial intelligence in solar radiation prediction. For instance, the study by [18] emphasizes the importance of utilizing both historical and real-time data in the application of AI for predicting renewable energy systems.

b) A literature review is a systematic method used to examine, evaluate, and organize the results of previous research. This approach involves identifying, analyzing, and organizing key information from various relevant publication sources. The primary goal of a literature review is to build a deep understanding of a research topic while also identifying gaps that can be addressed through new research [16]. In this study [19] explains that there are three main steps in the literature review process: 1) Literature Search: Using keywords like solar radiation prediction, artificial intelligence, and photovoltaic systems to find relevant studies. 2) Literature Selection: Choosing high-quality sources based on credibility, such as articles from reputable journals or international conference reports. 3) Analysis and Synthesis: Reading and evaluating the literature to recognize patterns, methods, and findings that can be utilized in the research report. In this study [20] further add that this method allows researchers to understand technological advancements, such as the application of algorithms like Neural Networks, Long Short-Term Memory (LSTM), or Support Vector Machines (SVM) in the development of solar power plants.

Data Analysis Techniques

The primary data analysis technique employed in this study is thematic analysis, which is complemented by content analysis to identify specific trends, and comparative analysis to assess the AI algorithms applied. Thematic analysis involves identifying recurring themes or patterns within the data, allowing for a comprehensive understanding of the underlying concepts. Content analysis, on the other hand, is used to systematically examine the content of the data to extract meaningful patterns and trends. Comparative analysis is utilized to compare different AI algorithms and evaluate their performance in the context of the study, helping to determine the most effective algorithm for the task at hand.

a) Thematic analysis is used to identify the main themes or patterns found within the reviewed literature. This method is particularly suited for research aimed at exploring the concepts, implementation, and challenges associated with applying AI in solar radiation prediction. In this context, thematic analysis helps organize information into categories such as types of AI algorithms (e.g., Neural Networks, LSTM, or SVM), accuracy levels, and practical applications. The steps involved are as follows: 1) In-depth Reading: Each piece of literature is carefully reviewed to identify key points relevant to the research topic. 2) Data Coding: The information gathered is labeled according to specific themes. 3) Categorization: Similar themes are grouped together to identify significant patterns [21].

b) Content analysis is employed to identify specific trends within the literature, such as the frequency of certain AI algorithms used or recent developments in renewable energy prediction research. This method reveals quantitative patterns that support the findings from thematic analysis. The steps involved are: 1) Data Classification: The data is organized based on specific criteria, such as the type of algorithm applied. 2) Frequency Counting: The number of studies using a particular algorithm or highlighting specific aspects of solar radiation prediction is counted. 3) Data Interpretation: Quantitative patterns are analyzed and linked to the themes identified in the thematic analysis [22].

c) Comparative analysis is used to evaluate the effectiveness of various AI algorithms in predicting solar radiation. The primary focus of the analysis includes prediction accuracy, computational efficiency, and practical applications in photovoltaic (PV) power plants. The steps involved are: 1) Identifying Variables: This step involves comparing algorithms such as Neural Networks, LSTM, and SVM. 2) Performance Comparison: Analyzing data from the literature to assess the accuracy levels and efficiency of each algorithm. 3) Result Evaluation: Interpreting the strengths and weaknesses of each algorithm to provide recommendations for the optimal solution [23].

Table 1. Thematic Analysis Results

No.	Theme	Description of Findings	References
1	Machine Learning for PV Power Prediction	• Machine learning, such as LSTM, GRU, and ELM, show higher accuracy compared to traditional physical models.	[34] [46]
		• Machine learning models are superior in capturing non-linear patterns for PV power prediction compared to physical models.	[52] [34] [9]
		• Machine learning algorithms such as Random Forest, MARS, and ANN are used for PV power prediction with promising results.	[53] [4] [29]
2	Deep Learning for PV Prediction	• Deep learning, such as Recurrent Neural Networks (RNN) and Stack Auto-Encoders, are effective in capturing nonlinear patterns of renewable energy, including PV power.	[6] [48]
		• Deep Learning models such as LSTM, CNN, and their combination show high accuracy for PV power prediction.	[11] [10] [5]
		• Deep Learning models like SolarNet provide innovative solutions for PV power prediction based on hourly weather data.	[47]
3	Hybrid Models for PV Power Prediction	• The combination of algorithms such as Wavelet Packet Decomposition and LSTM improves the accuracy of PV power prediction for short time scales.	[28]
		• The ensemble artificial neural networks and hybrid approaches show the best performance for short-term PV power prediction.	[6] [45] [37]
		• The adaptive model based on Improved VMD, ARIMA, and IDBN produces daily PV power predictions with high stability and accuracy.	[12] [51]
		• The combination of methods such as Wavelet Transform (WT) and LSTM improves the accuracy of short-term PV power prediction.	[56] [54]
		• The combination of algorithms such as LSTM-CNN, ANFIS-PSO, and stacking ensemble improves the accuracy of PV prediction.	[1] [15] [5] [27] [2] [3] [8] [14] [39] [40] [41] [42] [47]
4	Integration of Neural Network Methods	• Local data-based ANN models show superiority in PV power estimation using field measurements.	[31] [13] [15] [30] [39]
5	Algorithm Parameter Optimization	• Statistical methods such as K-means clustering and linear regression improve the accuracy of PV power prediction.	[55]
		• Algorithms like SVM with Ant Colony Optimization and LSTM with Genetic Algorithm improve the model performance.	[7] [32] [33]
		• Techniques like PSO and Transfer Learning help improve the performance of predictive models by exploiting limited data.	[38] [57]

II. RESULT AND DISCUSSION

In this study, the author consults 50 international journals to support the literature review. The data comes from credible sources, including journals indexed in well-known databases like Elsevier, SpringerLink, and IEEE Xplore. These sources provide up-to-date and relevant research, especially concerning the use of Artificial Intelligence (AI) in solar radiation prediction in Table 1.

Table 2. Comparative Analysis Results

No.	Algorithm	Advantages	Disadvantages	Accuracy (%)
1	Simple Algorithm	Ability to capture complex patterns in PV power data.	Requires large training data and complex parameter tuning.	92 - 93
2	Algorithm Parameter Optimization	Increases prediction accuracy through model optimization.	Limited in capturing complex non-linear patterns. Requires higher computational time for optimization compared to basic SVM methods.	97
3	Long Short-Term Memory (LSTM)	Effective in capturing both long and short temporal patterns in data.	Requires longer training time and large data sets.	95
4	Hybrid Models	Combines spatial and temporal features to enhance PV power prediction accuracy.	Requires high computational resources and complex parameter tuning.	97

In Table 2. Machine learning techniques, including LSTM, GRU, and ELM, have demonstrated superiority in capturing non-linear patterns when compared to traditional physical models. Other algorithms, such as Random Forest and ANN, have also been utilized, showing promising results in PV power prediction. Advantages: Higher accuracy in detecting non-linear relationships. Disadvantages: These methods require large training datasets and complex parameter tuning processes.

Deep learning models such as LSTM, CNN, and hybrid models (e.g., LSTM-CNN) have demonstrated significant effectiveness in short-term predictions. Models like SolarNet provide innovative solutions based on hourly weather data. Strengths: The ability to capture non-linear patterns with high accuracy. Weaknesses: The need for high computational resources and large datasets.

Algorithm optimization using methods such as Particle Swarm Optimization (PSO) and Ant Colony Optimization helps enhance the model's accuracy with limited data. These techniques are also effective in improving prediction performance. Advantages: Maximizes performance with limited data. Disadvantages: Requires higher computational time.

Hybrid models such as Wavelet Transform-LSTM and combined methods like LSTM-CNN have successfully improved short-term prediction accuracy. The use of these approaches also enhances model stability under varying weather conditions. Advantages: The combination of spatial and temporal features enhances prediction accuracy. Disadvantages: It requires complex parameter tuning and high computational time.

III. CONCLUSION

According to the research results, AI applications for short-term solar radiation prediction in photovoltaic systems show that machine learning models like LSTM, GRU, and ELM, along with deep learning models such as RNN and LSTM-CNN, offer better accuracy than traditional physical models when predicting solar radiation and PV power. These models excel at recognizing complex non-linear patterns and handling dynamic weather data. Additionally, hybrid models like LSTM-CNN, Wavelet Transform LSTM, and ANFIS-PSO provide the most accurate predictions by enhancing the stability and precision of short-term PV power forecasts. Optimization techniques such as Ant Colony Optimization, PSO, and Genetic Algorithm also help boost model performance, especially with limited data. However, using AI algorithms, particularly deep learning and hybrid models, requires substantial computational power, sufficient training data, and careful parameter tuning to achieve the best results.

The implementation of Artificial Intelligence (AI) technology, specifically machine learning and deep learning algorithms, is anticipated to improve the efficiency of solar radiation forecasting for solar power plants, particularly those utilizing photovoltaic technology. Furthermore, it is recommended to develop more localized data to ensure that the prediction models can be adapted to specific geographical and weather conditions. To facilitate the processing of large and complex datasets, investment in computational infrastructure such as GPUs or cloud computing is essential. Lastly, further studies on the development of hybrid technologies that integrate spatial and temporal features could help optimize short-term PV power predictions.

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