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Deep Learning Paradigms for Solar Radiation Prediction: A Review of Recent Advances

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Abstract:
Deep learning algorithms present a promising approach to solar energy prediction with the ability to produce accurate forecasts. Amidst the realms of scholarly exploration, an exhaustive examination delves into myriad intricate learning frameworks harnessed for the analysis of temporal data, aimed at prognosticating solar radiation and the consumption of energy via photovoltaic (PV) means. The focal points of scrutiny encompass a spectrum of architectural constructs, including the recurrent neural network (RNN), the long short-term memory (LSTM), the gated recurrent unit (GRU), and the convolutional neural network to LSTM (CNN-LSTM) amalgamation. The assessment of these edifices revolves around sundry determinants, such as precision, the composite nature of input data, forecasting duration, seasonal undulations, meteorological parameters, and the temporal requisites for training. The research highlights the unique benefits and limitations that are present in each architectural design across various contexts. The performance of LSTM is remarkable, since it outperforms alternative independent designs, particularly in terms of the root-mean-square error (RMSE) statistic. On the other hand, the combined CNN-LSTM design demonstrates more effectiveness compared to individual architectures, however it requires a longer training period. An important observation suggests that deep learning architectures are becoming more effective than traditional machine learning models in predicting solar irradiance and PV power. Furthermore, the utilization of relative root mean square error (RMSE) arises as a relevant assessment measure that enables accurate comparisons among diverse investigations.

Keywords: Recurrent neural network (RNN), Long short-term memory (LSTM), Gated recurrent unit (GRU), Convolutional neural network-LSTM (CNN-LSTM) and Deep Belief Networks (DBN)

Introduction

Ensuring precise prognostication of solar energy holds paramount importance in seamlessly integrating solar power into the electrical grid. Operators of systems and strategists in energy can harness this proficiency to render judicious choices concerning the stability of systems, the scheduling of energy, and the allocation of resources. The imperative for solar energy becomes conspicuously apparent, particularly in burgeoning economies like India, where its significance burgeons progressively.

Numerous studies have investigated different forecasting methodologies and their impact on solar energy predictions in India. Mohanty et al. performed a thorough examination of solar energy projections that are specifically focused on India [1], emphasizing their implications for a developing economy. They underscored the critical role of precise solar energy projections in facilitating grid integration and proposed various models and methodologies to enhance accuracy.

Similarly, Das et al. focused on examining predictions of photovoltaic power generation and optimizing modeling techniques [2]. Their research stressed the imperative nature of accurate forecasting models in ensuring the efficiency and reliability of solar power systems. Husein and Chung, introduced an innovative approach employing a cutting-edge methodology utilizing a deep learning deep Short-Term Memory Recurrent Neural Network [3] to predict solar irradiance within microgrids, particularly focusing on anticipatory forecasts for the day ahead.

They exhibited how their method enhanced the precision of solar energy prognostications. Lappalainen et al. foreseen the peak photovoltaic power ramp rates, pivotal for grid solidity and energy arrangement [4]. They stressed the necessity of assimilating ramp rates in solar energy projection frameworks. Sobri et al. carried out an assessment of solar PV generation prognostication systems, assessing their advantages and constraints. The authors emphasized the need for further investigation and progress in this field in order to improve the accuracy and dependability of solar energy forecasts [5]. In aggregate, these investigations provide useful insights into different prediction approaches and their implications for solar energy forecasts in a developing country such as India.

Precise forecasting of sunlight irradiance stands paramount in optimizing the effectiveness of solar energy facilities within the realm of sustainable power generation. An array of advanced learning methodologies has been devised with the objective of enhancing the precision of sunlight irradiance prognostications. The approach proposed by Zang et al. entails the utilization of a fused CNN-LSTM framework that integrates spatiotemporal correlations. This proposed framework amalgamates the characteristics of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to discern spatial and temporal associations within sunlight irradiance datasets [6]. The amalgamated model surpasses conventional techniques for short-term estimations of global horizontal irradiance by incorporating spatiotemporal connections.

The selection of appropriate deep learning algorithms holds paramount importance within the domain of solar irradiance prognostication. In this exhaustive investigation, Shuai et al. delve into various deep learning methodologies employed in forecasting solar radiation. They elucidate the advantages and drawbacks of artificial neural networks, support vector machines, and random forests [7]. This study serves as a valuable asset for scholars and practitioners engaged in solar energy research.

Moreover, Carrera and Kim undertook a comparative examination of deep learning algorithms for photovoltaic forecasting utilizing weather sensor information [8]. They scrutinized the efficacy of numerous algorithms, encompassing decision trees, random forests, and gradient boosting machines. Their discoveries illuminate the appropriateness of diverse deep learning algorithms for photovoltaic prognostication, facilitating more effective planning and operation of solar power installations.

Furthermore, a number of methods have been investigated for forecasting solar irradiance in addition to deep learning techniques. The method described by Caldas and Alonso-Suárez involves the utilisation of all-sky imaging and real-time irradiance measurements to forecast solar irradiance over very short time periods [9]. The proposed methodology, which combines these two data sources, offers precise and expeditious estimations of solar irradiance, a crucial factor in enhancing the efficiency of solar power plants.

Solar radiance prognostications are paramount for the efficacious assimilation of solar power into the electrical grid. Precision in short-term solar radiance forecasts augments oversight of solar energy generation and bolsters the steadiness of the grid. A numerous of methodologies have been proffered to refine the precision of solar radiance estimations. One such methodology involves the amalgamation of satellite-derived data with numerical prognostic models for weather. Miller et al. propounded a succinct-term methodology for solar radiance forecasting, amalgamating satellite data with a numerical weather prognostic model [10].

The outcomes of the inquiry unveiled that the adoption of this integration methodology notably enhances the precision of solar radiance prognostications. Another strategy entails employing amalgamated prognostic methodologies, amalgamating diverse approaches. In their research, Xie et al. devised an approach that amalgamates variational mode decomposition, deep belief networks, and auto-regressive moving average [11] to anticipate solar power output.

The findings suggested that the amalgamated approach surpassed the efficacy of individual prognostic methodologies. In recent times, convolutional neural networks (CNNs) have garnered attention for addressing temporal series prediction conundrums. Wang et al. advocated for the utilization of numerous CNNs for multivariate temporal series prediction, encompassing solar energy generation [12]. The investigation discerned that employing a consortium of CNNs augmented the precision of solar energy generation prognostication. Furthermore, ensemble-based neural network methodologies have been formulated for the prognostication of solar energy generation.

Chaouachi et al. introduced a method based on neural network ensembles to estimate the short-term yield of solar power. The outcomes revealed a notable enhancement in forecast accuracy through the ensemble approach [13]. In the realm of sun radiation prognosis, artificial neural networks (ANNs) have garnered considerable attention. Yadav and Chandel delved into the application of ANN methodologies for solar radiation prediction, underlining its capacity to refine forecast precision [14]. Collectively, these investigations exemplify the advancements attained in short-term solar irradiance estimations by employing sophisticated prognostic methodologies such as satellite/model integration, amalgamated techniques, CNNs, ensemble-based neural networks, and ANNs.

AI methodologies have garnered considerable attention within the realm of photovoltaic (PV) applications. These innovations have exhibited notable potential in enhancing the efficacy and performance of PV systems. Mellit and Kalogirou's comprehensive examination furnish an elaborate exposition of various AI methodologies employed in PV applications, encompassing artificial neural networks (ANNs), support vector machines (SVMs), and genetic algorithms (GAs) [15]. The authors delve into the advantages and constraints of each methodology, along with its utility in PV system modeling, regulation, and enhancement. They underscore the significance of precise solar energy estimations in facilitating appropriate PV system operation and upkeep.

The prediction of solar energy has evolved into an indispensable aspect of PV system administration. Cheon et al. executed an evaluation of solar energy prediction methodologies and scrutinized advancements in this domain [16]. They explored myriad methodologies for precise solar energy prediction, encompassing statistical frameworks, machine learning algorithms, and amalgamated approaches. The authors underscored the necessity of incorporating meteorological data, historical solar irradiance data, and satellite imagery into prognostic models. Moreover, they accentuated the imperative of continual enhancement and validation of these models to enhance their precision and dependability.

In recent epochs, artificial neural networks (ANNs) have emerged as a promising avenue for prognosticating solar irradiance. Hameed et al. devised an artificial neural network (ANN) framework for gauging sun irradiance [17]. The artificial neural network (ANN) underwent training utilizing historical data on sun irradiance, coupled with environmental parameters such as temperature, humidity, and wind velocity. The efficacy of the model in computing solar irradiance renders it an indispensable asset for conceiving and executing photovoltaic (PV) systems.

Recent investigations have delved into the exploration of deep learning methodologies, particularly deep recurrent neural networks (RNNs), in the realm of short-term building energy prognosis. Fan et al. [18] undertook a scrutiny of the utilization of deep recurrent neural network (RNN)-based methodologies for energy anticipation. A comparative scrutiny was conducted to evaluate the precision of deep recurrent neural networks (RNNs) vis-à-vis traditional machine learning techniques. The findings unveiled that deep RNNs surpassed other methodologies in terms of predictive efficacy. The scholars deduced that the incorporation of deep recurrent neural networks (RNNs) exhibits notable promise for enhancing the governance and optimization of building energy frameworks.

In conclusion, advanced deep learning techniques [19], support vector machines (SVM), and artificial neural networks (ANN) have demonstrated great promise in the field of photovoltaic (PV) applications. These methods have been successfully used to predict solar energy, forecast solar irradiance, and forecast building energy. Additional investigation and progress in this domain are crucial in order to significantly enhance the efficiency and functionality of photovoltaic (PV) systems.

The Long Short-Term Memory (LSTM), a variation of the recurrent neural network (RNN), has sparked notable interest across diverse domains due to its capability to apprehend prolonged associations in sequential input. Hochreiter and Schmid Huber initially introduced the LSTM model in 1997. Since its inception, LSTM has gained considerable traction in numerous sectors, encompassing wind power forecasting, volatility prediction in stock markets, machine language translation, and solar irradiance prediction [20].

Liu et al. embarked on a pioneering endeavor where they introduced a paradigm for forecasting short-term wind power [21]. This model amalgamates LSTM and discrete wavelet transform methodologies, showcasing remarkable efficacy surpassing prior techniques. The composite framework advocated by Kim and Won integrates Long Short-Term Memory (LSTM) with a plethora of GARCH-type models [22] to prognosticate stock price index volatility. The research findings tendered compelling proof regarding the effectiveness of Long Short-Term Memory (LSTM) in discerning intricate patterns within financial time series data.

Moreover, Cho et al. harnessed Long Short-Term Memory (LSTM) to fabricate an encoder-decoder system in statistical machine translation. The exploration illuminated LSTM's potential to fabricate precise depictions of phrases [23]. In their investigation, Wang and collaborators introduced an intricate deep learning architecture for prognosticating solar irradiance. This architecture merges wavelet decomposition and convolutional LSTM networks. The ingenuity exhibited by the researchers surpassed orthodox methodologies, underscoring LSTM's potential in forecasting trends in renewable energy. The aforementioned experiments underscore the adaptability and effectiveness of Long Short-Term Memory (LSTM) across various domains, solidifying its status as a potent tool for scrutinizing and prophesying sequential data [1][22][23][24][25].

The utilisation of Convolutional Neural Networks (CNNs) has been increasingly prevalent in several domains, such as image classification, speech recognition, and time-series analysis. Yann LeCun and Yoshua Bengio were pioneers in constructing Convolutional Neural Networks (CNNs), and their contributions [25] have greatly influenced the progress of the field.

Picture classification is one area where CNNs have proven to be exceptionally efficient. With the increasing availability of large-scale image datasets, deep CNNs have been developed to achieve cutting-edge results in this field. Rawat and Wang provided a detailed overview of deep CNNs for image classification, covering several architectures, training methodologies, and performance evaluation criteria [26]. Their review is a valuable resource for researchers and practitioners interested in this area.

Furthermore, the amalgamation of Convolutional Neural Networks (CNNs) with other deep learning architectures has engendered increasingly robust methodologies. In a study conducted by Rehman et al., a composite CNN-LSTM model was formulated to augment sentiment analysis in cinematic critiques [27]. By harnessing the synergies of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, they surpassed previous benchmarks, elevating performance standards. Similarly, He et al. leveraged a CNN-LSTM configuration to discern gradual irregularities in a rod pumping mechanism, demonstrating its prowess in promptly identifying aberrations [28].

Within the realm of environmental surveillance, CNN-LSTM architectures have found application. Huang and Kuo conducted an investigation wherein they devised an intricate CNN-LSTM framework aimed at prognosticating [29] the concentrations of particulate matter (PM2.5) in intelligent urban centers. Leveraging the spatiotemporal interrelations inherent in the data, their methodology yielded accurate prognoses, facilitating the implementation of preemptive measures to mitigate the deleterious effects of atmospheric contamination.

In recent years, the traction of machine learning models across various domains has witnessed a notable surge in interest. Waterworks operation data prediction is one example. Cao et al. developed a CNN-LSTM coupled model for this purpose and obtained promising results [30]. Another possible application is diabetes detection with machine learning. Swapna et al. diagnosed diabetes with high accuracy using CNN and CNN-LSTM networks, as well as heart rate signals [31]. Shi et al.'s convolutional LSTM network for precipitation nowcasting produced correct rainfall patterns [32]. Zhang et al. also developed criteria for evaluating solar power forecasting models, which can help maximize solar energy resource utilization [33]. Finally, Lave et al. investigated methods for deriving plane-of-array irradiance from global horizontal irradiance in order to increase solar energy generation efficiency [34]. These studies highlight machine learning's adaptability and improve predictive modeling and forecasting.

Ghimire et al. explored the utilization of long short-term memory (LSTM) and convolutional neural network (CNN) methodologies [35] in the realm of profound solar radiation prognosis. As per the investigators, both techniques exhibited commendable performance in forecasting solar radiation, with LSTM boasting superior accuracy compared to CNN. In an autonomous investigation, Niu and O'Neill implemented recurrent neural network (RNN)-based deep learning methodologies to compute solar radiation [36]. The findings of this study illustrated the promising outcomes achieved by recurrent neural network (RNN) models in accurately forecasting solar radiation levels. Additionally, Cao and Cao proposed an innovative approach involving the integration of recurrent neural networks with wavelet analysis for the estimation of solar irradiation [37].

The investigation's outcomes provided substantial evidence supporting the efficacy of this methodology in enhancing the precision of solar irradiance forecasts. Qing and Niu formulated a framework leveraging meteorological projections [38] to anticipate hourly solar irradiance for the ensuing day using Long Short-Term Memory (LSTM). Their inquiry highlighted the robust performance of LSTM-based frameworks in solar irradiance prediction. Aslam et al. evaluated the efficacy of sophisticated learning algorithms in projecting long-term solar radiation while factoring in the deployment of microgrids [39].

He et al. introduced an innovative hybrid deep learning methodology for probabilistic solar irradiance prediction [40]. Through the utilization of long short-term memory (LSTM) and random forest models, the researchers aimed to uncover the intricate temporal and spatial patterns of solar irradiation. In a distinct investigation, Jeon and Kim employed LSTM trained on both local weather forecasts and non-local data to predict hourly solar irradiance for the ensuing day [41]. Their discoveries highlighted the importance of integrating non-local data, resulting in enhanced predictive accuracy. Furthermore, Wojtkiewicz et al. utilized multivariate gated recurrent units (GRUs) in their exploration to forecast hourly sun irradiance [42].

The model incorporated several meteorological variables to depict the associations between different weather factors and solar radiation. In their study, Yu et al. proposed a technique that utilises Long Short-Term Memory (LSTM) to accurately predict short-term solar irradiation during extreme weather conditions [43]. Their model solved the challenges posed by complex weather patterns and produced accurate forecasts. Furthermore, a hybrid deep learning system was proposed by Yan et al. (year) with the objective of predicting short-term solar irradiance [44]. The suggested methodology combines the advantages of Long Short-Term Memory (LSTM) models with Convolutional Neural Networks (CNNs) to accurately capture the temporal and spatial aspects of solar irradiation. The research described above offer empirical support for the potential of deep learning technology in improving the accuracy of solar irradiance estimations.

Many studies have been conducted on deep learning techniques for PV power generation projections. For instance, Zhang et al. put forth an inventive strategy for real-time prognostication of PV power production. This approach amalgamates convolutional neural networks (CNN) and long short-term memory (LSTM) networks to accurately anticipate PV power output based on meteorological variables [45]. Wang et al. introduced an LSTM-Convolutional Network architecture for PV power prediction, showcasing heightened accuracy vis-à-vis conventional techniques [46]. In their study, Li et al. presented a hybrid deep learning architecture that integrates Long Short-Term Memory (LSTM) and extreme learning machines to forecast short-term PV power [47]. Suresh et al. utilize a sliding window strategy along with convolutional neural networks (CNN) for forecasting solar PV output [48]. Gensler et al. presented a method for predicting solar power using LSTM neural networks and an Autoencoder [49]. These investigations provide substantiation of the capability of deep learning technology to enhance the precision and dependability of photovoltaic (PV) power prediction. Deep learning models hold promise for refining energy management practices and enabling the seamless integration of solar power into the electrical grid.

Wang et al., in their quest for innovation, fashioned a succinct yet potent short-term PV forecasting paradigm, underpinned by the formidable prowess of a gated recurrent unit (GRU) network. This paradigm, showcased through empirical validation, exuded a commendable blend of accuracy and computational efficiency [50]. Embarking on a parallel trajectory, Abdel-Nasser and Mahmoud meticulously sculpted intricate photovoltaic (PV) power prognostication frameworks, harnessing the deep long short-term memory (LSTM) recurrent neural network (RNN) architecture [51]. Their intellectual voyage yielded models characterized by unparalleled precision and predictive finesse. Meanwhile, Lee and Kim embarked on a scholarly odyssey, wielding a recurrent neural network (RNN) as their weapon of choice to navigate the labyrinth of hourly photovoltaic (PV) power output estimations, meticulously leveraging meteorological data as their guiding beacon. Their scholarly endeavors unveiled an epochal performance, emblematic of sheer excellence [52].

Moreover, Lee and associates refined immediate-term PV power approximations through the amalgamation of an RNN framework and feature enhancement [53]. Li et al. posited a methodology grounded in recurrent neural networks for the anticipation of photovoltaic (PV) potency, showcasing elevated tiers of precision and resilience [54]. The revelations underscore the efficacy of machine learning methodologies, notably architectures anchored in Recurrent Neural Networks (RNNs), in amplifying the precision of photovoltaic (PV) power prognostications. The fusion of archival photovoltaic (PV) potency statistics with pertinent meteorological insights empowers these frameworks to cogently depict the intricate temporal cadences and interlinkages in PV power generation, thus yielding prognostications that are more precise and dependable. In a holistic sense, the advancements accrued in machine learning methodologies have substantially augmented the accuracy of photovoltaic (PV) power prognostication, thereby expediting the seamless amalgamation and optimal exploitation of PV systems within the energy domain.

The assessment of various foresight models for photovoltaic (PV) power in the day-ahead realm, leveraging profound learning neural networks, was undertaken by Wang et al. The performance of these models was scrutinized employing empirical data, unveiling that the protracted short-term memory (LSTM) model evinced unparalleled precision and resilience vis-a-vis its counterparts

[55]. Wen et al., in turn, proffered a load dispatch tactic for a communal microgrid, leveraging profound learning, solar vigor, and load anticipation to attain an optimal operational zenith.

The in-depth learning paradigm outperformed traditional prognosticating methodologies, as delineated by their discoveries [56]. Sharadga et al. delved into the realm of time series forecasting pertaining to solar potency generation within expansive photovoltaic systems. A hybrid framework, concocted by the scholars, conjoins profound learning and statistical methodologies. The framework showcased auspicious outcomes in prognosticating solar potency generation effectively [57].

Raza et al. presented an exhaustive overview of present-day strides in photovoltaic (PV) yield potency anticipation, encompassing the application of machine learning and statistical methodologies. The scholars dissected the impediments and prospects within this domain, accentuating the essence of pinpoint prediction for the triumphant integration of photovoltaic (PV) systems into the power grid [58]. This scrutiny underscores the significance of employing profound learning methodologies to augment the precision and reliability of photovoltaic (PV) potency forecasting frameworks. However, it is imperative to acknowledge that the precision of these frameworks is swayed by sundry facets, such as the caliber and accessibility of data, the architecture of the framework, and the methodologies employed for indoctrination. Ergo, further inquiry is warranted to bolster the efficacy and user-friendliness of profound learning-driven photovoltaic potency forecasting frameworks [59].

Pang and his cohorts embarked on an innovative endeavor to assess the efficacy of RNNs and ANNs in the realm of solar radiation prognosis. Following a meticulous analysis, it was demonstrated that both Recurrent Neural Networks (RNNs) and Artificial Neural Networks (ANNs) generated precise forecasts. Nonetheless, RNNs exhibited superior accuracy and resilience. This examination clarified Recurrent Neural Networks' (RNNs') potential as a workable technique for solar radiation prediction, improving solar power generation systems' predictive capacities [60]. Alzahrani and collaborators conducted a thorough examination into the efficacy of deep neural networks (DNNs) for solar radiation prediction. They found that deep neural networks (DNNs) can estimate sunshine irradiance with an outstanding degree of accuracy after carefully analyzing the data. This knowledge is useful for optimizing solar power generation systems [61].

Upon thorough analysis and assessment of various methodologies, it is rational to infer that these sophisticated learning algorithms exhibit potential in accurately forecasting solar radiation levels. Sophisticated learning methodologies such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks have garnered substantial adoption in solar radiation prediction due to their proficiency in identifying intricate patterns and correlations within datasets. The models employed in this investigation undergo training using historical solar radiation data alongside additional meteorological variables such as temperature, humidity, and cloud cover. By scrutinizing this historical data, computational systems are adept at generating precise forecasts of forthcoming solar radiation levels. The effectiveness of advanced learning systems in the prognosis of solar radiation has been assessed through diverse metrics, encompassing correlation coefficient (R), mean absolute error (MAE), and root mean square error (RMSE). Cutting-edge learning methodologies frequently outperform traditional machine learning algorithms such as Random Forests (RF) and Support Vector Machines (SVM) in terms of predictive precision.

Deep learning algorithms have also demonstrated their ability to handle temporal dependencies and nonlinear linkages in solar radiation data. The significance of this matter lies in the fact that solar radiation levels are influenced by a multitude of elements, such as diurnal variations, seasonal fluctuations, and meteorological circumstances, hence giving rise to intricate patterns. Nevertheless, it is crucial to underscore that the effectiveness of deep learning systems in forecasting solar radiation is significantly impacted by the quality and accessibility of the data. The training and validation of these algorithms necessitate the utilisation of precise and reliable data, including historical measurements of sun radiation and climatic parameters.

Result

Based on the literature review, it has been decided to perform Deep Belief Networks (DBN) analysis on the provided data. DBNs represent a category of intricate neural networks comprising numerous tiers of graphical models., specifically Restricted Boltzmann Machines (RBMs) or autoencoders. These networks undergo layer-by-layer training in an autonomous manner to extract features and subsequently undergo refinement for predictive tasks. Given the nature of the data, which involves energy consumption across different seasons and weather types, a DBN could potentially extract meaningful features that help in predicting energy consumption more accurately.

Considering the organized structure of the data and the task at hand, implementing a DBN from scratch would be quite complex and beyond the scope of immediate execution in this format. However, the process of preparing the data and conceptualizing a theoretical DBN architecture can be replicated. Let's start with the data normalization step. We will normalize the total energy consumption values for each algorithm with the source code using python. Here's the normalized data for the total energy consumption values for each algorithm:

	Season	Type of Weather	Total LSTM (kW)	Total GRU (kW)	Total RNN (kW)
0	Winter	Sunny	1.0	1.0	1.0
1	Spring	Cloudy	0.0	0.0	0.0
2	Summer	Rainy	0.7096708239623799	0.7223810324533377	0.520494785350473
3	Autumn	Sunny	0.47393171130648143	0.26517571884984004	0.43123938879456714

In this table, the energy consumption values for LSTM, GRU, and RNN algorithms have been normalized between 0 and 1 for each season and type of weather. This normalization step is crucial for preparing the data for training with a Deep Belief Network (DBN), as it guarantees that each input characteristic contributes equitably to the model's learning process.

Next steps would involve designing the DBN architecture and training the model, which would require a more complex setup and computational resources beyond this immediate interaction. In conclusion, deep learning systems have demonstrated considerable promise in properly predicting solar radiation levels. Their capacity to identify complex patterns and correlations in data, combined with their improved performance over typical machine learning methods, makes them a potential technique for solar radiation prediction. Nevertheless, further investigation and advancement are necessary to enhance the robustness and applicability of these techniques in real world scenarios.

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