RESEARCH PAPER

AI-Driven Hybrid Models for Solar Energy Forecasting: A Comparative Analysis

[1]Kanchan Choudhary, [2]Priyanka Vashisht, [3]Anvesha Katti and [4]Udit Mamodiya

[1,2,3]ASET, Amity University Haryana, India
[4]FET, Poornima University Jaipur, Rajasthan
[1]choudharykanchan300@gmail.com, [2]Pvashisht@ggn.amity.edu, [3]akatti@ggn.amity.edu and [4]assoc.dean_research@poornima.edu.in

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ABSTRACT

Meeting the rising energy demands of India's growing population while transitioning to cleaner sources has emerged as one of the most pressing challenges of recent decades. Solar power, as an abundant and sustainable renewable resource, offers a viable pathway to reducing greenhouse gas emissions. Solar irradiance is influenced by several environmental factors, including atmospheric sunshine levels, cloud cover, geographic location, panel tilt angle, and orientation, all of which significantly affect the efficiency of solar photovoltaic (PV) systems. Machine Learning (ML) and Artificial Intelligence (AI) techniques are increasingly being adopted to address these complexities. By analyzing historical weather patterns, these methods detect nonlinear trends and generate accurate predictions of solar irradiance through techniques such as regression analysis and neural networks. This paper reviews and compares state-of-the-art solar irradiance forecasting approaches, including machine learning algorithms, numerical weather prediction (NWP) models, and hybrid methods, evaluating their accuracy, advantages, and limitations. It also highlights opportunities for improvement in forecasting performance, with emphasis on the potential of interdisciplinary methodologies and emerging technologies.

Keywords: Renewable Energy, Artificial Intelligence, Hybrid Approaches

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INTRODUCTION

The world requires a constant and stable supply of energy while simultaneously minimizing environmental damage caused by its production [12]. The ongoing energy crisis presents a major constraint on development across industry, business, and technology, all of which depend on reliable energy availability. As energy demand rises, so does the consumption of fossil fuels. Coal, natural gas, and oil underpin the conventional "brown" energy infrastructure, which is both environmentally harmful and economically unsustainable in the long run. Solar energy, by contrast, is abundant and cost-effective, offering a clean and renewable alternative. A sustained transition toward solar energy could significantly reduce the carbon emissions associated with fossil fuel-based systems [13].

The graph in Fig. 1below shows the demand for energy in India during the window of 2020-2025, obtained from Google Trends. The graph illustrates the demand for renewable energy sources, which has ups and downs but a positive trend. On the other hand, the demand for fossil fuels remains low with minimal fluctuations. The two graphs together indicate that there is an increasing interest in renewable energy sources compared to fossil fuels.

**Author for Correspondence: choudharykanchan300@gmail.com*

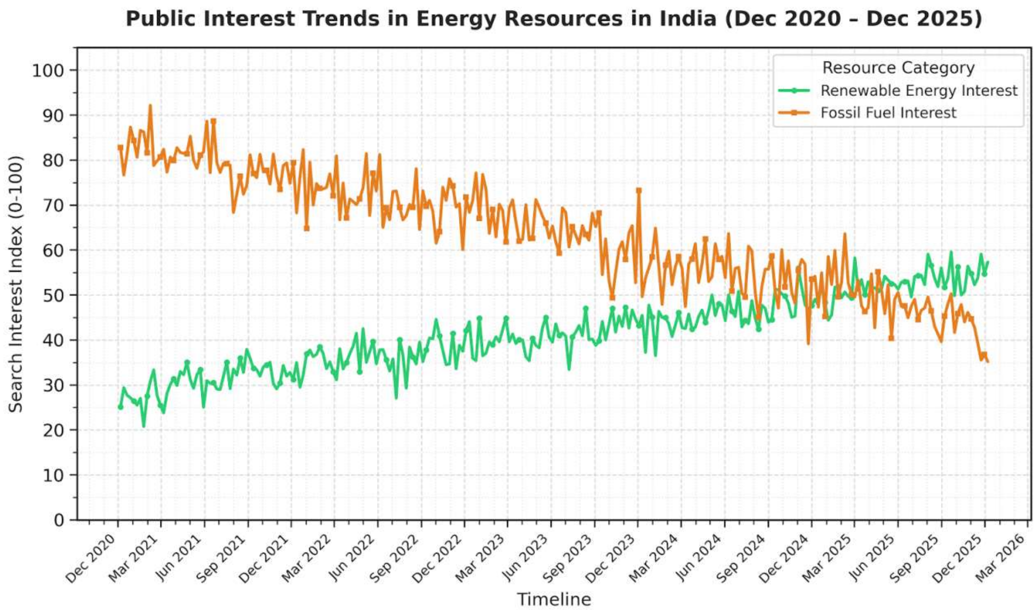

FIGURE 1: ENERGY DEMAND (2020-2025)

The energy produced by a solar PV cell is not consistent from day to day; rather, it varies depending on the weather and location. It is difficult to accurately determine the amount of energy that can be produced because many variables are involved, such as clouds, humidity, and temperature, to name a few. This is why it is not possible to have a 100% accurate forecast. To overcome this problem, several solar PV forecasting techniques have been developed and improved by various researchers. They can be generally divided into three categories, including physical models, data-driven models, and hybrid models. The input parameters differ for each of these models, typically including weather information, past power output, and solar irradiance [14].

Accurate forecasting of solar energy output is essential for the smooth operation of energy systems. By anticipating fluctuations in solar generation, grid operators can prepare appropriate responses and maintain system stability. Artificial intelligence and machine learning algorithms are increasingly being adopted to improve the accuracy of such predictions. The insights derived from these algorithms support the design of more efficient and responsive energy systems [15].

This paper summarizes the existing knowledge on prediction models for renewable energy generation and provides a detailed comparative analysis of datasets, modeling approaches, and performance outcomes.

In Figure 2, the various methods of Solar PV forecasting to predict the generation of solar power are presented. It categorizes the strategies as having three broad categories: Physical Models, Data-Driven Models and Hybrid Models. Physical models are based on weather and atmospheric data like NWP models, satellite data and sky images. The data-driven models are based on historical data and machine learning algorithms, such as ANN/LSTM, CNN/RNN, SVM, XgBoost and Random Forest. Hybrid models are physical and machine learning models, which include CNN-LSTM and Physical + ML models, to enhance the precision and reliability of solar power forecasting.

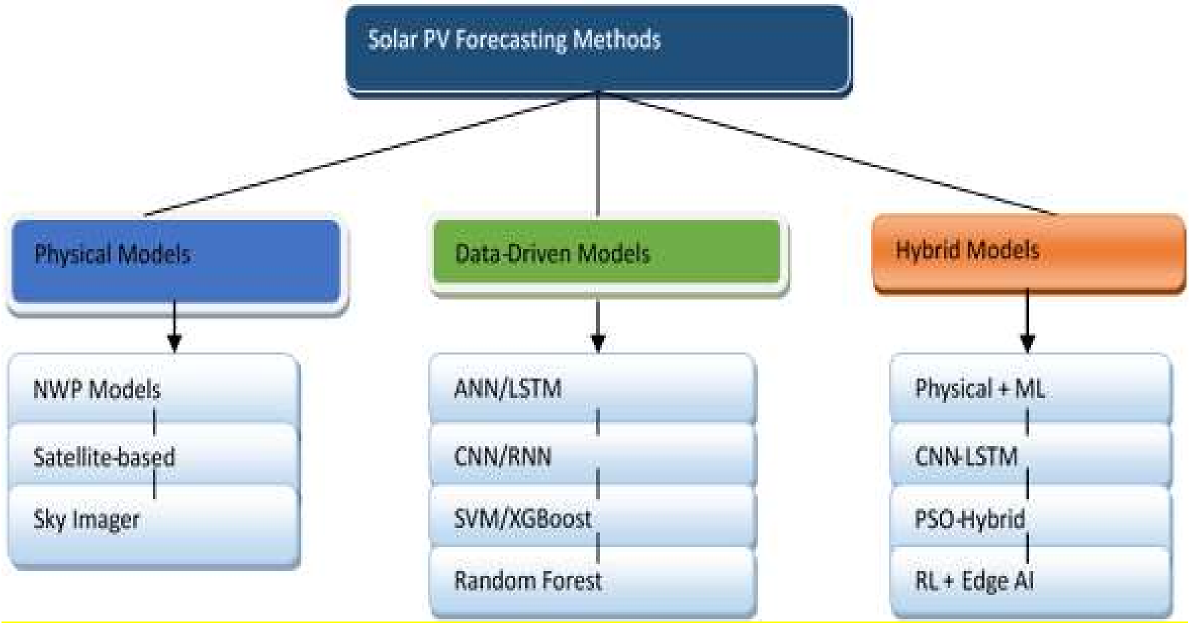

FIGURE 2: TAXONOMY OF SOLAR PV FORECASTING APPROACHES

Overview of Renewable Energy

Solar energy is among the most productive, clean, and sustainable renewable resources, with enormous potential to contribute to global sustainable development goals. Among renewable technologies, solar photovoltaics (PV) have become the least expensive option and are consequently expanding at a rapid pace worldwide. By 2017, solar and wind together accounted for over 50 percent of new electricity generating capacity globally, with solar installations surpassing new fossil fuel and nuclear power plants. Continued advancement in photovoltaic technology, particularly in semiconductor materials, has improved the process of electron-hole pair generation and transport, thereby enhancing conversion efficiency. Nevertheless, solar energy still accounts for a relatively small share of total global energy production, and its further adoption will depend significantly on supportive policy frameworks, energy market innovation, and improved economic competitiveness [5].

Between 2006 and 2016, advances in technology and improved government policies collectively reduced the production cost of solar electricity by approximately half. Achieving net-zero carbon emissions by 2050 will, however, require a comprehensive transformation of the global energy system. Continued innovation has produced a diverse range of photovoltaic cell types, including crystalline silicon, thin-film, concentrator, and perovskite cells. Perovskite solar cells have attracted particular interest due to their low manufacturing cost and simpler production processes compared to silicon-based alternatives. Concentrated solar power (CSP) systems, which include parabolic troughs, solar towers, and dish/engine configurations, harness solar heat to generate electricity at large scale; however, they remain costly and face challenges related to scalability [5].

Solar energy has much more extensive positive impacts than power generation that include augmented energy security, a reduced reliance on fossil energy, and reductions in greenhouse gas emissions. It is one of the major solutions to the increasing electricity demand in the world without causing harm to the environment. However, issues about disposal and recycling of solar panels still persist especially with regard to the toxicity of the material used and the waste disposal. Further research on the improvement of efficiency, durability, and recyclability should be done to offer a sustainable solar energy life cycle [5].

Data-Driven Solar Power Forecasting

AI and ML-driven techniques have emerged as transformative tools for improving predictive accuracy across a wide range of domains, including renewable energy systems. In the context of photovoltaic (PV) energy generation, the adoption of AI and ML methods has grown substantially, owing to their ability to handle high-dimensional data, correct systematic biases, and reveal hidden correlations within complex, nonlinear datasets. By leveraging data-driven intelligence, these approaches enable efficient forecasting of solar irradiance and electricity production, thereby supporting grid stability, optimized energy dispatch, and sustainable power management [6].

Artificial Intelligence is a branch of computer science concerned with developing systems capable of performing tasks that typically require human-level reasoning. Such systems are designed to recognize patterns, make informed decisions, and improve through interactions with their environment. Machine Learning (ML) is a core subfield of AI that focuses on building algorithms capable of learning from data and improving their performance incrementally, without being explicitly programmed for each task. By processing both historical and real-time inputs, ML models identify underlying statistical structures and generate forecasting insights that are applicable under the dynamic and uncertain conditions characteristic of solar power generation [6].

Hybrid Approaches

Hybrid approaches to solar power prediction and distribution integrate multiple modeling paradigms, such as deterministic models, probabilistic models, and machine learning models, in order to leverage the strengths of each methodology while mitigating individual limitations. Physical models can represent solar irradiance behavior with respect to environmental conditions and panel characteristics, while data-driven models are well-suited to capturing complex, nonlinear relationships in historical and real-time data. By combining these complementary techniques, hybrid systems are capable of producing more accurate and reliable solar power forecasts, particularly under varying weather patterns and seasonal fluctuations [10].

Beyond forecasting, hybrid solutions play a key role in enabling effective energy distribution within smart grid systems. Precise solar power forecasts support scheduling, load balancing, and energy storage management, all of which are essential for maintaining grid stability and minimizing energy wastage. Although hybrid methods may increase computational demands, they are instrumental in optimizing the integration of renewable energy and advancing sustainable, low-carbon energy systems [10]. This paper presents a comparative study of hybrid and AI-based methods for solar energy prediction and distribution optimization.

The following are important contributions made in this work:

1. Makes a full literature review of the available literature on AI-based solar irradiance prediction.
2. Determines gaps and outstanding challenges in research in the field.
3. Critically compares methodology, tools and model effectiveness and applicability in solar energy forecasting.
4. Identifies the most important issues and future perspectives of AI-based research on solar irradiance.

Related Work

Ajith, M., and Martínez-Ramón, M. (2021) developed a deep learning model for short-term solar power forecasting under overcast conditions by fusing infrared cloud imagery with solar radiation measurements using a multi-modal CNN-LSTM network with transfer learning. Evaluated on both cloudy and clear-sky datasets, the proposed model outperformed existing methods, achieving a classification accuracy of 99.23% and a 46.42% reduction in Mean Absolute Percentage Error (MAPE). The study identified forecasting under cloudy conditions as particularly challenging due to inherent model limitations. The authors recommended that future work focus on real-time deployment, multi-agent system integration, and further optimization to improve forecasting reliability [11].

In their article, *Mostafa, N., Ramadan, H., and Elfarouk, O. (2022)* applied data-driven analytics to renewable energy management in smart grids, employing Linear Regression, Random Forest, Decision Tree, CNN, and GBDT models on a decentralized dataset of 60,000 instances. Linear Regression achieved the highest accuracy at 96%, while other models ranged between 78% and 87%. Although the dataset was not sufficiently large to constitute a full big data analysis, the study contributed a useful predictive framework for improving grid stability and recommended future work with larger, more diverse, multi-country datasets to enhance the predictability of renewable energy systems and grid efficiency [9].

The article by *Mystakidis, A., Ntozi, E., Afentoulis, K., et al. (2023)* examined energy generation forecasting optimization in smart grid applications using ML and deep learning approaches. The study evaluated building-scale energy datasets sampled at multiple temporal resolutions (15-minute, 1-hour, and 1-day intervals) across various ML and DL architectures, using the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) as performance metrics. Results demonstrated that ensemble combinations of diverse models improved prediction accuracy and enhanced the alignment between energy supply and demand, thereby improving smart grid efficiency. The study noted, however, that model selection remains largely empirical, making consistent performance replication difficult. The authors proposed the development of automated and hybrid forecasting frameworks to improve reliability and simplify model selection for future energy prediction tasks [8].

The study by *S.M. Malakouti, M.B. Menhaj, and A.A. Suratgar (2023)* focused on improving the accuracy of solar farm power prediction using advanced machine learning optimization techniques. Ten-fold cross-validation combined with grid search was applied to tune Decision Tree, LightGBM, and Extra Trees models, using solar power data collected in California from 2019 to 2021. The results demonstrated that systematic hyperparameter optimization yielded significant improvements in model predictive performance. However, the study was geographically restricted to a single region, indicating the need for future research incorporating multi-site data and broader environmental conditions to improve the generalizability of the findings [7].

Noorollahi et al. (2024) compared the efficiency of photovoltaic (PV) and solar thermal collectors in meeting the heating and cooling needs of a fully solar-powered residential building. Their evaluation of an on-grid smart building using Particle Swarm Optimization (PSO) in MATLAB demonstrated that a hybrid PV/T system produced 10.6 percent more energy (551 kWh/m²) than a

PV-only system, indicating greater efficiency in space-constrained settings. The study highlights the advantages of PV/T integration and recommends further research into hybrid configurations combining gas and electric boilers to enhance overall system efficiency [4].

Taloba and Rayan (2025) also used ANN with Adam Optimizer, Random Forest, LSTM, Gradient Boosting, and SVM to forecast the energy requirements in the agricultural sector based on Economic growth, population statistics, and energy requirements, and expenditures. The ANN model according to the study, was the most accurate in its prediction (R 2 = 0.95, RMSE = 0.051, MSE = 0.0026) compared to the other methods. Although the research contributes to the shift towards renewable energy and sustainability in agriculture, it mentions the lack of attention to regional differences and factors of operation. Future directions the research will be expanded to real-time energy management and model customization to the regions in the future [3].

Singh et al. (2025) investigated ML-based forecasting of rooftop photovoltaic solar power to improve grid stability. Using ensemble ML models and time-series analysis of meteorological and solar power data from a commercial building in Saudi Arabia, they found that Extreme Gradient Boosting (XGBoost) delivered the highest prediction accuracy, with an R^2 of 0.975 and an MSE of 0.0036. The study highlights the underutilization of ML in solar forecasting in Saudi Arabia and demonstrates that improved forecasting accuracy can substantially enhance grid performance. The authors recommend extending ML-based solar forecasting research to a broader range of sites and climatic conditions [2].

Mamodiya et al. (2025) offered a hybrid development model of the artificial intelligence-based solar energy systems based on the idea of intelligent and scalable systems that allow adjusting to environmental changes. The model incorporates CNN-LSTM to predict power, reinforcement learning to track the sun, and uses Edge AI, hybrid nanocoatings, perovskite-silicon cell, blockchain, and AI-based energy storage. A one year field trial at Sitapara, Jaipur (India) showed considerable improvements, 41.4% increased energy output, 18.7% improvement in spectral absorption, 11.9 o C cooler panels, and 60 percent longer battery life, and a shortening in the energy dispatching latency. Although the complexity and scalability of integration is still an issue, this research gives a good evidence of concept of smart, self-adaptive solar systems, and the next step of research will be to increase the scope of implementation to areas and integrate wind and hybrid systems [1].

Performance Comparison of Predictive Models for Solar Photovoltaic Output

Recent research has produced a wide variety of models for PV power forecasting, each offering distinct advantages alongside inherent limitations. Predictive performance across these models can vary considerably, with the relative success of any given method typically depending on data characteristics and quality, modeling methodology, and the optimization strategies applied. As a result, certain models outperform others under specific conditions or with particular datasets. A systematic review and comparison of existing forecasting approaches is therefore necessary to understand these differences. Table I also indicates some of the significant works on PV power forecasting that have been done between 2021 and 2025.

TABLE I. A COMPARATIVE STUDY OF DATA-DRIVEN MODELS FOR PV FORECASTING

Authors	Year	Description	Models	Limitations	Performance Metrics	Key Findings
Ziad Ullah et al. [12]	2025	LSTM-Based Online Learning for Real-Time Solar Power Forecasting	LSTM	Sensitive to faulty or missing sensor data	MAPE:0.17, RMSE: 4.72, R^2:0.99	The model predicts solar power very accurately and handles seasonal changes well, outperforming CNN-LSTM
Ahmed I. Taloba , Alanazi Rayan [21]	2025	Machine learning based on reliable and sustainable electricity supply from renewable energy sources in the agriculture sector	ANN model with Adam optimizer	Implementation depends on technology, infrastructure, and local adoption	R^2 0.95, RMSE 0.051, MSE 0.0026	ANN accurately predicts agricultural energy needs better than other models.
Upma Singh et al.[18]	2025	Forecasting rooftop photovoltaic solar power using machine learning techniques	ML, XGBoost	Focused on one location; depends on meteorological data quality	MSE: 0.0036, RMSE: 0.0191, MAPE: 0.6898, MAE: 0.0130, R^2: 0.975	XGBoost predicts solar power most accurately with minimal errors.
PanneeSuanpang and	2024	Machine Learning Models for Solar Power Generation	ML models: LightGBM	LGBM requires longer training	LGBM: R^2 0.84, RMSE 5.77, MAE	LGBM is more accurate and robust across seasons,

PitchayaJamjuntr [22]		Forecasting in Microgrid Application Implications for Smart Cities	(LGBM) and KNN	time and higher memory usage	3.93; KNN: R^2 0.77, RMSE 6.93, MAE 4.34	suitable for microgrid applications
S. Sankaranant h et al. [17]	2023	AI-enabled metaheuristic optimization for predictive management of renewable energy production in smart grids	Hybrid AI + metaheuristic (LSTM-RL, RL-SA, CNN-PSO)	data-dependent, limited generalization, complex implementation.	R^2: 0.78, MSE: 345.12, MAE: 15.07, RMSE: 18.57, MAPE: 7.83	Accurately forecasts energy, balances loads, and improves smart grid performance.
D. K. Dhakedet al.[19]	2023	Power output forecasting of solar photovoltaic plant using LSTM	LSTM & BPNN	Location-specific and data-dependent.	BPNN(Summer): MAE: 421.16, RMSE: 747.24, RMSPE:19.51, R^2:0.940	LSTM predicts solar power more accurately than BPNN across seasons
R. K. Patel et al. [20]	2022	AI-Empowered Recommender System for Renewable Energy Harvesting in Smart Grid System	AI-RSREH	Dependent on data quality; focused only on residential SPV	MAPE: 0.0092, RMSE: 34.89	Accurately predicts solar energy generation and recommends where SPV installation can most reduce the demand–supply gap.
Meftah Elsaraiti, Adel Merabet [16]	2022	Solar Power Forecasting Using Deep Learning Techniques	LSTM, MLP	Sensitive to data quality and requires careful tuning.	Winter; MAE:236.35, MAPE:2.17, RMSE:317.4, and R2: 0.938 Summer; MAE:676.37, MAPE: 0.275, RMSE:883.5, R2 :0.745	LSTM predicts solar power more accurately than MLP.
Bouchaib Zazoum [23]	2021	Solar photovoltaic power prediction using different machine learning methods	ML algorithms: SVM and GPR	Factors like PV size, dust, and wind not fully considered; further studies needed	RMSE: 7.967, MAE: 5.302, R^2: 0.98	Matern 5/2 GPR algorithm predicts PV power accurately and reliably

Table II presents a comparative analysis of the performance of various solar power forecasting approaches. LSTM achieved the highest overall accuracy, with an R^2 of 0.99 and a low RMSE of 4.72, demonstrating superior predictive capability. XGBoost also performed strongly, with an R^2 of 0.975 and minimal RMSE, MAE, and MAPE values, confirming its reliability. The ANN model demonstrated effective prediction of agricultural energy requirements, with R^2 of 0.95 and a very low MSE. The SVM/GPR models achieved high accuracy (R^2 = 0.98) but produced slightly higher RMSE and MAE values. LGBM and KNN yielded moderate results, with R^2 values of 0.84 and 0.77, respectively. The CNN-PSO hybrid model achieved an R^2 of 0.78 along with comparatively larger RMSE, MAE, and MAPE values. The AI-RSREH model performed poorly in residential SPV energy prediction, recording a very low R^2 of 0.0092 and a high MAPE. Overall, LSTM and XGBoost emerge as the most reliable models for solar power prediction, achieving the highest levels of accuracy, while the suitability of other models remains dependent on the specific data characteristics and deployment context.

TABLE II. COMPARATIVE ASSESSMENT OF DIFFERENT FORECASTING MODELS

Comparative Assessment of Different Forecasting Models					
Models	**R^2**	**RMSE**	**MAE**	**MAPE**	**MSE**
LGBM	0.84	5.77	3.93	NA	NA

Comparative Assessment of Different Forecasting Models					
Models	R^2	RMSE	MAE	MAPE	MSE
KNN	0.77	6.93	4.34	NA	NA
SVM/GPR	0.98	7.967	5.302	NA	NA
ANN	0.95	0.051	NA	NA	0.0026
XGBoost	0.975	0.0191	0.0130	0.6898	0.0036
CNN-PSO	0.78	18.57	15.07	7.83	345.12
AI-RSREH	0.0092	NA	NA	34.89	NA
LSTM	0.99	4.72	NA	0.17	NA

In the graph given in Fig. 3 the performance is compared among various Solar PV forecasting models based on the coefficient of determination (R^2). The graph shows that models like LSTM, XGBoost, SVM/GPR, and ANN are very accurate with R^2 values of approximately 0.95 and above. In contrast, other models such as, LGBM, KNN, and CNN-PSO have moderate performances with lower R^2 values. The general trend of the graph shows that machine learning and deep learning models are more accurate when it comes to solar PV forecasting than other models.

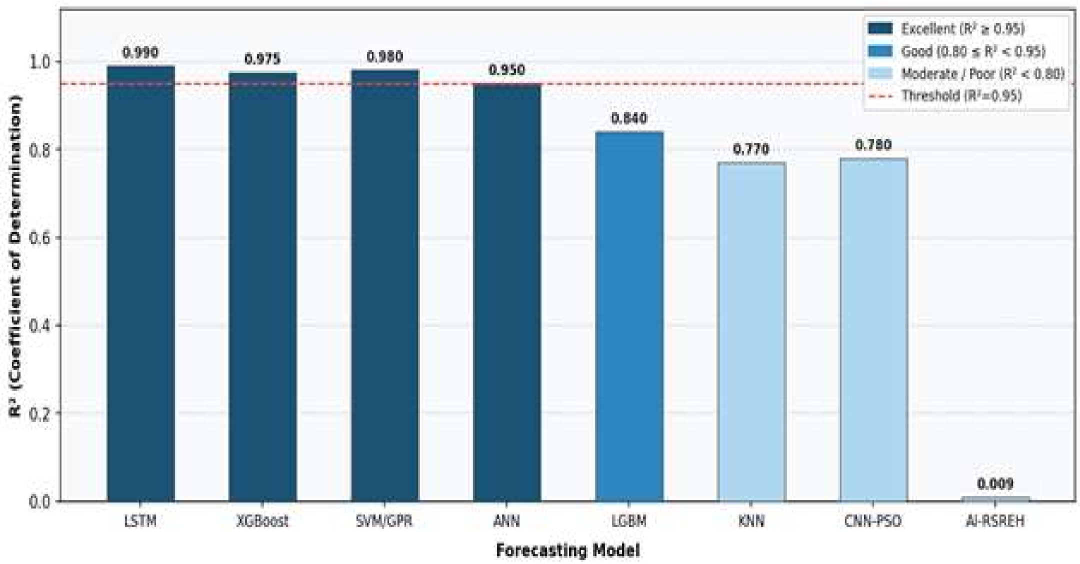

FIG. 3: PERFORMANCE COMPARISON OF SOLAR PV FORECASTING MODELS

In Fig. 4 shows the design of an AI-driven hybrid solar forecasting model developed to enhance the precision of the solar irradiance forecasting. The model combines several sources of data such as satellite imagery, weather station measurements and the data of IoT sensors, which is initially processed in a data preprocessing and feature extraction phase. A CNN module is a network that takes spatial features in satellite images, and an LSTM network is one that takes temporal patterns in sequential data. Simultaneously, a physical Numerical Weather Prediction (NWP) model is a model offering physics-based weather information. The results of these elements are combined via a hybrid fusion layer which produces an improved solar irradiance forecast. The last prediction is in favor of grid operations and energy management, which allows planning and incorporation of solar energy into the power network more accurately.

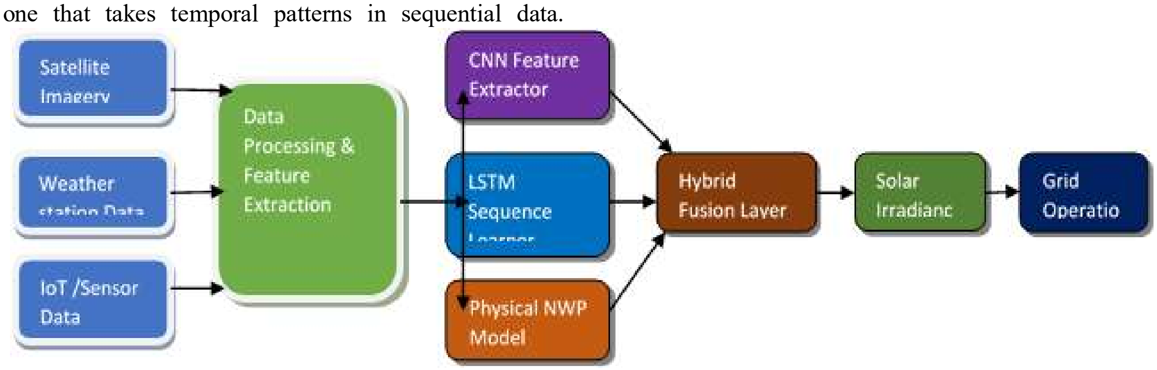

FIG. 4: ARCHITECTURE OF THE AI-DRIVEN HYBRID SOLAR FORECASTING MODEL

Research gap analysis

- Limited robustness and generalizability of existing models across diverse environmental conditions and site-specific parameters.
- Insufficient exploration of optimized hybrid multi-source renewable energy integration in smart grids and microgrids.
- Challenges in handling noisy, incomplete, or missing data in real-time energy prediction pipelines.
- Difficulty in coupling accurate prediction models with energy management and load balancing mechanisms for practical real-world deployment.

Conclusion and Future Work

This paper presents a detailed comparative analysis of AI-based methods for photovoltaic (PV) power prediction. The key factors influencing PV output forecasting accuracy are discussed, with particular emphasis on weather conditions and forecasting horizons. Solar PV system performance is governed by a range of variables, including solar irradiance intensity and ambient temperature, both of which fluctuate according to prevailing weather conditions. Accurate weather forecasting can substantially improve the ability to estimate PV power output, although the most influential meteorological factors may differ depending on the geographic location of the installation. This study reviews the current state of solar irradiance forecasting methods, with critical attention to the merits and limitations of each approach. Findings consistently indicate that accurate solar irradiance prediction is a central enabler of improved solar energy production. As global electricity demand continues to rise, solar energy represents a critical pillar of sustainable generation. AI-based and ML-driven approaches have demonstrated considerable effectiveness by leveraging historical weather data to produce more accurate forecasts.

While existing strategies, including regression models, neural networks, and hybrid techniques, have shown significant promise, they are not without limitations in real-world deployment. Current models frequently underperform under adverse weather conditions, exhibit limited generalizability across geographic locations, are inadequately optimized for multi-source hybrid systems, struggle with noisy or incomplete data, and remain difficult to integrate seamlessly into operational grid management systems.

Future research directions include developing robust forecasting models that generalize effectively across diverse weather conditions and geographic locations, improving prediction accuracy for combined renewable energy systems, enhancing model resilience against noisy or incomplete datasets, and facilitating seamless integration of forecasting tools into real-world smart grid operations. The fusion of real-time data streams from satellites, IoT sensors, and weather stations with AI-based predictive models is expected to significantly improve forecasting accuracy. Hybrid frameworks that combine physical simulation models with machine learning algorithms represent a particularly promising avenue for performance enhancement. Furthermore, interdisciplinary collaboration spanning meteorology, data science, and renewable energy engineering will be essential in advancing the development of smarter, more efficient, and adaptive solar energy systems.

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