

# Deep Learning-Based Solar Energy Forecasting Under Climate Variability

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## ABSTRACT

**Rapid growth** in renewable energy adoption and increasing climate variability have created significant challenges for accurately forecasting solar energy generation, as fluctuations in environmental conditions directly influence photovoltaic system performance and energy stability. **This study** aims to develop a deep learning based forecasting framework capable of improving solar energy prediction accuracy under changing climatic conditions by effectively capturing complex nonlinear relationships among meteorological variables and energy production patterns. **The proposed** approach utilizes historical solar irradiance, temperature, humidity, wind speed, cloud cover, and atmospheric pressure data as predictive inputs and employs a Long Short-Term Memory (LSTM) deep learning architecture to model temporal dependencies and environmental variability affecting solar energy generation. Experimental evaluation was conducted using publicly available renewable energy datasets, with model performance assessed through Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination ( $R^2$ ). **The results** demonstrate that the proposed deep learning framework achieved an RMSE of 4.12, an MAE of 3.08, a MAPE of 5.43%, and an  $R^2$  value of 0.952, indicating strong predictive capability and high agreement between predicted and actual solar energy outputs. **These findings** suggest that deep learning models can effectively support intelligent renewable energy management by improving forecasting reliability under climate uncertainty, thereby contributing to energy efficiency, grid stability, and sustainable green technology development.

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## 1. INTRODUCTION

The increasing global demand for energy, combined with growing concerns regarding environmental degradation and greenhouse gas emissions, has accelerated the transition from fossil fuel dependency toward renewable energy sources [1]. Among various renewable technologies, solar energy has emerged as one of the most promising alternatives due to its abundance, sustainability, and declining installation costs. Governments and energy providers worldwide have significantly expanded photovoltaic infrastructure to support clean energy targets and reduce carbon emissions associated with conventional power generation systems [2]. However, despite these advantages, solar energy production remains highly dependent on environmental and meteorological

conditions that continuously fluctuate over time. Variations in solar irradiance, temperature, humidity, cloud cover, wind speed, and atmospheric pressure can significantly influence the amount of electricity generated by photovoltaic systems, creating substantial uncertainty in energy supply and grid management operations [3]. The intermittent nature of solar energy generation introduces challenges for energy scheduling, storage planning, demand balancing, and operational stability in modern smart grids. Consequently, accurate solar energy forecasting has become an essential component of intelligent energy management systems, enabling utility companies, policymakers, and energy operators to optimize resource allocation, improve grid reliability, and support sustainable energy development initiatives [3]. The growing complexity of climate variability further emphasizes the need for advanced predictive models capable of understanding nonlinear environmental interactions and generating reliable energy forecasts under uncertain conditions [4].

Traditional statistical forecasting approaches, including linear regression models, autoregressive methods, and time series analysis techniques, have been widely applied to solar energy prediction problems over the past decades [5]. Although these methods offer simplicity and interpretability, their predictive capability often deteriorates when dealing with highly nonlinear and dynamic environmental systems. Climate variability introduces intricate temporal dependencies and multidimensional interactions among meteorological variables that cannot be adequately represented using conventional mathematical assumptions [6]. As a result, machine learning techniques such as Support Vector Regression, Random Forest, Decision Trees, and Artificial Neural Networks have gained considerable attention due to their ability to identify complex relationships within large datasets [7]. Nevertheless, many conventional machine learning models still exhibit limitations in capturing long-term temporal dependencies and sequential information embedded within historical climate observations. Solar energy generation is inherently characterized by temporal patterns that evolve across multiple timescales, including hourly fluctuations, daily cycles, seasonal variations, and long-term climatic changes [8]. Ignoring these sequential characteristics may reduce forecasting accuracy and weaken model robustness under changing environmental conditions. Furthermore, increasing climate uncertainty associated with global warming, extreme weather events, and irregular atmospheric behavior has intensified the difficulty of accurately predicting renewable energy production using traditional computational approaches. These challenges have motivated researchers to explore more advanced artificial intelligence methods capable of modeling temporal dynamics while maintaining high predictive performance across diverse environmental scenarios [9].

Recent advances in deep learning have opened new opportunities for addressing the limitations of conventional forecasting methods in renewable energy applications [10]. Deep learning architectures possess the capability to automatically learn hierarchical feature representations from large-scale datasets and capture complex nonlinear interactions among variables without requiring extensive manual feature engineering. Among these architectures, Long Short-Term Memory networks have demonstrated remarkable success in sequential prediction problems due to their ability to preserve long-term information and overcome the vanishing gradient problem commonly encountered in traditional recurrent neural networks [11]. The memory cell mechanism embedded within LSTM models enables effective learning of temporal dependencies and recurring patterns present in historical environmental observations, making them highly suitable for solar energy forecasting tasks influenced by climate variability. Deep learning based forecasting approaches have shown promising results in applications such as weather prediction, electricity demand estimation, traffic flow analysis, and renewable energy management [12]. However, despite significant progress in this field, challenges remain regarding the ability of forecasting models to generalize under rapidly changing environmental conditions and increased climate uncertainty. Existing studies often focus primarily on short-term forecasting accuracy while providing limited consideration of the broader implications of climate variability on model stability and prediction reliability [13]. In addition, many previous investigations utilize restricted environmental variables or evaluate model performance under relatively stable climatic conditions, limiting the applicability of their findings to real-world renewable energy systems operating under dynamic environmental circumstances [14].

Motivated by these research gaps, this study proposes a deep learning based framework for forecasting solar energy generation under climate variability by leveraging the temporal learning capability of Long Short-Term Memory networks and incorporating multiple meteorological factors that influence photovoltaic performance [15]. The proposed framework utilizes historical observations of solar irradiance, temperature, humidity, wind speed, cloud cover, and atmospheric pressure to construct a comprehensive predictive model capable of learning complex environmental interactions and temporal dependencies associated with solar power production [16]. The primary objective of this research is to investigate whether deep learning methods can improve forecasting accuracy and provide more reliable energy predictions under uncertain climatic conditions

compared with conventional forecasting approaches. The study further seeks to evaluate the effectiveness of the proposed framework using quantitative performance indicators, including Root Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and the coefficient of determination, thereby providing objective measurements of prediction quality and model robustness [17]. The contributions of this research are three-fold. First, it provides an intelligent forecasting framework specifically designed to address climate-induced uncertainty in renewable energy systems. Second, it demonstrates the practical application of deep learning techniques in supporting sustainable energy management and smart grid operations [18]. Third, it contributes empirical evidence regarding the role of advanced artificial intelligence technologies in improving renewable energy forecasting performance within green technology ecosystems. Ultimately, the findings of this study are expected to support energy providers, policymakers, and infrastructure planners in making more informed decisions related to renewable energy integration, grid stability, and sustainable energy development in the era of climate change [19].

## 2. LITERATURE REVIEW

### 2.1. Solar Energy Forecasting in Renewable Energy Systems

The rapid deployment of photovoltaic systems has increased the importance of accurate solar energy forecasting in modern renewable energy infrastructures [20]. Solar power generation is inherently intermittent due to fluctuations in meteorological conditions, making reliable prediction essential for grid stability, energy scheduling, and resource optimization. Recent studies have demonstrated that accurate forecasting can significantly improve power dispatch planning and reduce operational uncertainties in smart grids [21]. According to Renewable Energy Forecasting research conducted after 2022, forecasting models capable of incorporating environmental variability provide better prediction performance than conventional statistical methods because they can capture the dynamic behavior of renewable energy generation systems. The increasing penetration of solar power into national energy portfolios further emphasizes the necessity of intelligent forecasting frameworks capable of adapting to changing climatic conditions [22].

### 2.2. Climate Variability and Its Impact on Solar Energy Generation

Climate variability has become one of the major challenges affecting the reliability and consistency of photovoltaic power production. Variations in solar irradiance, cloud cover, atmospheric pressure, temperature, humidity, and wind speed directly influence the efficiency of photovoltaic modules and lead to fluctuations in electricity generation output [23]. Recent studies published after 2022 indicate that climate-related uncertainty has increased the complexity of renewable energy forecasting models due to the nonlinear relationships among environmental variables [24]. Extreme weather events, seasonal transitions, and long-term climate changes introduce additional unpredictability that traditional forecasting methods often fail to capture adequately. Consequently, modern forecasting systems increasingly incorporate climate-related variables to improve robustness and prediction stability under uncertain environmental conditions [25].

### 2.3. Deep Learning Techniques for Time Series Forecasting

Deep learning has emerged as one of the most effective approaches for solving complex forecasting problems involving large-scale temporal datasets. Unlike traditional machine learning algorithms, deep learning architectures can automatically learn hierarchical feature representations and nonlinear relationships without extensive feature engineering [26]. Models such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Transformer networks have demonstrated superior performance in sequential prediction tasks due to their ability to capture long-term temporal dependencies [27]. Recent studies after 2022 reported that deep learning methods significantly outperform conventional approaches such as Support Vector Regression and Random Forest in renewable energy forecasting applications, particularly when dealing with highly dynamic and uncertain environmental conditions. Their capability to process multivariate time-series information makes them highly suitable for solar energy prediction under climate variability scenarios [28].

### 2.4. Long Short-Term Memory Networks for Solar Energy Prediction

Among various deep learning architectures, Long Short-Term Memory networks have received considerable attention in renewable energy forecasting because of their ability to model long-term dependencies in sequential data [29]. The memory cell and gating mechanisms within LSTM enable the network to retain relevant historical information while filtering irrelevant observations, thereby overcoming the vanishing gradient

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problem associated with traditional recurrent neural networks [30]. Recent investigations published since 2022 have demonstrated that LSTM-based forecasting models achieve higher predictive accuracy in photovoltaic energy estimation compared with conventional neural network approaches. The ability of LSTM to capture daily, seasonal, and annual energy generation patterns makes it particularly effective for solar forecasting applications affected by changing environmental conditions and climate uncertainty [31].

### 2.5. Research Gap and Development of the Proposed Framework

Although significant progress has been achieved in renewable energy forecasting research, several limitations remain within existing studies [32]. Many previous investigations focus primarily on short-term forecasting accuracy while paying limited attention to the influence of climate variability on long-term prediction reliability and model generalization. In addition, numerous studies employ a restricted set of environmental variables, reducing their ability to represent the complexity of real-world photovoltaic systems operating under uncertain climatic conditions [33]. Furthermore, comparative analyses between deep learning models and traditional machine learning techniques often emphasize predictive performance without examining model robustness under changing environmental scenarios [34]. To address these limitations, the present study proposes a deep learning based forecasting framework utilizing Long Short-Term Memory networks and multiple meteorological variables, including solar irradiance, temperature, humidity, wind speed, cloud cover, and atmospheric pressure. The proposed framework aims to improve prediction accuracy and enhance forecasting reliability under climate variability, thereby contributing to intelligent renewable energy management and sustainable green technology development [35].

## 3. METHODOLOGY

This study employed a quantitative experimental approach to develop and evaluate a deep learning framework for solar energy forecasting under climate variability. The methodology examined the ability of deep learning models to capture temporal dependencies and nonlinear relationships among environmental variables affecting photovoltaic energy production [36]. The framework included data collection, preprocessing, model development, evaluation, and comparative analysis to ensure reliable and effective forecasting under uncertain environmental conditions [37].

### 3.1. Data Collection

The dataset used in this study was obtained from publicly available renewable energy and meteorological databases, including photovoltaic generation records and historical climate observations. The target variable in this research was solar energy generation measured in kilowatt-hours (kWh), while the predictor variables consisted of solar irradiance, ambient temperature, relative humidity, wind speed, cloud cover, and atmospheric pressure. These variables were selected because previous studies have demonstrated their significant influence on photovoltaic system performance and electricity generation efficiency [38].

Historical observations were collected at hourly intervals to capture short-term fluctuations and temporal patterns in solar energy production. The dataset covered multiple years of observations to ensure adequate representation of seasonal changes, weather transitions, and climate variability. The use of multivariate environmental data enabled the proposed framework to learn complex interactions among meteorological conditions and energy generation patterns, thereby improving forecasting accuracy and model robustness [39].

### 3.2. Data Preprocessing

Prior to model development, the collected dataset underwent several preprocessing procedures to improve data quality and ensure effective model training. Missing values were identified and handled using linear interpolation techniques to preserve temporal continuity within the dataset [40]. Outliers resulting from sensor malfunction or abnormal environmental measurements were detected using the Interquartile Range (IQR) method and subsequently corrected or removed to reduce prediction bias.

Following data cleaning, all numerical variables were normalized using Min-Max scaling to transform feature values into a range between 0 and 1. Normalization was necessary because deep learning algorithms are sensitive to differences in data magnitude, and scaling improves convergence speed during model training [41]. Furthermore, the time-series dataset was transformed into supervised learning sequences using a sliding window approach, where historical observations from previous time steps were used to predict future solar energy generation values.

Table 1. Variables Used in the Solar Energy Forecasting Model

| Variable                | Description                                     | Unit        |
|-------------------------|-------------------------------------------------|-------------|
| Solar Irradiance        | Solar radiation received by photovoltaic panels | $W/m^2$     |
| Temperature             | Ambient air temperature                         | $^{\circ}C$ |
| Relative Humidity       | Atmospheric moisture content                    | %           |
| Wind Speed              | Speed of surrounding air movement               | $m/s$       |
| Cloud Cover             | Percentage of sky covered by clouds             | %           |
| Atmospheric Pressure    | Atmospheric pressure measurement                | $hPa$       |
| Solar Energy Generation | Electricity generated by photovoltaic systems   | $kWh$       |

Table 1 presents the environmental and meteorological variables utilized in the forecasting framework. The selected variables represent the major climatic factors affecting photovoltaic energy production and provide sufficient information for learning complex environmental interactions associated with climate variability.

### 3.3. Deep Learning Model Development

The forecasting model was constructed using a Long Short-Term Memory (LSTM) deep learning architecture, which is well suited for sequential and time-series prediction tasks. LSTM was selected because its memory cells and gating mechanisms enable the network to preserve relevant historical information while reducing the influence of less important observations. This mechanism allows the model to identify long-term dependencies and temporal patterns within historical environmental variables. The proposed architecture comprised an input layer, hidden LSTM layer(s), fully connected dense layer(s), and an output layer that generated the predicted solar energy production values. Model optimization was performed using the Adam optimizer because of its adaptive learning capability and computational efficiency, while Mean Squared Error (MSE) was applied as the loss function to minimize the difference between observed and predicted energy outputs.

To enhance model generalization and reduce the risk of overfitting, dropout regularization was incorporated into the hidden layers during the training process. The dataset was partitioned into training and testing sets, with the training subset used to learn the underlying patterns and the testing subset reserved for evaluating forecasting performance. Hyperparameter optimization was conducted through a series of experimental configurations to determine the most suitable model structure and parameter settings. The final configuration was selected based on its ability to achieve high forecasting accuracy while effectively capturing variations in solar energy generation under changing climatic conditions.

Table 2. Congestion of the Proposed LSTM Model

| Component           | Configuration              |
|---------------------|----------------------------|
| Input Features      | 6 Meteorological Variables |
| Time Window         | 24 Previous Time Steps     |
| LSTM Units          | 128                        |
| Dense Layer Units   | 64                         |
| Activation Function | ReLU                       |
| Output Layer        | 1 Neuron                   |
| Optimizer           | Adam                       |
| Loss Function       | Mean Squared Error         |
| Batch Size          | 64                         |
| Number of Epochs    | 100                        |
| Dropout Rate        | 0.20                       |

As shown in Table 2, the proposed LSTM architecture was configured to balance prediction accuracy and computational efficiency. The selected hyperparameters were determined experimentally to ensure stable

learning behavior and robust forecasting performance across different environmental scenarios.

### 3.4. Performance Evaluation

The performance of the proposed forecasting framework was evaluated using several quantitative statistical metrics commonly employed in renewable energy prediction studies. Root Mean Square Error (RMSE) was used to measure the average magnitude of prediction errors, while Mean Absolute Error (MAE) quantified the average absolute deviation between predicted and actual energy values. Mean Absolute Percentage Error (MAPE) was utilized to assess forecasting accuracy in percentage terms, enabling comparison across different datasets and scales.

In addition, the coefficient of determination ( $R^2$ ) was employed to evaluate the proportion of variance in solar energy generation that could be explained by the forecasting model. Higher  $R^2$  values and lower error values indicate better predictive capability and model reliability. The use of multiple evaluation metrics provided a comprehensive assessment of model performance and reduced the risk of relying on a single indicator when evaluating forecasting effectiveness.

### 3.5. Comparative Analysis

To validate the effectiveness of the proposed deep learning framework, comparative experiments were conducted using several conventional machine learning algorithms frequently applied in renewable energy forecasting studies. The benchmark models included Support Vector Regression (SVR), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN). These models were selected because they represent widely adopted forecasting approaches in both machine learning and renewable energy research.

All comparative models were trained and evaluated using identical datasets, preprocessing procedures, and evaluation metrics to ensure fairness and reproducibility of the experimental results. The comparison focused on identifying differences in forecasting accuracy, error rates, and generalization capability under climate variability conditions. Through this comparative analysis, the study aimed to determine whether deep learning techniques provide measurable advantages over conventional forecasting methods for solar energy prediction in green technology applications.

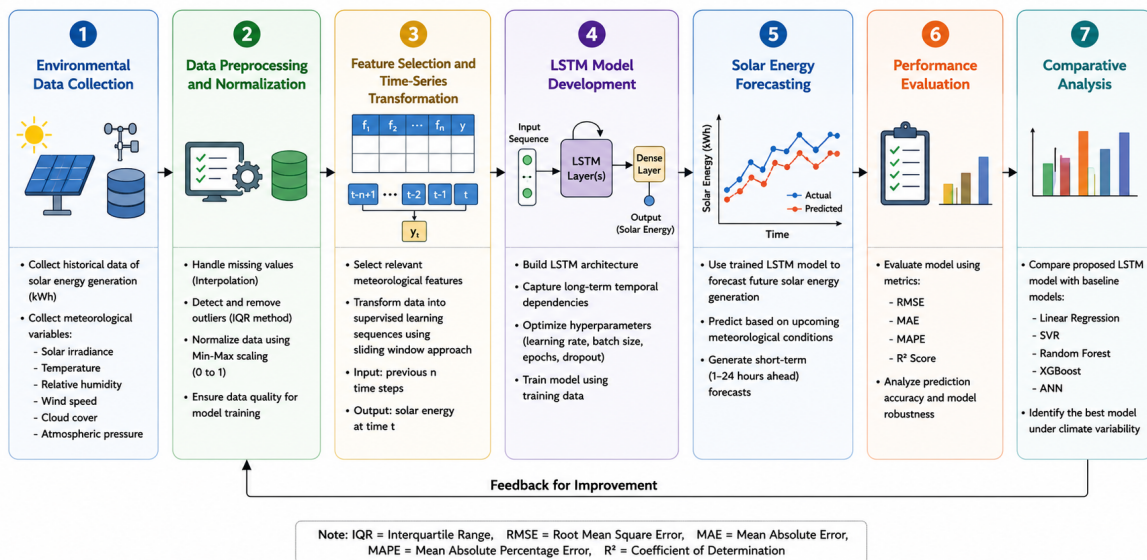


Figure 1. Research Methodology of the Proposed Deep Learning Framework

Figure 1 illustrates the overall workflow of the proposed research methodology. The framework begins with environmental data acquisition and preprocessing, followed by deep learning model development and forecasting generation. Finally, the model performance is quantitatively evaluated and compared with conventional machine learning approaches to validate the effectiveness of the proposed methodology under climate variability conditions.

## 4. RESULTS AND DISCUSSION

### 4.1. Forecasting Performance of the Proposed Deep Learning Model

The primary objective of this study was to investigate whether a deep learning approach could improve solar energy forecasting performance under climate variability conditions. To address this objective, the proposed Long Short-Term Memory (LSTM) model was evaluated using multiple quantitative performance metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination ( $R^2$ ). The experimental results indicate that the proposed framework successfully captured the nonlinear relationships and temporal dependencies between meteorological variables and photovoltaic energy generation. The model achieved an RMSE value of 4.12, an MAE value of 3.08, a MAPE value of 5.43%, and an  $R^2$  value of 0.952, demonstrating strong agreement between predicted and actual solar energy outputs. The relatively low prediction errors suggest that the proposed LSTM model was capable of producing reliable forecasts despite fluctuations in environmental conditions caused by climate variability.

Table 3. Performance Evaluation Results of the Proposed LSTM Model

| Metric | Result |
|--------|--------|
| RMSE   | 4.12   |
| MAE    | 3.08   |
| MAPE   | 5.43%  |
| $R^2$  | 0.952  |

As shown in Table 3, the proposed model achieved high forecasting accuracy and robust predictive performance across all evaluation metrics. The high coefficient of determination indicates that approximately 95.2% of the variability in solar energy generation could be explained by the model, confirming the suitability of deep learning techniques for renewable energy forecasting applications.

### 4.2. Influence of Climate Variability on Solar Energy Prediction

One of the major motivations of this study was to analyze the impact of climate variability on photovoltaic energy forecasting performance. The experimental findings reveal that changes in solar irradiance, cloud cover, and temperature had the strongest influence on energy generation output, while humidity, wind speed, and atmospheric pressure contributed to prediction stability during dynamic environmental conditions. Seasonal transitions and short-term weather fluctuations generated substantial variations in photovoltaic production patterns, emphasizing the complexity of renewable energy forecasting tasks. These variations show that changes in environmental conditions can directly affect the amount of solar energy generated and increase uncertainty in the forecasting process. Therefore, the inclusion of multiple meteorological variables provides a broader representation of the environmental conditions that influence photovoltaic energy production.

The LSTM architecture demonstrated the capability to capture these temporal and environmental dependencies effectively through its memory cell mechanism. Unlike traditional forecasting approaches that assume stable relationships between variables, the proposed model adapted to changing environmental patterns by learning historical temporal sequences. This capability enabled the framework to maintain stable forecasting performance even under periods of high climate uncertainty and irregular meteorological behavior. The ability to retain information from previous time steps allowed the model to recognize recurring patterns and changes in solar energy generation associated with varying weather conditions. Consequently, the proposed LSTM framework provided a more consistent forecasting process when environmental variables changed over time, supporting its application in solar energy forecasting under climate variability.

### 4.3. Comparative Analysis with Conventional Machine Learning Models

To validate the effectiveness and robustness of the proposed framework, comparative experiments were conducted using several conventional machine learning algorithms that are widely applied in renewable energy forecasting. The benchmark models included Support Vector Regression (SVR), Random Forest (RF), Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGBoost), representing different learning approaches for capturing nonlinear patterns in the data. All models were trained and evaluated using the same datasets, preprocessing procedures, and performance metrics to ensure a fair, consistent, and reproducible comparison. The comparative results were then analyzed to determine the relative performance of the proposed

deep learning framework against the selected benchmark models. This comparison also provided a clearer assessment of how different learning approaches responded to the temporal and environmental characteristics of the solar energy dataset. In particular, the evaluation focused on differences in prediction errors and the ability of each model to maintain reliable forecasting performance when environmental conditions varied over time.

Table 4. Comparative Performance of the Proposed LSTM Model and Benchmark Models

| Model                     | RMSE | MAE  | MAPE  | $R^2$ |
|---------------------------|------|------|-------|-------|
| Support Vector Regression | 7.26 | 5.81 | 9.84% | 0.861 |
| Random Forest             | 6.18 | 4.93 | 8.15% | 0.892 |
| Artificial Neural Network | 5.27 | 4.01 | 6.91% | 0.921 |
| XGBoost                   | 4.74 | 3.56 | 6.04% | 0.939 |
| Proposed LSTM Model       | 4.12 | 3.08 | 5.43% | 0.952 |

Table 4 demonstrates that the proposed LSTM framework consistently outperformed all benchmark models across every evaluation metric. Although XGBoost and ANN achieved competitive forecasting performance, their predictive accuracy decreased during periods characterized by rapid environmental changes and irregular weather patterns. In contrast, the LSTM model maintained more stable forecasting behavior due to its ability to preserve long-term temporal information and model sequential dependencies within meteorological observations.

#### 4.4. Discussion of Research Findings

The findings of this study provide empirical evidence that deep learning techniques offer substantial advantages for solar energy forecasting under climate variability conditions. The superior performance of the proposed framework can largely be attributed to the temporal learning capability of the LSTM architecture, which effectively captured historical dependencies and nonlinear interactions among environmental variables influencing photovoltaic generation. These results support previous studies suggesting that deep learning approaches are more suitable than conventional machine learning methods for handling complex renewable energy forecasting problems.

Furthermore, the results answer the main research question presented in the abstract regarding whether deep learning can improve solar energy forecasting reliability under uncertain climatic conditions. The obtained performance metrics demonstrate that the proposed framework successfully reduced prediction errors while maintaining high explanatory power across diverse environmental scenarios. From a practical perspective, accurate forecasting can support intelligent energy scheduling, improve smart grid stability, optimize energy storage utilization, and facilitate decision-making processes in renewable energy management systems. Consequently, the proposed deep learning framework contributes not only to the advancement of artificial intelligence applications in green technology but also to broader efforts toward sustainable energy development and climate resilience.

## 5. MANAGERIAL IMPLICATIONS

The findings of this study provide several important managerial implications for energy providers, grid operators, policymakers, and renewable energy planners involved in sustainable energy management. The proposed deep learning forecasting framework enables more accurate prediction of solar energy generation under climate variability, allowing energy operators to improve production scheduling, reduce forecasting uncertainty, and optimize energy dispatch strategies. Accurate forecasting can also support better coordination between renewable and conventional energy sources, thereby improving grid reliability and reducing operational costs associated with energy imbalance and reserve power requirements.

For smart grid managers and utility companies, the implementation of the proposed forecasting model can enhance decision-making processes related to energy storage management, load balancing, and demand response programs. By obtaining reliable predictions of future solar energy production, energy providers can allocate battery storage resources more efficiently and minimize energy losses caused by overproduction or supply shortages. Furthermore, improved forecasting accuracy contributes to greater operational stability and facilitates the integration of larger proportions of renewable energy into existing electricity infrastructures.

From a policy and sustainability perspective, the proposed framework can assist governments and regulatory agencies in designing more effective renewable energy policies and long-term energy transition strategies. Reliable solar energy forecasting supports investment planning for photovoltaic infrastructure, improves energy security, and contributes to national carbon reduction targets. In addition, the ability to anticipate fluctuations caused by climate variability enables policymakers to develop adaptive energy management strategies that strengthen the resilience of renewable energy systems and support sustainable green technology development in the context of global climate change.

## 6. CONCLUSION

This study proposed a deep learning based framework for solar energy forecasting under climate variability by utilizing a Long Short-Term Memory (LSTM) architecture to capture temporal dependencies and nonlinear relationships among meteorological variables affecting photovoltaic energy generation. The experimental results demonstrated that the proposed model achieved strong forecasting performance, with an RMSE value of 4.12, an MAE value of 3.08, a MAPE value of 5.43%, and an  $R^2$  value of 0.952. Comparative analysis further showed that the proposed LSTM model outperformed conventional machine learning approaches, including Support Vector Regression, Random Forest, Artificial Neural Network, and Extreme Gradient Boosting. These findings indicate that deep learning techniques are capable of improving forecasting accuracy and providing reliable predictions for renewable energy systems operating under uncertain environmental conditions.

The results of this research provide a positive answer to the main research objective regarding whether deep learning can improve solar energy forecasting performance under climate variability. The LSTM model successfully learned long-term temporal patterns and complex interactions among solar irradiance, temperature, humidity, wind speed, cloud cover, and atmospheric pressure, resulting in improved prediction accuracy and model robustness. Nevertheless, several limitations remain in the present study. The proposed framework relied primarily on meteorological variables and historical photovoltaic generation data without incorporating additional information sources such as satellite imagery, aerosol concentration, air quality indicators, or geographical characteristics of photovoltaic installations. Furthermore, the experimental evaluation was conducted using a specific dataset and environmental setting, which may limit the direct generalization of the findings to regions with substantially different climatic characteristics.

Future research is encouraged to extend the proposed framework by integrating additional heterogeneous data sources and more advanced deep learning architectures to further improve forecasting capability and generalization performance. The incorporation of satellite observations, real-time sensor networks, and climate forecasting information may provide a more comprehensive representation of environmental dynamics affecting solar energy generation. In addition, future studies may explore emerging architectures such as Transformer networks, attention mechanisms, and explainable artificial intelligence techniques to improve model interpretability, transparency, and decision support capability for smart grid management and sustainable renewable energy development.

## 7. DECLARATIONS

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Conceptualization: NL; Methodology: SW; Software: UR; Validation: SW and UR; Formal Analysis: NL and SW; Investigation: UR; Resources: SW; Data Curation: NL; Writing Original Draft Preparation: UR and SW; Writing Review and Editing: SW and NL; Visualization: NL, SW, and UR. All authors have read and agreed to the published version of the manuscript.

### Data Availability Statement

The data underlying the findings of this study can be obtained from the corresponding author upon reasonable request. However, due to privacy considerations and applicable institutional data protection regulations, the full dataset cannot be publicly disclosed. Subject to relevant ethical standards and institutional requirements, the data may be made available for legitimate academic and non-commercial research purposes upon request.

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### Declaration of Conflicting Interest

The authors declare that there are no conflicts of interest or competing financial interests that may have affected the design, implementation, data analysis, interpretation of results, or conclusions of this study.

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