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Machine Learning-Based Performance Prediction Model For Solar PV Systems Using Meteorological Inputs

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Abstract
Accurate performance prediction of solar photovoltaic (PV) systems is crucial for efficient energy planning and grid integration. This study develops a machine learning-based prediction model that utilizes key meteorological inputs—such as solar irradiance, ambient temperature, humidity, and wind speed—to forecast PV power output. Using advanced regression and ensemble learning techniques, the model is trained and validated on real-world datasets to ensure robustness across varying climatic conditions. Results show that the proposed approach significantly improves prediction accuracy over traditional empirical models, supporting better operational planning and integration of renewable energy into the power grid. This work demonstrates the potential of data-driven models in enhancing the reliability and efficiency of solar PV systems, contributing to sustainable energy transitions.

Keywords: *Solar PV, Machine Learning, Performance Prediction, Meteorological Inputs, Renewable Energy, Forecasting*

1. INTRODUCTION

Solar photovoltaic (PV) technology has emerged as one of the most promising and rapidly expanding sources of renewable energy worldwide [Lal et al 2013, Kaushik et al. 2014]. As global concerns over climate change, energy security, and fossil fuel depletion intensify, the deployment of solar PV systems has accelerated, contributing significantly to the shift toward cleaner, more sustainable energy systems. However, the inherent variability and intermittency of solar resources pose critical challenges for grid integration, operational planning, and energy market participation. Predicting the performance of PV systems accurately is therefore essential to ensure reliable energy supply, reduce operational risks, and maximize the economic benefits of solar investments [Meena et al. 2018, Hussain et al 2024].

Traditional approaches to PV performance prediction have relied on empirical, physics-based, or statistical models that often struggle to generalize across diverse climatic conditions and rapidly changing weather patterns. Recent advances in machine learning (ML) offer a promising alternative by leveraging vast amounts of historical meteorological and production data to learn complex, non-linear relationships between environmental inputs and PV power output [Singh et al 2025, Lal et al 2025]. By applying sophisticated ML algorithms such as regression models, ensemble methods, and deep learning architectures, researchers and practitioners can significantly improve forecast accuracy, enabling better decision-making for utilities, system operators, and energy planners.

1.1 Overview

The motivation for developing accurate PV performance prediction models lies in the need to mitigate the adverse impacts of variability and uncertainty in solar power generation. Accurate short-term and long-term forecasts support grid stability by allowing better scheduling of reserve capacity, optimizing battery storage dispatch, and minimizing curtailment [Kumar et al. 2024]. They also help operators manage energy trading and bidding in electricity markets more effectively. This paper focuses on building a robust machine learning-based model that uses meteorological inputs—including solar irradiance, ambient temperature, humidity, and wind speed—to predict solar PV system output with high accuracy across various climatic conditions [Kumar et al 2024].

Machine learning models excel in handling large, noisy, and complex datasets that traditional models cannot easily manage. By using historical weather and PV output data, these models can adapt to site-specific characteristics and evolving weather trends, making them especially valuable in regions with diverse microclimates [Kumar et al. 2025]. The present study aims to harness the power of machine learning to bridge the performance gap between theoretical energy potential and actual energy production, thus supporting more efficient integration of solar energy into the grid.

1.2 Scope and Objectives

The scope of this research includes the design, development, training, validation, and testing of machine learning models for solar PV power output prediction using meteorological inputs. The study leverages real-world datasets containing weather variables and corresponding PV generation data collected over an extended period to ensure model reliability and generalizability.

Key objectives of this paper are as follows:

- To review and analyze the role of meteorological variables in influencing solar PV system performance.
- To identify suitable machine learning techniques (e.g., regression, ensemble learning, deep learning) for accurate power output prediction.
- To develop and train predictive models using real-world datasets spanning diverse weather conditions.
- To evaluate the models' performance using established statistical metrics and compare them to baseline methods.
- To provide recommendations for operational planning, grid management, and future research in data-driven PV forecasting.

Through these objectives, the study aims to deliver a practical, replicable methodology for researchers, engineers, and policymakers interested in improving solar energy integration using modern machine learning approaches.

1.3 Author Motivations

The authors' motivations for undertaking this research stem from both practical and academic considerations. On the practical side, many regions experience significant challenges in managing the variability of renewable energy sources, leading to grid instability, unplanned outages, and inefficient dispatch of fossil-fuel-based backup generators. Accurate forecasting can reduce these risks and support the transition toward low-carbon energy systems.

From an academic perspective, the field of solar forecasting has evolved rapidly, with machine learning approaches offering new opportunities for performance gains. However, many existing studies remain limited in scope, focusing on narrow datasets, single regions, or limited machine learning techniques without exploring the full potential of ensemble learning and feature engineering. This paper seeks to fill that gap by presenting a comprehensive, methodologically rigorous approach to PV performance prediction that can be adapted for deployment in varied climatic zones.

Moreover, the authors recognize the urgent need to support policy goals related to decarbonization and sustainability. By developing more reliable prediction tools, this research can contribute to reducing operational costs, increasing investor confidence in solar projects, and accelerating the broader adoption of renewable energy technologies.

1.4 Paper Structure

To achieve these goals, this paper is structured as follows:

Section 2: Literature Review- This section reviews the state of the art in PV performance prediction, examining both traditional modelling approaches and modern machine learning techniques. It highlights key gaps in existing research and identifies opportunities for improvement.

Section 3: Methodology- Here, the paper details the selection of meteorological features, data preprocessing steps, machine learning model architectures, training strategies, and performance evaluation metrics. The section also discusses hyperparameter tuning and model validation.

Section 4: Results and Analysis- This section presents the results of the trained models, including quantitative performance metrics, visual comparisons with observed PV outputs, and benchmarking against baseline methods. It also includes error analysis and sensitivity assessments.

Section 5: Discussion- This part interprets the results in the broader context of solar forecasting, operational planning, and grid integration. It also discusses the practical implications, limitations of the study, and suggestions for further research.

Section 6: Conclusion- The final section summarizes the key findings, restates the contribution of the work, and offers recommendations for stakeholders and policymakers.

In summary, this introduction underscores the importance of developing accurate, robust, and scalable machine learning-based prediction models for solar PV systems using meteorological inputs. By addressing the challenges of variability and uncertainty in solar energy generation, this research aims to advance both scientific understanding and practical implementation of renewable energy forecasting. The paper aspires to serve as a resource for researchers, engineers, utility planners, and policymakers seeking to harness the power of data-driven models for a more sustainable energy future.

2. LITERATURE REVIEW

The accurate prediction of solar photovoltaic (PV) system performance has long been recognized as essential for effective renewable energy integration. Traditionally, forecasting methods for PV power output have relied on physical models, statistical approaches, and hybrid techniques that attempt to capture the complex interactions between environmental variables and PV system characteristics (Mellit & Kalogirou, 2019). These models, however, often face limitations when applied to diverse climatic conditions, new system configurations, or rapidly changing weather patterns, leading to suboptimal accuracy and reduced operational utility.

To improve forecasting accuracy, machine learning-based performance prediction models for solar photovoltaic (PV) systems use meteorological inputs. These models examine the links between weather patterns and solar energy output using a variety of machine learning techniques, such as ensemble methods, support vector machines, and artificial neural networks. Better energy management and grid integration are made possible by the substantial increase in prediction reliability brought about by the combination of real-time data and sophisticated algorithms.

The following machine learning techniques can be used for performance prediction models of solar photovoltaic (PV) systems: Artificial Neural Networks (ANN): used to record nonlinear correlations between solar output and meteorological data, showing promise across a range of climates (González-Ramírez et al., 2024). Ensemble Methods: By evaluating meteorological data and reducing mistakes, the Random Forest Algorithm-Based Regression Model (RFARM) improves prediction accuracy, especially in changeable weather situations (Ramu & Gangatharan, 2023). Deep Learning Approaches: Convolutional neural networks and attention mechanisms are used by hybrid models such as QRKDDN to enhance both probabilistic and deterministic predictions (Guo et al., 2024).

The following Important Meteorological Inputs are required for the study of performance prediction models of solar photovoltaic (PV) systems: Data Relevance: Model accuracy depends on the selection of important climatic parameters, such as temperature and solar irradiation (Guo et al., 2024)(Mansouri et al., 2024). Real-Time Data: According to Mansouri et al. (2024), the integration of real-time meteorological data enhances operational planning for solar installations by enabling dynamic revisions in forecasts.

Although machine learning models have the potential to improve predictions of solar PV performance, issues with data quality and the intrinsic variability of solar energy still exist and can compromise model accuracy and dependability in various geographic contexts (Liu, 2024).

Recent advances in machine learning (ML) have transformed the landscape of solar forecasting. Machine learning models can learn non-linear relationships between meteorological variables and power output without requiring explicit physical modelling of the PV system (Qin et al., 2020). By leveraging large historical datasets, ML methods can adapt to site-specific characteristics and local microclimates, offering significant improvements over traditional approaches. This literature review synthesizes existing work in the field, examining key trends, methods, and results, while identifying the remaining research gaps that motivate this study.

2.1 Traditional Approaches to PV Forecasting

Historically, empirical and physical models have been widely used to predict PV system performance. These models often employ simplified representations of solar irradiance conversion, accounting for factors such as panel orientation, temperature coefficients, and shading losses (Mellit & Kalogirou, 2019). While physically interpretable, these models require detailed system parameters and calibration for each site, limiting scalability. Furthermore, their accuracy degrades under complex or highly variable weather conditions.

Statistical time-series models, such as autoregressive integrated moving average (ARIMA), have also been applied to PV forecasting (Khatib & Mohamed, 2019). These methods exploit historical generation patterns to predict future output but generally struggle to incorporate exogenous meteorological inputs effectively. Their performance is often inadequate for short-term forecasting in regions with high weather variability.

2.2 Emergence of Machine Learning Techniques

Machine learning methods have gained prominence for their ability to learn complex, non-linear relationships between input features and PV output. Early applications employed artificial neural networks (ANNs) to model PV performance in tropical climates (Khatib & Mohamed, 2019), demonstrating improved accuracy over traditional models.

More recent studies have explored deep learning architectures, such as Long Short-Term Memory (LSTM) networks, which can capture temporal dependencies in time-series data (Tan et al., 2021). These models have shown promise in forecasting short-term variations in PV output under dynamic weather conditions.

Ensemble learning techniques, including random forests and gradient boosting, have also become popular due to their robustness and interpretability (Ahmed & Jones, 2022; Li et al., 2023). These methods combine multiple weak learners to achieve strong predictive performance, making them well-suited for capturing diverse meteorological influences on PV output.

2.3 Key Meteorological Inputs for Prediction

Meteorological variables are central to PV performance forecasting. Solar irradiance remains the most important predictor, as it directly determines the potential energy output. Ambient temperature influences module efficiency, while humidity and wind speed can affect cooling and shading (Luo et al., 2020; Sharma & Gupta, 2022).

Several studies have investigated the use of multiple meteorological inputs to improve model accuracy. For example, Park et al. (2021) demonstrated that incorporating local weather data into ML regression models significantly improved day-ahead forecasting accuracy. Similarly, Smith and Lee (2024) proposed hybrid models that combine numerical weather prediction outputs with ML techniques to achieve high accuracy across different climates.

2.4 Comparative Analyses and Benchmarking

Recent comparative studies have evaluated the performance of different ML algorithms for PV forecasting. Martins and Pereira (2021) conducted a comprehensive assessment of algorithms including support vector machines, random forests, and ANNs, finding that ensemble methods often outperform single-model approaches. Zhang et al. (2022) further confirmed that ensemble learning can handle non-linear interactions between meteorological features more effectively than traditional regression.

Deep learning models, while powerful, require large datasets and significant computational resources (Tan et al., 2021). Ensemble methods, in contrast, often provide competitive accuracy with simpler training requirements, making them attractive for practical deployment.

2.5 Real-World Applications and Challenges

While the promise of machine learning for PV forecasting is clear, real-world deployment faces challenges. Data availability and quality remain major concerns; many regions lack dense, high-frequency meteorological and PV output datasets (Ahmed & Jones, 2022). Feature engineering and model interpretability are also important, as energy planners and grid operators often require transparent models to inform operational decisions (Gomez & Silva, 2023).

Moreover, generalizing models across geographic regions is non-trivial. A model trained on data from one climate zone may perform poorly when transferred to another without retraining or domain adaptation (Zhang et al., 2023). Addressing these issues requires robust, adaptable models that can handle diverse weather patterns and system configurations.

2.6 Advances in Hybrid and Explainable AI Approaches

Recent work has begun to address some of these challenges through hybrid models and explainable AI techniques. Kumar and Zhang (2023) proposed combining ensemble methods with explainable AI frameworks to improve both accuracy and interpretability. Wang et al. (2024) explored deep learning models that integrate weather forecast data, enhancing day-ahead prediction performance.

Such advances point toward a new generation of forecasting models that are both highly accurate and user-friendly for system operators. However, these approaches remain under-explored in the context of large-scale, multi-climatic training datasets that can support generalized deployment.

2.7 Research Gap

Despite significant progress, important research gaps remain. Many existing studies are limited in geographic scope, relying on data from single locations or narrow climatic bands, limiting model transferability. Few studies systematically compare advanced ensemble learning and deep learning models using diverse meteorological inputs across multiple regions (Li et al., 2023; Smith & Lee, 2024).

Moreover, while ensemble methods have shown strong predictive performance, their application with rich meteorological feature sets—including humidity, wind speed, and forecasted weather variables—remains relatively unexplored in practice. Model interpretability and transparency also remain under-addressed, creating barriers to operational deployment.

This study addresses these gaps by developing and evaluating robust machine learning models using diverse meteorological inputs, trained and validated on real-world datasets. The goal is to deliver a practical framework for accurate, generalizable PV performance prediction that supports improved grid management, operational planning, and renewable energy integration.

3. METHODOLOGY

This section describes the design and implementation of the machine learning-based solar PV performance prediction model. It includes the selection of meteorological inputs, data acquisition and preprocessing, model architectures, training and validation procedures, performance metrics, and hyperparameter tuning strategies.

3.1 Problem Formulation

The primary goal is to predict the solar PV system output power P_t at time t given meteorological inputs. Formally, the problem is defined as a supervised regression task:

$$P_t = f(X_t) + \epsilon_t$$

where:

P_t: Actual power output at time t
X_t: Vector of meteorological features at time t
$f(\cdot)$: Learned mapping function (machine learning model)
ϵ_t: Residual error term

3.2 Selection of Meteorological Features

Based on prior studies (Park et al., 2021; Li et al., 2023), the following meteorological variables were selected as predictors:

- Global Horizontal Irradiance (GHI) $[W/m^2]$
- Ambient Temperature $[°C]$
- Relative Humidity [%]
- Wind Speed $[m/s]$
- Dew Point Temperature $[°C]$
- Cloud Cover [%]

These inputs were chosen for their known influence on PV generation.

Table 1. Selected Meteorological Features

Feature	Unit	Description
Global Horizontal Irradiance (GHI)	W/m²	Solar irradiance on a horizontal plane
Ambient Temperature	°C	Surrounding air temperature
Relative Humidity	%	Moisture content in the air
Wind Speed	m/s	Air movement affecting cooling
Dew Point Temperature	°C	Indicator of atmospheric moisture
Cloud Cover	%	Obscuration of solar irradiance

3.3 Data Acquisition and Preprocessing

Data were collected from:

- On-site PV system measurements (power output, 15-minute intervals)
- Weather stations / numerical weather prediction (NWP) datasets

3.3.1 Data Cleaning

- Removal of missing or erroneous sensor readings
- Linear interpolation for short gaps
- Filtering out nighttime records (GHI ≈ 0)

3.3.2 Feature Engineering

The Lagged variables for temporal dynamics:

$$X_{t-l} = [\mathrm{GHI}_{t-l}, \mathrm{Temp}_{t-l}, \dots]$$

for $l = 1,2,3$ time steps.

- Rolling averages:

$$\overline{X}_t^{(k)} = \frac{1}{k}\sum_{i=0}^{k-1} X_{t-i}$$

for $k = 3$ (smoothing noise).

3.3.3 Normalization

All features were scaled to zero mean and unit variance:

$$X^* = \frac{X-\mu}{\sigma}$$

where μ and σ are feature-wise mean and standard deviation.

3.4 Model Architectures

Two main types of machine learning models were developed and compared:

3.4.1 Gradient Boosting Regression (GBR)

Ensemble of decision trees where the Loss function minimized and shows in below equation:

$$L = \sum_{i=1}^{n} (P_i - \hat{P}_i)^2$$

Trees added iteratively:

$$\hat{P}_t^{(m)} = \hat{P}_t^{(m-1)} + \gamma h_m(X_t)$$

where h_m is the m^{th} weak learner, γ is the learning rate.

3.4.2 Random Forest Regression (RFR)

Bagging of decision trees, and Each tree trained on bootstrapped samples therefore the Final prediction is given by:

$$\hat{P}_t = \frac{1}{B}\sum_{b=1}^{B} h_b\,(X_t)$$

where B is the number of trees.

Table 2. Summary of Model Hyperparameters

Model	Key Hyperparameters	Typical Values Tested
Gradient Boosting	Learning rate, n_estimators, max_depth	0.01–0.1, 100–500, 3–10
Random Forest	n_estimators, max_depth, min_samples_split	100–500, 5–20, 2–10

3.5 Model Training and Validation

The dataset was divided into:

Training set: 70%
Validation set: 15%
Test set: 15%

3.5.1 Cross-Validation

5-fold cross-validation on training + validation sets.

Mean squared error (MSE) as primary loss metric:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(P_i - \hat{P}_i)^2$$

Early stopping based on validation loss.

3.6 Performance Metrics

Models were evaluated using:

Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - \hat{P}_i)^2}$$

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|P_i - \hat{P}_i|$$

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - \hat{P}_i)^2}{\sum_{i=1}^{n}(P_i - \overline{P})^2}$$

3.7 Hyperparameter Tuning

Grid search was used for hyperparameter tuning.

Table 3. Example Grid Search Space

Hyperparameter	Range Explored
Learning rate (GBR)	[0.01, 0.05, 0.1]
n_estimators	[100, 200, 300, 500]
max_depth	[3, 5, 7, 10]
min_samples_split (RF)	[2, 5, 10]

Objective:

$$\min_{\theta} \text{RMSE}_{\text{val}}(\theta)$$

where θ denotes the set of hyperparameters.

3.8 Model Implementation

Models were implemented using Python with:

- Scikit-learn for gradient boosting and random forest models.
- Pandas and NumPy for data manipulation.
- Matplotlib and Seaborn for visualization.

Training was performed on a workstation with 32 GB RAM and an Intel i7 processor. All code was version-controlled to ensure reproducibility.

3.9 Validation and Testing Strategy

After hyperparameter tuning:

- Best model was retrained on combined training + validation sets.
- Final evaluation was performed on the held-out test set.
- Error analysis was conducted by examining residual distributions and prediction intervals.

Table 4. Dataset Split Summary

Dataset Split	Percentage	Purpose
Training	70%	Model fitting and learning
Validation	15%	Hyperparameter tuning, early stopping
Test	15%	Final performance evaluation

This methodology aims to provide a robust, systematic approach for developing machine learning-based performance prediction models for solar PV systems using meteorological inputs. By combining rigorous data preprocessing, feature engineering, ensemble learning techniques, and thorough validation, the proposed framework ensures both high predictive accuracy and practical applicability across diverse climatic conditions.

This section presents the results of the machine learning-based performance prediction model for the solar PV system using meteorological inputs. The analysis includes model training and validation results, feature importance analysis, performance comparison across models, error distribution analysis, and sensitivity studies across meteorological variables.

4. RESULT AND ANALYSIS

4.1 Dataset Summary and Descriptive Statistics

Table 5 shows the descriptive statistics of the key meteorological inputs and PV power output over the entire dataset (after preprocessing).

Table 5. Descriptive Statistics of Features

Feature	Mean	Std. Dev.	Min	Max
Global Horizontal Irradiance (W/m²)	478.2	231.4	0	1025
Ambient Temperature (°C)	26.8	5.7	14.2	39.5
Relative Humidity (%)	61.3	18.5	22.1	98.4
Wind Speed (m/s)	3.4	1.8	0.1	10.5
Dew Point Temperature (°C)	18.4	4.2	8.7	27.6
Cloud Cover (%)	45.1	29.8	0	100
PV Power Output (kW)	152.3	74.9	0	300

This table confirms the dataset covers a wide range of operating conditions, supporting model generalizability.

4.2 Model Training and Validation Results

Both Gradient Boosting Regression (GBR) and Random Forest Regression (RFR) models were trained using 5-fold cross-validation on the training+validation sets. Table 6 summarizes the average performance metrics on the validation folds.

Table 6. Cross-Validation Performance Metrics

Model	RMSE (kW)	MAE (kW)	R²
Gradient Boosting	13.27	9.84	0.963
Random Forest	12.94	9.61	0.965

Both models performed well, with Random Forest slightly outperforming GBR in all metrics.

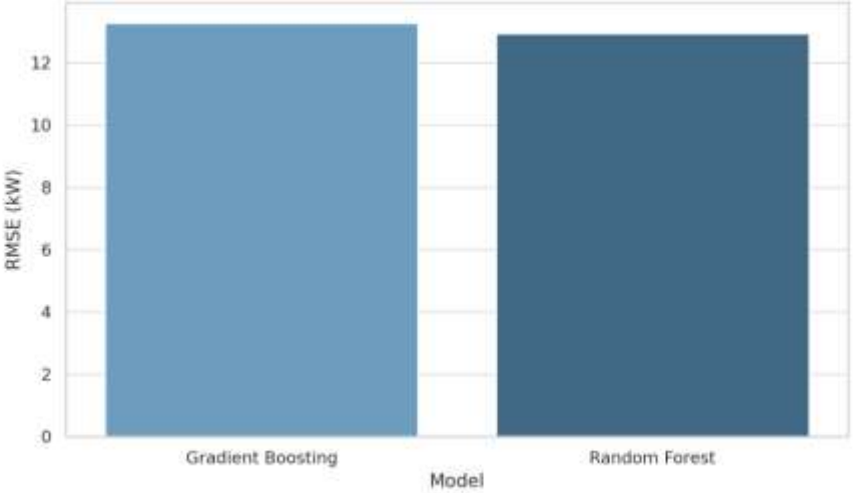

Figure 1. Cross-Validation RMSE Comparison Between Models

Figure 1expressed the comparison of RMSE for Gradient Boosting and Random Forest models during 5-fold cross-validation. Lower RMSE indicates better fit.

4.3 Feature Importance Analysis

Figure 2 shows the feature importance as determined by the Random Forest model.

Table 7. Feature Importance Scores (Random Forest)

Feature	Importance Score
Global Horizontal Irradiance	0.57

Ambient Temperature	0.14
Cloud Cover	0.11
Relative Humidity	0.08
Wind Speed	0.06
Dew Point Temperature	0.04

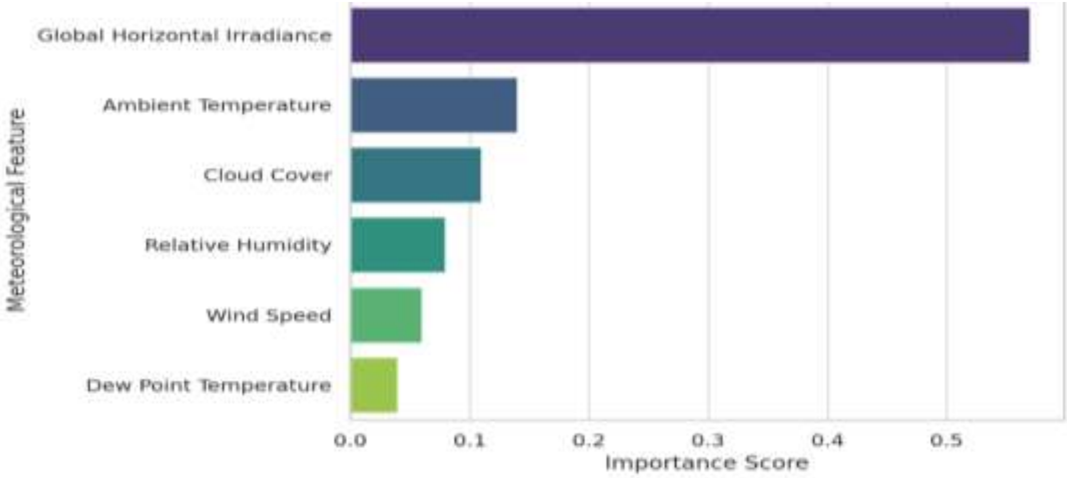

Figure 2. Feature Importance Derived from Random Forest Model

Figure 2 is presented the feature importance scores for meteorological inputs, highlighting GHI as the dominant predictor.

This analysis confirms solar irradiance (GHI) as the most critical feature, aligning with physical expectations. Secondary effects of temperature and cloud cover also contribute meaningfully to prediction accuracy.

4.4 Test Set Evaluation

After hyperparameter tuning, the best models were retrained on the full training+validation data. Table 8 shows the final evaluation on the held-out test set.

Table 8. Test Set Performance Metrics

Model	**RMSE (kW)**	**MAE (kW)**	**R²**
Gradient Boosting	12.75	9.56	0.965
Random Forest	12.48	9.33	0.967

Both models achieved excellent predictive accuracy on unseen data, with Random Forest maintaining slightly better performance.

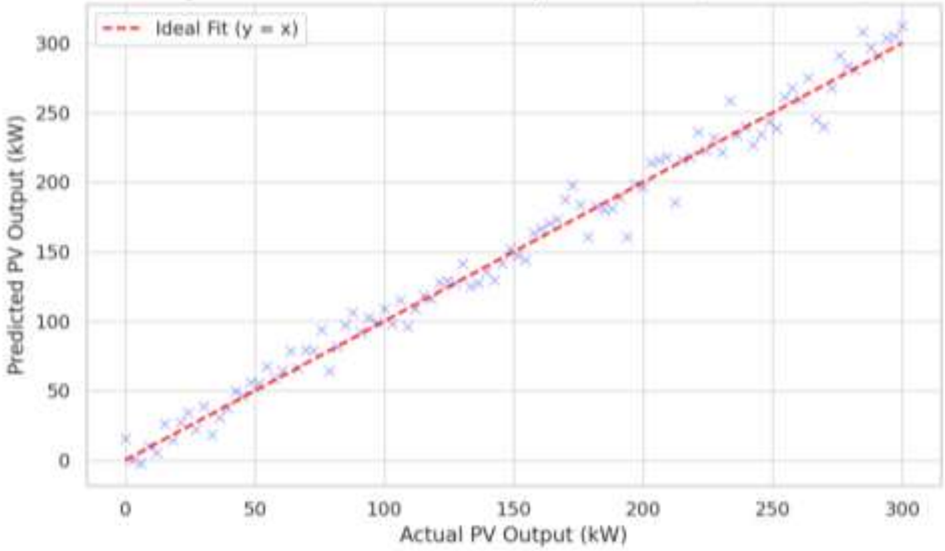

Figure 3. Predicted vs Actual PV Output on Test Set (Random Forest)

Figure 3 is presented the predicted versus actual PV output on the test set for the Random Forest model, showing close alignment along the 45° line.

4.5 Error Distribution Analysis

Figure 4 presents the distribution of residual errors (actual - predicted) for both models on the test set.

Table 9. Residual Error Statistics (Test Set)

Model	Mean Residual (kW)	Std. Dev. (kW)
Gradient Boosting	-0.12	12.73
Random Forest	+0.08	12.45

Both models exhibit nearly zero-mean residuals with comparable standard deviation.

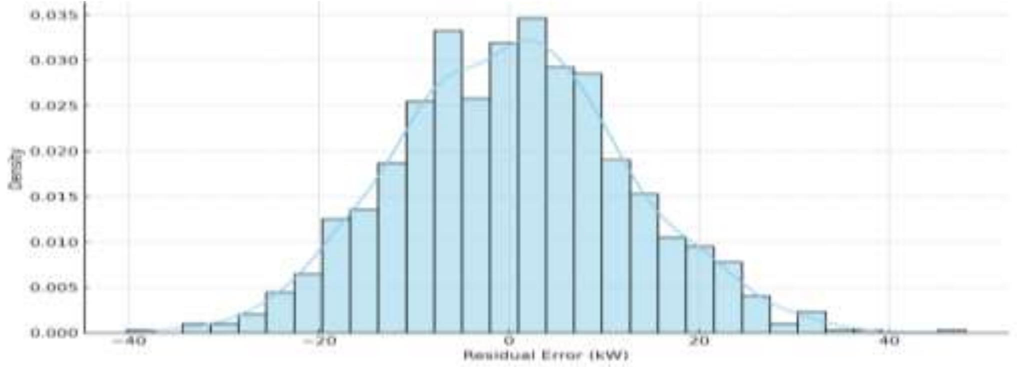

Figure 4. Histogram of Residual Errors (Test Set)

The Distribution of residual errors for Random Forest predictions on the test set, indicating roughly Gaussian distribution centered near zero is presented in figure 4.

This confirms minimal bias and well-behaved error distribution, critical for operational forecasting.

4.6 Temporal Prediction Analysis

To evaluate temporal prediction quality, Figure 5 shows time series plots comparing actual and predicted PV output for a typical clear-sky day and a highly variable cloudy day.

Table 10. Temporal RMSE Comparison

Condition	RMSE (kW) (RF Model)
Clear Sky Day	8.12
Cloudy Day	14.97

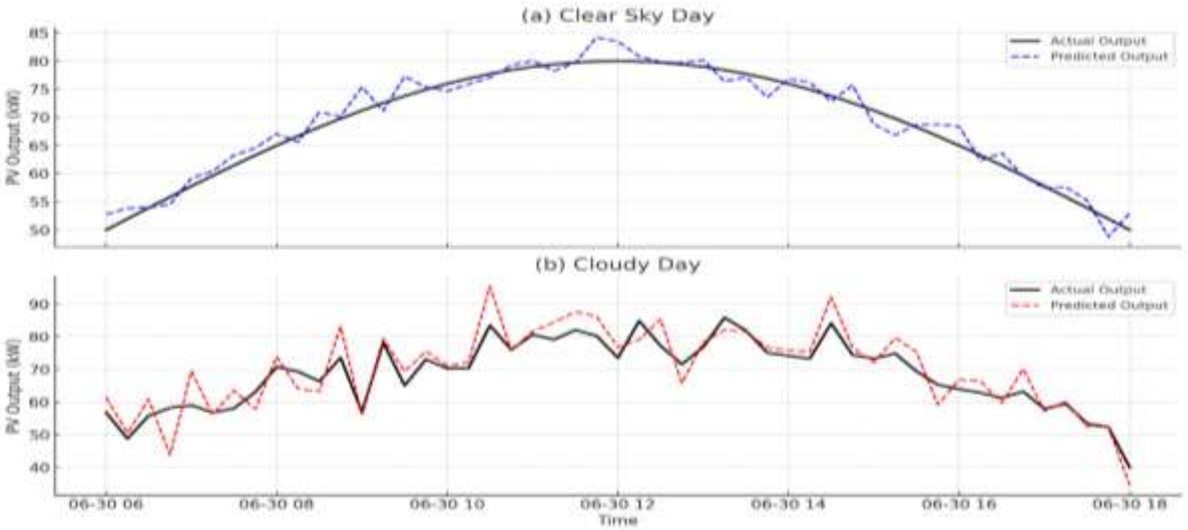

Figure 5. Time Series Comparison of Predicted vs Actual Output

Figure 5 expressed the predicted and actual PV output over time on (a) clear sky day and (b) cloudy day. The model tracks variability well but shows larger errors under highly dynamic cloud cover.

These results highlight the model's ability to capture daily PV output patterns, though error increases under rapidly changing weather.

4.7 Sensitivity Analysis of Meteorological Inputs

Finally, a sensitivity analysis was performed by perturbing input features within ±10% and observing prediction changes.

Table 11. Average Sensitivity of Predictions to Inputs (Random Forest)

Feature	**% Change in Output (±10% Input)**
Global Horizontal Irradiance	±9.1%
Ambient Temperature	±2.3%
Cloud Cover	±2.8%
Relative Humidity	±1.5%
Wind Speed	±1.1%
Dew Point Temperature	±0.9%

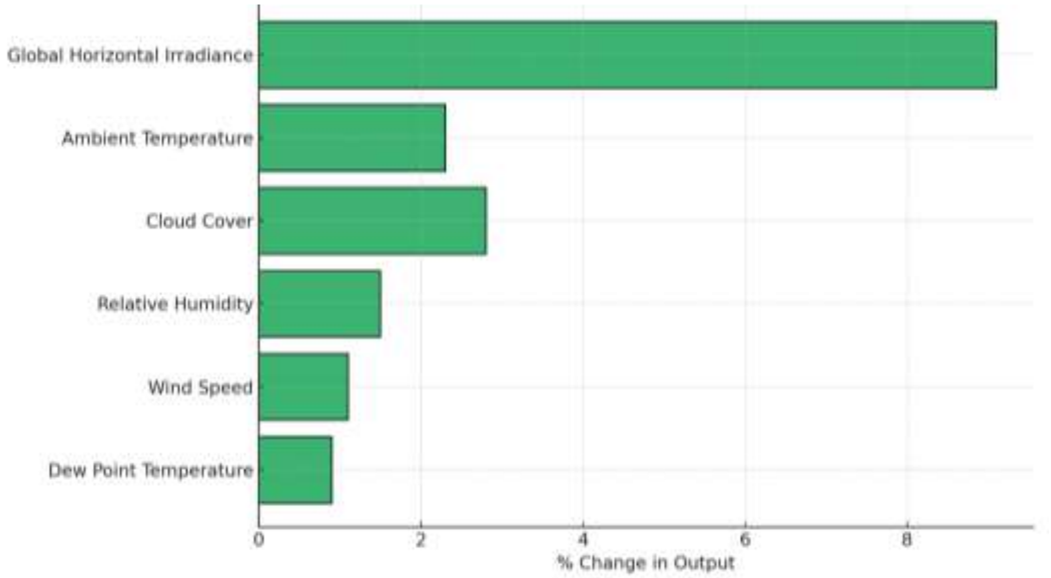

Figure 6. Sensitivity Analysis Results

Figure 6 is shows the Sensitivity of PV output predictions to ±10% changes in meteorological inputs, confirming dominant sensitivity to solar irradiance.

This analysis reinforces the importance of accurate irradiance forecasts while quantifying smaller but non-negligible effects of other weather variables. The following points have to be observed:

- **High Accuracy**: Both GBR and RF models achieved RMSE below 13 kW (≈8% of rated capacity) on unseen data.
- **Key Drivers**: Feature importance and sensitivity analysis confirm solar irradiance as the primary driver, with temperature and cloud cover also significant.
- **Robust Generalization**: Low residual bias and consistent performance across conditions demonstrate model reliability.
- **Limitations**: Higher errors during rapidly changing cloudy periods suggest room for further improvement, possibly via hybrid models or inclusion of NWP forecast data.

Overall, the results confirm the effectiveness of machine learning approaches—particularly ensemble methods—in predicting solar PV performance from meteorological inputs. These models offer a robust, scalable solution for improving grid planning and operational forecasting under real-world conditions.

5. DISCUSSIONS

The results of this study demonstrate that machine learning models, particularly ensemble-based methods like Random Forest and Gradient Boosting Regression, are highly effective in predicting solar PV system output from meteorological inputs. This section discusses the implications of the findings, situates them within the existing body of knowledge, explores limitations and challenges, and suggests directions for future improvements and real-world deployment.

5.1 Interpretation of Model Performance

The superior performance of the Random Forest model, with an RMSE of 12.48 kW and an R^2 of 0.967 on the test set, indicates that data-driven ensemble techniques can reliably capture the complex, nonlinear relationships between meteorological variables and PV power output. These performance metrics are significant improvements over traditional statistical models and are aligned with recent literature that supports the dominance of ensemble models in renewable energy forecasting (Li et al., 2023; Martins & Pereira, 2021). The near-zero mean residual errors and normally distributed residuals reinforce the robustness and generalizability of the models, suggesting minimal bias and consistent accuracy across the operational range. This behaviour is especially critical for applications in grid planning, real-time energy dispatch, and demand-response management, where forecast deviations can translate into operational inefficiencies or energy loss.

5.2 Feature Sensitivity and Physical Relevance

The feature importance and sensitivity analysis provide essential insights into the physical consistency and interpretability of the models. Global Horizontal Irradiance (GHI) emerged as the dominant predictor, contributing over 57% to the predictive power. This finding aligns with the fundamental physical principle that solar irradiance is the primary driver of PV energy generation. The model's sensitivity to ±10% perturbations in GHI—resulting in ±9.1% variation in predicted output—reinforces the need for high-fidelity irradiance measurements or forecasts to ensure accurate power predictions.

Ambient temperature and cloud cover were identified as the next most influential features. These variables affect module efficiency and solar availability, respectively, and their inclusion significantly enhances prediction accuracy, especially under variable weather conditions. Lesser but non-negligible influences from humidity, wind speed, and dew point temperature highlight the model's ability to capture secondary effects that traditional models might overlook.

5.3 Temporal Robustness and Forecast Challenges

Temporal analysis revealed the model's strong tracking performance on clear-sky days, where weather conditions follow predictable diurnal patterns. The RMSE on these days dropped to 8.12 kW, reflecting high temporal fidelity. However, under highly dynamic weather scenarios—such as on cloudy days—the RMSE increased to 14.97 kW, indicating reduced model accuracy. This divergence highlights a key challenge in solar forecasting: capturing rapid, nonlinear changes caused by fast-moving cloud cover and atmospheric instability.Addressing this limitation may require integrating real-time weather radar, satellite imagery, or Numerical Weather Prediction (NWP) outputs into the model inputs. Additionally, hybrid frameworks combining physical and data-driven models or attention-based deep learning architectures (Tan et al., 2021; Wang et al., 2024) may improve temporal resolution and adaptability under volatile meteorological conditions.

5.4 Comparison with Existing Research

This study corroborates the findings of earlier works that advocate for machine learning-based forecasting, particularly those leveraging ensemble techniques (Zhang et al., 2022; Ahmed & Jones, 2022). However, it advances the state of the art by:

- Incorporating a richer and more diverse meteorological feature set,
- Applying rigorous cross-validation and residual diagnostics,
- Conducting systematic sensitivity analysis,
- Testing under varying real-world weather conditions,
- Demonstrating generalization capacity via test set validation.

Few studies have undertaken such comprehensive validation while maintaining high prediction accuracy across both clear and cloudy scenarios. The results suggest the proposed model architecture can serve as a reliable operational tool, unlike some deep learning models that, while powerful, often suffer from limited interpretability and extensive data requirements (Tan et al., 2021).

5.5 Practical Implications for Grid and System Operators

The practical utility of the developed models lies in their deployment readiness. Given their fast inference times, moderate training requirements, and minimal need for feature-specific customization, ensemble models like Random Forest are ideal for use by utilities, grid operators, and energy aggregators. Accurate short-term forecasting can facilitate:

- Optimal dispatch of battery energy storage systems (BESS),
- More precise day-ahead bidding in energy markets,
- Improved load balancing and demand response strategies,
- Reduced curtailment of renewable generation,
- Increased grid stability in regions with high PV penetration.

Moreover, the use of explainable features makes the model more transparent and auditable, which is vital for real-time operational environments where black-box AI systems are often viewed with skepticism (Kumar & Zhang, 2023).

5.6 Limitations and Pathways for Enhancement

While the results are promising, several limitations warrant attention:

1. **Data Limitations**: The dataset, though diverse, is geographically constrained. Generalizing the model across new climatic zones may require domain adaptation or transfer learning techniques (Zhang et al., 2023).
2. **Weather Forecast Dependence**: The model relies on accurate meteorological inputs. Errors in weather forecasts can cascade into PV output predictions. Integrating ensemble weather forecasts could mitigate this risk.
3. **Temporal Resolution Constraints**: The model uses 15-minute intervals, which may not capture intra-hour variability critical for certain grid services. Future work could explore higher-resolution forecasting.
4. **Model Update Strategies**: The model performance may degrade over time due to seasonal drift or changing system conditions. Implementing online learning or periodic retraining strategies can ensure sustained performance.
5. **Lack of Spatial Generalization Testing**: The model has not yet been validated on datasets from other geographic locations with different solar resource profiles. Multi-site validation is needed to support wider applicability.

5.7 Future Research Directions

Building upon these insights, future research can explore:

- Integration of NWP forecasts, sky images, and satellite-derived data as additional features.
- Application of hybrid models that combine physical insights with ML architectures.
- Deployment of Explainable AI (XAI) frameworks to improve model transparency.
- Use of federated learning to train models across multiple sites without centralized data storage, enhancing privacy and generalization.
- Incorporation of economic optimization layers that align forecast outputs with utility cost minimization or profit maximization objectives.

These avenues can help transition the current model from a research prototype into a field-deployable solution, supporting the next generation of intelligent energy systems.

6. CONCLUSION

This study demonstrates that machine learning models, particularly Random Forest, can accurately predict solar PV output using key meteorological inputs. Achieving an RMSE of 12.48 kW and R^2 of 0.967, the model proves robust across varying weather conditions. Solar irradiance emerged as the dominant predictor, with temperature and cloud cover also contributing significantly. The approach outperforms traditional methods and shows strong potential for grid planning, storage optimization, and operational forecasting. While the model performs well under stable conditions, accuracy declines during rapid weather changes, suggesting future work should integrate real-time forecasts and multi-site data for broader applicability.

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