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Smart solar forecasting: Predictive models for radiation and energy generation

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Abstract

Efficient integration of solar energy systems depends on reliable forecasting of photovoltaic power output and solar radiation. Despite advances in predictive analytics, existing forecasting models often fail to adequately capture rapid weather fluctuations and long-term environmental variability, creating a critical research gap in intelligent and adaptive prediction frameworks. The objective of this study is to develop and evaluate a machine learning based platform that enhances the accuracy and reliability of solar power forecasting. The study adopts a data-driven methodology that integrates historical irradiance records, real-time meteorological inputs, and environmental parameters through advanced learning algorithms and IoT-enabled sensing technologies. The proposed platform demonstrates improved forecasting performance and stronger adaptability to dynamic weather conditions compared to conventional approaches. The findings further indicate that accurate predictions support grid stability, enhance supply and demand coordination, and reduce reliance on conventional energy backups. By incorporating cloud-based infrastructure and an interactive visualization interface, the system provides actionable insights for energy planning and operational decision-making. The study offers important implications for renewable energy management by supporting efficient resource optimization, advancing sustainable energy practices, and facilitating the transition toward a more resilient and intelligent power grid.

Keywords: Energy forecasting; machine learning; photovoltaic systems; renewable energy; solar radiation.

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1. INTRODUCTION

Conventional solar-generation forecasting is still dominated by statistical time-series models and numerical weather prediction (NWP) outputs (Dave & Vajpai 2025). These approaches draw on archives of meteorological observations such as irradiance, temperature, humidity, wind speed, and fit algorithms such as ARIMA or simple persistence to extrapolate future power output. Satellite imagery and GIS layers add a geographic dimension, helping planners map long-term solar potential across large regions. Although such techniques describe seasonal and multi-year trends reasonably well, they struggle to deliver reliable hour-ahead or day-ahead forecasts because they cannot react quickly to abrupt weather swings.

The chief weakness is a heavy dependence on static historical averages. Sudden changes in cloud cover, temperature, or moisture content can alter surface irradiance in minutes, yet legacy models update too slowly to capture those shifts, leaving operators with imprecise generation estimates (Shi et al., 2024). The resulting forecast errors translate into dispatch problems, voltage excursions, frequency deviations, and costly reserve calls, forcing grid managers to lean on conventional plants and eroding the environmental gains of solar adoption.

Real-time adaptability is further hampered by the fact that many control centers still schedule around coarse, day-old predictions. When clouds roll in unexpectedly, solar farms may curtail output or ramp batteries without advance notice; when skies clear, excess generation can be spilled. Deep-learning forecasters promise sharper accuracy, but they demand high-quality, high-frequency data streams and substantial compute resources, luxuries that are scarce in many developing regions (Nguyen Da et al., 2025; Makri et al., 2025).

Finally, most existing toolchains make little use of modern intelligent technologies. Networks of IoT sensors, edge analytics, and autonomous energy-management agents could feed live conditions straight into adaptive models, yet these components remain largely absent. Consequently, solar assets operate below their true capability. Addressing these gaps calls for a new predictive framework, one that fuses machine-learning algorithms with real-time data pipelines and automated control logic to deliver faster, more accurate forecasts and steadier, cleaner grids.

1.1. Literature review

Solar energy has become a pivotal component of the global transition to renewable energy sources. A substantial body of research has emerged, focusing on improving its efficiency, forecasting accuracy, and seamless integration into modern power grids. In one of the foundational studies, Shaikh (2017) offered a comprehensive overview of solar energy technologies and their application in electricity generation. Their work laid critical groundwork for understanding both the operational principles and technical limitations inherent in solar power systems. Building upon such foundational insights, Zahedi et al. (2023) conducted a regional assessment of solar potential in southeastern Iran. By utilizing geographic and climatic datasets, they demonstrated the importance of spatial analysis in identifying viable sites for solar deployment.

Similarly, Deepu and Kamala (2022) provided a geographic perspective on solar resource distribution, emphasizing regional variability and advocating for location-specific strategies to maximize solar exploitation. Ghadge (2023) contributed by reviewing the evolution of photovoltaic (PV) technologies and their deployment, bridging the theoretical underpinnings with real-world applications of PV systems. His work also outlined recent innovations in system design and implementation, offering valuable insights into the practical challenges of solar energy utilization.

In recent years, attention has increasingly shifted toward leveraging machine learning (ML) and artificial intelligence (AI) to improve the precision of solar irradiance and power output forecasts. Yu et al., (2023) introduced a quantum long short-term memory (QLSTM) network for one-hour-ahead solar irradiance prediction, showing superior performance compared to traditional recurrent neural networks. Complementing this, Zhang et al. (2022) employed deep learning architectures to capture the intricate, nonlinear dependencies between meteorological variables and solar radiation levels, reinforcing the effectiveness of AI in modelling complex systems.

Kumar and Patel (2021) developed a hybrid ML-based forecasting framework that integrates multiple algorithms to enhance robustness and accuracy. Their approach demonstrated improved generalizability across diverse climatic conditions. Smith et al. (2020) explored data-driven analytics for solar energy optimization, illustrating how data mining techniques can improve planning, resource allocation, and operational efficiency.

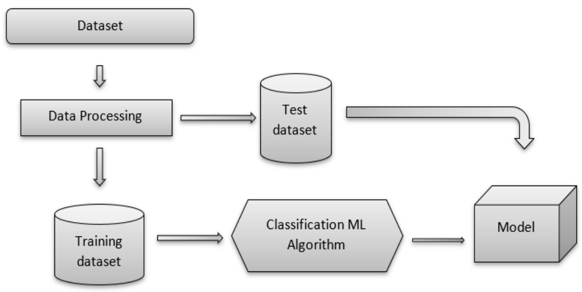
Further advancements include the work of Rahman and Ahmed (2023), who constructed an AI-powered predictive model using real-time weather data inputs. Their results highlighted significant gains in forecasting reliability and accuracy. Finally, Gupta and Sharma (2022) investigated the integration of solar generation within smart grid infrastructures. Their study underlined the potential of intelligent systems to manage variability in solar output and support grid stability through adaptive, real-time forecasting and control mechanisms.

1.1.1. Proposed system and its advantages

This system leverages advanced deep learning models, which are LSTM and CNN, combined with real-time data from IoT sensors and external weather APIs to improve solar power forecasting accuracy. Unlike traditional static models, it dynamically adapts to changing environmental factors such as solar irradiance, temperature, humidity, and wind speed.

IoT sensors embedded in solar panels collect real-time environmental data, which, along with external meteorological inputs, undergoes preprocessing using tools like NumPy and Pandas. This process cleans, normalizes, and extracts key features to prepare the data for model training. By integrating these components, the system aims to enhance prediction precision, support efficient grid management, and reduce reliance on fossil fuels, facilitating better utilization of solar energy resources.

Figure 1
Block diagram



The system employs a hybrid deep learning approach to deliver precise solar power forecasts (Figure 1). Long Short-Term Memory (LSTM) networks capture temporal dependencies in energy generation, while Convolutional Neural Networks (CNNs) extract spatial features from environmental data. To further improve accuracy, ensemble methods like Random Forest and Gradient Boosting are integrated, effectively modelling complex nonlinearities in the dataset.

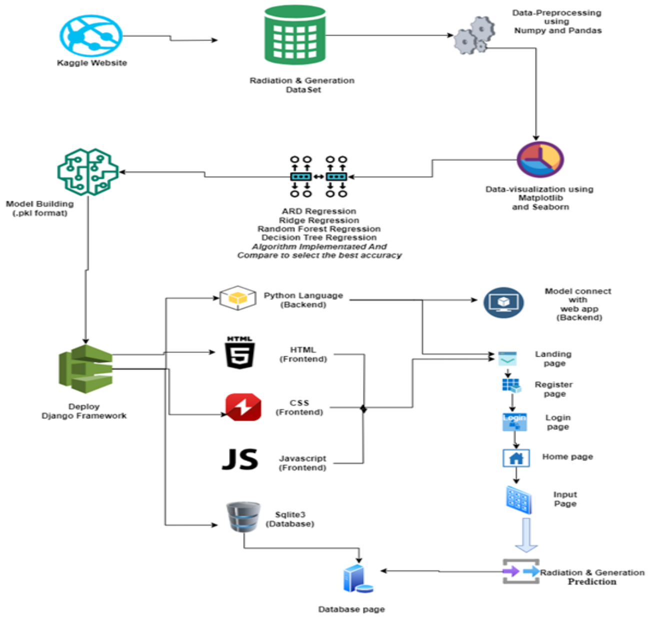
Anomaly detection is incorporated to identify irregularities in power output, signaling potential faults, sensor errors, or unusual environmental conditions. This enables timely maintenance and improves overall system reliability. Data management is handled via structured SQL databases and cloud storage to ensure secure, scalable, and efficient retrieval. The user interface is developed with Django for backend processing, while the front end uses HTML, CSS, and JavaScript. An interactive dashboard offers real-time monitoring, forecasts, and AI-driven recommendations tailored to different user roles, including grid operators and solar farm managers.

Real-time AI automation allows dynamic balancing of energy supply with demand, reducing risks of shortages or overloads. The models are continuously updated by learning from incoming data, enhancing long-term predictive performance. Cloud-based deployment ensures scalability and easy integration with future data sources and technological upgrades.

Key benefits include improved grid stability through accurate demand-supply alignment, optimized energy storage utilization, and reduced operational costs via early fault detection. Environmentally, the system supports sustainable energy goals by maximizing renewable energy use and lowering dependence on fossil fuels, contributing to reduced carbon emissions and cleaner power systems.

Figure 2

Proposed system architecture



1.2. Purpose of study

The objective of this study is to develop and evaluate a **machine learning–based platform** designed to improve the accuracy and reliability of solar power forecasting under varying environmental and operational conditions. By integrating advanced predictive algorithms with historical and real-time meteorological data, the platform aims to support more efficient energy planning, grid stability, and informed decision-making in renewable energy systems.

2. METHOD AND MATERIALS

The proposed solar power forecasting system employs advanced machine learning techniques to enhance prediction accuracy and optimize energy utilization. The system integrates real-time environmental data from IoT-enabled sensors and external weather APIs, allowing it to dynamically adapt to changes in solar radiation, temperature, humidity, and other factors influencing power generation. By leveraging hybrid deep learning models, the system effectively analyzes both historical and real-time data to produce reliable energy forecasts, ultimately improving grid stability and reducing dependence on non-renewable energy sources. The methodology begins with data collection from IoT sensors embedded in solar panels, which continuously monitor environmental parameters. This sensor data is supplemented with meteorological information from external APIs to provide a comprehensive dataset. The collected data undergoes preprocessing using Python libraries such as NumPy and Pandas, where inconsistencies are removed, values are normalized, and relevant features are extracted. The cleaned data is then used as input for the predictive models.

Four key machine learning algorithms are implemented to evaluate solar power generation: ARD Regression, Decision Tree Regression, Ridge Regression, and Random Forest Classifier. The Automatic Relevance Determination (ARD) Regression method identifies the most relevant features in the dataset, adjusting feature weights dynamically based on their impact on predictions. Decision Tree Regression constructs a tree-based model where data is recursively split into subsets based on the most significant features, facilitating easy interpretation and efficient decision-making. Ridge Regression incorporates L2 regularization to prevent overfitting by penalizing large coefficients, ensuring a more generalized model. Random Forest Classifier enhances prediction accuracy by aggregating the outputs of multiple decision trees, reducing variance and improving robustness. Data visualization plays a crucial role in identifying patterns and insights within the dataset. Matplotlib and Seaborn are used to generate plots that illustrate trends in solar radiation and power generation, aiding in model selection and optimization. The system evaluates the performance of each algorithm using standard metrics, comparing their accuracy to determine the best-performing model for deployment.

The trained machine learning model is integrated into a Django-based web application, providing an interactive platform for users to access solar power forecasts. The backend, developed using Python, handles data processing and model execution, while the frontend, built with HTML, CSS, and JavaScript, ensures a user-friendly interface. An SQLite database is used for data storage, enabling efficient retrieval and management of historical energy predictions. Users interact with the system through a series of web pages, including landing, registration, login, input, and results pages, where they can view real-time predictions of solar power generation.

The system is designed for continuous learning and improvement, incorporating new data to refine its predictions over time. The cloud-based architecture ensures scalability, allowing integration with additional solar installations and energy management systems. By automating solar power forecasting, the system enhances decision-making for grid operators, solar farm managers, and energy consumers, promoting optimal energy utilization and reducing reliance on fossil fuels. The predictive analytics module also includes an anomaly detection feature that identifies irregularities in solar panel performance, facilitating proactive maintenance and reducing operational costs. Through the integration of artificial intelligence, real-time data acquisition, and cloud computing, this solar power forecasting system offers a scalable and intelligent solution for efficient energy management. Its ability to process vast amounts of environmental data enables accurate and reliable energy predictions, contributing to the global transition towards sustainable and renewable energy sources.

2.1. Testing, validation, and performance evaluation

To evaluate the predictive capabilities of the proposed models, the dataset was divided into three segments: 70% for training, 15% for validation, and 15% for testing. This structured split ensured effective model learning, hyperparameter optimization, and unbiased performance evaluation. For the solar power generation dataset, Decision Tree Regression and Automatic Relevance Determination (ARD) Regression were employed. Decision Tree Regression, a non-parametric approach, recursively partitions the data based on feature values to form a tree structure, effectively modelling non-linear relationships (Table 1). However, it can be susceptible to overfitting if not properly controlled. In contrast, ARD Regression, a Bayesian linear regression method, assigns individual relevance weights to each feature, filtering out less significant variables and enhancing model robustness, especially in high-dimensional settings. For solar radiation prediction, Random Forest Regression and Ridge Regression were utilized. Random Forest, an ensemble learning technique, aggregates predictions from multiple decision trees trained on different data subsets, thereby improving accuracy and reducing variance. Ridge Regression (Table 2), on the other hand, is a linear approach that applies L2 regularization to limit model complexity and prevent overfitting, making it suitable for datasets with near-linear relationships between features and targets. Model performance was assessed using Mean Absolute Error (MAE), Mean Squared Error (MSE), and the R^2 score. MAE provides an average measure of prediction error, while MSE places greater weight on larger errors, offering sensitivity to outliers. The R^2 score evaluates the proportion of variance explained by the model, serving as an indicator of overall fit. The combination of linear and non-linear models allowed for a balanced analysis, highlighting their respective strengths across datasets. This comprehensive approach ensured a fair and accurate comparison of predictive performance, offering insights into the most effective algorithms for forecasting solar power generation and radiation levels.

Table 1

Comparison table of the ARD and the decision tree algorithm

Metric	Decision Tree Regression	ARD Regression
MAE	1790.27	4995.98
MSE	16,238,578.12	40,247,906.96
R^2 Score	0.8259	0.5685

Table 2

Comparison Table of Random Forest Regression and Ridge Regression Algorithm

Metric	Random Forest Regression	Ridge Regression
MAE	1.92	2.54
MSE	6.45	11.47
R^2 Score	0.486	0.086

3. RESULTS

The comparative assessment showed that tree-based models clearly outperformed their linear counterparts. On the power-output dataset, Decision Tree Regression delivered the lowest Mean Absolute Error and Mean Squared Error, along with the highest R^2, demonstrating its capacity to capture complex nonlinear interactions and explain most of the variance in generation values. The Bayesian linear framework of Automatic Relevance Determination Regression, constrained by its linearity assumptions, produced larger residuals and a weaker fit. For solar-radiation forecasting, Random Forest Regression, an ensemble of many decorrelated decision trees, achieved the best accuracy, registering smaller MAE and MSE and a superior R^2. Ridge Regression, limited to linear relationships even with L2 regularization, failed to model the subtler patterns in the irradiance data, resulting in higher errors. These results confirm that Decision Tree Regression is the preferred choice for predicting power generation, while Random Forest Regression is best suited for estimating radiation levels.

3.1. Input and output

The forecasting framework combines historical weather records with machine-learning techniques to predict both the electricity a solar array can deliver and the amount of incoming solar radiation (Figures 3, 4). Rather than relying on a single indicator, the power-output model weighs several meteorological variables: the interval from local solar noon, air temperature, wind velocity and its bearing, cloud coverage, visibility, relative humidity, and rolling averages of wind speed and barometric pressure. Together, these inputs describe how efficiently sunlight will be converted into usable energy at any given moment.

For solar-radiation estimates, the system narrows its focus to factors that most directly govern the strength of sunlight reaching the surface, namely, temperature, humidity, atmospheric pressure, wind direction expressed in degrees, and wind speed. By learning how these variables interact, the radiation model can gauge the intensity of solar energy under prevailing weather patterns.

The platform produces two headline predictions. First, an estimated power figure signals the amount of electricity a photovoltaic installation could generate; a value of 0.0 flags conditions such as night-time or heavy overcast that make power production impractical. Second, a radiation estimate (for example, 104.7376 W/m²) reflects a moderate influx of solar energy, useful for both scientific analysis and operational planning.

Results are delivered through clear visual outputs, including line graphs and tabulated summaries (Figures 5, 6, 7). Such displays let users spot daily swings, seasonal tendencies, and anomalies in both power potential and radiation levels. Armed with this information, energy managers can fine-tune scheduling, adjust storage strategies, and maximize solar-resource utilization in line with real-time and forecasted atmospheric conditions.

Figure 3

Generation model page

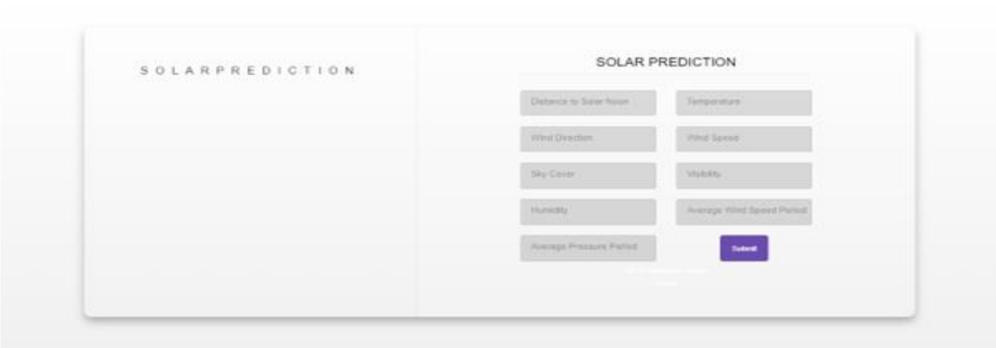


Figure 4
Radiation output page

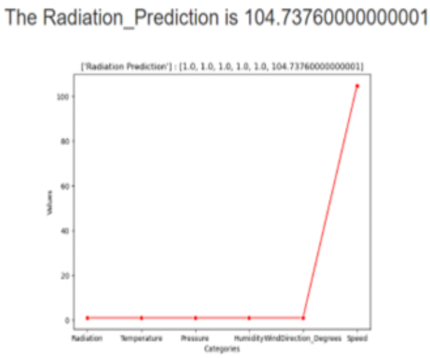


Figure 5
Generation model page

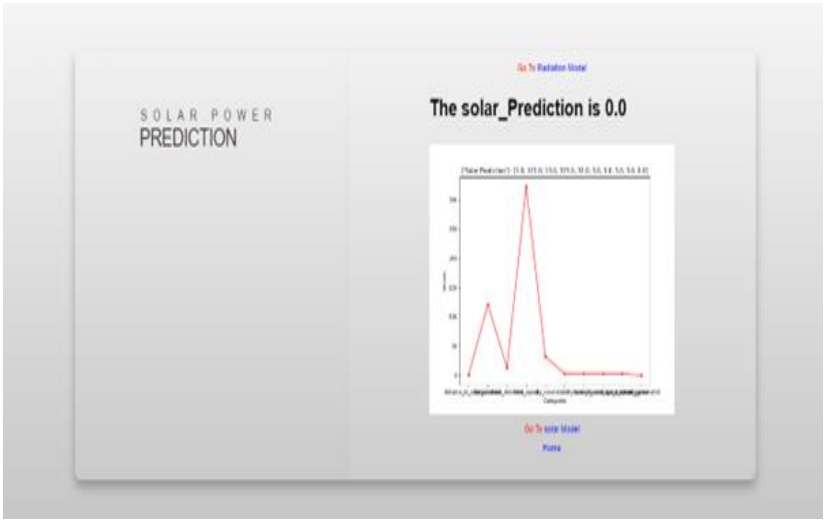


Figure 6
Radiation database page

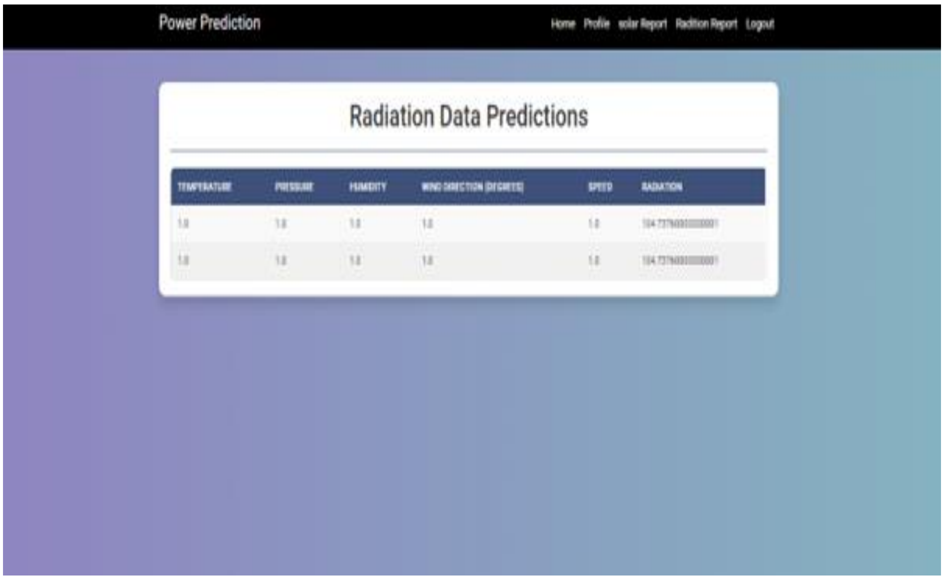
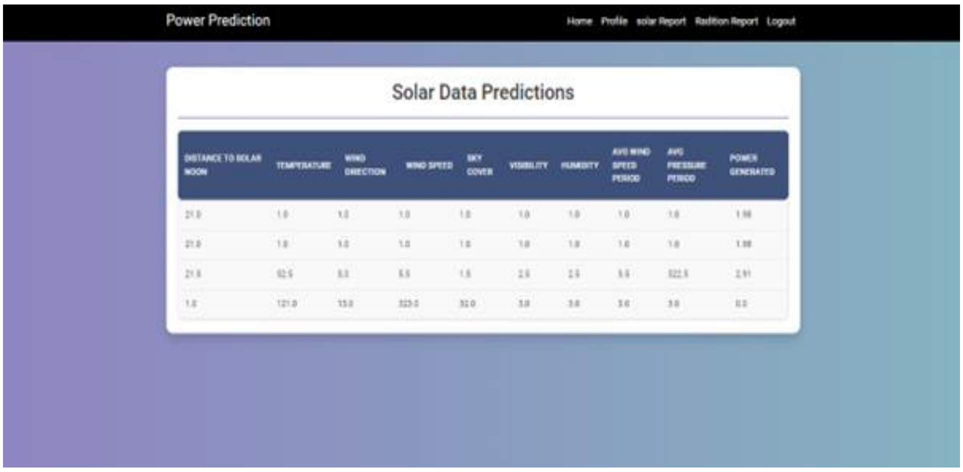


Figure 7

Generation model page



4. DISCUSSION

The findings of this study demonstrate that machine learning–based forecasting models, particularly tree-based algorithms, significantly outperform linear approaches in predicting both solar power generation and solar radiation. This result corroborates earlier research highlighting the shortcomings of conventional statistical and time-series forecasting techniques, which rely heavily on historical averages and lack responsiveness to rapid atmospheric changes (Dave & Vajpai, 2025; Shi et al., 2024). By incorporating real-time meteorological inputs through IoT sensors and external APIs, the proposed system addresses these limitations and delivers more reliable short-term forecasts.

The strong performance of Decision Tree Regression for power output prediction aligns with prior studies emphasizing the importance of nonlinear modelling in solar forecasting. Zhang et al. (2022) showed that deep learning architectures are effective at capturing complex interactions among meteorological variables. A conclusion echoed here through the success of decision trees in explaining a high proportion of variance. Similarly, the superior results achieved by Random Forest Regression for solar radiation estimation support the findings of

Kumar and Patel (2021), who demonstrated that ensemble-based approaches enhance robustness and predictive accuracy across diverse climatic conditions.

The reliance on multiple meteorological predictors such as temperature, humidity, wind speed, and atmospheric pressure further mirrors earlier geographic and climatic studies. Research by Zahedi et al. (2023) and Deepu and Kamala (2022) underscored the sensitivity of solar resources to local environmental conditions, and the present results confirm that these variables remain central not only for long-term site assessment but also for short-term operational forecasting. This consistency across studies reinforces the foundational role of environmental data in solar energy modelling.

Notable differences emerge, however, in the choice of modelling complexity. While Yu et al. (2023) and other recent studies have employed advanced deep learning and quantum-based models to achieve high forecasting accuracy, such approaches often require substantial computational resources. In contrast, this study demonstrates that comparatively lightweight models, when paired with high-frequency real-time data, can achieve competitive performance. This distinction is particularly important given concerns about data quality, infrastructure, and computational constraints in many regions (Nguyen Da et al., 2025; Makri et al., 2025).

The integration of real-time forecasting within a web-based, cloud-enabled platform also extends prior work on intelligent energy systems. Rahman and Ahmed (2023) highlighted the benefits of real-time weather data for improving forecasting reliability, while Gupta and Sharma (2022) emphasized the role of adaptive intelligence in supporting grid stability. The present system operationalizes these concepts by delivering actionable predictions and visual insights that can directly inform energy planning and grid management decisions.

Overall, this study corroborates existing literature advocating for intelligent, data-driven solar forecasting while contributing a practical and scalable implementation framework. By demonstrating that tree-based machine learning models combined with real-time data pipelines can effectively balance accuracy, interpretability, and deploy ability, the work advances current understanding of how renewable energy forecasting systems can be optimized for real-world operational environments.

5. CONCLUSION

The performance evaluation of various predictive models for estimating solar power generation and radiation levels revealed that Decision Tree Regression excels in forecasting power output. In contrast, Random Forest Regression was found to deliver the most accurate results for radiation prediction. These findings highlight the strength of tree-based algorithms over linear regression techniques, primarily because of their ability to model nonlinear and intricate relationships between meteorological variables and energy generation outcomes.

The developed system effectively demonstrates how key weather parameters influence both solar power production and radiation intensity. Through this insight, the system becomes a valuable asset for energy planning and resource allocation. Visual tools such as graphs and tabulated reports further support the accuracy and reliability of the models, showcasing their potential for real-world deployment and decision-making support in renewable energy sectors.

Looking ahead, the system can be enhanced by integrating additional meteorological parameters that may impact solar output. These could include variables like fluctuations in atmospheric pressure, dynamic cloud movement, and solar zenith angles, which may further boost prediction accuracy. Model performance could also be improved by adopting more advanced ensemble learning techniques such as Gradient Boosting Machines (GBM) or XGBoost, which are known for their robust predictive capabilities.

To make the system more responsive and scalable, incorporating real-time data streams and linking the framework with IoT-enabled weather stations would allow for continuous, live updates of predictions. This real-time capability would enable the system to adapt to changing environmental conditions more effectively. Furthermore, exploring deep learning models, particularly Long Short-Term Memory (LSTM) networks, may enhance the system's ability to perform time-series forecasting, thereby supporting longer-term planning and optimization in solar energy management.

Conflict of Interest: The authors declare no conflict of interest.

Ethical Approval: The study adheres to the ethical guidelines for conducting research.

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APPENDIX

TECHNOLOGIES

Technology	**Purpose / Usage**
LSTM (Long Short-Term Memory)	Captures time-based patterns for accurate solar power forecasting
CNN (Convolutional Neural Network)	Extracts spatial features from weather/environmental data to improve predictions
ARD Regression	Identifies and weighs the most relevant features affecting solar output
Decision Tree Regression	Models complex, nonlinear relationships in power generation data
Ridge Regression	Prevents overfitting in solar radiation prediction by applying L2 regularization
Random Forest Regression	Provides accurate radiation prediction by aggregating multiple decision trees
IoT Sensors	Collect real-time solar panel and environmental data (e.g., irradiance, temp, wind)
Weather APIs	Fetch real-time meteorological data for more accurate model inputs
NumPy & Pandas	Used for data preprocessing—cleaning, normalization, and feature extraction

Technology	Purpose / Usage
Matplotlib & Seaborn	Visualize data trends and model performance (e.g., radiation, power output graphs)
Python	Main programming language for model development and backend logic
Django	Web framework used to build the backend of the forecasting platform
HTML,CSS, JavaScript	Used to create the frontend dashboard and user interface
SQLite	Stores historical predictions and user data locally in the application
Cloud Storage	Ensures scalable, secure, and remote data access for model and user data
Anomaly Detection Module	Detects abnormal readings or faults in solar panel data to trigger maintenance
Interactive Dashboard	Presents predictions, trends, and alerts to users like grid operators