Enhanced integration of renewable energy and smart grid efficiency with data-driven solar forecasting employing PCA and machine learning

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ABSTRACT

A significant obstacle to preserving grid stability and incorporating renewable energy into smart grids is variations in solar irradiation. To improve solar power management's dependability, this research proposes a short-term solar forecasting framework powered by AI. Multiple machine learning models, such as long short-term memory (LSTM), random forest (RF), gradient boosting (GB), AdaBoost, neural networks (NN), K-Nearest neighbor (KNN), and linear regression (LR), are integrated into the suggested system, which also uses principal component analysis (PCA) for dimensionality reduction. The Abiod Sid Cheikh station in Algeria (2019–2021) provided real-world data for the model's validation. With a two-hour-ahead RMSE of 0.557 kW/m², AdaBoost had the most accuracy, whereas LR had the lowest, at 0.510 kW/m². In addition to increasing computing efficiency, PCA preserved 99.3% of the data volatility. In addition to increasing computing efficiency, PCA preserved 99.3% of the data volatility. These findings highlight the efficiency of hybrid AI models based on PCA for accurate forecasting, which is crucial for smart grid stability.

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1. INTRODUCTION

This work emphasizes the need of accurate photovoltaic (PV) forecasting to enhance solar energy management and increase smart grid dependability by addressing problems such as grid instability and fluctuating power outputs using state-of-the-art methods. To ensure dependable assumptions, the study evaluates performance metrics like R2, RMSE, and MAE using a detailed analysis of Algerian solar data (2019–2021). The research will focus on forecast accuracy over a variety of time horizons and optimize data processing to encourage sustainable energy integration, reduce dependency on non-renewable sources, and enhance system efficiency. These findings demonstrate how new technologies have the ability to promote the usage of renewable energy sources.

Transformation of electric grids for climate adaptation: opportunities and problems are discussed by Kasperson and Ram [1] and Stephens *et al*. [2]. According to Jäger-Waldau *et al*. [3], photovoltaics can help reduce emissions in the EU. The statistical foundations of regression models are examined by Krämer and Sonnberger [4], while the sustainability of renewable energy is reviewed by Owusu and Sarkodie [5]. For energy forecasting, Shapi *et al*. [6] use machine learning [7] looks at robust optimization and adaptive grid management techniques. For solar energy forecasting, recent works [8]–[21] have concentrated on machine learning and deep learning methods such as artificial neural network (ANN), random forest (RF), gradient boosting (GB), and long short-term memory (LSTM). Principal component analysis (PCA) [22] and correlation approaches are used to improve prediction accuracy and processing efficiency.

The works in [23]–[25] separated photovoltaic forecasts into three categories: image-based methods utilizing cloud motion vectors (CMVs), statistical methods (e.g., ARIMA, AI-based SVMs, ANNs), and numerical weather prediction (NWP) models. CMVs employ satellite or ground images for short-term forecasts, while NWP models, like WRF and its urbanized equivalent uWRF, do well across one to three-day timescales. Under various conditions, these techniques increase the accuracy of solar forecasting by taking into account various temporal and spatial requirements [23]–[25].

Figure 1 shows the Abiod Sid Cheikh solar power station location. This study makes use of a large dataset from a 23 MW solar facility at Abiod Sidi Cheikh, Algeria, which included 726,012 measurements taken at 15-minute intervals between January 2019 and December 2021. Date and time, sun irradiation, temperature, pressure, humidity, wind speed, and power output are the seven crucial characteristics that are recorded in the dataset. According to seasonal study, energy production peaks in the spring and summer, with an 8.62 GW output in April 2019. According to statistical analysis, the average solar irradiation is 455 W/m2, and there is moderate variation in the irradiance, humidity, and pressure (33–60% CV), but there are notable variations in temperature and wind speed (up to 314% CV). This dataset highlights the region's potential for producing renewable energy and aids in the creation of precise solar forecasting models by offering insightful information on daily and seasonal fluctuations.

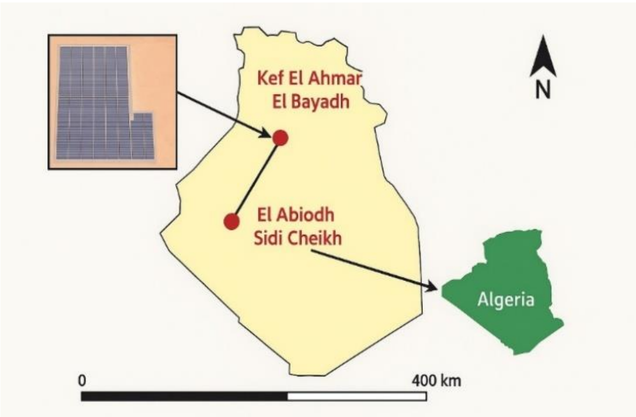

Figure 1. Abiod Sid Cheikh solar power station location

2. METHOD

The supply forecast framework, which forecasts global horizontal irradiance (GHI) for PV panels across short to long time horizons, the initial stage of the solar energy forecast methodology. The model is based on a huge dataset that was gathered using a pyranometer at 10-second intervals over a period of six years. Missing values, outliers, and clear-sky irradiance (GHIcs) are all part of data preprocessing. Nighttime data is also removed, and the clear-sky index (kcs) is calculated. To ensure better consistency and precision of the data and capture variations, seasonal trends, and derivative features are included. Key GHI measures, derivatives, and seasonal indicators are among the improved feature set that is produced by down-sampling the data to accommodate various forecasting intervals. The mean irradiance across specified time periods is predicted leveraging a deep learning model based on LSTM. Time-series cross-validation with R2, AE, and RMSE metrics serves to validate the capability of the model. As demonstrated in the suggested architecture in Figure 2, this technique permits precise solar forecasting, assisting with smart grid optimization and electricity market planning.

This study starts with thorough data cleaning and preparation to remove missing values, outliers, and anomalies, ensuring a solid foundation for analysis. A dimensionality reduction approach known as PCA is then applied to determine essential parameters, reducing data dimensionality for more efficient processing and presentation. PCA detects a smaller collection of uncorrelated variables, reducing computation time, removing noise, and improving algorithm performance while maintaining 99.3% of data variance. Using covariance approaches, the dataset is reduced to a lower dimension, making further analysis easier.

By lowering the number of variables while keeping the most important information, the PCA technique helps to simplify datasets. By determining the covariance of the variables, finding trends, and reorganizing the data, it examines the connections between them. In essence, PCA creates a new dataset Y (of size $q\times n$), from a dataset X (dimensions $m\times n$), where m stands for variables and n for observations, with q being much lower than m. The quality of the data for analysis is improved, computational efficiency is increased, and redundant or noisy information is eliminated. PCA makes tasks like visualization, algorithm optimization, and increasing forecasting or classification accuracy easier by lowering the dimensionality of the dataset. It's particularly helpful for efficiently managing huge, connected information in domains like meteorology.

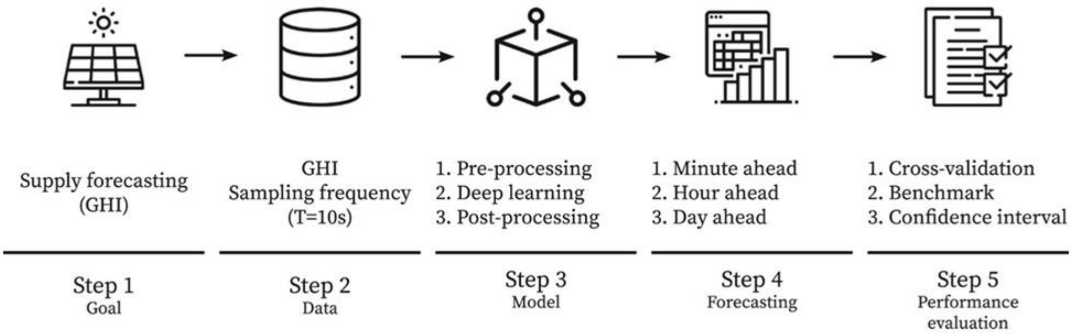

Figure 2. Proposed supply forecasting framework

Hourly, monthly, and annual solar power generation during the study period are displayed in Figures 3(a) and 3(b). Measures such as mean absolute error (MAE), root mean square error (RMSE), R2, and Adjusted R2 will be used to evaluate the effectiveness of each machine learning model used in this investigation. These measures evaluate the models' prediction performance by contrasting expected values (Xi) with actual measurements (Yi). The computations also take into account the mean of the observed values to give a thorough assessment of the accuracy and dependability of the models. Table 1 shows the PCA findings and specific properties.

2.1. Models of forecasting

The six machine learning forecasting techniques evaluated in this study include RF, neural networks (NN), k-nearest neighbor (KNN), AdaBoost, LR, and GB. Each algorithm applies a unique learning approach and optimization strategy to improve forecasting accuracy and model performance. Their comparative assessment offers meaningful insights into identifying the most effective technique for achieving reliable and precise forecasting results.

2.1.1. Random forest (RF)

The random forest (RF) classifier enhances prediction accuracy by constructing multiple decision trees on different subsets of the input data. It then combines or averages the results from these trees to produce a more reliable and stable output. Figure 4 illustrates the schematic diagram of the RF algorithm used in this study.

2.1.2. K-nearest neighbor (KNN)

The supervised machine learning method KNN classifies new data points by comparing them to existing categories based on similarity. The process involves selecting the number of neighbors (K), calculating the Euclidean distance to find the nearest neighbors, listing these neighbors, counting data points in each class within K, and assigning the new point to the class with the highest count. The Euclidean distance formula is defined as: Ed=√(x2-x1)2(y2-y1)2. This simple yet effective algorithm is widely used in classification tasks. Figure 5 shows the KNN algorithm.

(a)

(b)

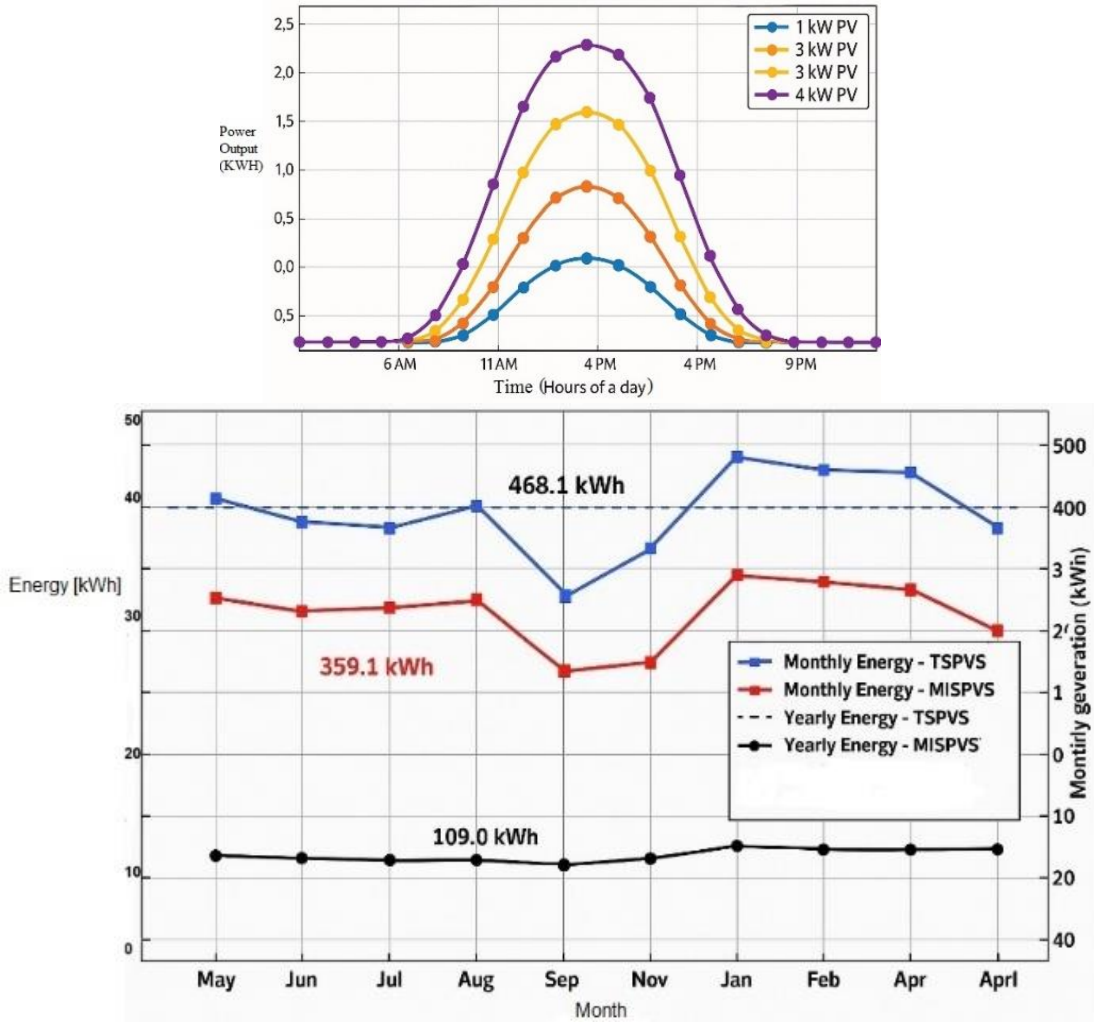

Figure 3. Solar power generation during the study period: (a) hourly solar power generation and (b) monthly and annual solar power production throughout the research period

Table 1. PCA results and selected features

T (C)	H %	Pr (h.Pa)	W (s/m)	G.Ird (w/mA^2)	Power (megawatt)	PCI	PCII	PCIII	PCIV
6.1	49.1	923	2.7	249	3.97	-6.91	211.8	220.5	-32.8
8.91	41.5	923	2.5	421	9.89	-90	84	224	-14.8
12.1	38.5	921	2.1	258	12.7	-9.9	175	53.7	-74.8
8.5	49.7	921	1.8	72	8.38	26.4	389	203.9	58.3
6.7	47.3	921	3.4	251	1.05	-3.9	158	-12.7	-91.6

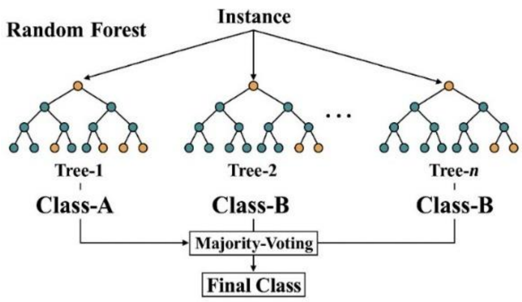

Figure 4. Random forest algorithm

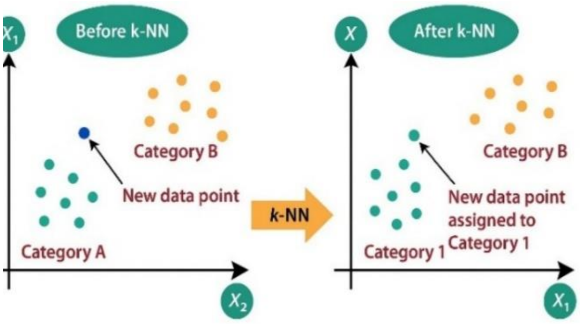

Figure 5. K-nearest neighbor (KNN)

2.1.3. Neural networks (NNs)

Neural networks (NNs) process solar irradiance data through layers, adjusting weights and biases to improve prediction accuracy. In this study, NNs play a key role in forecasting solar photovoltaic (PV) power, aiding efficient solar energy integration into smart grids. Figure 6 shows a neural network algorithm.

$$Z=(\Sigma x_k^{j-1}W_{k,i}-b_k) \text{ limits } k=1 \text{ to } N_{j-1}$$

Wk,i is the weight associated with the connection from node k to all nodes in the previous levels, and bi is the node's bias. xk j−1 represents the data received by the kth node in the jth layer. Furthermore, the number of nodes in layer j − 1 is denoted by Nj−1. The activation function then receives the total.

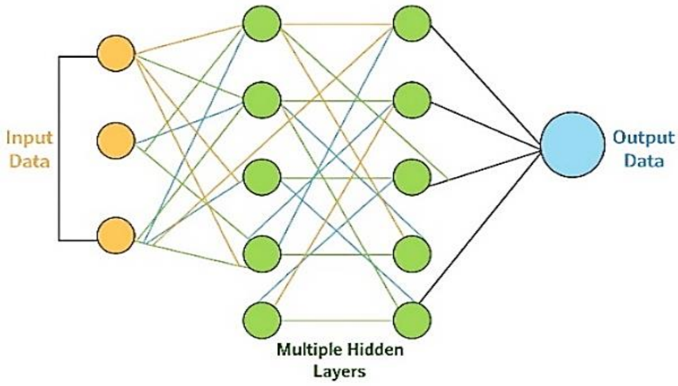

Figure 6. Neural network

2.1.4. AdaBoost

Through an ongoing process of modifying weights on incorrectly categorized instances, boosting transforms weak models into stronger predictions. By applying a base learner over rounds (t = 1,...,T), AdaBoost increases attention to difficult cases. The weak learner lowers error rates for increased overall accuracy by producing hypotheses (ht) based on updated weights. Figure 7 shows the AdaBoost algorithm.

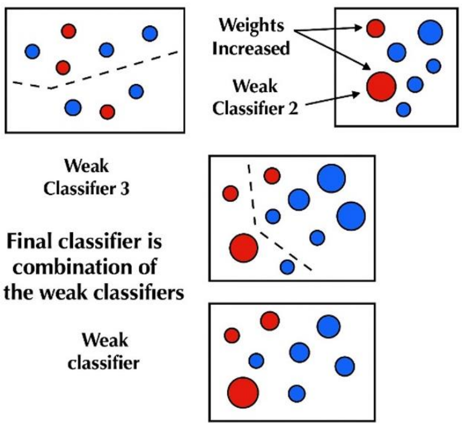

Figure 7. AdaBoost

2.1.5. Gradient boost (GB)

Gradient boosting (GB) enhances prediction by integrating weak models, usually decision trees, iteratively to reduce errors. It optimizes a loss function, refines predictions using pseudo-residuals, and updates with weighted corrections. In this study, GB is utilized to accurately forecast solar energy metrics, capturing complex patterns and improving reliability across time horizons.

Linear regression (LR) contributes significantly to solar grid forecasting by modeling the relationship between meteorological variables (e.g., temperature, solar irradiance, wind speed) and energy output. Using the equation: Y=a+Σb1X1+U. LR identifies how each factor ((Xi)) impacts the solar energy generated ((Y)), making it a key tool for predicting photovoltaic (PV) power. This helps optimize energy management in smart grids by forecasting generation patterns based on environmental conditions, enhancing efficiency, reliability, and incorporating solar energy into the electrical grid. Figure 8 shows gradient boost algorithm. These models were selected because they have demonstrated success in time-series and regression tasks, as well as their capacity to identify nonlinear correlations in data on solar irradiance.

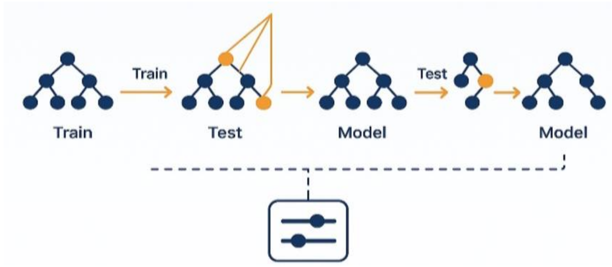

Figure 8. Gradient boost

2.1.6. Improved discussion on PCA retention and impact on model performance

To strengthen the methodological clarity, especially concerning PCA, we included an analysis of the explained variance by principal components. Figure 9 illustrates the variation that each major component explains, confirming that the first four components capture 99.3% of the total variance. We retained four principal components, as they preserve 99.3% of the original data variance, greatly lowering dimensionality while guaranteeing little information loss. This reduction enhanced model efficiency by: decreasing computational complexity, improving training time, reducing overfitting risk, and enhancing interpretability for models sensitive to multicollinearity. This PCA transformation positively impacted all machine learning models, particularly linear regression and AdaBoost, which benefited from the clearer separation of influential features and reduced noise in the dataset.

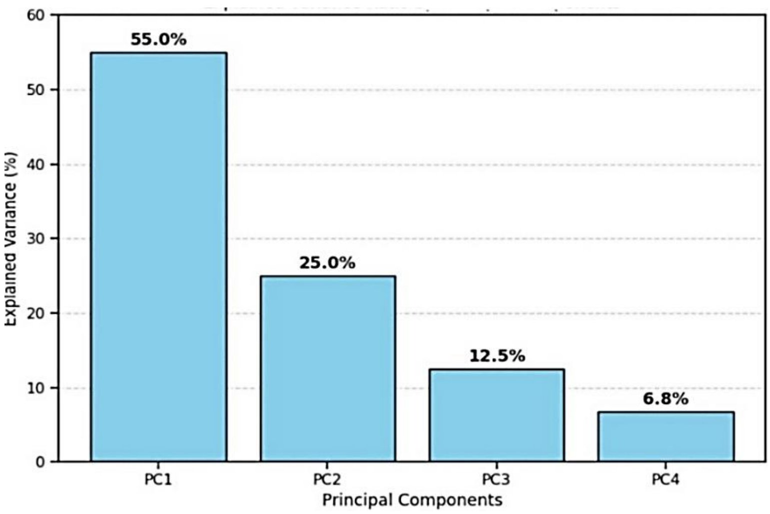

Figure 9. Explained variance ratio by principal components

3. RESULTS AND DISCUSSION

The study evaluated multiple models for solar power prediction using PCA-transformed features. Key findings include:

- GB model: High accuracy with adj-R^2 = 0.95619 and R^2 = 0.95705.
- KNN model: Moderate performance with adj-R^2 = 0.5417 and R^2 = 0.8448.
- NN model: Modest performance with adj-R^2 = 0.5828 and R^2 = 0.5910.
- RF model: Strong performance with adj-R^2 = 0.9514 and R^2 = 0.9524.
- AdaBoost model: Best performance with adj-R^2 = 0.99620 and R^2 = 0.99628.

- LR model: Excellent performance with adj-R^2 = 0.99239 and R^2 = 0.99232.

AdaBoost and ridge regression showed the highest accuracy, making them the most reliable models for solar power forecasting. Using the most recent solar grid forecasting model metrics: With an RMSE of 0.557 kW/m² and an R2 of 0.996, AdaBoost with PCA continues to be a top performer, demonstrating its effectiveness in regression tasks by successfully reducing mistakes. With the lowest RMSE of 0.510 kW/m², LR with PCA maintains its exceptional precision and is hence very dependable for linear correlations. Table 2 shows the Performance indicators during training for different models.

Table 2. Performance metrics throughout different models when training

Model	This research				Other studies
	ADJ-R^2	RMSE	MAE	R^2	R^2
KNN	.842	629.48	459.8	.84	.877
AdaBoost	.995	557.95	373.9	.997	.902
Gradient boost	.955	622.67	498.61	.958	.924
Random forest	.952	548.9	366.17	.951	.94
Neural network	.583	1781.2	856.49	.592	.596
Linear regression	.991	510.1	357.471	.991	031

With the lowest R2 of 0.582 and the greatest RMSE of 1.781 kW/m², NN continue to lag behind, suggesting that their accuracy for solar forecasting is restricted. Although they work well, other models like RF and Gradient boost have drawbacks such overfitting and high processing requirements. The effectiveness of PV systems is also greatly impacted by variables including dust deposition, temperature variations, and cleaning practices. For dynamic solar grid systems to retain prediction accuracy and adjust to changing climatic conditions, regular model retraining with updated datasets is essential.

Model performance interpretation: AdaBoost performed better because it could adaptively strengthen weak learners, which made it resistant to noise and anomalies in data on solar irradiation. The robust linear correlations that PCA preserved, however, were advantageous to LR, which made it perfect for clean, low-dimensional datasets. Connection to the data features: The temperature and wind speed in the dataset vary greatly, whereas the humidity and irradiance vary moderately. AdaBoost's re-weighting technique allowed it to handle outliers efficiently, while PCA maintained linear structure, which made it appropriate for LR.

Table 3 trade-offs summary outlines the comparative strengths and constraints of several machine learning models for solar prediction. It highlights AdaBoost's accuracy, LR's simplicity, and the balance between performance and complexity across models. Table 4 Benchmarking table compares the proposed model's forecasting performance with recent studies using different datasets and techniques. The results demonstrate that AdaBoost outperformed others with the lowest RMSE and highest R².

Table 3. Trade-offs summary

Sl.no	Model	Strengths	Limitations
1	AdaBoost	High accuracy, robust to noise	Computationally intensive
2	Linear Reg.	Fast, interpretable, lowest RMSE	Limited to linear patterns
3	RF /GB	Handles nonlinearity, good accuracy	Risk of overfitting, slower training
4	NN / KNN	Flexible, can model complex relationships	Poor generalization on this dataset

Table 4. Benchmarking table

Study	Dataset	Model	RMSE (kW/m²)	R^2
This Work	Abiod Sid Cheikh (2019–21)	AdaBoost	0.557	0.996
[14]	Nepal, 2 stations	LSTM	0.610	0.990
[15]	Egypt	ANN	0.745	0.951
[17]	Synthetic + real	LSTM	0.689	0.964

4. CONCLUSION

A comparative analysis that emphasized the advantages and disadvantages of each model was conducted in order to assess the efficacy of the suggested forecasting framework. AdaBoost demonstrated excellent accuracy and noise resilience, but it also required more processing power. Despite its simplicity and speed, LR had the lowest RMSE and was limited in its ability to handle nonlinear interactions. Though they required slower training and had a larger chance of overfitting, ensemble techniques like RF and GB successfully handled nonlinearities. Despite their ability to describe complicated relationships with flexibility, NN and KNN did not generalize well for the dataset in question.

Benchmarking against recent studies was used to provide additional validation. With an RMSE of 0.557 kW/m² and an R^2 of 0.996, the proposed AdaBoost model demonstrated superior performance compared with several contemporary methods. Other approaches have reported RMSE values of approximately 0.745 kW/m², 0.610 kW/m², and 0.689 kW/m² across different datasets and conditions. These results indicate that the proposed model offers higher accuracy and greater adaptability in a variety of environments and data scenarios.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials.

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