International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 14s, 2025
https://www.theaspd.com/ijes.php

Forecasting Solar And Wind Energy Production Using Artificial Intelligence

Morooj Akram Fallatah[1], Razan Abdullah Alharbi[2], Lama Al Khuzayem[3]
[1]King Abdulaziz University (KAU),mero0oa2019@gmail.com
[2]King Abdulaziz University (KAU),razan3251@gmail.com
[3]Department of Computer Science, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah 21589, Saudi Arabia. lalkhuzayem@kau.edu.sa

Abstract

Background: Saudi Arabia's Vision 2030 aims to generate 50% of electricity from renewables by 2030, leveraging abundant solar and wind resources. However, variable weather conditions challenge accurate energy production forecasting, requiring advanced AI models to ensure grid stability and efficient energy management.Aim: To develop an AI-based model integrating machine learning (ML) and deep learning (DL) to enhance solar and wind energy forecasting accuracy using meteorological data, supporting Vision 2030's sustainability goals.Patients and Methods: Using Kaggle datasets with weather variables (temperature, solar radiation, wind speed, humidity), the study preprocessed data to address missing values and outliers. ML models (Random Forest, XGBoost, K-Nearest Neighbors, Extra Trees) and DL models (Deep Neural Networks) were trained and evaluated via RMSE, MAE, and R^2. A Streamlit dashboard was built for real-time forecasting.Results: XGBoost excelled, with the lowest RMSE (402.94 for solar, 187.61 for wind) and highest R^2 (0.9737 for solar, 0.9794 for wind). Random Forest performed well, while DNN showed lower accuracy (R^2 = 0.5269 for solar). The model predicted 102,568.73 MWh daily solar output, supporting 3.4 million homes and reducing CO2 emissions by 96,414.61 tons daily.

Conclusions: The AI model, particularly XGBoost, enhances renewable energy forecasting, aiding grid stability and aligning with Vision 2030. The interactive dashboard improves usability. Future work should explore advanced DL and real-time data integration.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, Solar Energy, Wind Energy, Forecasting, Vision 2030, Renewable Energy

INTRODUCTION

Saudi Arabia's natural resources, particularly solar and wind, play a vital role in its economy. In alignment with Vision 2030, the Kingdom targets generating 50% of its electricity from renewable sources by 2030 (Al-Sarihi, 2019). Major projects like the 300 MW Sakaka Solar Power Plant and the 400 MW Dawmat Al-Jandal Wind Farm reflect growing investment in clean energy (1).Despite their environmental benefits, solar and wind power are affected by variable weather conditions, which complicates energy production planning (2). Photovoltaic systems rely on solar irradiance, while wind turbines depend on wind speed and direction (3). These dependencies make forecasting essential for grid stability and efficient energy management (4).Traditional forecasting models struggle with the nonlinear and complex nature of meteorological data. Recent studies highlight the advantage of Artificial Intelligence (AI), especially Machine Learning (ML) and Deep Learning (DL), in enhancing accuracy and adaptability (5).Aligned with Vision 2030 and global sustainability efforts, this research proposes an AI-based model integrating DL and ML for forecasting solar and wind energy production to improve system reliability and energy planning.Problem Statement: Renewable energy production depends heavily on changing weather conditions, making accurate forecasting a challenge. Traditional statistical and ML methods often fail to capture nonlinear relationships among climatic variables, leading to suboptimal predictions (3).Moreover, most existing models focus on either solar or wind energy independently. This research addresses the gap by developing a unified forecasting system using DL models like RNN and DNN and ML models such as Random Forest and XGBoost. By integrating multiple meteorological factors, the model aims to improve prediction accuracy and support energy grid stability in line with Vision 2030.Project Scope: The study focuses on building and evaluating ML and DL models (e.g., SVM, RF, LSTM, DNN) to forecast renewable energy using real-time and historical weather data. Performance will be assessed using MAE and RMSE. The project uses data from a high-potential renewable region and aims to support grid management and decision-making in clean energy systems.Project Importance: Academically, the project contributes to research on AI applications in renewable energy forecasting, offering comparative analysis of model performance. Industrially, it supports operational planning and storage efficiency, reducing system losses and costs. It also advances the transition toward sustainable and resilient energy infrastructures, aligning with Vision 2030.The aim of this study was to improve energy forecasting accuracy using AI techniques for solar and wind energy production based on meteorological inputs such as temperature, solar radiation, wind speed, and humidity.

Forecasting Approaches for Renewable Energy

Recent advancements in forecasting solar and wind energy using Traditional, Machine Learning, and Deep Learning methods are reviewed. Sixteen studies were categorized by energy type: wind (7), solar (6), and combined (3), as shown in Figure (1).

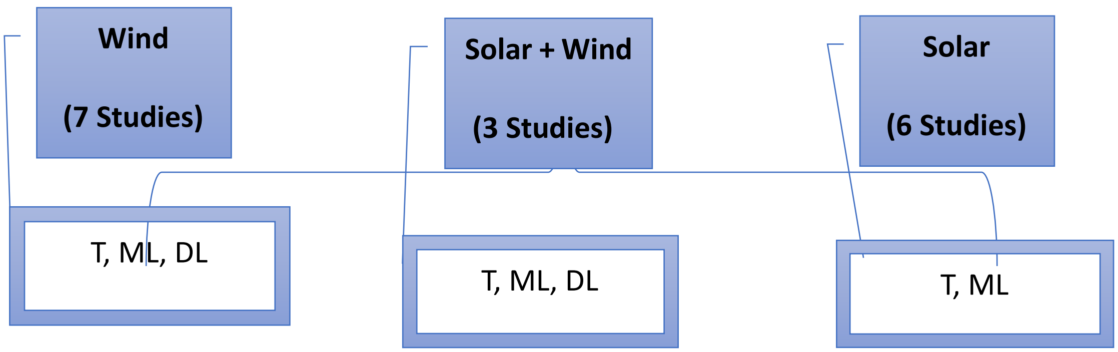

Figure 1:
Classification of reviewed studies by energy source and forecasting technique

Related Work

Wind Power Forecasting State-of-the-art Approaches

Recent studies have explored AI-based wind energy forecasting using various machine learning and deep learning models. Alazmi et al. (6) found that Random Forest Regression (RFR) achieved the highest accuracy compared to other models, including DTR, SVR, RNN, and LSTM. Similarly, Brahimi et al. (7) showed that RF slightly outperformed ANN and other ML algorithms in predicting wind speed in Saudi Arabia. Al-Dosari et al. (8) proposed a hybrid model (WPD-SAM-BiLSTM) which significantly improved prediction accuracy compared to standard DL models. Huang et al. (9) used Echo State Networks (ESN) with PCA for wind power prediction, achieving higher accuracy than traditional models and identifying optimal wind farm locations. Sánchez (10) developed an adaptive multi-model forecasting system using Kalman filters, which enhanced short-term prediction without the need for frequent recalibration. Lin et al. (11) demonstrated that Temporal Convolutional Networks (TCN) outperformed LSTM and RNN in long-range forecasting. Singh et al. (12) found Gradient Boosting Machines (GBM) to be the most effective ML model using SCADA wind farm data. Overall, RF, GBM, and hybrid deep learning approaches achieved superior performance, although real-time implementation remains limited in current research.

Table (1): Wind Energy Forecasting State-of-the-art Approaches

Paper	Approach Type	Used Techniques	Results
Alazmi et al. (6)	ML/DL	DTR RFR SVR RNN LSTM	**RFR**: MSE = **0.1102** **DTR**: MSE = **0.1678** **SVR**: MSE = **12.4723** **LSTM**: MSE = **0.1779** **RNN**: MSE = **0.7670**

Brahimi (7)	ML/DL	ANN RF SVM, RepTree RT	**RFR**: MSE = 0.1102 **DTR**: MSE = 0.1678 **SVR**: MSE = 12.4723 **LSTM**: MSE = 0.1779 **RNN**: MSE = 0.7670
Al-Dosari et al. (8)	DL	WPD SAM BiLSTM LSTM	**One hour** (WPD-SAM-BiLSTM): MAE = 0.1169 RMSE = 0.1523 R^2 = 0.9953 **Five hours** (WPD-SAM-BiLSTM): MAE = 0.2574 RMSE = 0.3654 R^2 = 0.9728
Huang et al. (9)	DL	ESNs PCA ARIMA Spatio-temporal stochastic models	11% accuracy improvement $1M annual savings ideal wind farm locations identified
Sánchez (10)	T/ML	Parametric & Nonparametric Models, Kalman Filter, Recursive Least Squares, Adaptive Forecast Combination	Outperformed single-model approaches in accuracy and grid integration.
Lin et al. (11)	DL	TCN LSTM RNN GRU	Best model: TCN (MAPE = 5.13% for 72-hour predictions).
Singh et al. (12)	ML	RF GBM k-NN DT ET	**GBM**: RMSE = 0.0634 MSE = 0.0040 R^2 = 0.9690 **RF**: R^2 = 0.9651 **DT (lowest accuracy)**: R^2 = 0.9497 RMSE = 0.0884

Solar Energy Forecasting State-of-the-art Approaches

Recent studies have applied various ML techniques to forecast solar energy in Saudi Arabia and similar regions. Kolsi et al. (13) found that simple models like SMA and Naïve achieved strong performance in desert climates, while advanced models like GPR and SVM offered competitive accuracy. Imam et al. (14) reported perfect prediction using Decision Tree (DT) and strong results from RF and ANN models for forecasting Global Horizontal Irradiance (GHI). Irfan et al. (15) confirmed the superiority of RF, XGB, and k-NN models, especially in Riyadh, due to its stable weather. *Ladmaoui et al. (2023)* showed that ANN and XGBoost outperformed others using real solar plant data from Morocco. Venilla et al. (16) demonstrated that hybrid ensemble approaches outperformed standalone models in forecasting under variable weather. Al-Araj et al. (17) validated the effectiveness of Ensemble Bagging in predicting PV output in Qassim, surpassing SVR models. Overall, models such as ANN, RF, DT, and XGBoost consistently showed high accuracy, though real-time deployment remains a key research gap.

Table (2): Solar Energy Forecasting State-of-the-art Approaches

Paper	Approach Type	Used Techniques	Results
Kolsi et al. (13)	ML	N SA SMA NAR SVM GPR NN	SMA (Best model): RMSE = 0.5863 MAPE = 6.7720% **S-N (Short-term performance):** RMSE = 0.6132 MAPE = 8.9361% **S-NAR (Lowest accuracy):** RMSE = 1.0092 MAPE = 10.4837%
Imam et al. (14)	ML	• **ANN** • **DT** • **RF** • **EN** • **LR** • **SVR**	**DT (Best model):** • R^2 = 1.0 • MSE = 0.0 **RF:** • R^2 = 0.9987 • RMSE = 0.0599 **EN (Lowest accuracy):** • R^2 = 0.8396 • RMSE = 0.6549 **ANN:** • R^2 = 0.9976 • MAPE = 0.0102%
Al-Araj et al. (15)	ML	Ensemble Bagging, SVR	• **Ensemble Bagging (Best model):** • RMSE = 19.66 W • MAE = 12.05 W • MAPE = 0.727% • **SVR:** • Lower accuracy (especially during low solar irradiance)
Irfan et al. (16)	ML	• **ENR** • **LR** • **RFR** • **k-NN** • **GBR** • **LGBM** • **XGB** • **DTR**	• **Riyadh:** • DTR: R^2 = 0.98, RMSE = 15.5 • RFR: R^2 = 0.99, RMSE = 11.46 • **Najran:** • RFR: R^2 = 0.94, RMSE = 80.61 • XGB: R^2 = 0.94, RMSE = 79.82 • **LR & ENR (Lowest accuracy):** • R^2 = 0.43 • High RMSE
Ladmaoui et al. (17)	ML	• **SVR** • **ANN** • **DT** • **RF** • **GAM** • **XGBoost**	• **ANN (Best model):** • R^2 = 0.99 • RMSE = 2.6e−08 • MAE = 0.00013 • **XGBoost & RF:** • Good performance • **GAM (Lowest accuracy):** • R^2 = 0.03 • Highest error rates

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 14s, 2025
https://www.theaspd.com/ijes.php

Venilla et al. (18)	ML/T	• **Ensemble ML** • **Statistical Methods**	Ensemble model outperformed individual ML models, reducing forecasting errors. Recommended further research into deep learning techniques.

Methodology
This study employs a multi-stage approach to forecast solar and wind energy using ML and DL models. Historical weather and energy data (e.g., temperature, radiation, wind speed) are preprocessed and analyzed to identify key predictors. Models including RF, XGBoost, k-NN, and DNN are trained and evaluated using RMSE, MAE, and R^2, with XGBoost showing the best performance. A user-friendly dashboard was also developed via Streamlit to display real-time forecasts and support decision-making in renewable energy management.

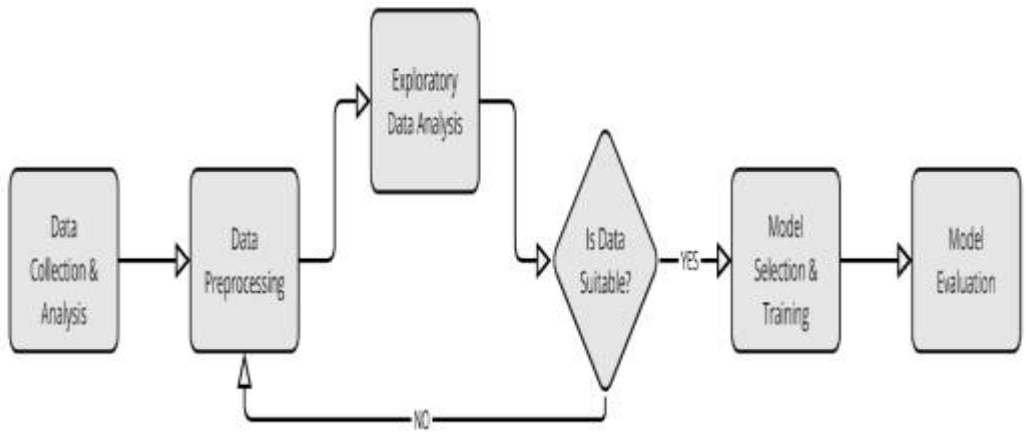

Figure 2: Detailed methodology flowchart for building a model.
Data Selection and Preprocessing: Two datasets from Kaggle were used: one for solar and one for wind energy, containing key climatic variables (e.g., temperature, solar radiation, wind speed, humidity, pressure). Preprocessing steps included handling missing values, normalization, feature selection, and temporal feature engineering (e.g., extracting day, month, hour). Outliers were identified and treated to enhance model robustness.
Exploratory Data Analysis (EDA): EDA involved visual tools such as heatmaps and scatterplots to analyze feature correlations. Wind speed showed strong positive correlation with energy output, while wind direction and temporal features had weak relationships. For solar data, time of day was the most influential factor; other atmospheric features had limited predictive power.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 14s, 2025
https://www.theaspd.com/ijes.php

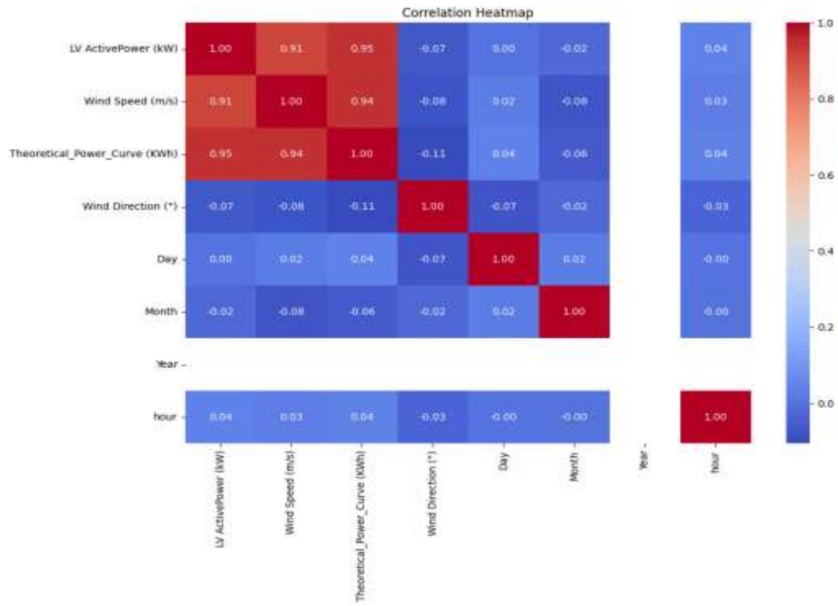

Figure 3: Wind Energy Data Heat map

Figure 3: The correlation heatmap shows strong positive links: LV ActivePower correlates highly with Wind Speed (0.91) and Theoretical Power Curve (0.95), confirming that higher wind speeds boost both actual and theoretical power. Wind Speed also strongly correlates with Theoretical Power Curve (0.94), supporting the model's reliability.Forecasting Models: Both machine learning (ML) and deep learning (DL) models were employed to capture the nonlinear and temporal characteristics of renewable energy data. Among the ML models, Random Forest (RF) offered a robust balance between speed and accuracy, while XGBoost achieved the highest overall accuracy. Extra Trees proved faster but slightly less accurate than RF and XGBoost, and K-Nearest Neighbors (KNN), though simple, underperformed due to its sensitivity to noisy data. On the DL side, a Deep Neural Network (DNN) was utilized to uncover hidden patterns in temporal features; however, it was less effective when dealing with structured numerical data and demanded greater computational power. The integration of both ML and DL models was intended to optimize predictive performance across different forecasting horizons.Web Application Development: An interactive dashboard was developed using Streamlit and hosted on Google Colab. Users can input weather variables and receive real-time forecasts for solar and wind energy. The tool enhances usability and supports scenario-based analysis for energy planning.Model Evaluation: Models were assessed using multiple evaluation metrics to ensure reliable and quantitative comparison. Mean Squared Error (MSE) was used during training as it penalizes larger errors more heavily. Root Mean Squared Error (RMSE), an interpretable metric where lower values indicate higher accuracy, was also applied. Mean Absolute Error (MAE) measured the average magnitude of errors, providing a straightforward view of performance. The R^2 Score indicated how well the model explained the variance in the data, with values closer to 1 reflecting better performance. Together, these metrics provided a comprehensive evaluation framework for model comparison.Tools and Technologies: The project utilized a combination of tools and platforms to support end-to-end development and deployment. Google Colab, along with Streamlit 1.33.0, was used for model training and interactive dashboard deployment. Visual Studio 2022 facilitated code development and debugging. Excel 365 served for initial data cleaning and statistical exploration, while Power BI (2024) enabled interactive visual analytics and reporting. Cross-platform implementation and testing were conducted using a MacBook Air (M1) and an HP Pavilion (i7, Windows 11), ensuring compatibility and performance across different environments.

Testing and Evaluation;Comparison Results of Solar and Wind Energy Forecasting

A set of ML and DL models were trained to predict solar energy and wind energy production using real climate data. The performance of each model was evaluated using three key metrics: RMSE, MAE, and R^2.

Table 3 shows a detailed comparison of the solar energy production forecasting models in terms of accuracy and predictive ability, while Table 4 shows the wind energy production forecasting models' results.

Table 3: Model Performance Comparison Solar Energy Forecasting

Model	RMSE	MAE	R^2
XGBoost	402.94	290.27	0.973713
RandomForest	683.70	509.35	0.924321
ExtraTrees	769.52	591.99	0.904128
KNeighbors	1048.94	776.43	0.821864
DNN	1709.52	1353.40	0.526850

Table 4: Model Performance Comparison for Wind Energy Forecasting

Model	RMSE	MAE	R^2
XGBoost	187.610706	97.193052	0.979356
RandomForest	210.529598	102.084288	0.974005
ExtraTrees	213.592614	98.923410	0.973243
KNeighbors	223.103929	103.227695	0.970807
DNN	243.969448	122.344280	0.965091

The evaluation results showed that solar energy prediction models achieved high accuracy, with the XGBoost model outperforming with the lowest RMSE (402.94) and the highest R^2 (0.97). The accuracy of the DNN model, however, declined significantly compared to the other models. In wind energy prediction, accuracy was generally higher, with XGBoost also achieving the best performance with an RMSE of 187.61 and an R^2 of 0.98, reflecting the model's stability with wind data. All models performed well, but XGBoost remained the best for both types of energy. (Table 3,4);Testing Scenarios;The results of this scenario indicate that the model predicted a solar energy production of 12,327.97 MW during the input operating hour, reflecting good efficiency under moderate morning conditions. The total estimated daily energy output was 102,568.73 MWh, a relatively high figure given the average temperature (77°F) and moderate humidity (45%), demonstrating that the model responds favorably to balanced climatic conditions. Based on this output, this scenario is expected to meet the energy needs of approximately 3,418,957 homes. This clean energy output also reduces carbon dioxide emissions by 96,414.61 tons per day, reflecting the positive environmental impact of renewable energy under optimal weather conditions **as illustrated in Figure 4 and 5**.

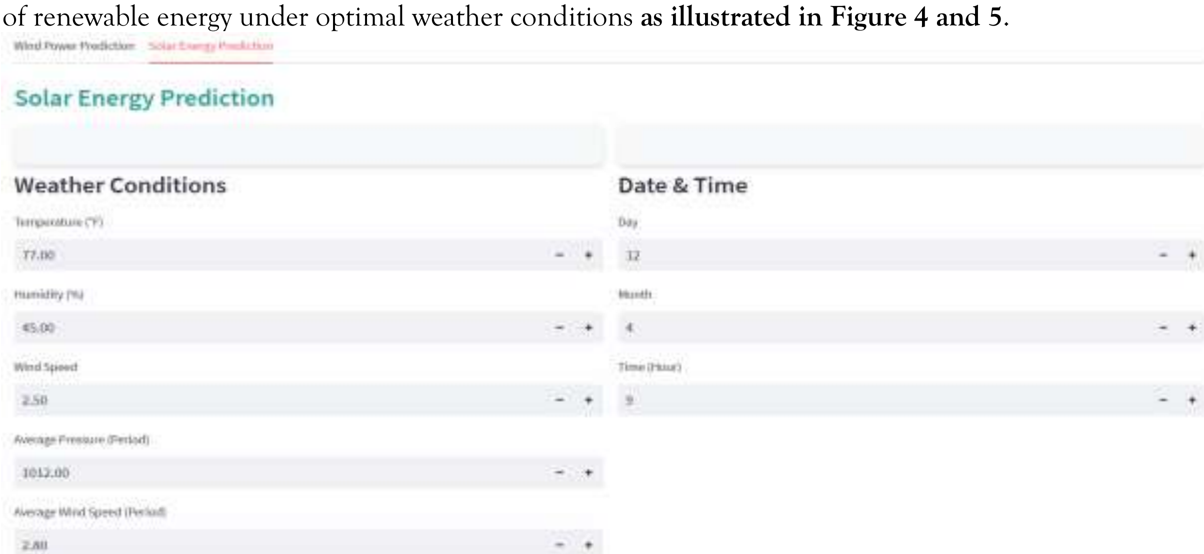

Figure 4: Solar Forecast Input Interface.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 14s, 2025
https://www.theaspd.com/ijes.php

Figure 5: Predicted Solar Output and Environmental Impact

Strengths and Weaknesses

The AI-based system performed well, especially XGBoost for solar during clear days and wind models across seasons. Minor drops in accuracy occurred with cloudy or humid weather and sudden wind changes, suggesting areas for future improvement.

Model Improvements and Adjustments

A key challenge was the low predictive accuracy using the initial wind dataset, which, despite its rich meteorological features, led to poor model performance. The DNN model showed the weakest results (R^2 = 0.5198, RMSE = 0.1985), while traditional ML models like XGBoost, KNN, and RF achieved slightly better but still unsatisfactory R^2 values (~0.67) and RMSEs > 0.16. Extra Trees performed best in the initial setup (R^2 = 0.6975, RMSE = 0.1575). To overcome this, a more relevant, higher-quality dataset was adopted, resulting in significant improvements—XGBoost reached R^2 = 0.979 and RMSE = 187.61—confirming the importance of suitable data for accurate wind forecasting.

Comparison of Results

To evaluate the impact of dataset refinement on model performance, the results before and after the changes were compared across five algorithms using three evaluation metrics: **R^2**, **RMSE**, and **MAE**. The initial results based on the original dataset showed limited predictive accuracy, with low R^2 scores and relatively high error rates. Among the models, Extra Trees achieved the best performance in the initial setup with an R^2 of **0.6975**, while the Deep Neural Network (DNN) recorded the weakest performance with an R^2 of **0.5198** and RMSE of **0. 1985.After** replacing the original dataset with a more comprehensive and feature-rich alternative, all models showed notable improvements. The **XGBoost** model achieved the highest accuracy, with an R^2 of **0.9794** and RMSE of **187.61**, followed by RF and ET, all exceeding R^2 values of **0.97**. This improvement demonstrates the critical role of data quality in enhancing predictive performance.(Table 5)

Table 5: Performance Comparison of Models Before and After Dataset Enhancement

	(Before)				(After)		
Model	R^2	RMSE	MAE		R^2	RMSE	MAE
XGBoost	0.6798	0.1621	0.1243		0.9794	187.61	97.19
RandomForest	0.6842	0.1609	0.1216		0.9740	210.53	102.08
ExtraTrees	0.6975	0.1575	0.1198		0.9732	213.59	98.92
KNeighbors	0.6736	0.1636	0.1240		0.9708	223.10	103.23
DNN	0.5198	0.1985	0.1505		0.9651	243.97	122.34

As evidenced by the data in Table 5 the refinement of the dataset led to measurable improvements in model performance, reflected in higher R^2 values and reduced RMSE and MAE scores. The deployed models were evaluated through real-world testing using the interactive web interface. Two main scenarios were tested to validate the prediction performance.

Ethical Considerations

The project ensures ethical AI use by adhering to data privacy laws (GDPR, CCPA), using anonymized public datasets, and applying fair, bias-mitigated models across diverse climates. Explainable AI and transparent methods support trust and accountability, aligning with global standards and Saudi Vision 2030 for responsible, sustainable energy forecasting.

CONCLUSION

This project represents an advanced applied experiment in employing AI to improve the efficiency of renewable energy production forecasting, using machine learning techniques and real climate data for wind and solar energy. Multiple models were developed, including XGBoost, Random Forest, and DNN, and compared using accurate indicators such as RMSE and R^2, enabling the best model to be identified in terms of performance and accuracy. The project was not merely a prediction experiment; it also included the design of an interactive dashboard using user-friendly visual tools. These tools displayed complex relationships between temperature, humidity, and wind speed and energy output, allowing end users to interact with the data in a realistic and seamless manner. The results demonstrate that artificial intelligence can provide accurate and effective solutions in the energy sector, enhancing forecasting capabilities and supporting national transformation plans towards sustainability and clean energy sources.

Future Work

Future directions for this research include enhancing deep learning models by incorporating advanced architectures like LSTM and BiLSTM for better long-term forecasting, especially under dynamic climate conditions. Integrating real-time data through APIs will improve model responsiveness and accuracy. Additional influencing factors—such as cloud cover, solar radiation, and terrain—will be considered to refine predictions. Geographic expansion will help assess model performance across various regions, aiding broader adoption. Finally, developing a user-friendly mobile application will enable easy, on-the-go access to forecasts, supporting wider accessibility and practical use.

REFERENCES

1. NS Energy. (2021). Sakaka Solar Power Plant, Saudi Arabia. NS Energy. Retrieved from https://www.nsenergybusiness.com/projects/sakaka-solar-project/
2. PACHAURI, Rajendra K.; REISINGER, Andy. Climate change 2007: Synthesis report. Contribution of working groups I, II and III to the fourth assessment report of the Intergovernmental Panel on Climate Change. Ipcc, 2007.
3. Wang Y, Zhang N, Bai Y. Energy production forecasting of photovoltaic and wind power: A review of the methods and practice. Renew Sustain Energy Rev. 2019;112:29–47.
4. Vennila, C., Titus, A., Sudha, T. S., Sreenivasulu, U., Reddy, N. P., Jamal, K., Lakshmaiah, D., Jagadeesh, P., & Belay, A. (2022). Hybrid machine learning and statistical approach for solar energy forecasting. International Journal of Photoenergy, 2022, 1–12. https://www.researchgate.net/publication/36029678
5. Singh, U., et al. (2021). Improving wind power production forecasting in smart grids using machinelearning. Energies, 14(8), 2801. https://www.mdpi.com/1996-1073/14/16/5196
6. ALAZEMI, Talal; DARWISH, Mohmed; ABBOD, Maysam. Wind Power Generation Forecast Using Artificial Intelligence Techniques. In: 2023 58th International Universities Power Engineering Conference (UPEC). IEEE, 2023. p. 1-5.
7. BRAHIMI, Tayeb. Using artificial intelligence to predict wind speed for energy application in Saudi Arabia. Energies, 2019, 12.24: 4669.
8. ALDOSSARY, Yasmeen; HEWAHI, Nabil; ALASAADI, Abdulla. Wind Speed Forecasting Based on Data Decomposition and Deep Learning Models: A Case Study of a Wind Farm in Saudi Arabia. arXiv preprint arXiv:2412.13356, 2024.
9. HUANG, Huang; CASTRUCCIO, Stefano; GENTON, Marc G. Forecasting high-frequency spatio-temporal wind power with dimensionally reduced echo state networks. Journal of the Royal Statistical Society Series C: Applied Statistics, 2022, 71.2: 449-466.
10. Sánchez, A. (2006). Statistical forecasting system for short-term wind energy prediction. International Journal of Forecasting, 22(3), 345–360. https://www.researchgate.net/publication/22388358
11. LIN, Wen-Hui, et al. Wind power forecasting with deep learning networks: Time-series forecasting. Applied Sciences, 2021, 11.21: 10335.
12. Singh, U., et al. (2021). Improving wind power production forecasting in smart grids using machinelearning. Energies, 14(8), 2801. https://www.mdpi.com/1996-1073/14/16/5196

13. KOLSI, Lioua, et al. Prediction of Solar Energy Yield Based on Artificial Intelligence Techniques for the Ha'il Region, Saudi Arabia. Sustainability, 2022, 15.1: 774.
14. Imam, A. A., Abusorrah, A., Seedahmed, M. M. A., & Marzband, M. (2024). *Forecasting global horizontal irradiance using machine learning techniques in northern Saudi Arabia*. *Mathematics, 12*(26), 2600. https://www.mdpi.com/2227-7390/12/16/2600.
15. IRFAN, Muhammad, et al. Global horizontal irradiance prediction for renewable energy system in Najran and Riyadh. AIP Advances, 2024, 14.3.
16. Vennila, C., Titus, A., Sudha, T. S., Sreenivasulu, U., Reddy, N. P., Jamal, K., Lakshmaiah, D., Jagadeesh, P., & Belay, A. (2022). Hybrid machine learning and statistical approach for solar energy forecasting. International Journal of Photoenergy, 2022, 1–12. https://www.researchgate.net/publication/36029678
17. ALARAJ, Muhannad, et al. Energy production forecasting from solar photovoltaic plants based on meteorological parameters for qassim region, Saudi Arabia. Ieee Access, 2021, 9: 83241-83251.