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Deep learning-based integrated XAI for photovoltaic power forecasting considering actual power production period

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ABSTRACT

This paper proposes a deep learning (DL)-based integrated explainable artificial intelligence (XAI) framework for photovoltaic (PV) power forecasting, explicitly considering the actual power production period to improve operational reliability. The framework uses solar irradiance, ambient temperature, and relative humidity as input features and evaluates nine DL architectures, including artificial neural networks (ANN), recurrent neural networks (RNN), convolutional neural networks (CNN), long short-term memory (LSTM), bidirectional long short-term memory (BiLSTM), CNN-LSTM, CNN-BiLSTM, RNN-LSTM, and RNN-BiLSTM. Model performance is evaluated using mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE). The results show that the residual-based RNN-LSTM model provides highest forecasting accuracy, achieving MAE of 1.21 kW, MAPE of 5.12%, and RMSE of 2.24 kW. In comparison, the LSTM and BiLSTM models exhibit substantially higher prediction errors, with MAPEs exceeding 21%, while hybrid convolutional models show moderate improvements but remain inferior. To enhance model transparency, XAI techniques are integrated to interpret feature contributions. The analysis confirms that solar irradiance is the dominant influencing factor, while temperature and humidity introduce secondary nonlinear effects captured effectively by recurrent architectures. The proposed framework provides a high-accuracy and interpretable solution for PV power forecasting, supporting reliable energy management and smart grid applications.

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1. INTRODUCTION

Photovoltaic (PV) power generation has experienced rapid growth in electricity production due to its significant role in the global transition toward low-carbon and sustainable energy systems [1], [2]. Owing to its environmental benefits and the continuous reduction in installation costs, solar energy has been widely deployed in both large-scale power plants and distributed generation systems [3]. However, the variability and intermittency of solar power, which are strongly influenced by meteorological conditions, pose substantial challenges to power system operation, energy management, and grid stability [4], [5]. Consequently, accurate forecasting of solar PV power generation has become a critical task for enabling reliable grid integration, optimal energy dispatch, and efficient utilization of renewable energy resources.

In recent years, numerous forecasting approaches have been proposed to estimate solar PV power output over various time horizons, ranging from minutes to several days ahead. Traditional statistical methods, such as the autoregressive integrated moving average (ARIMA) model and exponential smoothing models [6], [7], have been widely adopted due to their simplicity and ease of interpretation. Nevertheless, these approaches often struggle to capture the nonlinear and complex relationships between PV power output and environmental variables, particularly under rapidly changing weather conditions [8], [9]. To overcome these limitations, machine learning (ML) techniques, including support vector regression and tree-based ensemble models, have been introduced and shown to improve forecasting accuracy [10], [11]. Despite their effectiveness, conventional ML models still face limitations when handling long-term temporal dependencies and large-scale time-series data [12], [13].

With advances in computational resources and increased data availability, deep learning (DL) techniques have emerged as powerful tools for solar PV power forecasting [14]. Various architectures, such as artificial neural networks (ANN) [15], recurrent neural networks (RNN) [16], convolutional neural networks (CNN) [17], gated recurrent units (GRU) [18], and long short-term memory (LSTM) networks [19], have demonstrated superior capability in modeling nonlinear dynamics and temporal relationships inherent in PV power generation data [20]. In particular, RNN architectures, including GRU and LSTM, have been widely adopted for time-series forecasting tasks due to their ability to capture long-term dependencies and diurnal patterns of solar power production [21]. As a result, DL models have consistently outperformed traditional statistical methods and shallow learning approaches in terms of forecasting accuracy.

Despite their high predictive performance, most DL models operate as black-box systems, providing limited insight into how input variables influence forecasting outcomes. This lack of transparency raises concerns regarding model reliability, trustworthiness, and practical deployment, especially in energy systems where decision-making often requires interpretability and accountability. Power system operators, energy planners, and policymakers demand not only accurate forecasts but also clear explanations of the factors driving model predictions, such as the relative influence of solar irradiance, ambient temperature, humidity, and historical PV power output. To address this challenge, explainable artificial intelligence (XAI) has gained increasing attention as a means of enhancing the transparency and interpretability of complex ML and DL models [22], [23]. The XAI techniques, such as Shapley additive explanations (SHAP), local interpretable model-agnostic explanations (LIME), and gradient-based attribution methods, enable the quantification and visualization of feature contributions to model predictions. In the context of solar PV forecasting, integrating XAI with DL models offers a promising approach to bridging the gap between high predictive accuracy and meaningful interpretability. However, most existing studies primarily focus on improving forecasting performance, while comprehensive investigations that combine multiple DL architectures with XAI-based interpretation remain limited.

Motivated by the aforementioned research gaps, this study proposes a comprehensive DL-based framework for solar PV power forecasting integrated with XAI. Multiple DL architectures, including ANN, RNN, CNN, GRU, and LSTM, are developed and evaluated using meteorological variables solar irradiance, ambient temperature, and relative humidity along with historical PV power output data. The forecasting performance of each model is systematically compared using standard evaluation metrics, while XAI techniques are employed to interpret model behavior and analyze the contribution of input features across different architectures. The comparative results of the proposed models can be effectively applied to PV power generation forecasting, supporting power system operation planning, energy management, and energy trading decision-making in future power grid applications.

2. METHOD

To systematically investigate the proposed DL–based PV power forecasting approach, a comprehensive system overview and research framework are established in this study. The methodology is designed to ensure both forecasting accuracy and model interpretability by integrating advanced DL architectures with XAI techniques. The proposed research framework encompasses the entire process, including data acquisition from a real PV system, selection of actual power production periods, data preprocessing, model development, performance evaluation, and explainability analysis. By structuring the methodology in this manner, the study enables a fair comparison among multiple forecasting models and provides transparent insights into the influence of meteorological variables on PV power generation. The following sections describe system architecture, research framework, and methodological procedures in detail.

2.1. System overview and research framework

The process begins with the acquisition of actual PV power output data along with meteorological variables, including solar irradiance, ambient temperature, and relative humidity. The collected data are then screened to retain only the actual power production periods, followed by data preprocessing steps such as missing data handling, noise reduction, and normalization. Subsequently, multiple DL models, including single, hybrid, and residual-based architectures, are developed and trained to capture the nonlinear and temporal characteristics of PV power generation. The forecasting performance of each model is evaluated using standard accuracy metrics, namely mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), and the coefficient of determination (R^2). Based on these metrics, the models are compared and ranked to identify the best-performing approach. Finally, XAI techniques are applied to interpret the forecasting results by analyzing the contribution of each input variable to the predicted PV power output. This step enhances model transparency and provides physically meaningful insights into the influence of meteorological factors on PV power generation. The operational flow of the proposed research framework for PV power forecasting based on DL and XAI is shown in Figure 1.

The input variables of the proposed model consist of solar irradiance, ambient temperature, relative humidity, and PV system output power, as illustrated in Figures 2 to 4. Figure 2(a) illustrates the annual PV irradiation profile, while Figure 2(b) presents the annual PV panel temperature profile. Figure 3 shows the annual ambient temperature and relative humidity profiles. Figure 4 depicts the annual PV system output power in the case study area.

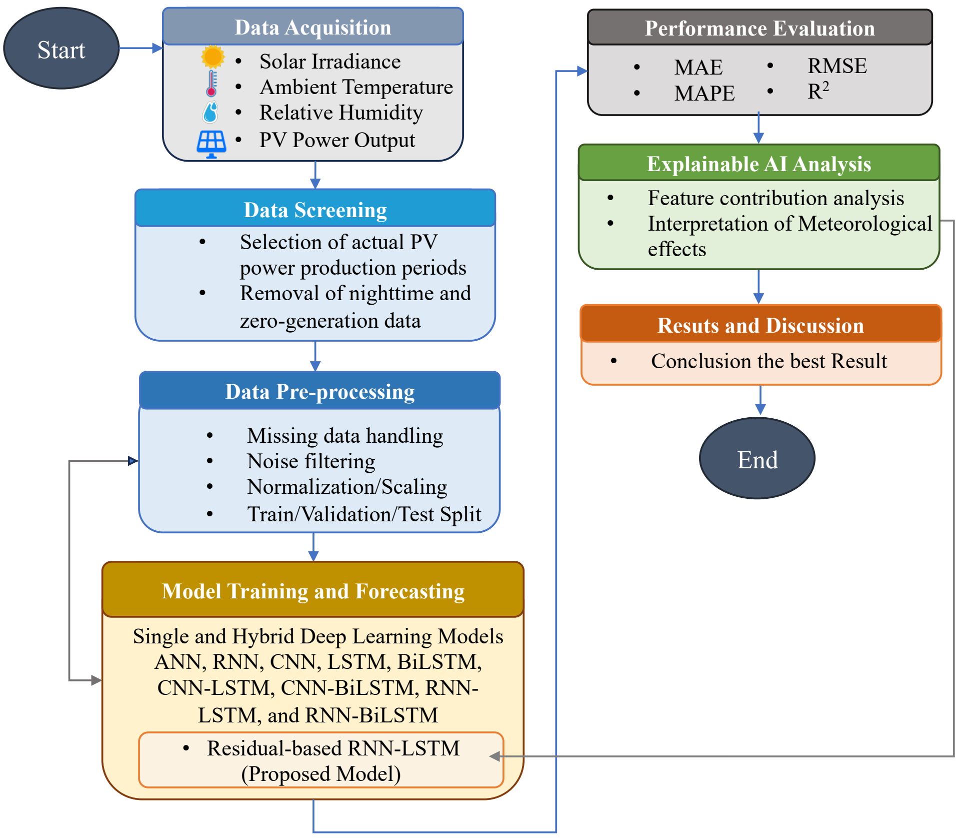
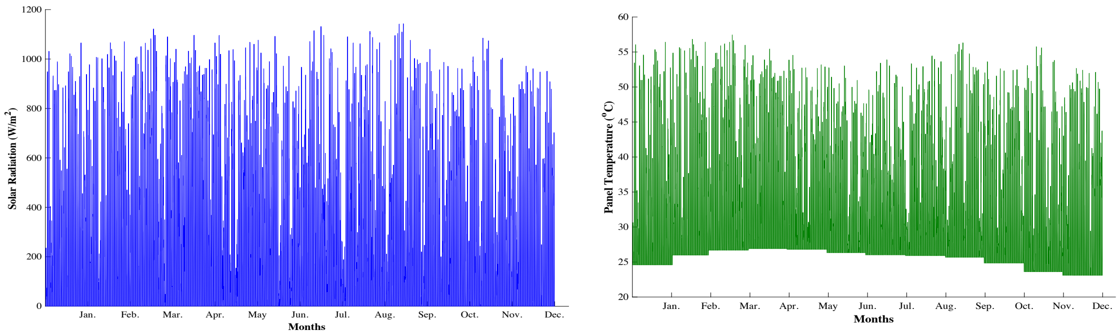


Figure 1. Schematic diagram of the proposed PV power forecasting framework



(a) (b)

Figure 2. Annual PV irradiation and panel temperature profile used as an input in the case study area: (a) PV irradiation and (b) PV panel temperature

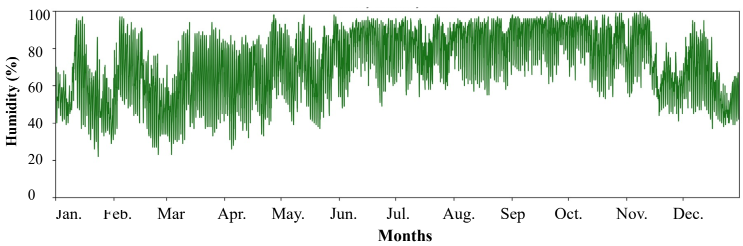


Figure 3. Annual ambient temperature and relative humidity profiles used as inputs in the case study area

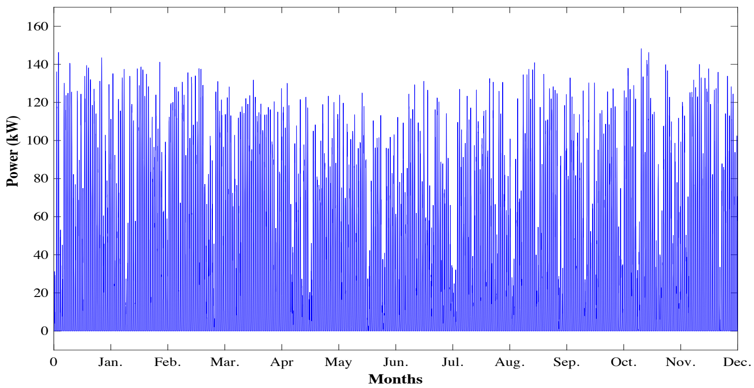


Figure 4. Annual PV system output power in the case study area

2.2. Artificial neural network

The ANN is employed as a baseline model to evaluate the fundamental nonlinear mapping capability between the input variables and PV power output. The ANN structure consists of an input layer receiving solar irradiance, ambient temperature, relative humidity, and system energy output, followed by one or more hidden layers with nonlinear activation functions, and an output layer producing the forecasted PV power. ANN is widely used due to its simplicity and effectiveness in modeling complex nonlinear relationships, although it lacks explicit temporal memory, which may limit its performance in time-series forecasting tasks. The ANN model is used to represent the nonlinear relationship between environmental variables and PV power output. The forecasting output is expressed as in (1).

$$\hat{P}_t = f\left(W\mathbf{x}_t + b\right) \tag{1}$$

Where $\mathbf{x}_t = [G_t, T_t, H_t, P_t]$ denotes the input vector at time t, consisting of solar irradiance G_t, ambient temperature T_t, relative humidity H_t, and historical PV power output P_t. The matrix W represents the network weight parameters, b is the bias term, and $f(\cdot)$ denotes the activation function. The ANN serves as a baseline model for evaluating the nonlinear mapping capability between meteorological variables and PV power output.

2.3. Recurrent neural network

The RNN is designed to capture temporal dependencies by introducing feedback connections within the hidden layers. This architecture allows information from previous time steps to influence current predictions, making it suitable for sequential PV power data. However, conventional RNNs suffer from vanishing and exploding gradient problems when handling long-term dependencies, which can affect forecasting accuracy in extended time horizons. The RNN model captures temporal dependencies in PV power generation by incorporating past information through hidden states. It is formulated as in (2).

$$\mathbf{h}_t = f\left(W_x \mathbf{x}_t + W_h \mathbf{h}_{t-1} + b\right), \qquad \hat{P}_t = g\left(\mathbf{h}_t\right) \tag{2}$$

Where $\mathbf{h}_t$ and $\mathbf{h}_{t-1}$ denote the current and previous hidden states, respectively. The matrices W_x and W_h represent the input-to-hidden and hidden-to-hidden weight parameters, while b is the bias term. The function $f(\cdot)$ is the hidden-layer activation function, and $g(\cdot)$ denotes the output activation function used to generate the predicted PV power output $\hat{P}_t$.

2.4. Convolutional neural network

The CNN is utilized to extract local and spatial features from the time-series input data. Through convolutional and pooling layers, CNN can identify underlying patterns and trends in PV-related variables, such as fluctuations in solar irradiance. Although CNNs are traditionally used for image processing, their ability to perform feature extraction makes them effective for one-dimensional temporal data in energy forecasting applications. The CNN model extracts local temporal features from PV time-series data using convolution operations, defined as in (3).

$$z_t = \sum_{k=1}^{K} w_k * x_{t-k} + b, \qquad \hat{P}_t = f\left(z_t\right) \tag{3}$$

Where w_k denotes the convolutional kernel, K is the kernel size, and $*$ represents the convolution operation. The variable z_t is the extracted feature at time t, while $f(\cdot)$ denotes the activation function. This convolutional operation enables the model to capture local and short-term temporal patterns in PV power generation.

2.5. Long short-term memory

The LSTM network is an advanced variant of RNNs designed to mitigate the vanishing gradient problem by introducing memory cells and gating mechanisms. These gates regulate the information flow, allowing the network to selectively retain or discard historical information over long time horizons. This characteristic makes LSTM particularly suitable for PV power forecasting, where power generation is highly dependent on temporal and environmental dynamics. The internal operations of the LSTM unit are expressed as in (4).

$$\begin{aligned}
\mathbf{f}_t &= \sigma\left(W_f \mathbf{x}_t + U_f \mathbf{h}_{t-1} + b_f\right), \\
\mathbf{i}_t &= \sigma\left(W_i \mathbf{x}_t + U_i \mathbf{h}_{t-1} + b_i\right), \\
\tilde{\mathbf{c}}_t &= \tanh\left(W_c \mathbf{x}_t + U_c \mathbf{h}_{t-1} + b_c\right), \\
\mathbf{c}_t &= \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t, \\
\mathbf{o}_t &= \sigma\left(W_o \mathbf{x}_t + U_o \mathbf{h}_{t-1} + b_o\right), \\
\mathbf{h}_t &= \mathbf{o}_t \odot \tanh\left(\mathbf{c}_t\right)
\end{aligned} \tag{4}$$

Where $\mathbf{c}_t$ and $\mathbf{h}_t$ denote the cell state and hidden state at time t, respectively. The variables $\mathbf{f}_t$, $\mathbf{i}_t$, and $\mathbf{o}_t$ represent the forget gate, input gate, and output gate, respectively. The operator $\odot$ denotes element-wise multiplication, $\sigma(\cdot)$ is sigmoid activation function, and $\tanh(\cdot)$ is hyperbolic tangent function. This gated memory structure enables effective modeling of long-term temporal dependencies in PV power generation.

2.6. Bidirectional long short-term memory

The bidirectional LSTM (BiLSTM) extends the conventional LSTM by processing input sequences in both forward and backward directions. This structure allows the model to utilize past and future contextual information simultaneously, improving prediction accuracy in scenarios where complete time-series data are available. BiLSTM is especially beneficial for capturing complex temporal patterns in PV power generation. The BiLSTM processes input sequences in both forward and backward directions to enhance temporal learning, given by (5).

$$\mathbf{h}_t = \left[\overrightarrow{\mathbf{h}}_t, \overleftarrow{\mathbf{h}}_t\right] \tag{5}$$

Where $\overrightarrow{\mathbf{h}}_t$ and $\overleftarrow{\mathbf{h}}_t$ denote the forward and backward hidden states at time t, respectively. The concatenation of these states enables the BiLSTM model to exploit complete temporal context, thereby improving forecasting accuracy for PV power generation.

2.7. Recurrent neural network - long short-term memory hybrid model

The RNN-LSTM hybrid model combines the simplicity of RNNs with the long-term memory capability of LSTM networks. The RNN layer is responsible for capturing short-term temporal dynamics, while the LSTM layer enhances the learning of long-term dependencies. By integrating both architectures, the hybrid model improves forecasting robustness by exploiting their complementary strengths. The mathematical formulation of the RNN–LSTM hybrid model is expressed as in (6).

$$\mathbf{h}_t^{\text{RNN}} = f\left(W_x \mathbf{x}_t + U_h \mathbf{h}_{t-1}\right), \qquad \mathbf{h}_t^{\text{LSTM}} = \text{LSTM}\left(\mathbf{h}_t^{\text{RNN}}\right), \qquad \hat{P}_t = g\left(\mathbf{h}_t^{\text{LSTM}}\right) \tag{6}$$

Where $\mathbf{h}_t^{\text{RNN}}$ denotes the hidden output of the RNN layer at time t, and $\mathbf{h}_t^{\text{LSTM}}$ represents the corresponding LSTM output used to generate the predicted PV power $\hat{P}_t$.

2.8. Convolutional neural network - long short-term memory hybrid model

The CNN-LSTM hybrid model integrates CNNs for feature extraction with LSTM networks for temporal sequence learning. The CNN layers first identify significant local patterns from the input variables, and the extracted feature maps are subsequently passed to the LSTM layer to model temporal dependencies. This hybrid approach is particularly effective for PV power forecasting, as it captures both spatial–temporal features and long-term trends. The CNN–LSTM model is formulated as (7).

$$\mathbf{z}_t = \text{CNN}\left(\mathbf{x}_t\right), \qquad \mathbf{h}_t = \text{LSTM}\left(\mathbf{z}_t\right), \qquad \hat{P}_t = g\left(\mathbf{h}_t\right) \tag{7}$$

Where $\mathbf{z}_t$ denotes the extracted feature maps produced by the CNN layer and passed to the LSTM network for PV power forecasting.

2.9. Convolutional neural network - bidirectional long short-term memory hybrid model

The CNN-BiLSTM hybrid model further enhances forecasting performance by combining CNN-based feature extraction with bidirectional temporal learning. In this architecture, BiLSTM layer processes the extracted features in both forward and backward time directions, enabling the model to fully exploit contextual information. This structure is particularly suitable for complex PV datasets characterized by nonlinear and bidirectional temporal relationships. The CNN–BiLSTM model is expressed as (8).

$$\mathbf{z}_t = \text{CNN}\left(\mathbf{x}_t\right), \qquad \mathbf{h}_t = \text{BiLSTM}\left(\mathbf{z}_t\right), \qquad \hat{P}_t = g\left(\mathbf{h}_t\right) \tag{8}$$

This architecture enhances PV power forecasting accuracy by effectively exploiting both spatial features and bidirectional temporal dependencies.

2.10. Recurrent neural network - bidirectional long short-term memory hybrid model

The RNN–BiLSTM hybrid model integrates RNN layers with BiLSTM networks to capture short-term temporal dynamics and bidirectional long-term dependencies simultaneously. The RNN layer extracts immediate temporal variations, while the BiLSTM layer models comprehensive temporal context in both directions. This hybrid structure improves prediction robustness under highly variable PV generation conditions. The RNN–BiLSTM hybrid model is formulated as (9).

$$\mathbf{h}_t^{\mathrm{RNN}} = f\left(W_x \mathbf{x}_t + U_h \mathbf{h}_{t-1}\right), \qquad \mathbf{h}_t = \mathrm{BiLSTM}\left(\mathbf{h}_t^{\mathrm{RNN}}\right), \qquad \hat{P}_t = g\left(\mathbf{h}_t\right) \tag{9}$$

This hybrid approach provides a comprehensive temporal representation, thereby enhancing forecasting robustness under fluctuating environmental and operational conditions.

2.11. Hyperparameter configuration and training settings

To ensure a fair and consistent comparison among all forecasting models, identical training conditions and hyperparameter settings are applied where applicable. The hyperparameters are selected based on empirical evaluation and commonly adopted practices in DL-based energy forecasting studies. All models are trained using the same dataset, optimization algorithm, and loss function to maintain experimental consistency and reproducibility. The detailed hyperparameter configuration for all forecasting models is summarized in Table 1.

Table 1. Hyperparameters setting for all forecasting models

Hyperparameters	Value
Input features	Solar irradiance, ambient temperature and relative humidity system energy output
Optimizer	Adam
Learning rate	0.001
Batch size	32
Number of epochs	100
Loss function	MSE
Activation function (hidden layers)	ReLU
Activation function (output layer)	Linear
Number of hidden units	64
Dropout rate	0.2
Weight initialization	He initialization
Training–testing split	80% – 20%

2.12. Forecast accuracy metrics

Forecast accuracy is a key indicator of how well predicted values correspond to actual observations. A forecasting model can be regarded as reliable and effective when the deviation between predicted and measured outputs is minimal. In PV power forecasting, accuracy evaluation plays a vital role in improving the integration of solar energy into power systems. Reliable forecasts enable utilities to balance electricity supply and demand more efficiently, enhance grid stability, and reduce operational and management costs. Various statistical indices are commonly employed to assess forecasting performance. Among them, MAE and MAPE are widely used to quantify average prediction deviations in absolute and relative terms. Another important metric for evaluating forecasting precision is the RMSE, which is extensively applied in fields such as energy management, finance, and meteorology. RMSE represents the square root of the mean of squared differences between predicted and observed values, providing a comprehensive indication of both the magnitude and dispersion of prediction errors, and thereby reflecting the robustness of the forecasting model [24], [25].

In addition to error-based metrics, this study also adopts the R^2 to assess model performance. This statistical measure indicates the proportion of variance in the dependent variable that can be explained by the independent variables, offering insight into the goodness of fit of the model. Accordingly, five performance indicators are utilized in this study, namely MAE, MAPE, percent error, RMSE, and R^2. The MAE represents the average absolute difference between predicted and actual values, while MAE and MAPE are computed using (10) and (11). Percent error and RMSE are determined using (12) and (13), respectively. The R^2 value ranges between 0 and 1, where a higher value signifies better predictive capability and stronger explanatory power of the model [25]. The calculation of R^2 is provided in (14).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{10}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{11}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{12}$$

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{13}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{14}$$

Where y_i and $\hat{y}_i$ denote the actual and predicted PV power outputs at the i-th time step, respectively, $\bar{y}$ represents the mean value of the actual PV power output, and n is the total number of forecasting time-series samples.

2.13. Explainable artificial intelligence

Although DL models exhibit strong predictive performance in PV power forecasting, their black-box nature limits interpretability and trust in real-world energy applications. To address this limitation, XAI techniques are integrated into the proposed framework to elucidate the decision-making processes of the forecasting models. In this study, XAI is employed to quantify the contribution and influence of each input variable, including solar irradiance G_t, ambient temperature T_t, relative humidity H_t, and historical PV power output P_t, on the predicted PV power $\hat{P}_t$.

The explainability mechanism enables the identification of dominant features affecting PV power generation under different operating conditions and time periods. By analyzing feature importance and attribution scores obtained from the XAI approach, the proposed framework provides transparency in model predictions and ensures physical consistency with PV system behavior. Furthermore, the integration of XAI enhances model reliability, facilitates performance comparison among different DL architectures, and supports informed decision-making in solar energy management and power grid operation.

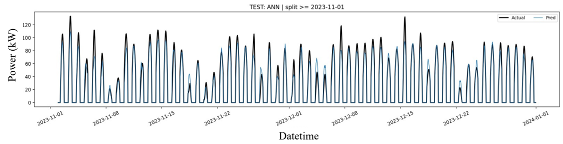
3. RESULTS AND DISCUSSION

This section presents and discusses the experimental results obtained from the proposed DL–based PV power forecasting framework integrated with XAI. The forecasting performance of all models, including ANN, RNN, CNN, LSTM, BiLSTM, and the proposed hybrid architectures, is systematically evaluated using multiple accuracy metrics. The comparative analysis focuses on both predictive accuracy and model robustness under varying environmental conditions, including changes in solar irradiance, ambient temperature, and relative humidity. The results are analyzed based on quantitative performance indicators such as MAE, MAPE, percent error, RMSE, and the R^2, allowing an objective assessment of each model's forecasting capability.

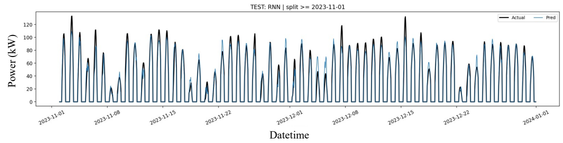
In addition to numerical performance evaluation, XAI-based interpretability analysis is employed to explain the contribution of individual input variables to PV power prediction. This analysis provides insights into the internal decision-making mechanisms of the DL models and verifies the physical relevance of the learned relationships. The combined evaluation of accuracy and explainability enables a comprehensive discussion on the strengths and limitations of each forecasting approach, supporting the identification of the most effective model for reliable PV power forecasting.

3.1. Data description and experimental results

This subsection presents the forecasting results obtained from all DL models considered in this study. The predicted PV power outputs are compared with the actual measured values to evaluate the capability of each model in capturing temporal variations under changing environmental conditions. Figures 5 and 6 shows the individual forecasting performance of each model, demonstrating how accurately the predicted values follow the actual PV power generation profiles over the studied period. Figures 5(a) to 5(i) show the annual PV power forecasting results of the ANN, RNN, CNN, LSTM, BiLSTM, CNN-LSTM, CNN-BiLSTM, RNN-LSTM, and RNN-BiLSTM models, respectively. Figure 6 provides a comprehensive comparison by summarizing the forecasting results of all models in a single visualization. This combined representation highlights the differences in prediction accuracy, stability, and deviation patterns among the models.



(a)



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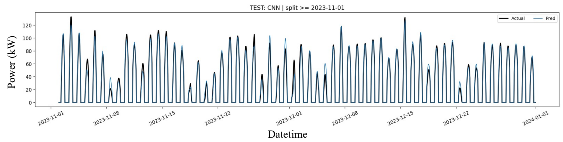

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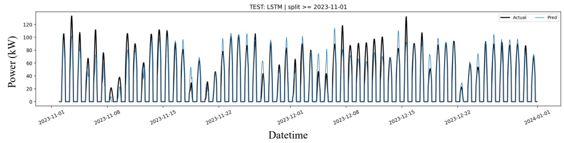

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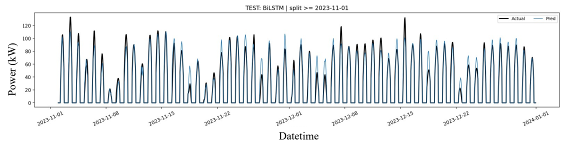

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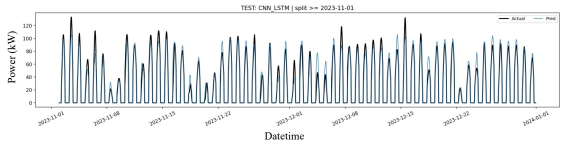

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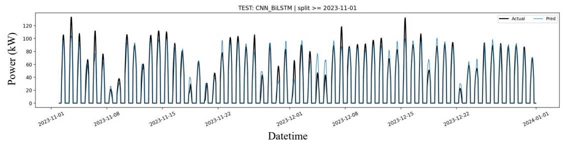

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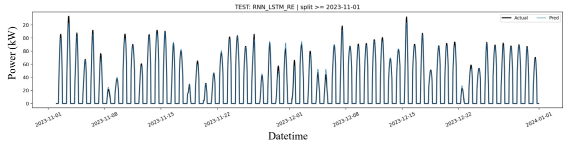

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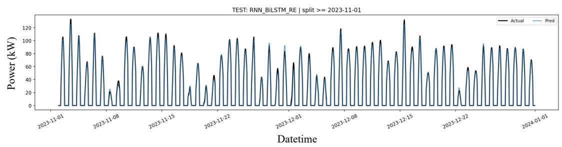

(i)

Figure 5. The annual PV power forecasting for the hybrid model: (a) ANN model, (b) RNN model, (c) CNN model, (d) LSTM model, (e) BiLSTM model, (f) CNN-LSTM model, (g) CNN-BiLSTM model, (h) RNN-LSTM model, and (i) RNN-BiLSTM model

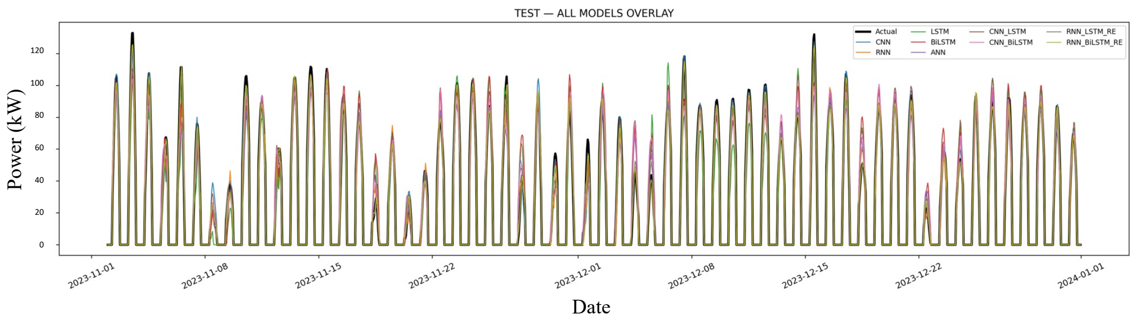

Figure 6. Comparative forecasting performance of all proposed DL models

3.2. Comparison of forecasting accuracy and error analysis

This subsection combines the comparative performance evaluation and error analysis of all forecasting models. The accuracy of ANN, RNN, CNN, LSTM, BiLSTM, and the proposed hybrid models is assessed using MAE, MAPE, percent error, RMSE, and the R^2. The models are ranked from the most accurate to the least accurate based on percentage error and overall performance consistency. Performance comparison of forecasting models as shown in Table 2.

Table 2. Performance comparison of forecasting models

Model	MAE (kW)	MAPE (%)	RMSE (kW)	R^2
ANN	3.83	17.34	7.33	0.9531
RNN	3.80	17.11	7.22	0.9521
CNN	1.86	9.25	3.78	0.9833
LSTM	5.01	21.75	9.40	0.9296
BiLSTM	4.46	21.01	8.60	0.9496
CNN–LSTM	4.27	18.40	8.09	0.9418
CNN–BiLSTM	4.15	18.94	8.00	0.9394
RNN–LSTM	1.21	5.12	2.24	0.9937
RNN–BiLSTM	1.65	7.05	2.91	0.9926

Table 2 compares the forecasting performance of all models using MAE, MAPE, RMSE, and R^2. Among the single models, CNN provides the best accuracy, achieving an MAE of 1.86 kW, MAPE of 9.25%, RMSE of 3.78 kW, and R^2 of 0.9833, significantly outperforming ANN and conventional recurrent models. In contrast, LSTM and BiLSTM show higher errors, with RMSE values of 9.40 kW and 8.60 kW, respectively. Hybrid models further improve prediction accuracy. The RNN-LSTM model delivers the best overall performance, recording the lowest MAE (1.21 kW), MAPE (5.12%), and RMSE (2.24 kW), together with the highest R^2 (0.9937). The RNN–BiLSTM model follows closely, with an MAE of 1.65 kW, RMSE of 2.91 kW, and R^2 of 0.9926. These results demonstrate that combining temporal learning with residual-based architectures substantially enhances the accuracy and robustness of PV power forecasting.

3.3. Explainable artificial intelligence - based interpretation and practical implications

The XAI analysis based on permutation importance demonstrates that the contribution of input variables to PV power forecasting is strongly dependent on the underlying model architecture. As illustrated in Figure 7, which presents the XAI results of the CNN model, the forecasting performance is predominantly driven by complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN)-derived signal components, particularly the mid- to high-frequency intrinsic mode functions (IMFs). This indicates that CNN effectively captures short-term fluctuations in PV power output caused by rapid variations in solar irradiance and transient weather conditions.

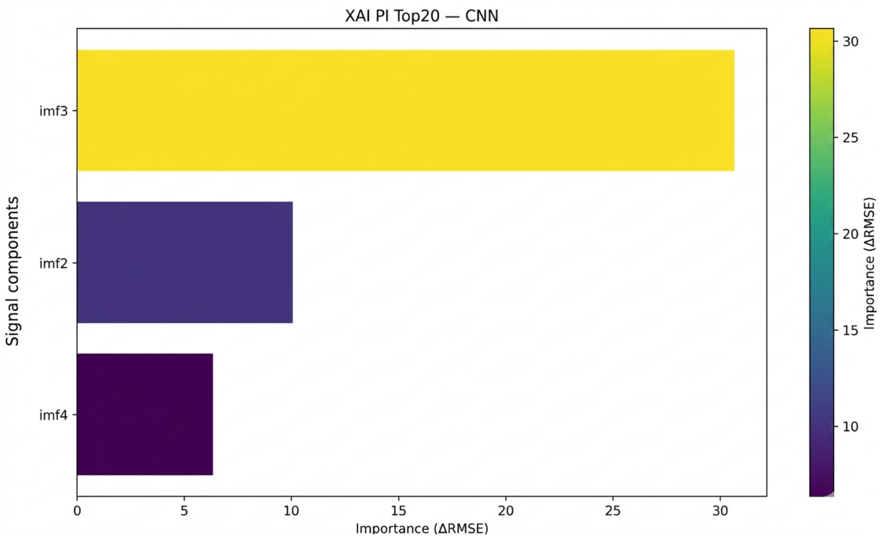

Figure 7. The XAI result of the CNN model

The importance of temporal information becomes more evident in sequence-learning models. As shown in Figure 8, the XAI results of the LSTM model reveal that cyclical time features and low-frequency IMFs play a dominant role, highlighting the ability of LSTM to learn long-term temporal dependencies and diurnal patterns in PV generation. Compared to conventional recurrent structures, LSTM exhibits greater stability in capturing seasonal and daily trends. The hybrid learning mechanism is clearly reflected in Figure 9, which depicts the XAI results of the CNN–BiLSTM model. In this case, signal-based features, temporal variables, and physical inputs collectively contribute to the forecasting process. This balanced importance distribution confirms that the integration of convolutional feature extraction and bidirectional temporal learning enhances both short-term fluctuation modeling and long-term trend representation.

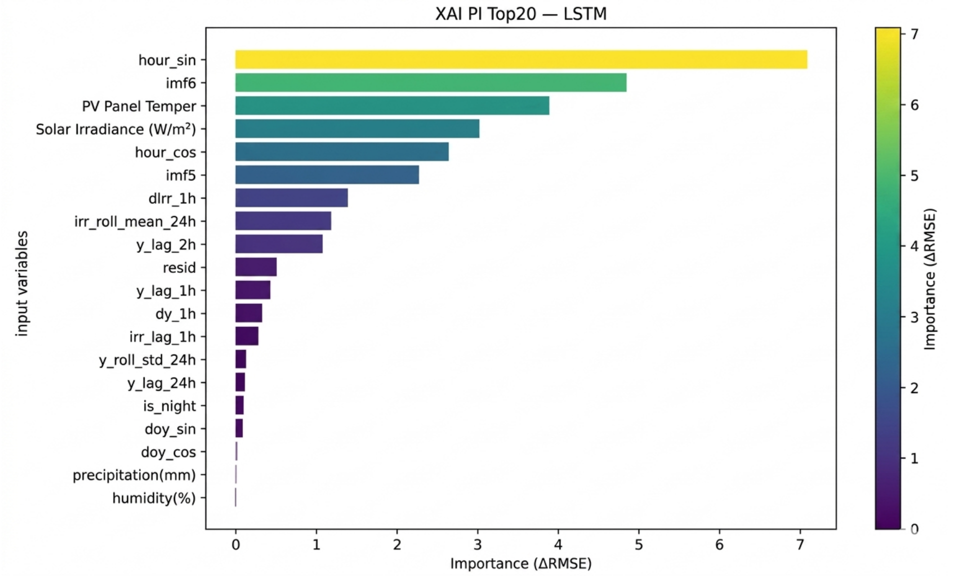

Figure 8. The XAI result of the LSTM model

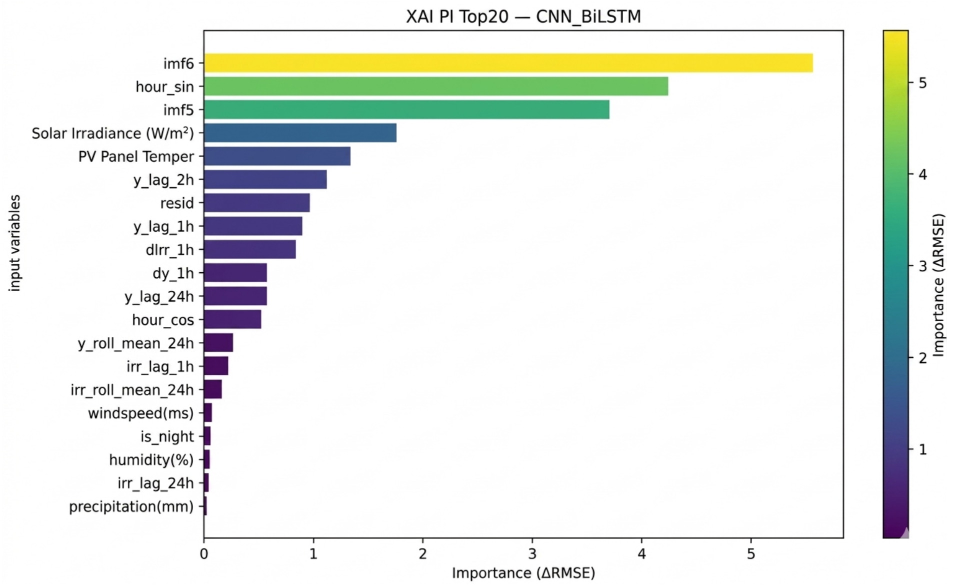

Figure 9. The XAI result of the CNN-BiLSTM model

Furthermore, Figure 10 presents the XAI analysis of the residual learning model. The results indicate that mid-frequency signal components are the most influential variables, suggesting that the residual structure primarily focuses on correcting prediction errors associated with short-term variability. This mechanism effectively mitigates the impact of noise and sudden changes in environmental conditions, thereby improving forecasting robustness.

The XAI analysis using permutation importance reveals that the influence of input variables on PV power forecasting strongly depends on the model architecture. Signal-driven models such as CNN primarily rely on CEEMDAN-derived components, particularly mid to high frequency IMFs, indicating their effectiveness in capturing short-term fluctuations caused by rapid irradiance variations. In contrast, ANN emphasizes low-frequency IMFs and physical variables, reflecting its dependence on long-term trends and overall system behavior. Temporal models, including RNN, LSTM, and BiLSTM, assign higher importance to cyclical time features and low-frequency IMFs, demonstrating their ability to learn diurnal and seasonal patterns of PV generation. Among them, LSTM and BiLSTM show superior capability in modeling long-term dependencies compared to conventional RNNs. Hybrid models such as CNN-LSTM and CNN-BiLSTM exhibit a balanced contribution from signal-based, temporal, and physical variables, highlighting the complementary learning mechanisms of convolutional and recurrent structures.

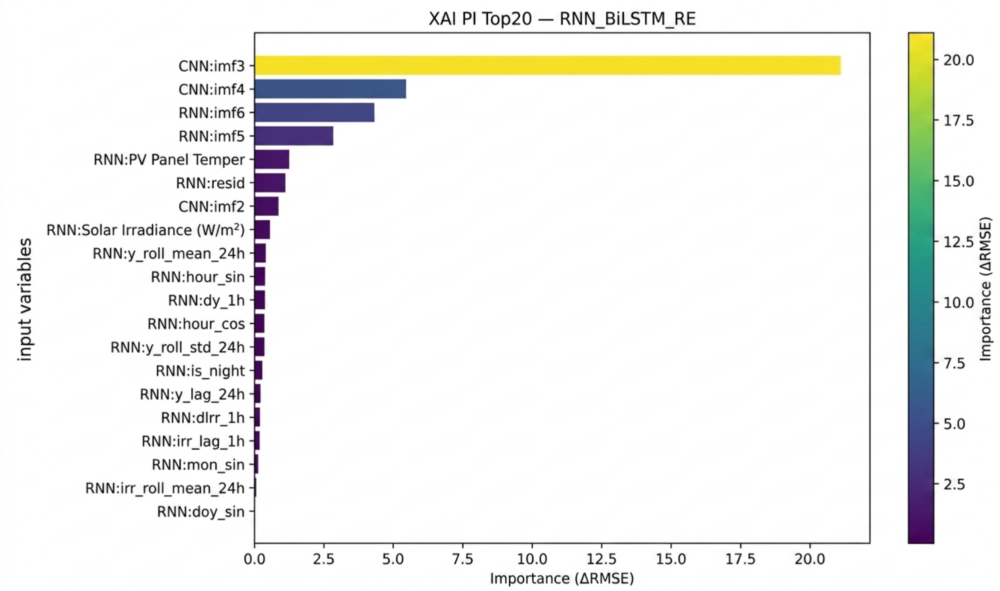

Figure 10. The XAI result of the RNN-LSTM model

4. CONCLUSION

This study proposed a deep learning–based integrated XAI framework for the PV power forecasting, explicitly accounting for the actual power production period. A comprehensive comparison of nine DL architectures was performed using the same meteorological inputs, including solar irradiance, ambient temperature, relative humidity, and historical PV power data, to ensure a fair and consistent evaluation. Based on the forecasting accuracy metrics, the residual-based RNN–LSTM model achieved the best overall performance, yielding the lowest MAE of 1.21 kW, MAPE of 5.12%, RMSE of 2.24 kW, and the highest R^2 = 0.9937. The RNN-BiLSTM model ranked second, with a MAPE of 7.05% and an R^2 value of 0.9926, confirming the effectiveness of bidirectional temporal learning combined with residual correction. Among the non-residual hybrid models, CNN demonstrated strong performance with a MAPE of 9.25% and R^2 of 0.9833, outperforming conventional recurrent and feedforward architectures. In contrast, stand alone models such as LSTM and BiLSTM exhibited higher prediction errors, with MAPE values exceeding 21%, indicating limitations in capturing complex nonlinear dynamics when applied independently. The integration of XAI through permutation importance analysis provided valuable interpretability by revealing that CEEMDAN-derived signal components and cyclical temporal features play a dominant role in PV power forecasting, while physical variables such as solar irradiance, panel temperature, and humidity contribute secondary nonlinear effects. These findings are consistent with the physical characteristics of PV systems and validate the learning behavior of the proposed models. Overall, the proposed integrated DL–XAI framework delivers high forecasting accuracy, robustness, and interpretability, making it well suited for practical deployment in smart grid operation and renewable energy management. Future research will focus on extending the framework to multi-site PV systems and real-time adaptive forecasting scenarios.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
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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

Authors state no conflict of interest.

INFORMED CONSENT

Not applicable. This study did not involve human participants.

ETHICAL APPROVAL

Not applicable, no human subjects or animal use was involved in this research; thus, institutional review board approval, Helsinki Declaration tenets, or animal care policies do not apply. The study adhered to general research integrity standards through computational methods and publicly available data only

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon, [WS], reasonable request.

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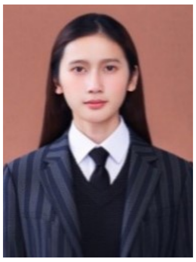

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