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Original Article

Analyzing the Impact of Environmental Factors on Solar Power Output Using Explainable Deep Learning Techniques

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Abstract - *An advanced prediction of power generation is necessary for renewable systems to achieve optimal efficiency and output. This paper explores advanced deep learning models: Long Short-Term Memory (LSTM), 1D Convolutional Neural Network (1D-CNN), and a combined LSTM-1DCNN model to predict output solar power using historical time series climatic data. The feature consists of the main characteristics, namely temperature, air pressure, sun radiation, and humidity of the solar power. Several evaluation metrics were used to better assess each model's performance and the extent to which it has addressed research questions. The best model that showed high accuracy and good generalization of the output data was chosen as the LSTM-1DCNN hybrid model. Regarding the projections, each feature's contribution was evaluated using SHAP values with the "SHAP" package. The analysis carried out by the study revealed that models were influenced most by sun radiation. As the three models are analyzed, the call for multiple deep-learning techniques increases the forecast level. This paper focuses on the potential of using hybrid deep learning models to enhance the accuracy of the power output predictions while, by SHAP analysis, underlining the requirement for the model explainability. However, such work offers significant viewpoints and room for other developments that can use more prominent datasets and elaborate details. However, the results also highlight the areas to learn about the possibility of increasing the reliability and interpretability of the model's outcomes while underlining the necessity to apply advanced modelling approaches to optimize energy systems.*

Keywords - *Deep learning, Explainability, Forecasting, Solar power, SHAP.*

1. Introduction

Due to their great capacities for electricity generation, Photovoltaic (PV) cells are one of the most sought and applied types of renewable energy resources. Incorporating PV systems with smart grids requires precise prediction of the electricity produced by the PV systems. Whenever many MW scale PV systems are interconnected with the utility or if a multitude of small-scale PV systems are connected at the utility side, having the ability to forecast the PV system's power output becomes crucial. Little attention has been focused on the present research topic, whereby a very limited number of research studies are available on forecasting the power generated by PV [1]. The overwhelming portion of the published literature is concentrated on estimating solar radiation. However, sun irradiance is just one factor determining a PV module's output power, which depends on several other features. Such factors may consist of the physical states of the cells, the kind of solar cells together with the electrical layout of the module, the angle of the incident rays, temperature, and so on. Solar power can be classified as one of the most important elements for the shift towards sustainable power resources. Today, against the backdrop of such negative consequences of climate change and the reduction in fossil fuels, the need for effective and stable solar energy generation has become especially pertinent. Several parameters, such as environmental conditions like temperature, humidity, irradiance, and atmospheric conditions, directly impact the efficiency of solar power systems. There is a need to comprehend how these factors affect the performance of solar power and make a correct prognosis of the phenomenon since the declination of those aspects ensures the effectiveness of the solar power output and the stability of the solar power system [2].

Over the last few years, huge improvements in deep learning have redefined data analysis and interpretation in many fields of science and industry. As part of deep learning methods, the neural network approach has shown good results when applied to image classification, speech recognition, and the prediction of time series data. Such approaches have a huge capability of capturing relationships and patterns in the data and, therefore, are most preferable for use in nonlinear models such as solar power forecasting. Nevertheless, contrary to their high predictive quality, deep learning models have been criticized for being "black boxes" and, therefore, having poor explainability of how inputs are translated into outputs [3, 4]. Another drawback of implementing deep learning models is the non-interpretable feature, which becomes problematic, particularly in crucial domains such as renewables forecasting. Engineers, policymakers, grid operators, and other stakeholders need simple and understandable models for decision-making regarding electricity generation, transmission, and investment in electricity networks. In this context, the emerging research field of Explainable Artificial Intelligence (XAI) intends to increase the safety of AI. XAI aims to explain the functioning of deep learning models or explain how particular input variables affect a model and which factors matter most in such decisions [5].

Out of all of the techniques that belong to the field of XAI, the most promising one appears to be SHapley Additive exPlanations (SHAP). SHAP is also derived from cooperative game theory and is claimed to give a clear interpretation of the prediction of models. It provides every feature with an important value for a specific prediction, therefore showing the effect of every environmental factor on the result of solar power generation. The values of SHAP are reliable and less sensitive to the model; therefore, the explanations are reliable and locally relevant. This technique is also useful for understanding the behaviour, improving the model's interpretations, and investigating possible biases in the data set or the chosen model [4].

Though conventional statistical and machine learning methods have been used in energy forecasting, they frequently fail to capture environmental data's intricate temporal and nonlinear relationships. Deep learning models are becoming increasingly useful because they can record minute patterns and correlations in huge datasets, making them powerful instruments. LSTMs and CNNs are two deep-learning architectures with great potential in feature learning and temporal forecasting. Several earlier techniques like linear regression, time series analysis (example: ARIMA), support vector machines (SVM), and random forest have been in prior use. Thus, simple and clear linear regression cannot detect nonlinear patterns and interactions between features [6, 7]. ARIMA models show fairly high accuracy for short-term forecasts but have several limitations for nonlinear relations and long-term dependencies. It is best applied in high dimensional space, but large data sets with complex patterns consume a lot of time. Although ensemble learning makes classification more accurate, random forests present the problem of handling them with high-dimensional data and might neglect temporal dependencies. The following are the disadvantages that bolster the necessity for superior methods to tackle the complex relations of renewable energy information [8, 9]. Because these algorithms can identify complex patterns, the predictions are very accurate. Alas, adopting these models in important decision-making processes remains somewhat impracticable, as often, a number of these pinpoints are shrouded in the veil of limited interpretability, resulting from the models' complexity. Explainability techniques such as SHAP values have been used to mitigate this problem. SHAP values improve the openness and confidence in the results produced by these models by clarifying the contributions of particular environmental conditions to the model's predictions. Machine learning models are interpreted, and feature importance is understood using a number of other techniques, such as Partial Dependence Plots (PDPs), Feature Ablation, and Permutation Feature Importance. The measure of a feature's relevance in permutation feature importance is the reduction in model performance caused by randomly shuffled feature values.

It might not, however, thoroughly capture feature interactions and can be computationally costly. By averaging the model predictions over a range of feature values, PDPs show the impact of a single feature on the projected outcome, but they frequently ignore feature interactions. Feature ablation is methodically eliminating characteristics from the model to see how it affects performance; nevertheless, for models with a lot of features, this approach can be problematic and, in the case of highly correlated features, may produce biased results. Such imposed limitations highlight the usefulness of SHAP, which provides a sound and comprehensive analysis of the allocation, interactions and importance of features [10]. This study employed the SHAP and advanced deep learning models to predict the output power of a solar power system. Three models were implemented: - LSTM model in this research, LSTM, 1D-CNN, and a combination of the two models LSTM-1DCNN will be used. The models ACC, AV, CTL, PAC, and PRC were trained using a dataset that included critical environmental parameters such as temperature, sunlight intensity, relative humidity, and atmospheric pressure. Finally, after training the models, the explanations of the patterns were given through SHAP, which revealed the contribution of each feature. This methodological approach 'solved' interpretability problems associated with complex machine learning techniques and presented secure future values with a better understanding of factors that define the output power [11–13].

The current research proposes an effective method to forecast solar power generation with the help of deep learning techniques, including LSTM, 1D-CNN, and LSTM-1DCNN with SHAP, improving interpretability. Unlike the traditional models, these approaches can miss the dynamic and nonlinear character of the environmental variables; thus, this study employs SHAP to identify the relevant features and leverages the advantages of deep learning in creating precise approaches. In this respect, there are beneficial implications of stressing accuracy and comprehensibility throughout the present research utilizing a systemic approach that identifies the determiners of solar power yield and offers high-performance metrics, thus filling a research gap in forecasting renewable energy.

2. Problem Identification

2.1. Predictive Deep Learning Models for Solar Power

Many models are already under development for the purpose of solar energy prediction due to the recent improvements in deep learning. The complexity of these models is growing. Compared to other techniques, these models are more accurate because they can identify complex patterns in the surroundings in which they are now immersed. Several instances have been given to show the benefits of deep learning models and their possible applications in solar power forecasting. Yaojian Xu et al. [14]. For example, the short-term power produced by solar cells in Beijing was predicted using a CNN-LSTM hybrid model. It was done from the viewpoint of the city. The idea exhibits significant gains over more conventional methods regarding future forecast accuracy. We used the already accessible weather data together with the historical power output to accomplish this aim. Deep learning developments recently have resulted in the development of ever more complex models for solar production predictions. Because these models can identify fine patterns in environmental data, accuracy levels that are higher than conventional techniques can be achieved; similarly, Kim et al. [15] demonstrated how efficient parallel processing is and how well transformer models can manage huge datasets by using them for real-time solar power control.

Table 1. Recent research on deep learning models for solar power forecasting

Ref	Method	Objective	Key Findings
[16]	COA-CNN-LSTM	PV/wind Power Forecasting in Smart Grid Applications	COA-CNN-LSTM model outperforms other techniques in terms of the Granger causality test and Nash-Sutcliffe analysis, showing precise and definitive wind power predictions for renewable energy management.
[17]	CEEMDAN-LSTM	Forecasting Total Electron Content (TEC) for GNSS Applications	The CEEMDAN-LSTM model demonstrated 50% and 70% better accuracy in RMSE and MAE, respectively, compared to LSTM and Neural Network models.
[18]	ARIMA-LSTM	Modelling and Forecasting CO_2 Emissions in China and its Regions	ARIMA-LSTM model is more accurate in predicting CO_2 emissions trends in China, providing valuable insights for carbon reduction policies.
[19]	Attention-based LSTM	Petroleum Production Forecasting	Attention-based LSTM network improved prediction accuracy and computational efficiency compared to traditional methods.
[20]	IWOA-LSTM	IoT Temperature and Humidity forecasting	The IWOA-LSTM model showed high accuracy, which is better than other forecasting models.
[21]	LSTM	Streamflow forecasting over a Canadian catchment	LSTM model forecasted streamflows are more reliable and accurate for lead times up to 7 and 9 days, respectively, compared to a process-based distributed hydrological model.
[22]	Optimized LSTM	Forecasting hourly PM2.5 concentration	The optimized LSTM model performed efficient and satisfactory forecasts within a 15 km radius, showing significant improvements in prediction accuracy over previous models.
[23]	LSTM-TCN	Accurate one-step and multistep forecasting of very short-term PV power	The LSTM-TCN model significantly reduced the Mean Absolute Error (MAE) compared to standalone LSTM and TCN models across different seasons and periods.
[24]	Merton-LSTM	Forecasting and trading Credit Default Swap (CDS) indices	The Merton-LSTM model achieved the lowest RMSE values and highest annualized Sharpe ratios, outperforming other models in forecasting accuracy and trading performance.
[25]	Improved Stacking Ensemble	Multi-timescale photovoltaic power forecasting	The improved Stacking ensemble model enhanced accuracy across multiple time scales.
[26]	LSTM	Regional groundwater sequential forecasting	The local LSTM models provided nearly identical performance compared to global models, with further improvements through Transfer Learning (TL) in coastal areas.
[27]	ConvLSTM-LSTM	Weather image-based short-term dense wind speed forecasting	The ConvLSTM-LSTM model significantly improved MAE, RMSE, and R^2 values, effectively forecasting wind speed with large amplitude variations and rapid frequency changes.

Table 2. Pros and cons of the deep learning model

Model	Pros	Cons
CNN	Effective in capturing local spatial patterns and handling multiple input sequences	Struggles with long-term dependencies and complex temporal relationships
LSTM	Excellent for capturing long-term temporal dependencies in time series data	Computationally intensive, especially for large datasets
GRU	Simplified architecture with fewer parameters than LSTM, leading to faster training	May not capture long-term dependencies as effectively as LSTM
Transformer	Excels in parallel data processing and capturing long-range dependencies	High computational cost and complexity in model training
Hybrid Models	Combines the strengths of different architectures, offering comprehensive pattern recognition	More complex to train and optimize, with potential overfitting due to multiple model integration

Xu et al. [14] used Gated Recurrent Units (GRUs) in a separate work to forecast solar radiation over the long term. The development of RNNs and GRUs has shown promise because of their quicker training periods and more straightforward construction than LSTMs. Taiwanese researchers found that GRU models offered precise and effective projections, qualifying them for long-term solar power plant planning.

The deep learning models covered similar research areas, compared in Table 2 [28–30]. The advantages and disadvantages of the several deep learning models applied to solar power forecasting are listed in this table and their limits.

2.1.1. LSTM (Long Short-Term Memory) Networks

A kind of recurrent neural network, LSTM networks operate especially well for managing sequential input and capturing long-term dependencies. Because these networks are excellent at time-series forecasting, they are perfect for anticipating solar power output from past environmental data. Several parts of an LSTM cell's design cooperate to control the hidden and cell states, enabling the network to pick up temporal patterns. An LSTM cell's input, output, forget, and cell state gates are its essential components. Equations such as these can characterize them:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}\, ,\, x_t] + b_f\right) \tag{1}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}\, , x_t] + b_i) \tag{2}$$

$$\tilde{c}_t = tanh(W_c \cdot [h_{t-1}\, ,\, x_t] + b_c) \tag{3}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \tag{4}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}\, ,\, x_t] + b_o) \tag{5}$$

$$h_t = o_t \cdot tanh(c_t) \tag{6}$$

Where input, recurrent data, and output of each cell at time t can be presented by x_t, h_t, and o_t respectively. The forget gate is represented by f_t, c_t represents the status of the LSTM's cell. W_f W_i, W_c, and W_o represent the network weights, the operator'·' used for the multiplication of two pointwise vectors and b_f, b_i, b_c are the system's bias [31, 32].

2.1.2. Convolutional Neural Networks of One Dimension (1D-CNN)

Time series are processed by convolutional operations applied over 1D-CNNs. Particularly good at detecting local patterns and characteristics in time-series data, these networks are appropriate for signal processing and time-series forecasting, including predicting solar power output depending on environmental conditions. A 1D convolution essentially applies a kernel (or filter) to the input data to generate an output feature map [33]. This is the numerical equation procedure:

$$x_k^l = b_k^l + \sum_{i=1}^{N_{l-1}} \operatorname{con} v1D\left(w_{ik}^{l-1}, s_i^{l-1}\right) \tag{7}$$

$$y_k^l = f\left(x_k^l\right) \text{ and } s_k^l = y_k^l \downarrow ss \tag{8}$$

Where the input data can be defined by x_k^l, the bias of the k^{th} neuron at layer l can be defined by b_k^l, s_i^{l-1} represents the i^{th} output of each neuron at $l-1$ layer, the kernel from the i^{th} neuron at layer $l-1$ is represented by w_{ik}^{l-1} to the k^{th} neuron at layer l.

The intermediate output, y_k^l, can be expressed by passing the input x_k^l through the activation function as expressed in equation (2). Where s_k^l represents the output of the k^{th} the neuron of the layer l, and "$\downarrow ss$" represents the down-sampling operation with a scalar factor, ss.

As an overview, the backpropagation algorithm is as follows. Error back propagation begins at the output MLP layer. Assume that the input layer is 1 and the output layer is $l = L$. Then, for an input vector p, and its target and output vectors, t^p $\left[y_1^L, \cdots, y_{N_L}^L\right]$, respectively. Let N_L be the number of classes in the database. Thus, the mean-squared error (MSE), E_p, for the input p in the output layer, NL can be expressed as follows:

$$E_p = \mathrm{MSE}\left(\boldsymbol{t}^p, \left[y_1^L, \cdots, y_{N_l}^L\right]'\right) = \sum_{i=1}^{N_l} \left(y_i^L - t_i^p\right)^2 \tag{9}$$

2.1.3. LSTM-CNN Hybrid Models

Strong points of the LSTM and CNN architectures are combined in hybrid LSTM-CNN models. Since CNN layers can extract spatial information from the input data and LSTM layers can capture temporal dependencies, these models perform exceptionally well in challenging time-series forecasting applications such as solar power production predictions [34].

When an LSTM-CNN model is used, the CNN layers are first applied to the sent data. The main job of these CNN layers is to find patterns and features in the nearby area. The CNN layers send their output, and then the LSTM layers look at the sequential input and find the temporal correlations that show up. This is what happens after the CNN layers are done working. This mixed method, which looks at time and space, lets a deeper look at the data. Given are some mathematical examples that show how the hybrid model is put together, where x_t represents the data that is being entered at a certain time:

$$y_t = \mathrm{LSTM}(CNN(x_t)) \tag{10}$$

2.2. Explainability in Deep Learning Models

Due to their quick acceptance in solar power forecasting, deep learning models have been perceived as difficult to interpret. Although these models are pretty accurate, their black-box design makes understanding how predictions are made challenging. Explainability techniques aim to close this gap by providing details about how these models make their decisions, thus improving their transparency and reliability [35]. One commonly used approach for characterizing the output of machine learning models is SHAP. Cooperative game theory-based SHAP values consider the role of each feature in the model's predictions across a range of scenarios to produce a single measure of feature relevance. The difficulty of model interpretability is resolved by this method, which quantifies the impact of specific characteristics on the prediction results.

The SHAP value for a feature $\boldsymbol{i}$ can be defined as follows within the framework of a prediction f(x):

$$\phi_i = \sum_{S\subseteq N\setminus\{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!}[f(S\cup\{i\}) - f(S)] \tag{11}$$

Where f(s) expressed the model prediction, N is the complete set of features, whereas S represents a subset of those features that do not contain $\boldsymbol{i}$. This equation provides a complete evaluation of the feature importance by estimating the marginal feature worth and then taking the average of the worth by all possible feasible features.

Thus, certain classes of models, including deep learning networks, complicate the identification of the contribution of individual input attributes. Due to the complexity of these models, this becomes a tough task. It is in such a situation where applying SHAP principles helps solve the problem. Understanding the relevance of SHAP values is critical for improving the interpretability and trustworthiness of the model's predictive outcomes. These values help in decision-making about features and contribute to distinguishing the most important of them, as well as giving a more accurate assessment than data visualization at the same time.

In the following sections, we will examine how the LSTM, 1D-CNN, and Hybrid LSTM-CNN models use SHAP values for their explanation. Thus, using the SHAP data, it is possible to find out to what extent the predictions concerning solar power generation depend on different factors of the environment. These include heat, intensity of light received from the sun, humidity and pressure in the atmosphere. In this way, the disposition of the models becomes more apparent, and identifying the most significant factors affecting solar energy production becomes easier.

As shown in Figure 1, we can identify the working process of the SHAP values in the analysis of the model results. The figure helps show several parameters of the environment regarding the results of a solar power prediction model, such as temperature, humidity, solar irradiance, atmospheric pressure, etc. Knowing how each element impacts the adjustment of the forecast is important to determine whether the forecast will be less than or more than the base rate. Thus, in this case, productivity increases with higher temperatures and amounts of sunlight while it decreases with higher humidity and air pressure. The characteristics illustrated in the above figure are very informative of this model's decision-making factors, which are greatly influenced by these aspects. This figure assists in identifying the parameters that exert the most significant impact on the model's decision [36].

Therefore, this work employs SHAP values to effectively explain how various environmental factors influence the forecasts of solar power generation by applying adequate interpretations to the problem of model interpretability. Ensuring transparency is the key to confirming the dependability of the model when making informed decisions regarding the enhancement of solar power systems.

3. Methodology

3.1. Models Setup

3.1.1. LSTM Model Setup

Some time series forecasting activities are solar power output, which depends on the environmental conditions likely to have a temporal relationship that the LSTM model grasps. An input layer in the model's design consists of feature sequences: temperature, solar irradiance, humidity, and atmospheric pressure. A 50-unit first LSTM layer with a ReLU activation function returns sequences that enable later LSTM layers. To avoid overfitting, a second 50-unit LSTM layer without sequence return and another 20% rate dropout layer are added. Eventually, a dense layer of one unit produces the anticipated solar power. MSE is used as the loss function in the Adam optimizer-compiled model, which is trained for 500 epochs with a batch size of 32 and verified using a different validation set [37–39].

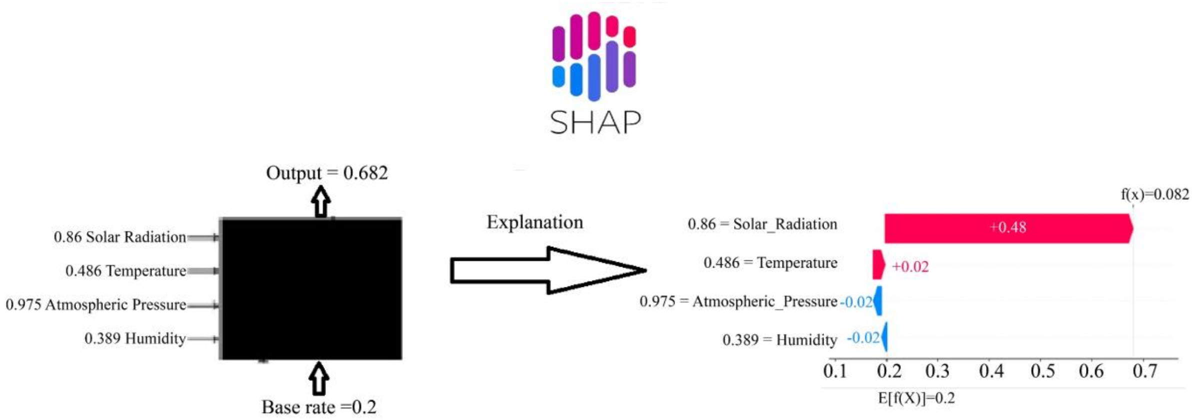

Fig. 1 SHAP value explanation graph

3.1.2. 1D-CNN Model Setup

Enhancing feature extraction for time series forecasting, the 1D-CNN model detects spatial correlations and patterns in the input data. An input layer of feature sequences—temperature, solar irradiance, humidity, and atmospheric pressure—makes up the model's architecture. The input is downsized by a max pooling layer with a pool size of 2 after a first convolutional layer applying 64 filters with a kernel size of 2 and a ReLU activation function. Another max pooling layer with a pool size of 2 comes after the second convolutional layer, which once more applies 64 filters with a kernel size of 2 and a ReLU activation function. A layer flattened the input to feed it into the fully connected layers. Then comes a 50-unit dense layer with a ReLU activation function, a 50% rate dropout layer to stop overfitting, and a 1-unit output layer to forecast solar power. The model is trained for 500 epochs with a batch size of 32 after being constructed with the help of the Adam optimizer and MSE as the function of loss. [7].

3.1.3. Hybrid LSTM-CNN Model Setup

The hybrid LSTM-CNN model integrates temporal and spatial dependency of data where LSTM captures temporal dependency, and CNN captures spatial dependency from the data. One of the model's inputs is the feature sequences, which include temperature, solar irradiance, humidity, and pressure. A max pooling layer with pool size 2 to downsample the input follows it. A flattened layer is used to prepare the data for LSTM layers: A convolutional layer that applies 64 filters with a kernel size of 2 and ReLU activation function follows it. Next is a 50-unit first LSTM layer with a ReLU activation function that sends sequences back for later LSTM layers to use. To avoid overfitting, a second LSTM layer of 50 units that does not return sequences and another dropout layer of 20% rate are introduced. Eventually, a dense layer of one unit produces the anticipated solar power. The model is built with MSE as the loss function and the Adam optimizer. It is trained for 500 epochs with a batch size of 32 and verified with a different validation set [40].

3.2. SHAP Analysis

The impact of temperature, solar irradiance, humidity, and atmospheric pressure on the solar power output estimates was identified and quantified using SHAP to improve the interpretability of the deep learning models. SHAP values give insights into the model's decision-making process by giving each feature an important value for a certain prediction, providing a consistent measure of feature relevance.

First trained on the training dataset were the models (LSTM, 1D-CNN, and Hybrid LSTM-CNN) for the SHAP analysis. The trained AL and QM prompts were followed by using SHAP to interpret these models' results. Specifically, based on the comparison of suitability for the utilized model and computational complexity, the DeepExplainer was used for the 1D-CNN model as well as LSTM and the Hybrid LSTM-CNN models. Some test data generated SHAP values per the requirements for summary and feature importance charts to depict how each played in concluding the model's output.

The distribution of the SHAP values for each characteristic overall forecast was shown in the summary charts, emphasizing the most important variables in solar power production prediction.

Additionally, the relative permutation importance scores derived from the average of the absolute SHAP values over the test dataset gave a worldwide outlook of feature importance as depicted in the importance plots. That the prediction models are clear, solid and consistent was made certain; in large measure paradoxically, the noted visuals and quantitative investigations authenticated the extent of the model's pointers to the relevant environment parameters [35].

3.3. Data Description

A specific distributed photovoltaic system dataset is chosen, and the PV system is installed on the rooftop of a factory located in a city in southern China. The dataset consists of historical measurements of PV power production (kW), temperature (°C), solar radiation (W/m2), and meteorological data, including air pressure (hPa) and humidity (%) [38, 41].

Figures 2 and 3 illustrate the output power, solar radiation, temperature, humidity, and air pressure performance over time.

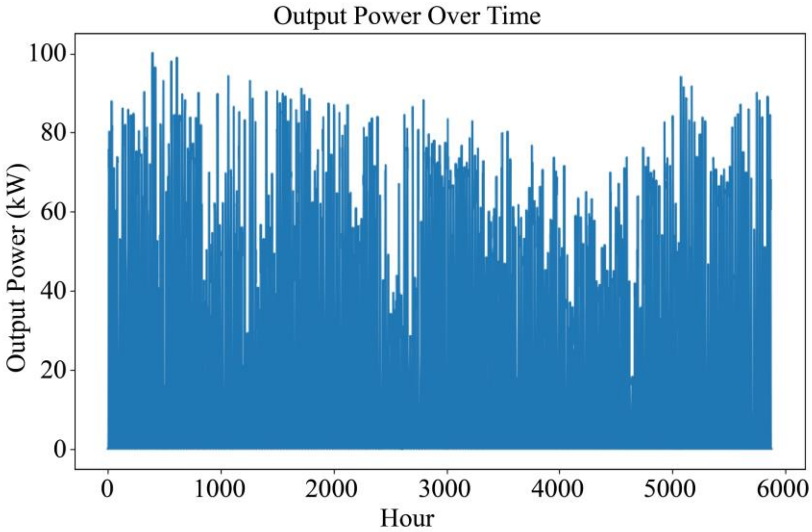

Fig. 2 Output power over time

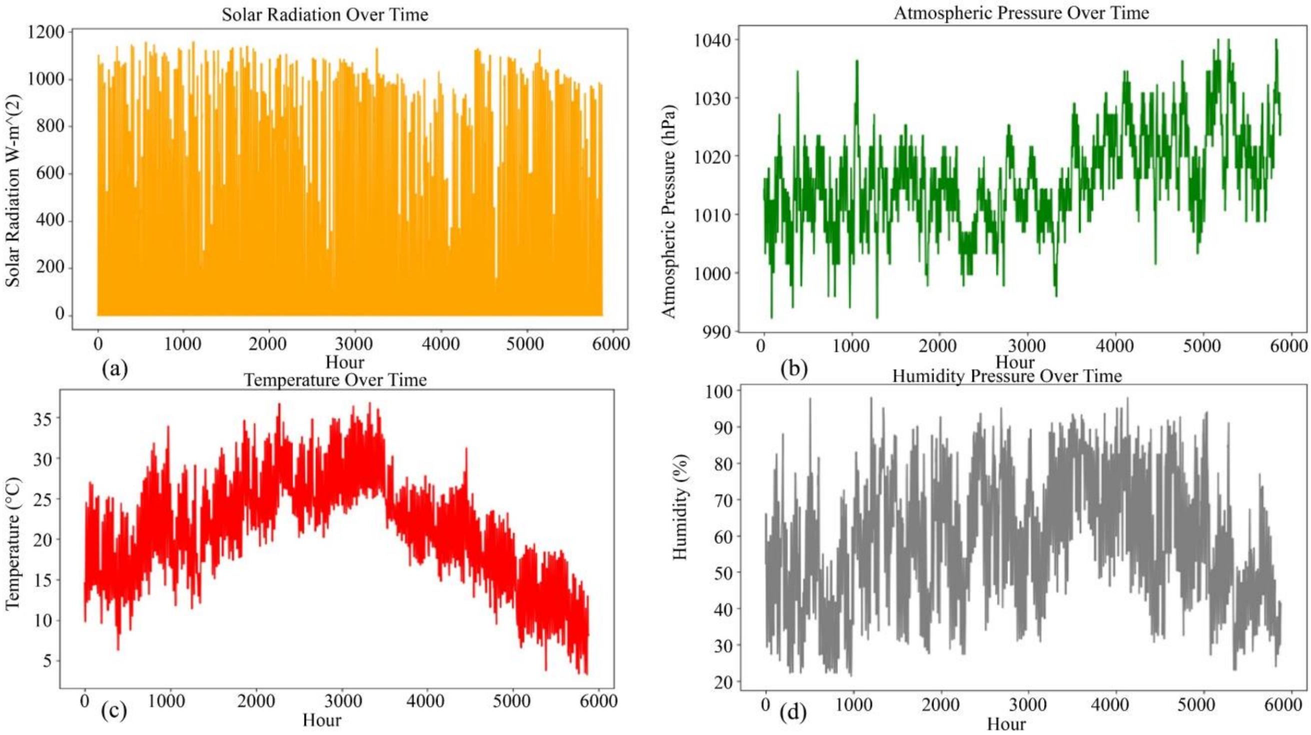

Fig. 3 Features performance over time, (a) Solar radiation (W/m²), (b) Atmospheric pressure (hPa), (c) Temperature (°C), and (d) Humidity (%).

3.4. Working Structure

As Figure 4 and the next paragraphs show, the study's work structure follows a systematic methodology:

- Gathering and condensing the data: Your responsibilities during this stage will be to collect information from the distributed PV system and thoroughly explain the operational features being used. Data was gathered from an operational distributed photovoltaic (PV) system perched atop a factory in a southern Chinese city. The dataset contains many meteorological parameters, such as air pressure and humidity. The compilation also contains historical statistics on solar radiation, temperature, and photovoltaic power generation.
- Data pretreatment: At this point, several cleaning and preparation procedures are applied to the collected data to maintain consistency and enhance the general performance of the model. This area of accountability is devoid of value management, data standards, and data preparation for analysis.
- The process of adding or changing features to a model to improve its overall performance is known as feature engineering. This stage is crucial if the models are to understand the connections between climatic conditions and solar power production.
- Instruction in Models Using preprocessed data, the research builds and trains three distinct models. The first model, a network, can capture temporal dependencies in the data well. The second model, a one-dimensional CNN, finds and analyses local trends in the temporal data. To capitalize on both temporal and local trends, the third model, a hybrid LSTM-CNN,

combines the best aspects of both LSTM and CNN architectures. All models use restricted input features, including temperature, humidity rate, air pressure, and sun radiation intensity. The forecasts of the power generated by the sun are made probable through these features.

- Model Evaluation: R2, MAE, MSE, and RMSE, which are generally used measures for evaluating the performance of build models, are incorporated here. These actions can also effectively determine the reliability of the developed models in forecasting the level of solar power depending on various environmental conditions. Therefore, the application of SHAP Analysis is to analyze deep learning model predictions. In this case, the method that has been selected especially is the SHAP method. SHAP values provide information about the individual contribution of each feature (temperature, humidity, atmospheric pressure, and solar radiation) to the model's predictions. The relevant components can be determined from the above to identify the components most related to the model's forecast. This explainability approach is useful for interpreting the factors that affect the predictions and increases the clarity of deep learning models.
- In the last step, "Results and Discussion," we carefully review the results, compare how well different models work, and have a deep conversation about our opinions. Therefore, the purpose of this part is to gain sufficient knowledge on how different environmental factors impact solar electricity generation and the performance of the deep learning techniques used.

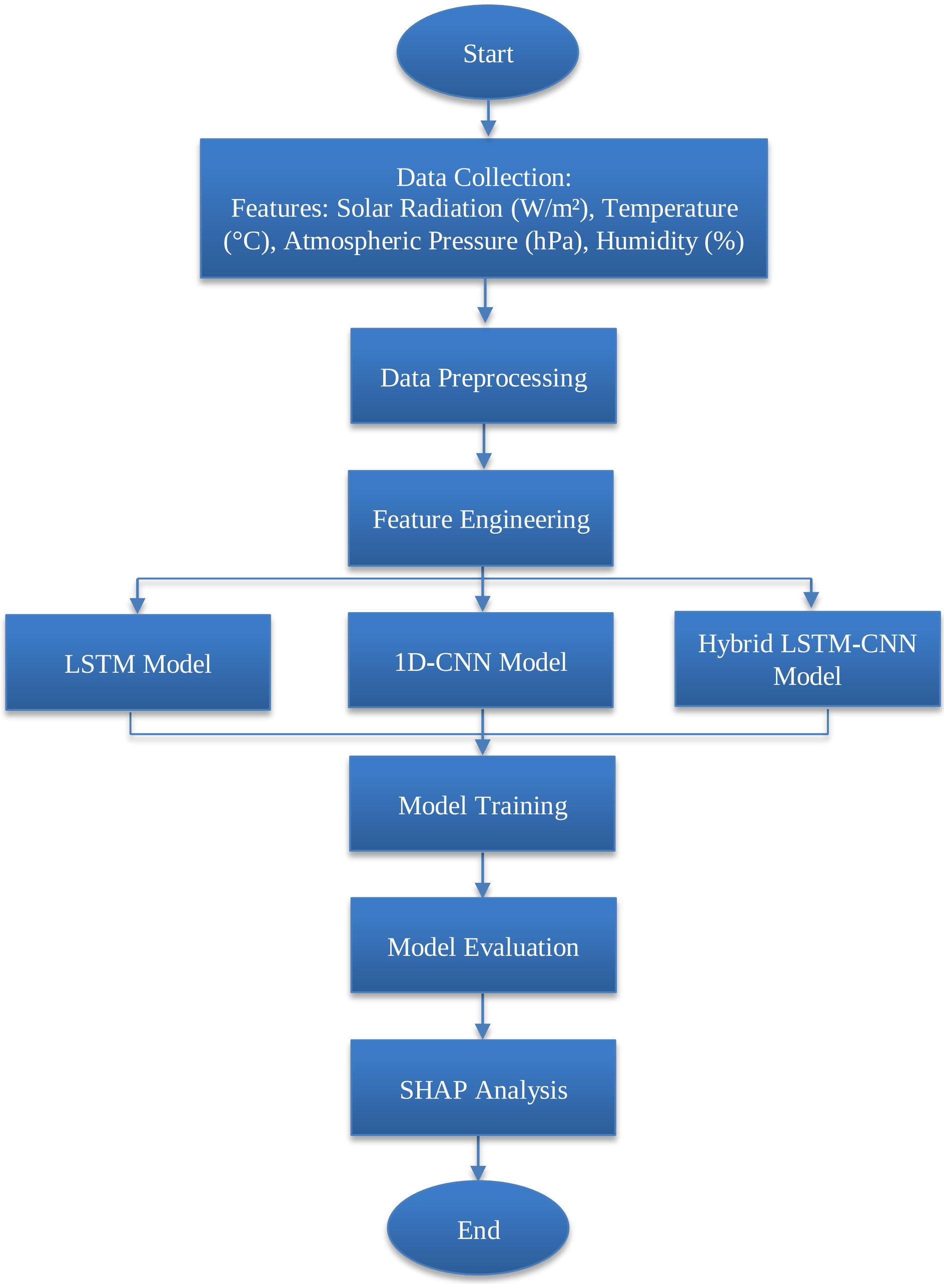

Fig. 4 Workflow for analyzing solar power output using deep learning and SHAP

4. Results and Discussions

4.1. Deep Learning Models Performance

As Table 3 explains, the performance indicators provide a comprehensive view of the predictive capacity of the three models—LSTM, 1D-CNN, and LSTM-1DCNN. With the LSTM model, the MAE between the predicted and real values is 0.0584.

On average error, however, the 1D-CNN model performs better than the LSTM model with a reduced MAE of 0.0495. With an average error of 0.0377, the hybrid model LSTM-1DCNN outperforms the other two models. The LSTM model produces an MSE of 0.00834 when considering the MSE. Compared to the LSTM model, the 1D-CNN model performs better with an MSE of 0.00788.

Both are much beaten by the LSTM-1DCNN hybrid model, which has an MSE of 0.0053. Less squared discrepancies between predicted and actual values indicate that the hybrid model fits the data more precisely, as this lower MSE value shows.

In a similar vein is the RMSE. The 1D-CNN model has better average squared differences performance with an RMSE of 0.08872 compared to the LSTM model's 0.09133. Once more, leading with the lowest RMSE of 0.0728, the LSTM-1DCNN hybrid model demonstrates how well it reduces prediction errors.

The R^2 values show even more how well the models account for the variation in the data. At R^2 of 0.862, the LSTM model explains 86.2% of the variation in the output power. A little improvement is indicated by the R^2 of 0.865 for the 1D-CNN model. With an R^2 of 0.924, which indicates that it can explain 92.4% of the variance, the LSTM-1DCNN hybrid model shines and shows its better ability to capture the underlying patterns in the data.

Table 3. Prediction models performance

Model	MAE	MSE	RMSE	R^2
LSTM	0.0584	0.00834	0.09133	0.862
1D-CNN	0.0495	0.00788	0.08872	0.865
LSTM-1DCNN	0.0377	0.00535	0.07281	0.924

The correlation matrix among the parameters employed in this work, such as temperature, solar radiation, humidity, atmospheric pressure, and output power, is shown on the heatmap in Figure 5. Perfect positive correlations are indicated by 1, perfect negative correlations by -1, and no correlation by 0. Output power and solar radiation show a substantial positive connection (0.9), indicating that increased solar radiation greatly increases power output. The somewhat positive correlation (0.3) between temperature and output power suggests a smaller but no less significant effect. In contrast, at -0.5 and -0.06, respectively, humidity and atmospheric pressure have smaller negative correlations with output power, suggesting that increases in these variables somewhat reduce power output. Furthermore, insights are revealed by the inter-feature correlations: While humidity has a little positive correlation with atmospheric pressure (0.2) and a moderate negative association with solar radiation (-0.5), temperature and atmospheric pressure are considerably negatively correlated (-0.6). This study makes the dynamics of environmental elements and their combined effect on solar power output easier to grasp.

The best loss reduction performance is shown by the hybrid model LSTM-1DCNN. Throughout the training phase, the validation loss remains extremely near to the training loss, and both training and validation losses drop off quickly. This behaviour suggests that the hybrid model captures the intricate relationships in the dataset and maintains a low error rate on unseen data in addition to learning fast and generalizing very well, as illustrated in Figure 6.

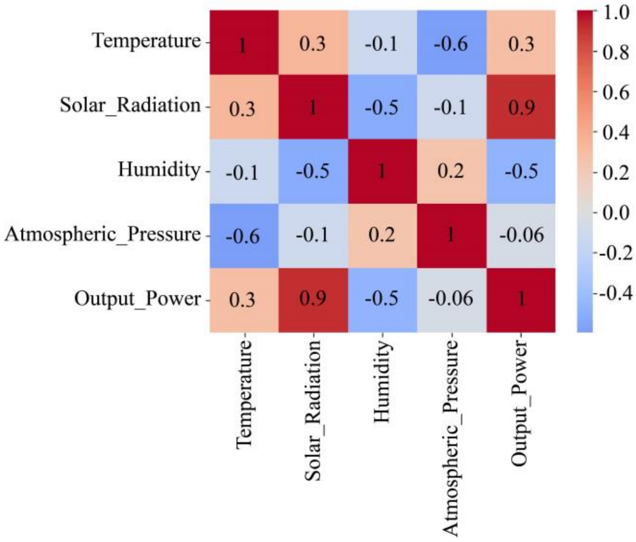

Fig. 5 Correlation matrix of environmental features and solar output power

4.2. Explainability in Deep Learning Models

This section explores how explainable the deep learning models employed in the study area are, stressing the need to comprehend how these intricate models generate their predictions. Using SHAP values allows one to analyze the models' decision-making processes, which improves openness and confidence in their results.

A single measure of feature relevance, SHAP values enable a consistent interpretation of the contribution of each feature to the predictions of the model across many models. Hence, in this work, three models, namely LSTM, 1D-CNN and Hybrid LSTM-CNN, are under consideration. The forecast of the output power of a distributed PV system depends on factors like temperature, solar radiation, humidity, and pressure.

Several techniques are then employed to explain the models' interpretability, thus comparing and contrasting the results. These visualizations include waterfall, bar, beeswarm, and scatter plots; each offers a unique view of the models' behavior and some factors' significance.

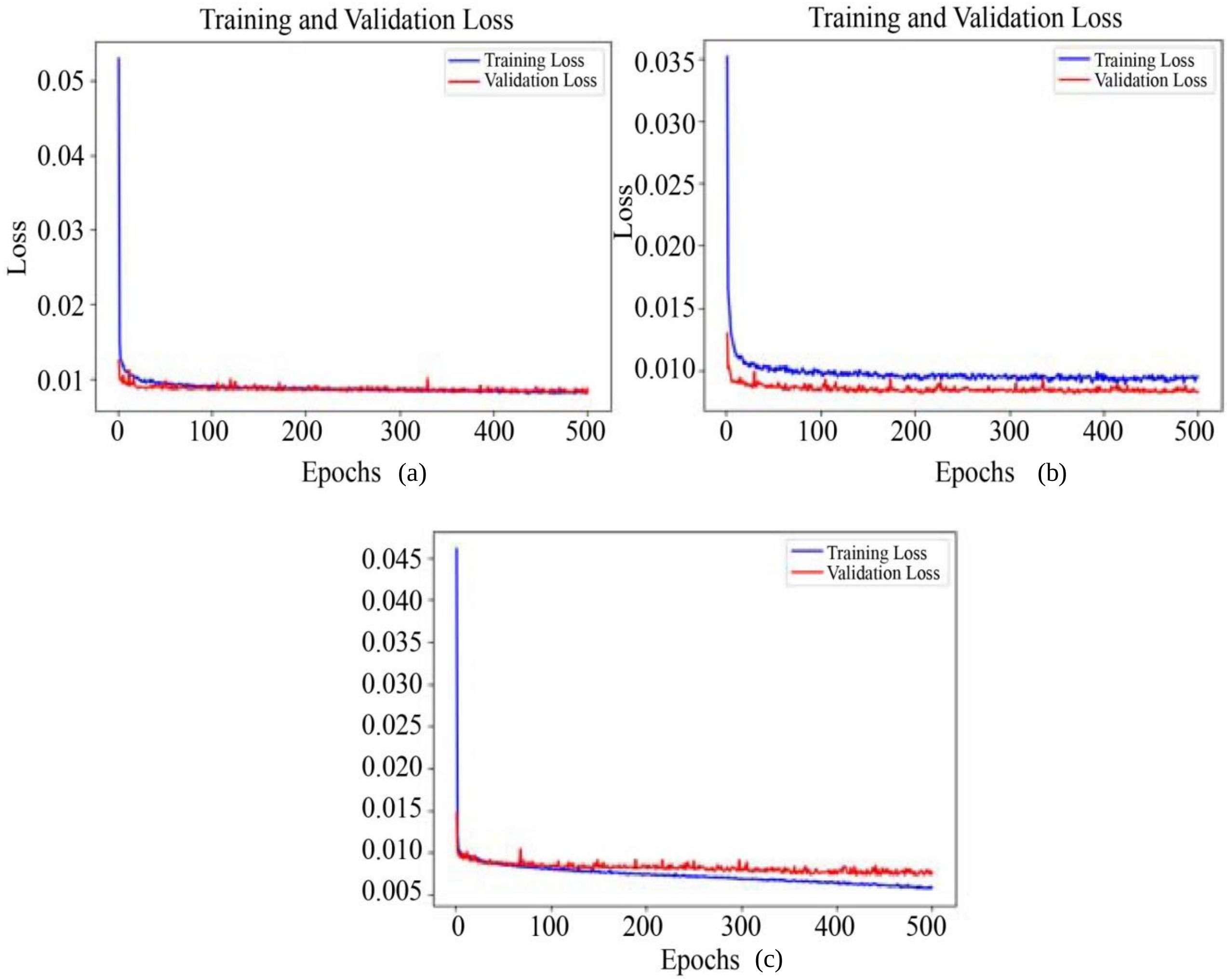

Fig. 6 Training and validation loss for (a) LSTM model, (b) 1D-CNN model, and (c) Hybrid LSTM-1DCNN model.

4.2.1. Interpreting Predictions with Waterfall Plots

To facilitate the understanding of how several characteristics influence the outcome, the plots lift the veil of the contributions made by each feature to the model's prediction of a specific case. f(x)=0.682 with an expected value E[f(x)]=0.202 for the LSTM model is mostly influenced by +0.48 solar radiation, as illustrated in Figure 7.

This suggests a considerable favourable impact on the forecast. With +0.02, the temperature has a little positive impact; -0.02 and -0.01, respectively, atmospheric pressure and humidity provide small negative contributions, respectively. This implies that other factors are but modest contributors to the prediction, mostly driven by solar radiation.

With an expected value of E[f(x)]=0.193, the prediction f(x)=0.642 in the 1D-CNN model further emphasizes the important contribution of solar radiation, as illustrated in Figure 8, which is +0.39.

Further factors, including temperature, humidity, and atmospheric pressure, each have a slightly positive impact of +0.02. This distribution shows that the other features together make a balanced contribution to the prediction, even if solar radiation continues to be the major component.

As illustrated in Figure 9, solar radiation makes the largest contribution, +0.52, to the prediction f(x)=0.76 with an expected value E[f(x)]=0.202. Following with a little contribution of +0.04, temperature, atmospheric pressure, and humidity all contribute a little positive influence of +0.01. Like the earlier models, this one emphasizes the significant influence of solar radiation and also shows a balanced integration of temperature and atmospheric pressure, implying a useful fusion of the advantages of the LSTM and 1D-CNN models.

To sum up, solar radiation always shows up as the most important factor in all models, greatly affecting the forecasts. Compared to solar radiation, which is essential for forecasting PV system output, the different contributions of temperature, atmospheric pressure, and humidity among the models show their comparatively small roles. The hybrid model especially shows a good balance by combining the advantages of 1D-CNN and LSTM and offering a thorough comprehension of the feature contributions to the predictions.

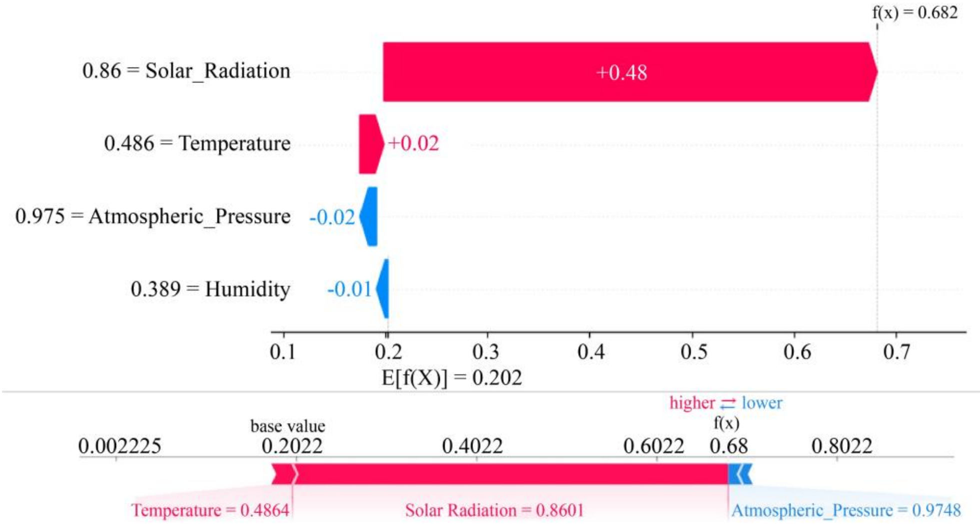

Fig. 7 Waterfall plot for LSTM model

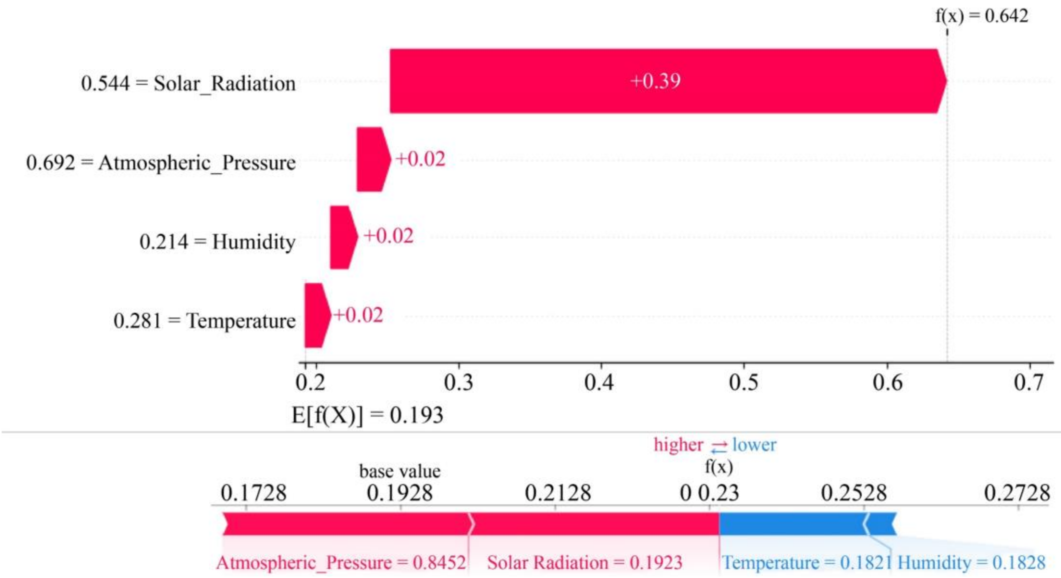

Fig. 8 Waterfall plot for 1D-CNN model

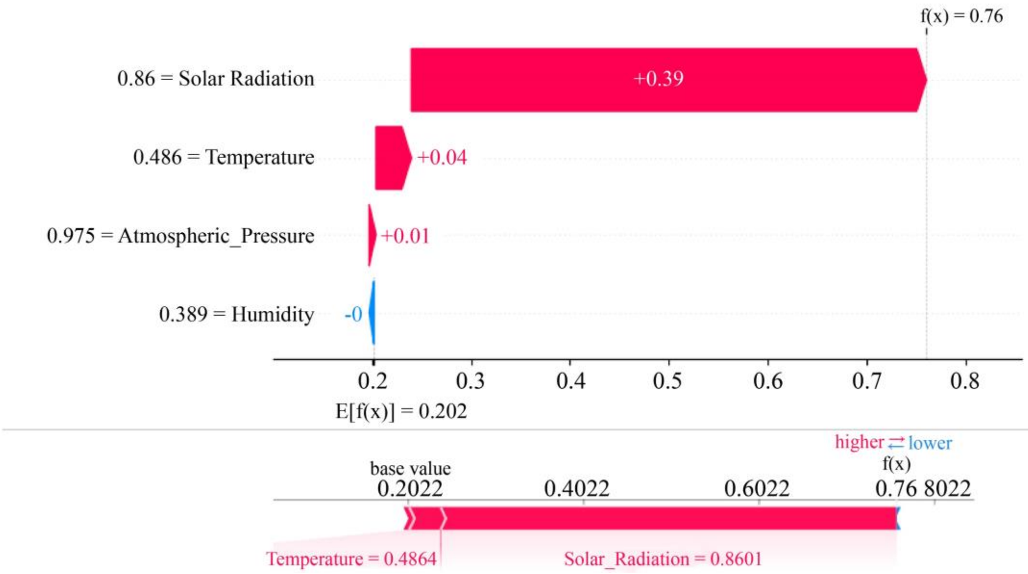

Fig. 9 Waterfall plot for hybrid LSTM-1DCNN model

4.2.2. Ranking Feature Importance Using Mean SHAP Values

A clear ranking of feature significance is provided by the Mean SHAP values for each model, as shown in Figure 10: LSTM, 1D-CNN, and the hybrid LSTM-1DCNN. With a Mean SHAP value of +0.23, solar radiation is shown to be the most important predictor of the output power for all three models. This agreement across multiple models emphasizes the crucial significance of Solar Radiation in estimating the output power of the PV system.

With Mean SHAP values of +0.01, temperature, atmospheric pressure, and humidity in the LSTM model contribute to predictions somewhat but equally to solar radiation. Comparably, the Mean SHAP value of +0.23 for solar radiation is the most important feature in the 1D-CNN model; the other three characteristics stay at +0.01. At a Mean SHAP value of +0.23, the hybrid LSTM-1DCNN model also highlights solar radiation. However, it gives temperature a little greater weight at +0.02, indicating that it picks up more subtleties in the data. Solar radiation is the most important predictor of output power in every model.

Overall, the Mean SHAP values, which consistently indicate the highest importance across all models, confirm that solar radiation is the main driver for estimating the output power of the PV system. Though important, the other factors, temperature, atmospheric pressure, and humidity, support the prediction process. This consistent ranking among several models gives strong proof of the vital significance of solar radiation in the model predictions.

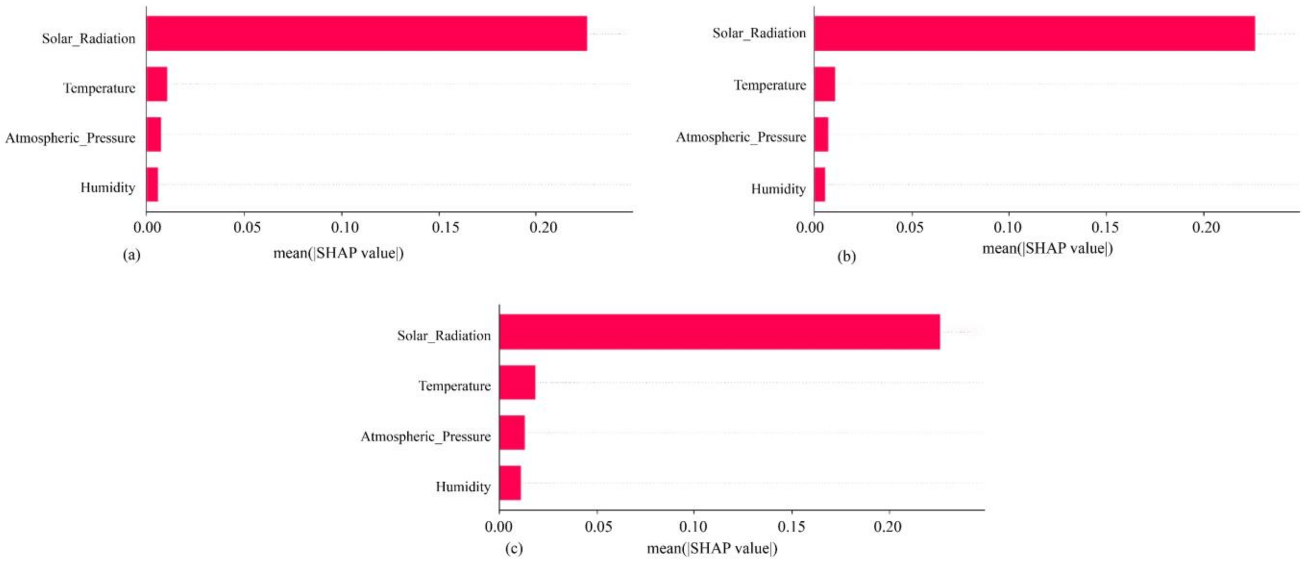

Fig. 10 Mean SHAP values for feature importance across models: (a) LSTM model, (b) 1D-CNN model, and (c) Hybrid LSTM-1DCNN model.

4.2.3. Visualizing Feature Effects through Beeswarm Analysis

A data visualization technique called beeswarm analysis or beeswarm plot shows how data points are distributed along a single axis, usually for discrete or categorical variables. Each model exhibits unique patterns in the Beeswarm analysis regarding the SHAP value's impact on the output. Solar radiation has a major effect on the output of the LSTM model (Figure 11-a), tending to produce positive SHAP values. Higher temperature SHAP values are skewed left, with a concentration near the centre. About the centre, atmospheric pressure shows a roughly symmetrical distribution with a greater concentration of positive SHAP values. Humidity SHAP values are centred, with larger values extending to the extremes.

Furthermore, solar radiation is dominatingly positive in the 1D-CNN model (Figure 11-b). Nearly symmetrical, the temperature and atmospheric pressure SHAP values are gathered around the centre. Values of humidity SHAP exhibit a centred distribution with extremes of high and low values. Solar radiation has a significant favourable effect on the hybrid LSTM-1DCNN model (Figure 11-c). High-temperature SHAP values spread to the left and right from the centre. The atmospheric pressure values are more positively skewed and almost symmetrical. High values of humidity SHAP are located on the right, and low values on the left. Solar radiation consistently has a major positive effect in all models, although the other factors have different patterns of effects.

4.2.4 Analyzing Feature Influence with Scatter Plots

This section uses scatter plots to illustrate the feature interactions for the hybrid LSTM-1DCNN model, which outperformed the LSTM and 1D-CNN models. The strongest contender for in-depth interaction analysis, the hybrid model's better metrics, lower MAE, MSE, RMSE, and higher R^2 indicate its capacity to capture complicated relationships within the data.

With temperature as a colour-coded interaction feature, Figure 12 illustrates the connection between solar radiation and its effect on the model's output. Higher temperatures show a linear trend in the plot, which suggests that solar radiation consistently affects the output power and that temperature adds a continuous interaction effect. The interaction feature between solar radiation and humidity is seen in Figure 12-b. High humidity levels have a concentrated effect when solar radiation is low; this influence decreases as solar radiation increases. The relationship between solar radiation and atmospheric pressure is examined in Figure 12-c, demonstrating that although solar radiation substantially impacts output power, atmospheric pressure's effect is more equally dispersed over the various solar radiation levels. The interactions from temperature, humidity, and atmospheric pressure add different degrees of complexity to the model's output. However, these scatter plots taken together show that solar radiation is the main component impacting it. The hybrid model was chosen for this in-depth investigation because of its capacity to capture these subtle interactions, which also emphasizes its robustness in comprehending and using several feature interactions to produce reliable predictions.

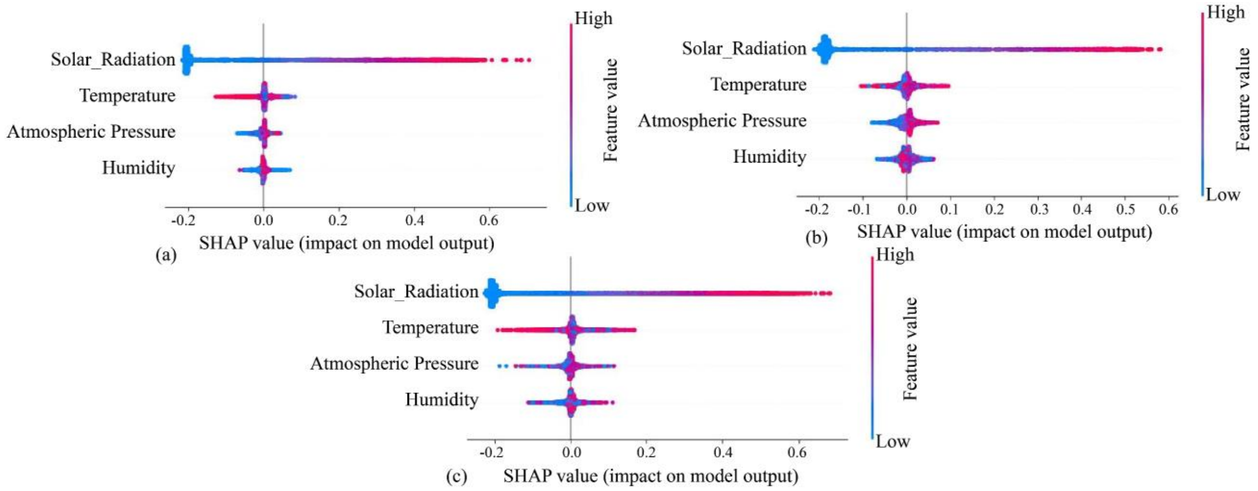

Fig. 11 Beeswarm plots of shap values for: (a) LSTM, (b) 1D-CNN, and (c) LSTM-1DCNN models.

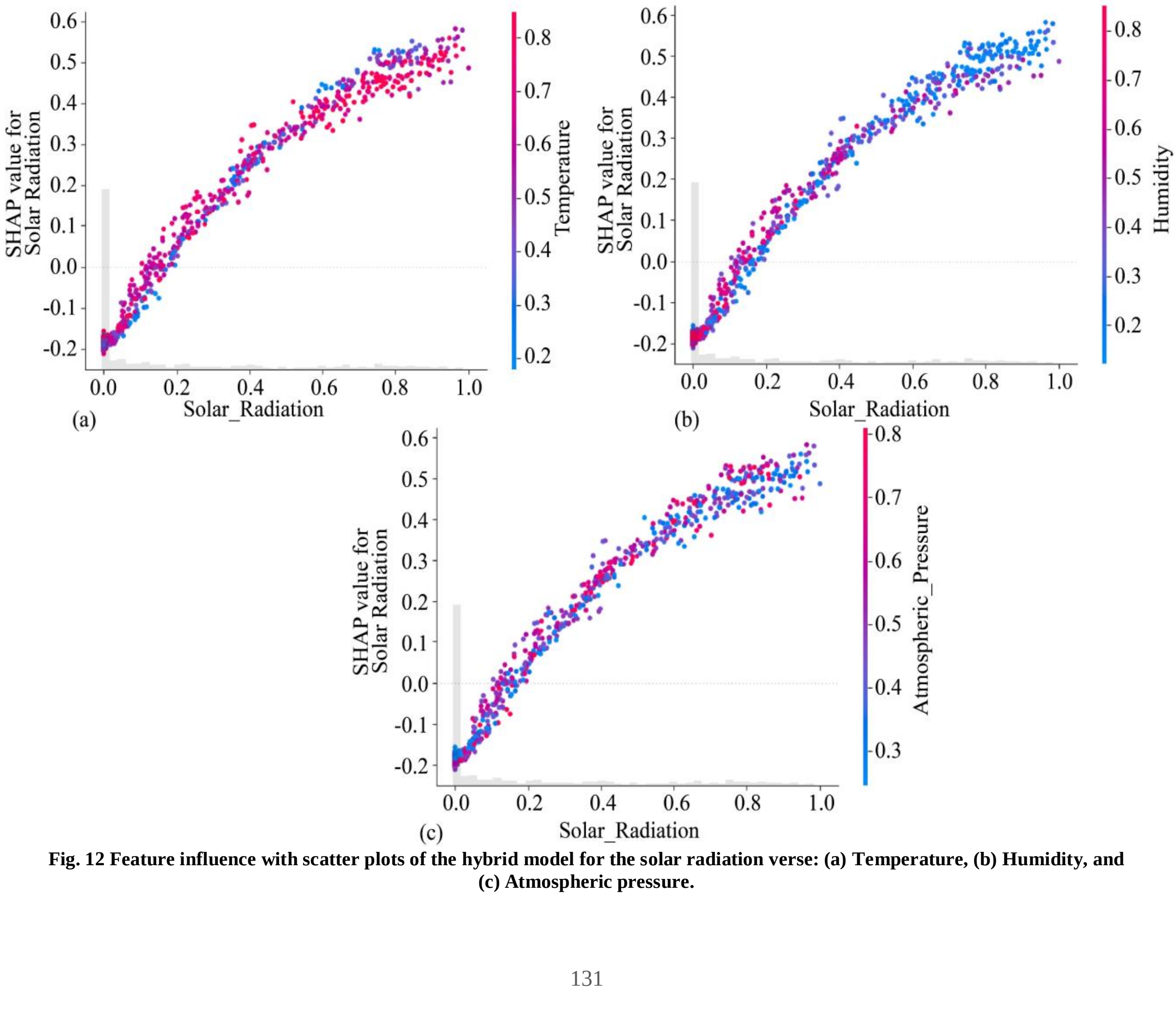

Fig. 12 Feature influence with scatter plots of the hybrid model for the solar radiation verse: (a) Temperature, (b) Humidity, and (c) Atmospheric pressure.

4.3. Experiment Analysis

This paper presents a new method for output power measurement by comparing the performance of three distinct deep learning models: LSTM, 1D-CNN, and a hybrid LSTM-1DCNN. This effort attempts to improve forecasting skills. This work is exceptional since numerous advanced deep learning techniques are integrated and compared, particularly those applied to environmental data that influence the output power. Using SHAP values for explainability provides a more detailed understanding of how each feature contributes to the model predictions for the interpretability of complicated models.

The primary contribution of this work is the comprehensive evaluation of model performance using multiple metrics, including MAE, MSE, RMSE, and R. Using SHAP values. Further in-depth investigations of the importance of features and their interactions are conducted. The results suggest that, for all parameters, the hybrid LSTM-1DCNN model outperforms the individual LSTM and 1D-CNN models in terms of accuracy and generalization. More precisely, the hybrid model's highest R2 and lowest MAE and MSE demonstrated robustness in capturing the complex interactions between environmental elements.

Very importantly, comparing the three models highlights the benefits and drawbacks of each strategy. Understanding sequential data allows the LSTM model to provide a knowledge of time-dependent patterns. A standard one-dimensional convolutional neural network model with a well-known learning speed implemented produces the spatial hierarchies. Compared between the two, the proposed hybrid LSTM-1DCNN model achieves better accuracy and more effectively learns the feature interactions and relation. The outcome of this compare and contrast study offers an adequate manual for future examinations and real-life implementations of selecting the right models for similar types of tasks.

While reflecting on the results, it is observed that the amount of solar radiation remained at the forefront for all the models, signifying that it has the maximum impact in delivering output power. The hybrid model might be able to express relations other than those of the existing one. Other parameters like temperature, air pressure, and humidity were affected to a certain extent. This knowledge is needed to increase the effectiveness of energy systems and fine-tune the power output forecast.

It is necessary to find the best method and understand the peculiarities of the models' work in order to compare them. This comprehensive analysis helps improve the hybrid model's performance over the others and underlines the importance of explaining the model's outcomes. This study probably means that, to affirm and extend the findings even further, future studies will investigate the capability of incorporating additional environmental elements, employing advanced ensemble methods into this framework, or applying these models to different datasets.

5. Conclusion

In this work, advanced deep learning models, such as LSTM, 1D-CNN, and a hybrid LSTM-1DCNN, are beneficial by proving their ability to predict output power based on environmental data. The purpose of this work was to demonstrate the usefulness of these models. The hybrid model showed better accuracy and generalization over a broad range of criteria than the separately built LSTM and 1D-CNN models. The most important element affecting output power is solar radiation, found using SHAP values. Providing helpful information about the importance of features and their relationships helped achieve this. This work will show the potential of hybrid deep learning models for enhancing power output forecast optimization and energy system efficiency. Future research must integrate more environmental components to record more comprehensive data exchanges. Furthermore, improving the accuracy and robustness of the model might involve studying complex ensemble methods or including data sources from outside the model. Moreover, using these models on various datasets to confirm the outcomes and assess their degree of generalization is recommended. A more in-depth understanding of the contributions and interactions of features would eventually result from improving the interpretability and explainability of model predictions by the application of advanced SHAP analysis or other techniques.

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Availability of Data and Materials

The data used in this paper are available online, as in reference [42]. These records are available at https://figshare.com/articles/dataset/pv_data_xlsx/10119314/1 (accessed on 06 June 2024).

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