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Research Paper

Artificial Intelligence Assisted Solar Energy Forecasting by Explainability Approaches with LIME and SHAP

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Abstract: Integrating renewable energy sources with new technologies such as artificial intelligence (AI) is important to balance energy supply and demand. The predictability of variable energy sources, such as solar energy, plays an important role in maintaining the stability and efficiency of power grids. This study examines the use of various algorithms in AI applications within renewable energy systems. The study critically evaluates existing methods and proposes an innovative approach for AI prediction in solar energy systems using advanced machine learning techniques. It focuses on the effectiveness of MLP, Ridge, and RF algorithms in forecasting Direct Current (DC). The results showed that the RF algorithm achieved the highest R^2 value (0.9999) and the lowest error RMSE (0.0024) and MAE (0.0006) measurements to demonstrate the superior ability of the models to explain variance in the data and make accurate predictions. In addition, the model developed with SHAP and LIME explainable AI algorithms is interpreted.

Keywords: Solar energy, Machine learning, Explainable AI, SHAP, LIME, Renewable energy.

1. Introduction

In recent years, there have been many studies on the increasing use of artificial intelligence (AI) methods, namely Deep learning (DL) and machine learning (ML) techniques in the field of solar energy forecasting. These studies address the challenges faced in grid management due to the variable nature of solar energy and utilize AI methods to improve forecasting accuracy. The studies compared deep learning and machine learning models to predict photovoltaic power generation. This study shows that models such as MLP, RNN, and CNN are compelling in accurately predicting power generation levels [1]. Another study examined the use of Deep Learning techniques for solar energy forecasting, namely Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). It reveals that RNN and LSTM perform slightly better than GRU, thanks to their capacity to maintain long-term dependencies in time series data [2]. Similar AI techniques, ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) for predicting PV energy production, environmental parameters such as solar temperature, radiation, and humidity were analyzed to predict energy production [3]. The study used various ML and DL models, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and XGBoost, to predict photovoltaic power generation; the ANN model had the highest accuracy compared to other models [4].

The other study used a hybrid Adaptive Neural Fuzzy Inference System (ANFIS) model to predict global solar radiation. ANFIS models provided more accurate predictions with lower error rates than traditional forecasting models [5]. In another study, solar energy production was estimated using environmental data. Meteorological factors such as temperature, humidity, and wind speed were considered. It strongly confirmed the impact of weather data on solar power generation [6]. In the other study, he examined different regression models for predicting Photovoltaic (PV) power generation. He compared machine learning models like Random Forest, Ridge, and Artificial Neural Networks. ANN showed the best performance in terms of accuracy [7]. ANFIS model was applied to estimate global solar radiation in Nigeria. The study found that despite poor data quality, the model provided accurate results and outperformed conventional methods [8]. In a previous study [9], the ensemble learning model achieved the highest R2 value (0.942) and the lowest error metrics MAE (0.040).

In this study, AI-based forecasting is performed for solar power generation. The forecasting is performed using MLP, RF, and Ridge regression algorithms. The accuracy of the models is evaluated using different parameters. Moreover, they were analyzed using Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME to improve the explainability of the model decisions. In this way, the factors on which the models make predictions are interpreted in detail, and the results are made more visible.

2. Material and Methods Method

2.1. DataSet

The dataset contains comprehensive information on solar power generation and environmental conditions. The dataset is available at https://www.kaggle.com/datasets/pythonafroz/solar-power. It consists of 136,472 observations and 12 variables. The dataset is divided into 80% training and 20% testing. To evaluate the performance of solar energy systems, a prediction model was developed using the variables DC_POWER, AC_POWER, DAILY_YIELD, TOTAL_YIELD, AMBIENT_TEMPERATURE, MODULE_TEMPERATURE. These parameters were selected based on their critical role in the solar power generation process. AMBIENT_TEMPERATURE: The ambient temperature around the solar panels is an important factor affecting their efficiency. MODULE_TEMPERATURE: The solar panels' surface temperature determines the cells' operating temperature, which directly affects energy efficiency. IRADIATION: Solar radiation represents the amount of solar energy received by the panels and is an important input for electricity generation. As solar radiation increases, the electrical power generated generally increases.

2.2. Multilayer Perceptron

MLP is a type of ANN that can process data organized in layers. The work presented by Rumelhart et al. in 1986 popularized this method by detailing MLP learning with a backpropagation algorithm [10]. ANN are structures inspired by the functioning of nerve cells in the human brain and information processing technology. These neural networks are an important artificial intelligence component, especially machine learning. They are used to model complex relationships between input and output values. A neural network contains interconnected units organized in layers. These units are called neurons. Each neuron receives input signals, processes these signals through an activation function, and produces an output signal transmitted to other neurons in the network. MLPs often perform strongly on nonlinear problems because they can perform nonlinear mappings with the help of hidden layers. Moreover, thanks to integrating various optimization algorithms and regularization techniques, modern MLPs can be successfully used on high-dimensional and complex datasets [11, 12]. The basic structure of a neural network is the neuron (Figure 1); the input variables (xi) are connected to the neuron through weighted connections (wi) that mimic dendrites, while the sum (Σ), bias (b), and activation function (h) play the role of the cell body. The propagation of the output is similar to the axon in a biological neuron. The behavior of the neural network is defined by the shape of the connections of its neurons or nodes and the weight values of these connections. These weights are automatically adjusted during training according to a learning algorithm until the network correctly performs the desired task [13].

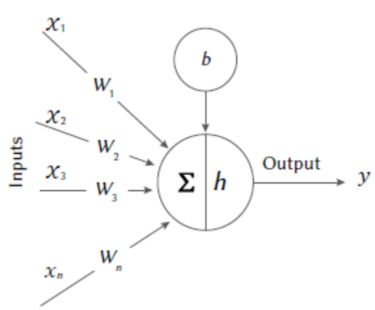

Figure 1. Neuron Model [13]

The weighted sum of the weights of a neuron input is called activation. Therefore, for neuron j of layer a^{ll} , activation is given as follows:

$$\mathbf{a}_{\mathbf{j}}^{\mathbf{l}} == \sum_{\mathbf{k=0}}^{\mathbf{n_{i-1}}} \mathbf{w}_{\mathbf{j}}^{\mathbf{l}}\ \mathbf{x}_{\mathbf{i}}^{\mathbf{l-1}} \tag{1}$$

The purpose of the MLP structure can be defined as learning the fundamental relationship between the input data and output variables in the training set and making accurate predictions. For training the MLP, the desired output values are determined for the desired input values. The MLP output is calculated for the desired input values. The difference between the desired output and the calculated output is used to update the weights of the MLP using the backpropagation algorithm. This process is called training or optimizing the MLP. Updating the weights is continued until the desired success value is achieved.

2.3. Random Forests

RF is a machine learning technique that combines multiple decision trees to create a more robust and generalizable model. The data set is randomly partitioned into small pieces to form decision trees. Overfitting is a major challenge in machine learning. RF method uses randomization with bootstrap sampling and random feature selection. The RF model is a machine-learning method that can be used for both classification and regression problems. In the forecasting stage, the forecasts of the decision trees formed from the data set are averaged. The reason for using the Random Forest Regression model in this study is that it largely avoids the problem of overfitting the historical data used during training; the data type is time series and is a method that gives successful results [14-16].

$$\mathbf{y} = \mathbf{mod}(\mathbf{y_1}, \mathbf{y_2}, \ldots., \mathbf{y_m}) \tag{2}$$

where y is the final predicted value, and m is the total number of trees in the forest.

2.4. Ridge

Ridge among the basic hyperparameters of regression is alpha (the regularization parameter). This parameter controls how much the model will adjust. The larger the Alpha value, the higher the amount of adjustment. There are also hyperparameters fit_intercept, which determines whether to add bias to the prediction; normalize, which sets True or False to scale the data; and solver, which is the algorithm that determines how the model is solved [16, 17].

2.5. Explainable AI

SHAP, one of the most widely used XAI techniques, is based on game theory and aims to fairly distribute the contribution of each feature to the model's output. It offers new approximation methods based on improved computational performance and predictions that show better consistency with human intuition. It has been shown that machine learning and deep learning models make decision-making processes transparent and make it easier for users to understand model insights. It ensures that descriptions are consistent and provide a singular importance value for each attribute. LIME is another well-known XAI technique [18]. The LIME method interprets individual model predictions based on estimating the model locally around a given prediction. As a result, for a fair comparison, we chose MLP, RF, and Ridge regression for explainability using SHAP and LIME explainers [19-21].

2.6. Performance Metrics

Using metrics to assess model performance allows us to understand and improve the predictive power of a model before deploying it for production on new data.

Mean Absolute Error (MAE): Predicting a numerical value in order to assess and report on the performance of a predictive regression model, the mean absolute error (MAE) is a frequently used error measure. MAE calculates the deviation between the predicted and actual values of a model. It evaluates how well a model generalizes and how well its predictions match the actual values. This study used MAE to find the closest predictive modeling to our experimental results, see the deviations from the experimental values, and capture the relationships between the dependent and independent variables [22].

$$\boldsymbol{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\boldsymbol{Y_i} - \boldsymbol{Y_{mean}}| \tag{3}$$

n number of data values, Y_i data values in the set, Y_{mean}, the mean value of the data set

R-Squared (R^2): It measures the proportion of variation in the dependent variable explained by the model's independent variables. It is calculated by squaring the Correlation Coefficient. R-squared does not account for overfitting. A regression model with too many independent variables may fit the training data well but not the test data. It is why adjusted R-squared is used. Adjusted R-squared addresses the problem of overfitting. It takes into account additional independent variables added to the model. The R-squared value, which expresses the relationship between actual and predicted values, varies between 0 and 1. The closer the R^2 value is to 1, the more the model is more successful [23-25].

$$\boldsymbol{R^2} = \boldsymbol{1} - \frac{\sum_i^N (Y - Y_i)^2}{\sum_i^N (Y_{mean} - Y_i)^2} \tag{4}$$

where N is the number of data points, Y_i data values in the set, Y_{pred} is the predicted values, and Y_{mean} is the mean value.

Mean Squared Error (MSE): provides an absolute number that shows how much your predicted results differ from the actual number. It gives a real number to compare with other model results and helps to choose the best regression model [22, 26].

$$\boldsymbol{MSE} = \frac{1}{N}\sum_i^N (\boldsymbol{Y_i} - \boldsymbol{Y_{pred}})^2 \tag{5}$$

N is the number of data Y_i data values in the set, and Y_{pred} is the predicted values.

3. Results

The repeatability of the models used in the study conducted with AI is critical. The study determined the best parameters in Table 1 by selecting cross-validation k-fold = 5. The parameters used in training are given in detail in Table 1.

Table 1. Hyperparameters

Models	Parameters	Best parameters
RF	n_estimators: [100, 200, 300], max_depth: [None, 5, 10, 15], min_samples_split: [2, 5, 10], min_samples_leaf: [1, 2, 4], max_features: [auto, sqrt, log2]	n_estimators=300, max_depth=None, max_features=sqrt, min_samples_leaf=1, min_samples_split=2, random_state=42
MLP	hidden_layer_size: [(50,), (100,), (50, 50), (100, 50), (100, 100)], activation: [tanh, relu], solver: [adam, sgd], alpha: [0.0001, 0.001, 0.01], learning_rate: [constant, adaptive]	activation=relu, alpha=0.001, hidden_layer_sizes=(100, 50), learning_rate=constant, solver=adam, max_iter=1000, random_state=42
Ridge	alpha: [0.1, 1.0, 10.0, 100.0, 1000.0]	alpha=0.1

The results compare the performance of different models with AI and machine learning methods for solar energy forecasting. MAE, RMSE, and R^2 metrics help us understand each model's accuracy and error level. According to the analysis results in Table 2, MLP: MAE = 0.0187, RMSE = 0.0479, R^2 = 0.9541. The MLP model performs quite well with relatively low error rates (MAE and RMSE). The R^2 value = 0.9541 indicates that the model explains the data well and accurately predicts. However, the error values of the MLP remain slightly higher than the other models. RF: MAE = 0.0006, RMSE = 0.0024, R^2 = 0.9999. The RF model shows the best performance. With the lowest MAE and RMSE values, this model minimizes the bias in its predictions. The R^2 value of 0.995504 indicates that the model provides almost perfect accuracy, and its predictions are very accurate. Ridge Regression: MAE = 0.0824, RMSE = 0.1182, R^2 = 0.7204. The Ridge regression model has higher error rates compared to the other models. Since MAE and RMSE values are higher, the predictions of this model are considered less accurate. Although the R^2 value is also lower than the other models, it performs well with 0.959601. Overall, the RF model outperforms the other two models by having the lowest values in terms of error rates and achieving the highest R^2 value. The MLP provides better results than the Ridge regression but is slightly inferior to the RF. The Ridge regression model has the lowest performance among the three models.

Table 2. Model Performances

Models	MAE	RMSE	R^2
MLP	0.0187	0.0479	0.9541
RF	0.0006	0.0024	0.9999
Ridge	0.0824	0.1182	0.7204

Comparing the three models, MLP Model: The MAE and RMSE values are moderate, indicating that the model's errors are relatively balanced. The RMSE value is higher than the MAE, meaning the model penalizes significant errors more. Ridge Regression: This model has the highest MAE and RMSE, making more errors than the other models. Ridge regression usually performs well with high linear dependencies, but it was not as effective in this case as the other models. RF Model: The model with the lowest MAE and RMSE values, which means it performs the best. Random Forest is generally known to be a model that balances the margins of error well, so the errors are minor than in other models.

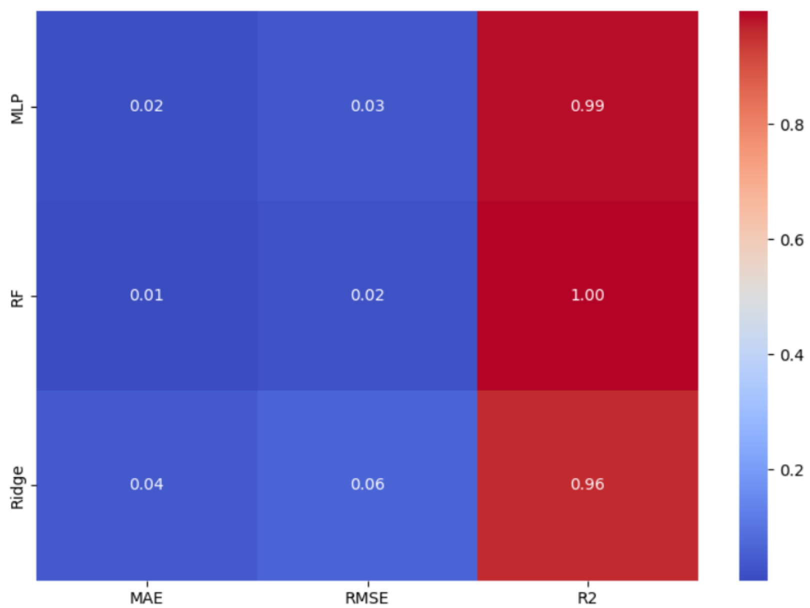

Figure 2. Performance Metrics

In the heatmap graph shown in Figure 2, the Random Forest (RF) model performed the best, while Ridge Regression performed the worst. The MLP model performed moderately well. These results show that RF is superior in accuracy and minimizes error rates. In addition, the model performances of the study were interpreted with XAI. The visualization of the RF model with LIME shows the prediction output and the importance of the relevant features in Figure 3. On the left side, a horizontal bar graph shows the predicted value ranging from -0.00 to 0.70. The predicted value of 0.03 on the bar indicates that the model's prediction lies between these minimum and maximum limits and is a production. In the middle section, the effects of the features on the forecast are divided into "positive" and "negative." IRRADIATION MODULE_TEMPERATURE shows a positive impact on the model. The values of the variables the model uses as inputs are shown on the right side. TOTAL_YIELD 0.54, IRRADIATION 0.77, MODULE_TEMPERATURE 0.65, AC_POWER 0.29, AMBIENT_ TEMPERATURE 0.56, DAILY_YIELD 0.17. DC_POWER is 0.03, indicating that energy is generated.

Solar irradiation and module temperature have the most significant impacts on model predictions. These features are the most important inputs in energy production prediction models. The negative impact of Total Yield suggests that historical production data may sometimes limit the prediction. In the future, the effects of this feature in different scenarios can be analyzed in detail. LIME outputs have effectively explained which features the model predicts and the relationships between these features, which have helped us better understand the prediction process.

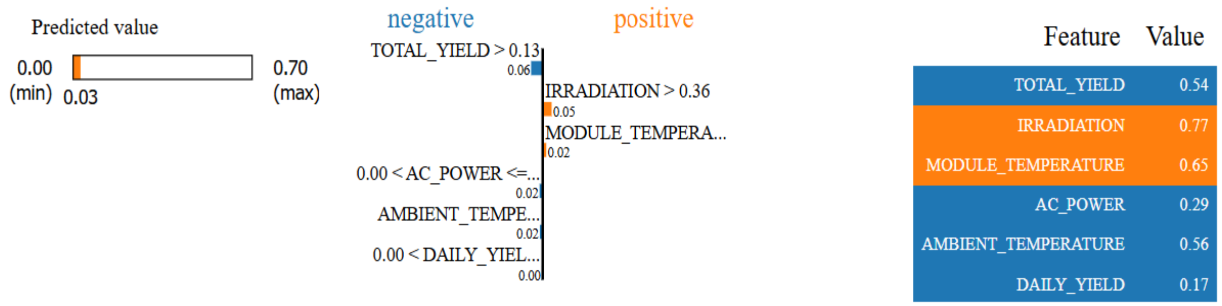

Figure 3. Demonstration of instantaneous energy generation using the LIME Model by a single instance

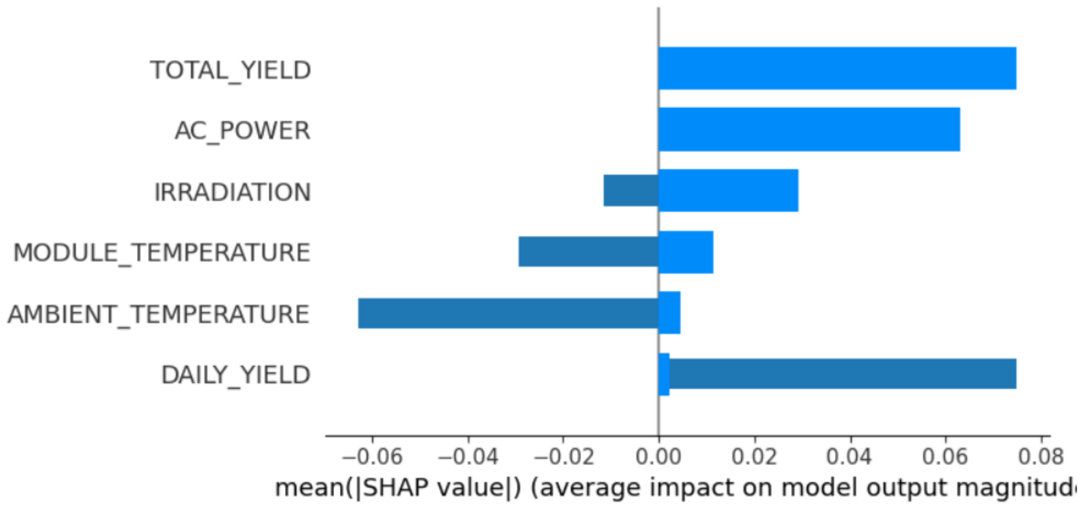

Figure 4. SHAP shows the global feature importance of the RF

As shown in Figure 4, SHAP was used to evaluate the performance of solar PV systems with XAI. In Figure 4, the horizontal axis shows the magnitude of the average effect of each input in the data set used on the model output. DAILY_YIELD and AC_POWER inputs stand out as having the highest impact. It is also observed that both of these two inputs make positive contributions. TOTAL_YIELD has a moderate impact. AMBIENT_TEMP, MODULE_TEMP, and DC_POWER are ranked with smaller effect sizes but are still significant in model performance.

4. **Discussion and** Conclusion

The predictability of solar electricity is critical for the balanced operation and efficiency of electricity grids. In this study, we focus on the role of AI algorithms in energy forecasting and optimization. In particular, the performance of algorithms such as MLP, Ridge Regression, and RF in Direct Current (DC) forecasting is compared. The study's findings show that the RF algorithm performs superior energy prediction, achieving high accuracy with an R^2 value of 0.9999 and the lowest error rates (RMSE: 0.0024, MAE: 0.0006). These results show that the RF algorithm can better model complex and variable energy data. While the performance of other models, such as MLP and Ridge Regression, is also noteworthy, the predictability of RF and its ability to explain the variance in the data provide a more suitable alternative for solar energy forecasting. However, each algorithm has different advantages and disadvantages based on data structure, training time, and computational cost. Therefore, each model needs to be tailored to specific application areas. In addition, the LIME and SHAP methods are used in this study to provide the proposed model with a more transparent and comprehensible explanation, thus making the forecast results more transparent and understandable. It increases the credibility of energy managers and policymakers in decision-making processes based on forecast results. In conclusion, this research presents an innovative approach based on explainable AI methods that can provide more accurate forecasts for solar energy systems. Going forward, combining different AI algorithms with hybrid models may further improve the forecast performance.

Although the RF algorithm has proven to be a powerful tool in combination with explainable artificial intelligence approaches, evaluating the model's performance on different datasets and improving its adaptability to real-world applications is an important research area for future work. SHAP and LIME analyses are used to explain the decision mechanisms of the model. In addition to feature importance levels, interactions between features are also examined and inferences are made in the context of solar energy forecasting. These analyses contribute to a better understanding of solar energy forecasting models and the development of more robust forecasting systems.

Authors’ Contributions

All the authors read and approved the final manuscript.

Competing Interests

The authors state that no competing interests are in existence.

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