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Advancing solar energy integration: Unveiling XAI insights for enhanced power system management and sustainable future

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ABSTRACT

Solar energy has emerged as a vital renewable alternative to fossil fuels, enhancing environmental sustainability in response to the pressing need to reduce carbon emissions. However, the integration of solar power into the electrical grid faces challenges due to its unpredictable nature, as a result of solar energy production variability. This research presents an advanced Explainable Artificial Intelligence (XAI) framework to explicate machine learning models decision-making processes, thereby improving the predictability and management of solar energy distribution. The influence of critical parameters such as solar irradiance, module temperature, and ambient temperature on energy yield is studied using the Local Interpretable Model-Agnostic Explainer (LIME). Rigorous testing using four advanced regression models identified Random Forest Regressor as the superior model, with an R^2 score of 0.9999 and a low Root Mean Square Error (RMSE) of 0.0061. Furthermore, Partial Dependency Plots (PDP) are used to emphasize the intricate dependencies and interactions among features in the dataset. The application of XAI techniques for solar power generation extends beyond explainability, addressing challenges due to various parameters in solar radiation pattern analysis, error estimation in solar performance, degradation of the battery function, and also provides interpretable insights for enhancing the lifespan of solar panels, contributing to advancements in sustainable energy technologies. The results of this study show how XAI has the potential to transform power system management (PSM) and strategic planning, propelling us toward a future of energy that is more resilient, efficient, and environmentally friendly.

1. Introduction

Over the past few years, India has embraced solar energy as a game-changer in its journey towards a cleaner energy future. As solar energy expanded rapidly, it not only transformed India's energy scene but also empowered rural communities by providing access to decentralized solar technologies. This growing use of solar power has sparked social and economic progress at the village level, boosting job opportunities and improving living conditions across the country.

India's solar industry is growing rapidly, especially in the area of grid-connected solar systems. Solar energy is now an important part of India's energy plan, helping to meet the growing need for electricity and make the country more energy secure. The government sees solar energy as crucial for India's sustainable development and for diversifying the country's energy sources.

Renewable energy sources, particularly solar energy, offers a viable and eco-friendly alternative to fossil fuels. Their widespread adoption brings numerous benefits, including vast production potential and a positive environmental impact, as highlighted by Zhao et al. (2016) [1], Hou et al. (2023) [2], Yang et al. (2023) [3] and Dincer et al. (2023) [4]. Furthermore, the enhancement of energy efficiency, which is a crucial aspect of modern energy systems, can be improved through precise forecasting of consumption patterns, as demonstrated by Liu et al. (2020) [5]. The integration of Artificial Intelligence (AI) into these

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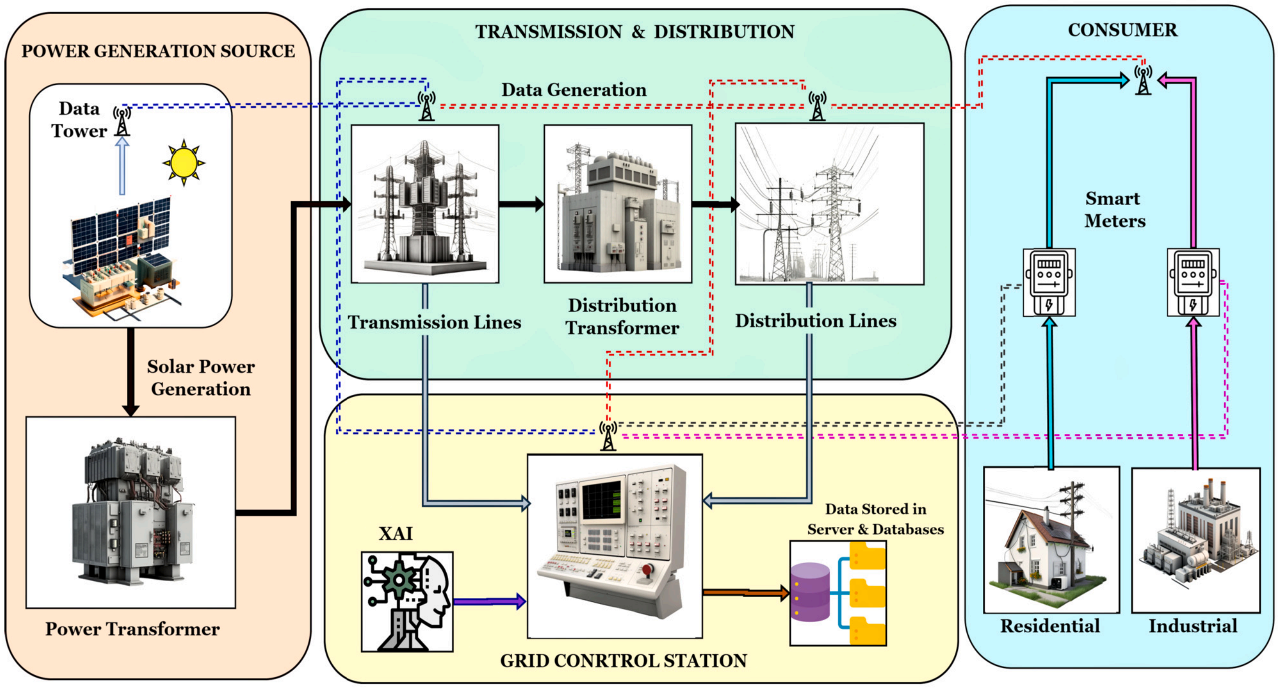

Fig. 1. Solar Power Generation and Distribution.

processes paves way to revolutionize the way we harness and manage solar power. The mechanisms of solar energy generation and distribution, essential for the understanding of this potential, are illustrated in Fig. 1.

Consumers struggle to determine the viability of solar energy as an investment due to the combined influence of changing climate patterns, in the panel installation locations and the impact these changes have on the panels' performance. A potential solution to this issue would be constructing a solar map showing how much sun energy each place receives each year. However, the expense involved in creating these maps is costly, making them largely inaccessible. Many potential solar energy self-producers abandon their plants, because they lack the necessary instruments to assess the project's technical and economic sustainability. The XAI implementation has gained considerable traction in recent years and its implementation in forecasting Solar Power distribution hasn't been explored before.

1.1. Challenges of integrating solar energy

Integrating solar energy into the electrical grid presents several challenges due to its inherent characteristics and the way the electrical system is traditionally structured. Here are some of the key challenges:

1. Intermittency and Variability: Solar energy is intermittent; it is only available during the daytime and varies with weather conditions, such as cloud cover. This variability can lead to mismatches between solar energy generation and electricity demand.
2. Storage: To manage the intermittency of solar power, energy storage systems are necessary. These systems can be expensive and are still an evolving technology, especially for large-scale applications.
3. Grid Infrastructure: The current electrical grid is mostly designed for centralized power plants. Integrating solar energy, which is often generated in a distributed manner (e.g., rooftop solar panels), requires upgrades to the grid infrastructure to handle the bidirectional flow of electricity.
4. Load Balancing: Grid operators must constantly balance supply and demand to maintain grid stability. The unpredictability of solar energy production makes this task more complex.
5. Power Quality: Solar energy integration can affect power quality in terms of voltage regulation, frequency stability, and harmonic distortion. Maintaining high power quality is essential for the proper functioning of electrical equipment.
6. Investment and Costs: The initial investment for solar infrastructure can be high. While costs have been decreasing, economic challenges still exist, including the need for incentives and subsidies to make solar projects viable.
7. Regulatory and Policy Issues: Regulatory frameworks and market structures may not be well-suited for accommodating renewable energy sources. Policies need to evolve to provide clear guidelines for integration and to incentivize investment in renewables and grid upgrades.
8. Scalability: As solar energy becomes a larger part of the energy mix, the challenges of integrating it into the electrical system increase. Grid operators must plan for scalability to ensure they can handle high levels of solar penetration.
9. Transmission and Distribution: Solar energy generation sites, particularly large-scale solar farms, may be located far from consumption centers, requiring investment in transmission and distribution networks to transport the electricity where it is needed.
10. Cybersecurity and Control Systems: With increased integration of solar energy and the need for advanced control systems, the grid becomes more susceptible to cybersecurity threats. Robust protection mechanisms are necessary to safeguard the grid.

To address these challenges, advancements in technology, grid management practices, and supportive policies are essential. Solutions such as smart grid technologies, improved forecasting methods, demand response programs, and enhanced grid storage capabilities are being developed to facilitate the integration of solar energy into the electrical system.

1.2. Contributions of the paper

- This study pioneers the application of XAI for the prediction of solar power distribution, offering a novel and cost-effective alternative to traditional solar mapping techniques. The approach is distinctive in

its ability to bypass the need for expensive solar irradiance maps while still providing reliable solar power output forecasts.
- The research addresses the prevalent issue of consumer uncertainty by delivering clear, interpretable explanations regarding the expected solar power distribution. It elucidates the quantity of power that can be anticipated for generation and distribution, thereby resolving consumer confusion and aiding in informed decision-making.
- The paper contributes a detailed analysis of the various factors affecting solar power production and distribution. It provides an in-depth understanding of how each parameter influences the overall solar power output, enhancing the transparency and accessibility of solar energy forecasts for potential investors and stakeholders.
- This research is unique in the solar power generation with realistic result on the Solar Power Yield. The local surrogate approximation with PDP provides detailed understanding on every data item and its significance about power generation.
- The important features are identified quantitatively and can be controlled in an efficient way for the enhancement of the power generation process.
- This provides the solution to the uncertainty of the machine learning models in the estimation of the demand of the power and the influence of the relevant parameters related to the solar power generation.

1.3. Organization of the paper

This paper is divided into seven parts. To begin, this study exemplifies earlier research efforts and outlines some significant contributions of these articles in Section 2. Section 3 discusses the work's system concept and architecture, as well as the dataset utilized and the mathematical modeling of the implementation. Section 4 examines the advantages of the current system and how XAI might help fill this research gap along with its advantages. Section 5 delves into the XAI's findings. Section 6 analyzes and discusses the acquired results. Finally, Section 7 contains the work's conclusions.

2. Literature review

The landscape of solar energy forecasting has been evolving constantly with the integration of Machine Learning (ML) and Deep Learning (DL) models. A variety of studies and research efforts have been contributed to this field, each offering a unique insight and advancement.

Elsaraiti et al. (2022) [6] used Long Short-Term Memory (LSTM) networks and Multi-Layer Perceptron (MLP) architectures to predict solar radiation. Their findings showed that these models can accurately predict solar radiation, making them valuable tools for improving solar energy predictions.

Vennila et al. (2022) [7] presented an ensemble approach that integrates multiple ML models to improve forecasting accuracy. This ensemble model proved to be not only more accurate than individual ML models but also was more cost-effective, setting a new benchmark for solar prediction models.

Sudharshan et al. (2022) [8] highlighted the role of solar energy as a pillar of renewable energy sources and identified the unreliability of the traditional energy sources as a major hindrance. They proposed that hybrid and federated learning models could yield the most precise estimations of solar radiation patterns, surpassing conventional models that heavily rely on the complex mathematical computations.

Pombo et al. (2022) [9] discussed the integration of ML predictors into Photovoltaic (PV) system. They underscored the challenges associated with obtaining consistent outcomes from ML models, particularly in Renewable Energy Systems (RES), which often depended on datasets from specific locations or climate zones. Their findings suggested that the best predictor can leverage the features of the proposed system, regardless of the ML model employed.

Li et al. (2022) [10] have developed a unique technique that improves the accuracy of solar energy predictions. They combined multiple DL models into a hybrid structure, which helps to reduce errors in forecasting photovoltaic (solar) energy production. This approach shows the potential for increasing the precision of solar energy forecasts.

Gumar et al. (2022) [11] conducted a comparison between three optimization algorithms, Genetic, Swarm, and Bee Colony, for improving the accuracy of solar energy forecasts using Artificial Neural Networks (ANNs). It was found that the Particle Swarm Optimization technique outperformed the others, achieving the highest accuracy of 99.71%. This highlights the effectiveness of Particle Swarm Optimization in optimizing solar energy prediction models.

Alkhayat et al. (2022) [12] developed the ENERGY model, which uses an automated approach to identify the most effective DL model for solar energy predictions. The model was trained on data from different parts of the world, and it outperformed the conventional statistical methods in terms of accuracy. Specifically, it achieved an impressive accuracy of 81%.

Zazoum et al. (2022) [13] compared two algorithms for predicting solar output: Matern 5/2 Gaussian Process Regression (GPR) and cubic Support Vector Machine (SVM). Their research showed that GPR outperformed SVM. GPR had lower Mean Squared Error (MSE) and Root Mean Square Error (RMSE) than SVM, indicating greater accuracy in solar output predictions.

Almaghrabi (2021) [14] proposed a cutting-edge approach for forecasting the next-day solar power generation based on the historical data. This technique utilizes a DL model called CNN-LSTM Encoder-Decoder (CLED), which merges Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks. Using datasets from Australia's Energy Market Operator (AEMO), the CLED model achieved exceptional accuracy in predicting solar power generation. This study highlights the effectiveness of combining LSTM and CNN for predictive analysis in the renewable energy domain.

Zhou et al. (2021) [15] proposed a model that utilizes sensors connected to the Internet of Things and advanced DL models like CNN and LSTM with clustering. This model enhances energy consumption prediction with exceptional precision, surpassing other models in the study. The model's accuracy is demonstrated by its low Root Mean Squared Error (RMSE) indicator.

Fara et al. (2021) [16] evaluated two methods for predicting the output of solar panels: ARIMA (a statistical model) and ANN. They tested these models in Southern Romania to compare their performance and accuracy. This study helps to understand the strengths and weaknesses of the statistical and machine learning approaches for solar energy forecasting.

Konstantinou et al. (2021) [17] explored the use of Recurrent Neural Networks (RNNs), specifically stacked LSTM models, for predicting the generation of solar power. To determine the most effective model, they optimized its hyperparameters using k-fold cross-validation and selected the model with the best performance.

Alkhayat (2021) [18] provided a thorough study on DL models, including CNN and RNN. They also covered how these models are used with techniques such as data decomposition, feature selection, and data correction. The review included a classification system based on key findings, as well as a critical evaluation of the current state of research in this area.

Shamshirband et al. (2019) [19] investigated approaches to minimize negative impacts on solar energy systems. They applied DL methods, such as RNN, LSTM, and Gated Recurrent Unit (GRU), to enhance the forecast on accuracy. Their research revealed that RNN and LSTM models performed exceptionally well for analyzing time-series data.

Abdelhakim et al. (2016) [20] discussed an Energy Management System (EMS) for the efficient generation of clean energy with Micro

Table 1
Summary of Solar Energy Forecasting Studies with XAI Considerations.

Author(s)	Year	Focus	Key Findings	Disadvantages	XAI to Address Disadvantages
Elsaraiti et al. [6]	2022	Predicting solar radiation using LSTM and MLP	Demonstrated the efficacy of deep learning algorithms in producing accurate solar radiation forecasts.	Limited discussion on computational resources and training times.	XAI tools can provide insights into model decisions, helping understand and optimize resource-intensive processes.
Vennila et al. [7]	2022	Ensemble machine-learning models for forecasting	Ensemble models were more accurate and cost-effective than individual ML models.	May require additional computational resources due to the combination of models.	XAI methods can enhance transparency, allowing stakeholders to understand the contributions of each model in the ensemble.
Sudharshan et al. [8]	2022	Role of solar energy and hybrid/federated learning models	Hybrid and federated learning models provide more precise solar radiation estimates than traditional models.	Complex implementation and potential communication challenges in federated learning.	XAI techniques can provide interpretability in complex models, aiding in understanding federated learning outcomes.
Pombo et al. [9]	2022	ML predictors in hardware models of PV systems	Best predictors are adaptable to different datasets and locations, enhancing consistency in outcomes.	Limited exploration of the impact of hardware constraints and real-time applicability.	XAI methods can shed light on the impact of hardware limitations, guiding the development of more efficient models.
Li et al. [10]	2022	Minimizing errors in photovoltaic prediction with hybrid neural networks	A novel approach that reconstructs deep neural network models to improve solar energy forecasts.	The hybrid approach may introduce additional complexity in model interpretation and tuning.	XAI tools can help in understanding the interactions between the components of hybrid models, aiding in effective tuning.
Gumar et al. [11]	2022	Optimization algorithms for ANN in solar prediction	Particle Swarm Optimization algorithm achieved the highest accuracy, indicating its effectiveness for solar forecasting.	The choice of optimization algorithm may be problem-dependent, and PSO might not always be the optimal choice.	XAI can provide insights into the decision-making process of optimization algorithms, aiding in selecting appropriate methods.
Alkhayat et al. [12]	2022	ENERGY model for auto-selective deep-learning model selection	Demonstrated superior accuracy with deep neural network-based models over traditional statistical methods.	The ENERGY model might be sensitive to the choice of hyperparameters and requires careful tuning.	XAI tools can help identify key hyperparameters and their impact on model performance, assisting in more effective tuning.

Grids (MG). Integrating EMS with forecasting techniques was found with enhanced performance of clean energy production.

Alamin et al. (2020) [21] created a model using an ANN to forecast energy output in High-Concentrator Photovoltaic (HCPV) systems. Their Radial Basis Function Neural Network (RBFNN) model, swiftly predicts the energy output for short-term periods, accurately capturing the performance of Concentrator Phot Voltaic (CPV) systems.

Mellit et al. (2020) [22] examined numerous Artificial Intelligence (AI) methods and their effectiveness in predicting solar power generation. Their analysis highlighted the need for extensive, top-quality datasets. They also underlined the importance of preprocessing these datasets to address any missing data or incorrect values. Additionally, they emphasized the significance of taking into account external factors that influence solar power production, such as cloud cover variations. Combining AI techniques with traditional physics-based models was deemed a promising approach to enhance solar power forecasting accuracy.

Zhang et al. (2018) [23] proposed an ensemble method to predict how much solar power could be produced in a region during each hour of the upcoming day. They used information from three different weather forecasting models to make their predictions. When they tested their method against the other base models, they found that their method, called Earth Declination Angle Change Limit Algorithm (EDAC), performed better than the others.

Collectively, these studies underscore the rapid advancements in solar power forecasting methodologies, highlighting the potential of ML and DL techniques to provide accurate and reliable predictions for solar energy generation. The state of the art research can be visualized in Table 1 and how the proposed research can improve the shortcomings from the existing work.

3. System model and architecture

This section presents the dataset description, system model, and proposed system architecture described in the subsections.

3.1. Dataset description

The dataset central to this research was meticulously compiled from two distinct solar power plants in India, encompassing a period of 34 days. The dataset is acquired from kaggle. At these facilities, power generation data is captured at a granular level, with individual inverters—each connected to several strings of solar panels—recording output metrics. Complementing this, a suite of sensors deployed across the plants provides a holistic collection of environmental and operational variables at the plant level.

The dataset is structured to include 9 independent variables, which serve as predictors for the dependent variable, AC power output (Y). The independent variables encompass a range of factors that influence solar power generation:

- DC Power: The direct current output from the solar panels.
- Irradiation: The solar radiation intensity received by the panels.
- Ambient Temperature: The temperature of the surrounding environment.
- Module Temperature: The temperature of the solar panel modules themselves.
- Date and Time: Timestamps associated with each data entry.
- Source Key: Unique identifiers for the individual inverters.
- Daily Yield: The total energy produced by the solar panels in a single day.
- Total Yield: The cumulative energy output of the solar panels over time.

This rich dataset comprises 67,699 instances allocated for training purposes, alongside 3,260 instances set aside for testing the models. A notable feature of this dataset is the absence of any class imbalance or missing values, which often pose challenges in predictive modeling. Additionally, the ‘Source Key’ and ‘Date and Time’ variables have been transformed into numerical values through linear encoding techniques, thereby facilitating their use in regression analysis and machine learning algorithms.

The careful curation and preprocessing of the dataset lay a robust foundation for the subsequent XAI techniques, ensuring that the insights derived are both reliable and rooted in comprehensive empirical evidence.

3.2. System model

The first implementation of the proposed work is an estimation of the regression. Mathematically the regression is expressed as per the below Eqn. (1)

$$Y = aX + b \tag{1}$$

where Y is the dependent and target variable and X are the independent variables and b is the slope that connects both X and Y. a is the bias. Various underlying parameters determine the performance of the regression. They are R^2 Score, Standard Deviation, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

The R^2 Score is expressed as per the Eqn. (2) and Eqn. (3).

$$R^2 \;\; Score = 1 - \frac{Sum\ Square\ Regression}{Total\ Sum\ of\ Squares} \tag{2}$$

$$R^2 Score = 1 - (\sum(y_i - \bar{y}_i)^2/(\sum(y_i - \bar{y})^2 \tag{3}$$

The MSE metrics of the regression are expressed as per the Eqn. (4).

$$MSE = \sum(Y_i - \bar{Y}_i)^2/n \tag{4}$$

where Y_i is the observed value and $\bar{Y}_i$ is target value of the specific data instance and n is total number of samples.

The RMSE metric for the regression is expressed as per the Eqn. (5).

$$RMSE = \sqrt{MSE} = \sqrt{\sum(Y_i - \bar{Y}_i)^2/n} \tag{5}$$

The variance metric of the regression is estimated as per the Eqn. (6).

$$\sigma^2 = \sum_{i=1}^{n}(Y_i - \bar{Y})^2/(n-1) \tag{6}$$

In the regression, the proposed work selects the random forest model which can be mathematically expressed as a function of MSE as per the Eqn. (7).

$$MSE = 1/N(\sum_{i=1}^{n}(F_i - Y_i)^2 \tag{7}$$

F_i is value obtained in the specific data point, Y_i is the value produced by the model and N is the total points of the data.

The Partial Dependency Plot is described for the Random Forest Regression model as per the Eqn. (8) mentioned below.

$$\bar{f}_s(x_s) = E_{xc}\lceil(\bar{f}(x_s, X_C))\rceil \tag{8}$$

where $\bar{f}_s$ is the training model and x_s is the dependent features and the X_C are the remaining available features in the dataset.

Finally LIME model is providing the explanation for the regression model as per the Eqn. (9).

$$Exp(z) = U(c, \upsilon, \pi_z) + \theta(\upsilon) \tag{9}$$

The value of υ belongs to the global model v where $\upsilon \in V$. The U is the unfaithful measurement, c is the variable defined as a complex function and π_z is the distance vector of g with its surrogate points. $\theta(\upsilon)$ is a complex function of the model. The overall process flowchart, with various sequences of action is illustrated in Fig. 2.

3.3. XAI architectures and framework

The comprehensive workflow that underpins our XAI-driven approach for solar power prediction is illustrated in Fig. 3. The process involves a series of well-defined steps that are carefully planned to improve the accuracy of the model's predictions by optimizing the input parameters.

Stage 1: initial model construction The initial phase involves constructing a model that can predict how much solar energy will be produced. This model uses data collected directly from solar power plants, as well as other important factors that have been identified through literature review. By combining real-world data with well-established principles, the model provides a strong basis for making predictions.

Stage 2: XAI analysis After getting the model's predictions, we use Explainable Artificial Intelligence (XAI) to figure out how the model makes decisions. By breaking down the model's internal workings, XAI shows us how each input (variable) affects the output (predicted solar power output), allowing us to categorize the variables into two groups: those that exhibit a positive correlation and those with a negative correlation to the predicted solar power output.

Stage 3: refinement of input variables The last step of this workflow is an ongoing process where the models predicting solar power are constantly being tested with all possible combinations of the variables that were identified as inputs. By carefully reviewing the effects of each group of variables, we can narrow down the input variables to only the ones that have the most impact. After being validated for their effectiveness using XAI analysis, this smaller group of variables is then used to make the predictive models more precise, resulting in solar power forecasts that are more accurate and reliable.

This structured approach, underpinned by XAI, not only makes the predictive models clearer but also helps us find the variables that have the greatest impact, thereby streamlining the prediction of solar power generation.

3.3.1. AI transparency using XAI architectures

In the pursuit of making AI systems more transparent, researchers have created Explainable Artificial Intelligence (XAI) frameworks. These frameworks help us understand how AI models make decisions, making them easier for humans to interpret. Here we delve into several XAI architectures that contribute to AI transparency:

- Deep Learning Architectures in XAI: DL models excel in providing dependable explanations in XAI systems, regardless of the scenario. The effectiveness of these explanations depends on the data quality, volume of data, and feature extraction methods used, as noted by [24]. Furthermore, the selection of hyperparameters plays a critical role in the various layers of DL architectures, with multidimensional XAI classification providing a framework for understanding these complex systems [25].
- Model-Centric Approaches: Model-centric interpretation is a cornerstone of AI transparency, ensuring that AI systems are developed with fairness, accountability, and clarity, as emphasized in [26]. By interpreting model outputs and accuracy, debugging is simplified, enabling the refinement of the AI system's performance.
- Hybrid XAI Frameworks: Given that many decisions within XAI systems are too intricate to be explained by a single rationale, hybrid frameworks, which facilitate an interactive dialogue-based system, are essential. This approach allows for multiple explanations, enhancing the social acceptance of the system's decisions and ensuring comprehensive explanations for each action, as proposed in [27].
- Stochastic Models in XAI: Stochastic XAI models employ probabilistic distributions to capture and convey uncertainties within the system. These models leverage random variables to represent potential outcomes, providing a spectrum of possibilities rather than a singular prediction. This approach enriches the model's forecasting capabilities and, when combined with explainable features, enables

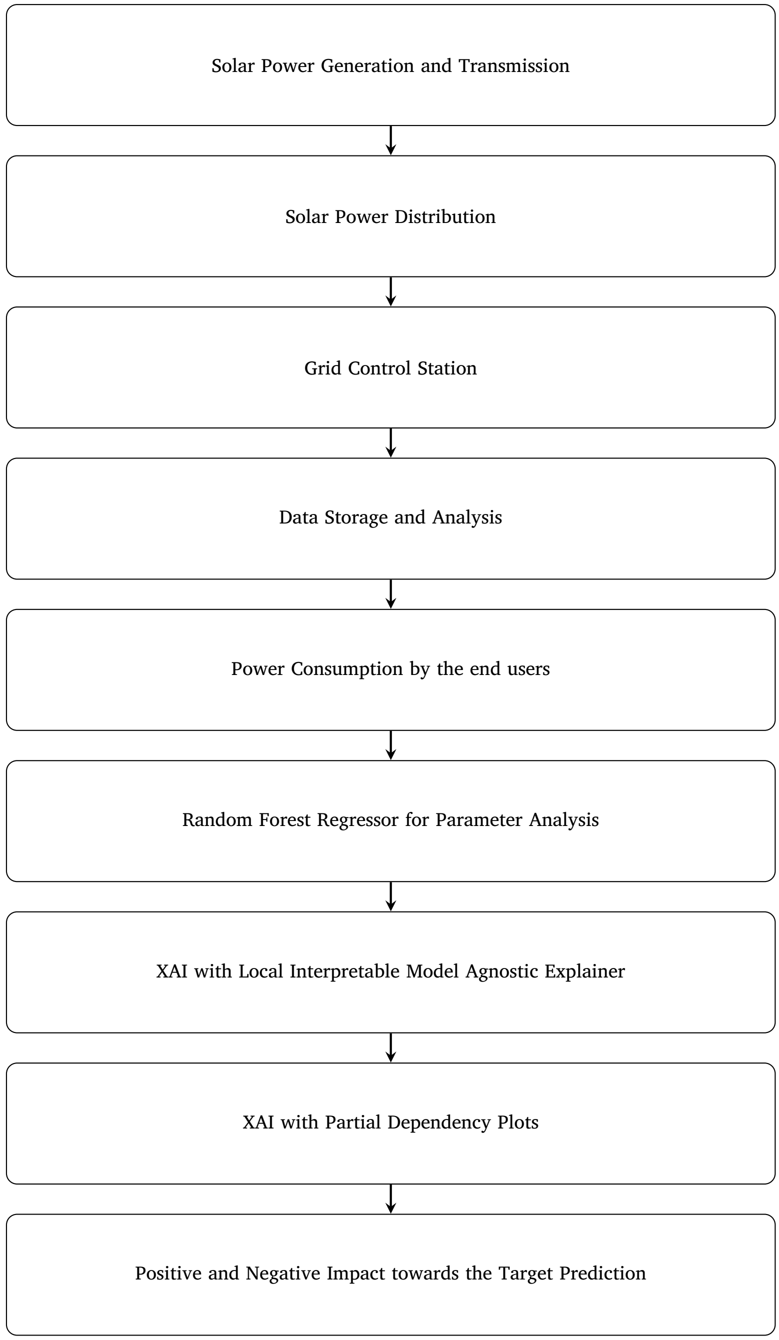

Fig. 2. Flowchart for Solar Power Generation and Analysis.

users to understand and manage associated risks more effectively, as detailed in [28].

- Data Visualization Techniques: Data visualization plays a pivotal role in XAI by presenting interactive and intuitive representations of the decision-making process. As outlined in [29], it employs an iterative approach that enhances the perception, analysis, and comprehension of the inputs and outputs of XAI models. This technique elucidates the sequence of events triggering actions, aiding users in making informed decisions.

3.3.2. Validation and calibration using XAI frameworks

To foster trust and understanding in AI systems, several tools and frameworks have been developed to provide explanations for the decisions made by these systems. Here we explore a selection of prominent XAI tools that contribute to AI transparency:

- AI Explainability 360 (AIX360) by IBM Research: The AIX360 toolkit is an open-source suite developed by IBM Research, designed to demystify AI decisions and build user trust. It prioritizes tasks based on risk factors and offers recommendations to enhance system adaptability for end-users. AIX360's algorithms are crafted to help users grasp the underlying models and data-driving AI systems, thereby bolstering interpretability, transparency, and accountability.
- Explain Like I'm 5 (ELI5): ELI5 is an explainability tool that distills complex models into simple, easily digestible explanations, akin to explaining a concept to a 5-year-old. As highlighted in [30], ELI5 aids in debugging ML classifiers and offers clear explanations for their predictions. It allows users to inspect model parameters, understand feature importance, and elucidate individual predictions,

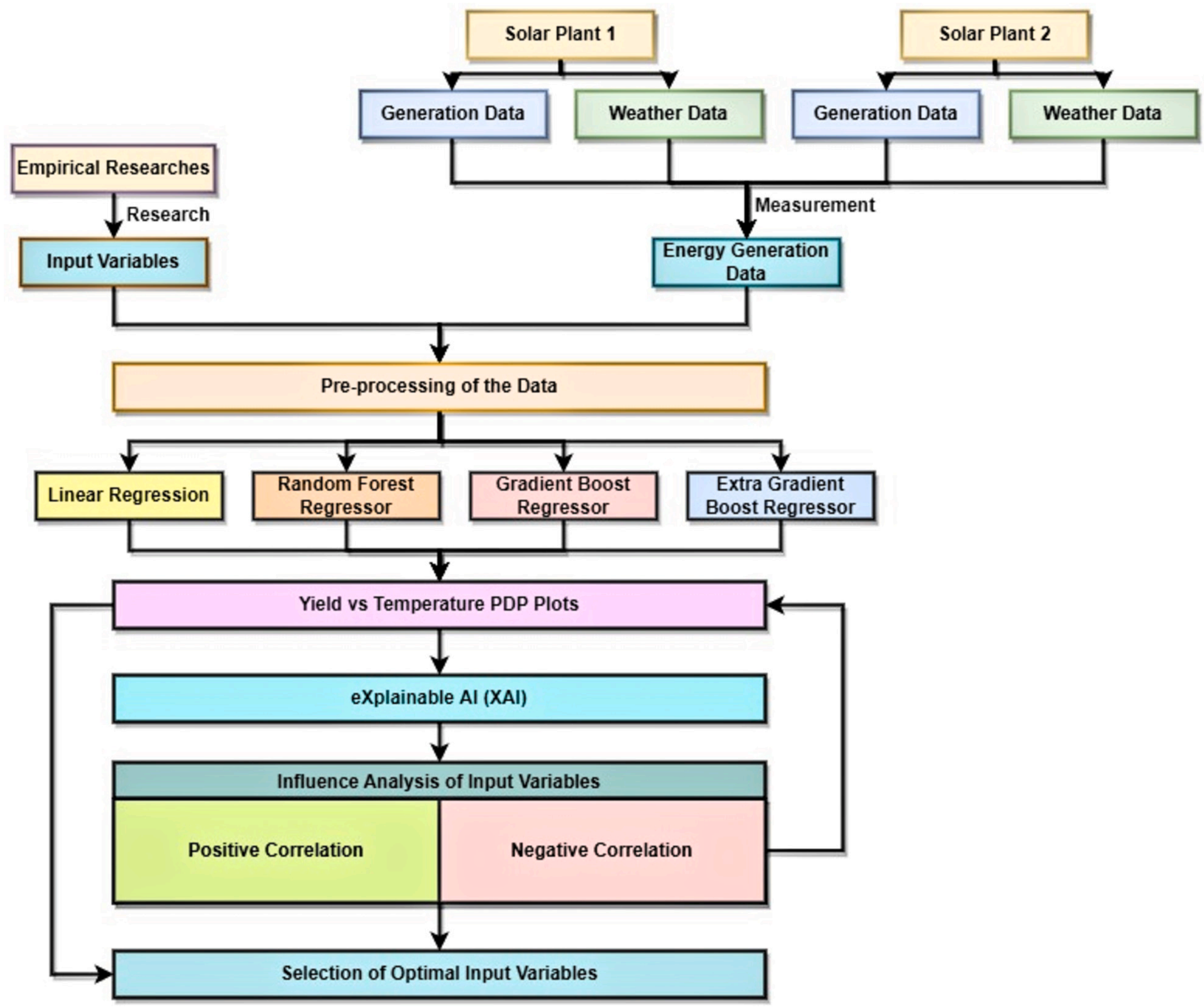

Fig. 3. Process flow for choosing XAI-based input variables for Solar Power prediction.

thereby enhancing the transparency and trustworthiness of AI systems.

- Local Interpretable Model-agnostic Explanations (LIME): LIME provides rapid and interpretable explanations for individual data samples and their predicted outcomes. According to [31], LIME operates under the assumption that a complex model behaves linearly at a local scale. It fits a simple model to approximate the global model's behavior in a localized context, offering tailored explanations for the complex model's predictions in that specific scenario.
- SHapely Additive exPlanations (SHAP): The SHAP framework is a method that provides insights into the predictions made by ML models, ranging from basic models to more advanced DL and natural language processing (NLP) techniques. It uses a model-agnostic approach, meaning it can work with various models. SHAP relies on Shapley values from cooperative game theory to explain how different input features contribute to the model's predictions as described in [31]. These values quantify the mean marginal contribution of each feature across all possible combinations, ensuring equitable attribution of influence to the features based on their impact on the model's output.
- Skater: Skater is an open-source toolkit that explains the features learned by an XAI model by providing explanation for specific predictions (local explanations) and overall behavior of the model (global explanations). [32]. Skater utilizes a comprehensive framework that enhances model interpretability. This framework enables users to readily understand and apply models in diverse situations. Skater leverages methods such as LIME and deep neural networks (DNNs) to provide insights into the characteristics of input data that influence the XAI model's predictions.
- What-If Tool (WIT) by Google: Google's WIT is a visual interface that makes it easier to study data and comprehend the results of XAI models. It can be smoothly incorporated into various platforms and cloud services with minimal coding effort, as outlined in a study [33]. WIT is important for creating models, analyzing data, and checking models before and after training. It helps developers understand how models work and make better models.

These tools make AI systems easier to understand, giving people the ability to question, comprehend, and rely on decisions made by AI. Users can utilize these frameworks to understand the intricate processes that lead to AI predictions, ensuring the responsible and transparent use of AI systems.

4. Overview of the proposed solution

Integrating solar power and other renewable energy sources into the power grid is a complex task. The electrical grid is a highly intricate system, and adding renewable energy sources with their unpredictable nature makes it even harder to manage. The current grid infrastructure has difficulty handling the variability of renewable energy, especially the fluctuations of solar power.

To address these challenges, it is crucial to create intelligent systems that can handle the integration of renewable energy sources into the grid and make them a significant part of electricity production. The proposed solution involves building a smart grid framework that incorporates cutting-edge predictive analytics, ML and XAI technologies.

This smart grid framework will be designed to:

1. Predict and Manage Variability: Utilize predictive models to forecast changes in solar energy output and develop strategies to maintain power grid stability.
2. Optimize Energy Distribution: Implement algorithms to balance the supply of renewable energy with demand, minimizing waste.
3. Enhance Grid Resilience: Strengthen grid resilience against the unpredictability of renewables through control systems that adapt to changing energy production levels.
4. Facilitate Renewable Integration: Streamline the integration process of renewable energy sources to the grid, making it efficient and seamless.
5. Promote Transparency and Trust: Use XAI techniques to make the decision-making of intelligent systems more transparent. This will build trust between stakeholders and regulators by ensuring they understand how the systems work and make decisions.

The envisioned smart grid will not only enable the efficient integration of renewable energy but will also ensure that these clean energy sources become a major and reliable contributor to the global energy mix. The proposed solution represents a forward-thinking approach to modernizing the electric grid, aligning with the global imperative to transition towards sustainable and environmentally friendly energy systems.

4.1. Advantages of AI in solar power distribution

By integrating AI into solar energy distribution, we can massively improve how power grids operate. Sensors and grid devices gather enormous amounts of data, which AI can analyze to find helpful information and make grid management better. Here are some key benefits of using AI in solar power distribution:

1. Intelligent Demand-Supply Balancing: AI-driven energy systems can monitor demand and supply in real-time. This allows energy companies to adjust electricity production to meet demand more precisely. By dynamically matching supply and demand, these systems minimize waste and prevent power outages.
2. Automated Power Management: Automated power management systems use AI to control high-energy devices like heaters and air conditioners. During times when power supply is low, these systems can automatically reduce the power used by these appliances. This helps in keeping the power grid stable and saves energy when demand is high.
3. Enhanced Energy Storage Utilization: The flow of energy supply can be strategically directed to the intelligent storage systems, leveraging AI to determine when to store surplus energy and release it back into the grid. This efficient management strengthens the resilience of the power grid and ensures a reliable energy supply.
4. Improved Renewable Integration: The deployment of smart sensors, coupled with sophisticated AI models, enables prediction of electricity demand and weather patterns with greater accuracy. This advancement significantly improves the effectiveness of integrating renewable energy sources, such as solar energy, into the existing power grid.
5. Microgrid Management: Microgrids are important for managing energy resources that are spread out. AI helps control these microgrids better. AI can solve problems with power quality, reduce congestion, and keep energy flowing smoothly.
6. Dynamic Grid Control: AI's integration into grid management allows for more advanced control, extending beyond just managing substations. With the ever-changing grid landscape, AI helps to optimize the system as new technologies and generation methods are added.
7. Safety, Efficiency, and Reliability: AI transcends its role in managing intermittent energy sources by optimizing the safety, efficiency, and reliability of the power grid. It enables businesses to analyze the consumption of data for understanding the usage patterns, identify inefficiencies and energy losses with continuous monitoring of the equipment health for preventive maintenance.

4.2. Advantages of XAI in solar power distribution

XAI plays a crucial role in making AI systems more reliable and trustworthy for solar power distribution. AI models are efficient and can make accurate predictions, but they often lack transparency, making it difficult to understand how they make decisions. This is especially concerning in the energy sector, where reliable decision-making is essential. XAI helps to overcome this issue by making AI systems more understandable and interpretable. By integrating XAI into solar power distribution, we can achieve the following benefits:

1. Enhanced Trust and Confidence: By making AI decision-making processes transparent, XAI builds trust among power system experts. These experts, with their deep knowledge and practical experience, can better understand how models make predictions. As a result, they are more likely to trust and use AI tools.
2. Facilitated Collaboration: XAI makes AI models easier to interpret, which fosters collaboration between data scientists and domain experts. This shared understanding enables them to work together to refine models and customize them for the unique challenges of the energy sector.
3. Improved Model Debugging and Validation: XAI provides insights into model behavior, making it easier to pinpoint and address errors, biases, or inefficient elements. This results in more reliable and accurate predictions, which is vital for managing fluctuations in solar energy.
4. Risk Mitigation: In the energy sector, where outages can have severe consequences, XAI equips operators with the knowledge to comprehend the rationale behind AI suggestions. This enables them to evaluate potential risks and make informed choices that ensures the uninterrupted operation of the grid.
5. Regulatory Compliance: Stricter transparency regulations for AI require solar power systems to be compliant. XAI ensures systems meet these standards, preventing legal and ethical concerns.
6. User Empowerment: XAI makes AI decision-making processes clear and accessible to all users. This understanding helps improve system acceptance and alignment with goals and limits.
7. Adaptability and Future-proofing: XAI enables AI models to be adjusted to handle changing conditions and new technologies. This ensures that solar power systems remain comprehensible even as they evolve.

4.3. Disadvantages of XAI in solar power distribution

XAI brings advantages to solar power distribution, but it also has drawbacks that need to be addressed to fully utilize its benefits. Here are some of the main challenges related to deploying XAI in solar power distribution:

1. Performance-Transparency Trade-off: One of the most pronounced challenges in implementing XAI is balancing model performance

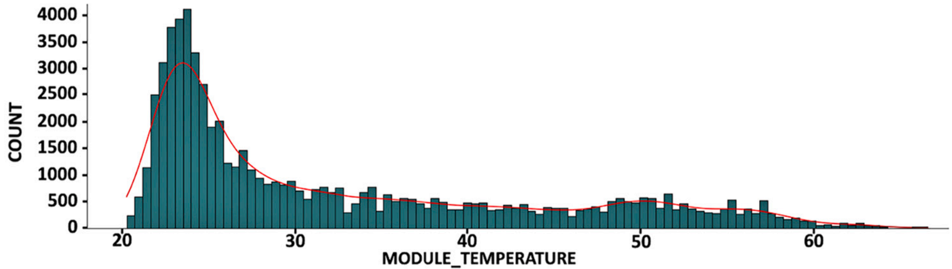

Fig. 4. Seaborn Visualization for Module Temperature vs Target.

with transparency. Complex models that offer high accuracy are often less interpretable, which poses a dilemma in power systems where both high performance and clear explanations are expected by the end-users.

2. Lack of Standardization: The field of XAI currently suffers from a lack of consensus on what constitutes explainability. Without universally accepted standards or definitions, different studies adopt varied approaches, such as emphasizing feature importance or relying on visualization techniques. This inconsistency complicates the understanding and comparison of XAI methods.
3. Diverse User Requirements: The users of ML models and XAI in solar power distribution are diverse, including consumers, power system experts, energy policymakers, and AI researchers. Each group has different objectives and operates at varying levels of technical expertise, contributing to the challenge of establishing a clear standard for XAI.
4. Evaluating Explanation Quality: Another significant drawback is the absence of metrics to assess the quality of explanations provided by XAI approaches. While it would be beneficial to have a measure of "explainability," such metrics should ideally provide a rating that reflects the accuracy and relevance of the explanations relative to the true underlying model dynamics.
5. Potential Overreliance on Explanations: Users may develop increased trust in the explanations provided by XAI, which can be positive, but there is a risk that the models' outputs may not always yield reliable advice. Over time, this overreliance could lead to complacency or misinterpretation of the AI's capabilities, especially if the explanations are not fully aligned with the actual behavior of the system.

To fully utilize XAI in solar power distribution, challenges must be overcome. Solutions include creating common guidelines, establishing reliable assessment methods, and improving XAI knowledge among users. By addressing these concerns, the energy industry can embrace XAI to improve model transparency while maintaining the high performance necessary for reliable and efficient solar power distribution.

4.4. Research gap

To address the challenges of XAI in solar power distribution, there are two main goals that need to be achieved. It is crucial to fulfill these goals to improve the understanding and usability of AI models in the energy industry. These goals include:

1. Traceability of Model Predictions: The first goal is to improve transparency by establishing a clear connection between the input data and the model's predictions. This includes exposing the model's internal mechanisms, such as weights and biases, to understand how they affect the outputs. This technical aspect of interpretability involves developing methods to break down complex models and reveal their inner workings. This transparency is crucial for validating predictions, improving the data, and enhancing the modeling process.
2. Domain-Specific Knowledge Integration: The second objective of the framework is to include knowledge about the specific domain being addressed. This will involve identifying the key characteristics and variables that most influence the model's predictions. The aim is to generate a comprehensive body of evidence that can substantiate the model's decisions, providing a cogent explanation for its behavior. This involves translating the technical details of the model's operation into a domain-relevant context that is accessible and meaningful to the stakeholders. By doing so, the explanations become not just technically accurate, but also contextually relevant, facilitating better understanding and trust among users.

The research gap, therefore, lies in developing XAI systems that not only demystify the AI's decision-making process but also contextualize these decisions within the specific domain of solar power distribution. This dual objective requires a concerted effort to integrate technical interpretability with domain expertise, ensuring that the explanations provided by XAI are both accurate and relevant to the energy sector. Filling this research gap will enable the deployment of AI models that are not only powerful and predictive but also transparent and trustworthy, fostering confidence in their use for managing and optimizing solar energy systems.

5. Results

Declaration: All the images used in this paper are the original work not derived from any other source. The images used in this section are derived from the dataset using python google collab environment. These images are produced through the execution of our code for various regression and XAI models.

The solar power system coupled with a power source is automated with AI and XAI. DC Power, Irradiation, Ambient Temperature, Module Temperature, Date and Time, Source Key, Daily Yield and Total Yield are recorded in the database from the solar power source and storage. The levels of these parameters are periodically monitored and any deviation in the parameters is addressed then and there. The experimentation is based on the data acquired from the power sources as datasets. These datasets are cleaned, pre-processed, analyzed and split for training and testing separately. In the proposed work 70-30% training and testing data are split. Then the regression models are trained and tested with the dataset and the results are tabulated.

Experimentation of Solar distribution of AC power is evaluated through the regression analysis. Since the data are numeric, it is infeasible to apply the dataset for categorical classification. Hence the explainable models are developed based on the regression analysis, in the proposed implementation. In general, the regression analysis estimates the correlation with the target attribute AC power, against the dependent attributes. Later these regression models are applied to estimate the explainability and importance of features in the prediction of the target.

AI can provide data visualizations through boxes, histograms, and whisker plots using Sea-born Data Visualizer (SNS plot). From the

Table 2
Performance Comparison of Various Regression Models.

Model	R2-Score	Variance	RMS Error
Linear Regression	0.99	0.99	0.007
Random Forest Regressor	0.9999	0.9999	0.0061
Gradient Boost Regressor	0.997	0.997	0.0062
Extra Gradient Boost Regressor	0.998	0.998	0.0062

dataset, the following histogram is produced to map the correlation between the target AC power and module temperature shown in Fig. 4.

In this visualization, the exponential change of AC power concerning the module temperature is analyzed. Then there is no clarity about the contribution of the module temperature to the AC power. The regression models tend to define the relationship between them. In the proposed system we estimated the relationship between the AC power and other variables using the Linear Regression. This provided an accuracy level of around 99.9% with a variance score of 0.99. Rest of the models used in the proposed work are Random Forest, Gradient Boost, and Extra Gradient Boost Regressors. The results obtained from various models are represented in Table 2.

These models provide an accuracy of around 100% with a root-mean-square error value of around 0.0061. The variations between these models are negligible, hence we prefer a Random Forest regressor that can be explained by various explainability models such as LIME and SHAPELY values.

The first explainable model is the Partial Dependency Plot (PDP) which determines the numeric correlation between two features in a dataset and provides a visualization about how the variation of one feature is affecting the other. For example how the increase of ambient temperature can increase or decrease the output AC power.

The relationship between the total yield and the module temperature is expressed in Fig. 5. This PDP plot uses the Random Forest regressor to provide an explanation. The figure shows the numerical increase of the total yield for the decrease of the module temperature. How the yield exponentially varies with the module temperature is quantitatively expressed in this plot.

The LIME model selects the features that are in a localized scope and explains how these features are interrelated. This also determines what features create a positive impact on the prediction and what feature has a negative impact on the prediction. This model can explain a specific instance in a dataset in such a way that, that particular instance is classified into a category or it provides a regression score based on the input feature weights and importance. The positive and negative feature estimation is shown in Fig. 6.

The DC power, total yield, and daily yield are the features that provide a positive impact to the regressor and if this value increases, then it increases the productivity of AC power. The ambient temperature and the module temperature are the features that provide a negative impact on the regressor since the increase of these features decreases the AC power productivity at the output. Thus the local explainer of the LIME provides the feature importance metric of the dependent variables and explains their impact on them for the prediction of the target ac power.

The last explainer discussed here is the extension of the local explainer of the LIME which is the notebook. This notebook explains as an independent record in the dataset, the threshold values for every feature, what are the weight importance of every feature, and if the threshold is breached, how much impact it creates on the regression process. The LIME notebook is presented in Fig. 7 & Fig. 8.

This notebook explainer provides the feature weights of every attribute, explains whether they are positive or negative, and also how well they contribute to the prediction of the target variable. The feature weights are represented in Table 3.

Table 3
Feature importance estimation using LIME Explainer.

Feature	Weight	Nature
DC Power	0.37	Positive
Data Yield	0.28	Positive
Total Yield	0.25	Positive
Irradiation	0.16	Positive
Ambient Temperature	0.07	Negative
Module Temperature	0.05	Negative

6. Discussion

6.1. Main findings of the proposed study

- This proposed work ensembles various regression models for the prediction of the target which is AC power and performs the explainability of the solar distribution. The study also employs AI and XAI techniques to interpret the importance and impact of distinctive features on the output. XAI derives the feature weights, signifies the importance of the input features in determining the output, and identifies the conditions that cause significant changes on the input side.
- The way an individual feature contributes to the output for local perception can be analyzed by LIME and on the other hand for global perception, it can be analyzed by SHAPLEY values. The LIME explainer identifies the positive impact of features such as DC Power, Data Yield, Total Yield, and Irradiation, while Ambient Temperature and Module Temperature have a negative impact.
- The study also uses XAI techniques such as PDP, and LIME Notebook to interpret the importance and impact of different features on the output.
- The observation that temperature has a negative impact on AC power production is also consistent with other works. The findings of the study highlight the significance of incorporating XAI methods to comprehend and interpret the connections among various input variables and the resulting output.

6.2. Implications

- The study demonstrates the effectiveness of Random Forest regressors in predicting solar power output and the importance of XAI techniques in interpreting and understanding the relationships between different input features and output. The proposed work can provide valuable insights in enhancing the decision-making process and optimizing solar power generation and distribution systems.
- The identification of important features can enable better decision-making and optimization of solar power generation and distribution systems. The use of XAI techniques can also improve transparency and trust since it converts black box classification or regression into the white box, therefore it explains how the classification and regression are performed.
- Dominant and important features are identified and controlled with the support of XAI, that enhances the solar power generation.
- Life time of the solar power plant is improved with automated control and monitoring systems.

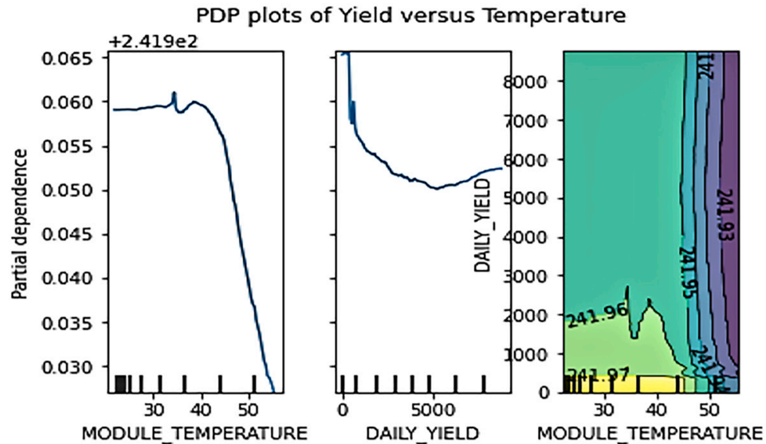

Fig. 5. PDP plot explainer for the dependency estimation between Total Yield and Module Temperature.

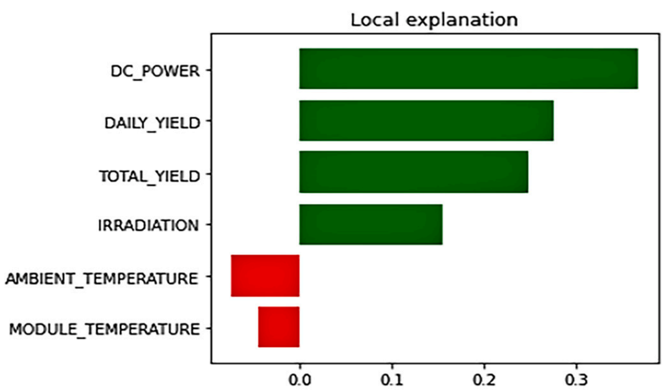

Fig. 6. LIME Explainer with Positive and Negative Features.

6.3. Challenges and possible solutions of solar panel industry

The increasing popularity of solar panels has created a significant demand for their adoption. While many people acknowledge the environmental benefits of solar panels, others are still hesitant to make the move owing to their perceived inefficiency. While panel efficiency has increased over time, it remains an issue that must be addressed.

Efficiency: Efficiency is a major challenge for the solar panel industry because most solar panels have an average efficiency rate of around 15-20 percent. While conventional silicon-based materials have traditionally been the primary component of solar panels, researchers have been investigating the usage of new materials such as perovskite. Perovskite has a crystal structure that enhances efficiency. Its high absorption capability surpasses that of traditional materials, enabling it to capture more sunlight. Additionally, multi-junction cells, consisting of multiple semiconductor layers with varying band gaps, offer potential improvements. By tailoring each layer to absorb specific wavelengths of the solar spectrum, these cells can convert a broader range of solar energy into electricity, outperforming conventional solar cell designs.

Cost: The high cost of solar panels remains an obstacle for the industry. Traditional energy sources, like coal and natural gas, are currently more affordable. One approach to address this cost concern is to enhance the manufacturing process. This could involve reducing the number of materials used and minimizing waste, leading to lower production expenses. Additionally, employing innovative materials and technologies that boost efficiency can cut overall costs as fewer panels are required to generate the same energy output.

Reliability: Given the challenges of harsh weather conditions like high winds and storms that solar panels face, their dependability is crucial. The industry needs to work towards enhancing their durability and safeguarding them from these conditions. Solutions like tempered glass and protective coatings can boost their resilience. Additionally, new installation methods, such as floating solar panels, can further improve reliability.

Regulation and Policy: To fully utilize solar energy's potential, the industry and policymakers must collaborate to overcome challenges. Regulations and the complexity of installation can hinder people from adopting solar panels. Governments can stimulate adoption through tax breaks and other incentives. Establishing clear policies and streamlining regulations will make the installation process more accessible and encourage greater use of solar energy.

Scalability: The quantity of solar energy that can be produced and distributed has limits, making it difficult to meet the rising demand for clean and renewable energy. To foster the growth and widespread adoption of solar energy, and improving its scalability is essential. Furthermore, to effectively incorporate solar energy into the power grid, the industry needs to focus on developing improved integration methods. This includes creating efficient systems for storing and distributing solar energy during periods of excess supply, as solar energy is not always available.

6.4. Advantages and disadvantages

6.4.1. Advantages

- Solar power generation is enhanced with Explainability and the end users are benefited.
- Uncertainty in the solar power production due to challenging weather conditions can be greatly supported by the XAI Explanations.
- Error rates and interference can be easily monitored and controlled.
- Efficiency of the overall power generation is greatly improved.
- Variable Climate Conditions are also greatly predicted and supported By AI.

6.4.2. Disadvantages

- The cost of the management and interpretation is high for solar systems with XAI.
- Data privacy and confidentiality issues pertaining to solar data is inevitable.
- False alarms during the production sometimes yield unrealistic predictions with XAI.
- Data inconsistencies lead to lack of feature analysis, model evaluation and explanation with XAI.

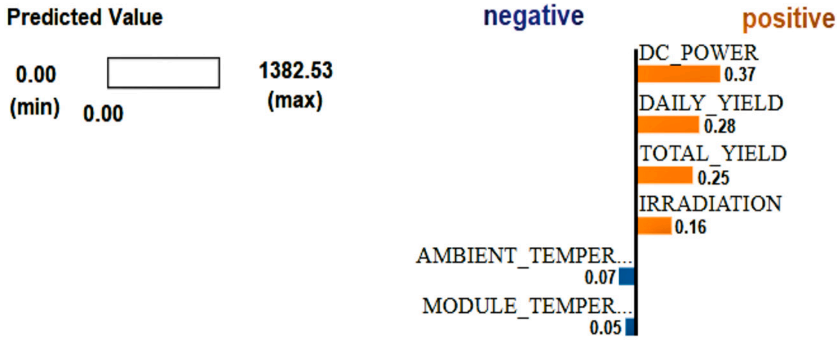

Fig. 7. LIME notebook Explainer for an Instance with Positive and Negative correlation.

Feature	Value
DC_POWER	0.00
DAILY_YIELD	1866.20
TOTAL_YIELD	111512591.00
IRRADIATION	0.00
AMBIENT_TEMPERATURE	27.00
MODULE_TEMPERATURE	25.06

Fig. 8. LIME notebook Explainer for an Instance with Feature Weight importance.

7. Conclusions and future directions

Solar power production is a challenging task. Especially power drawn from solar radiation is influenced mainly by naturally controlled attributes like wind pressure which acts against the gravity of panels, Irradiation, temperature etc. The next challenge is distribution. The power accumulated at grids and distribution of the power to both residential and industrial sectors requires meticulous processing and effort. The proposed work provides a solution for the distribution process which provides an alternative to human efforts through AI-based research analysis of the power distribution from the grid. The AI-supported model with a higher regression score of 0.9999, the random forest is selected for explainability using applications like PDP and LIME. This work can be possibly applied to both domestic and industrial applications with the support of AI. The proposed work provides real-time support with the explanation through LIME and SHAPELY in the local surrogacy, pertaining to every instance of the data in the dataset. The proposed work identifies the influential features for the solar power generation and handling these features to enhance and manage the solar power production.

The proposed model provides the solution in the local surrogacy with LIME and PDP which provides detailed analysis for a local instance or a real-time data efficiently. To review power generation, a global surrogate model such as SHAPELY can be used. The challenge in SHAPELY is that the variable data types and ranges of the data pertaining to the solar power generation could make the models non-interpretable for the global surrogacy. This could be addressed in the future work to enhance study on the global surrogates as well.

The Random Forest Regressor has an R2-score of 0.9999, showing that the model explains 99.99 percent of the variance in the data. This result depicts that the model has an excellent fit for the data and can accurately predict the AC power output. The variance score is also 0.9999, which tells that the model is not over-fitting the data. The RMS error is 0.0061, which is lower than that of the Linear Regression model.

The Gradient Boost Regressor has an R2-score of 0.997, which tells that the model can explain 99.7 percent of the variance in the data. The results show the better predictability of the output by the model. The variance score is also 0.997, which suggests that the model is not over-fitting the data. The RMS error is 0.0062, which is slightly higher than that of the Random Forest Regressor.

The Extra Gradient Boost Regressor has an R2-score of 0.998, which shows that the model can explain 99.8 percent of the variance in the data. Results indicate higher rate of the accuracy for the target prediction. The variance score is also 0.998, which suggests that the model is not over-fitting the data. The RMS error is 0.0062, which is the same as that of the Gradient Boost Regressor. Overall, the results suggest that the Random Forest Regressor is the best suited model for the explanation in-terms of the efficiency and performance. Further works can be focused on the following applications but are not limited to,

- Application of the XAI for the solar radiation explanation
- Application of the XAI for the solar panel error parameter evaluation
- Application of the XAI for the battery load and discharge control process
- Application of the XAI for error estimation on the smart grid and batteries

The purpose of the proposed work is to indicate the influence of the attributes in the estimation of the target AC power in smart grid-based solar distribution systems.

Declaration of competing interest

The authors declare that there are no conflicts of interest.

Data availability

The data used in the proposed work is available in the open source platform kaggle as, https://www.kaggle.com/datasets/pythonafroz/solar-power.

Declaration of generative AI and AI-assisted technologies in the writing process

There is no generative AI and AI-assisted technologies were used in the writing process.

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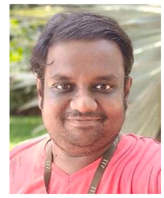

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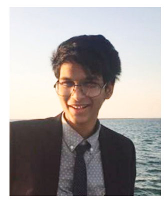

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