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Optimizing solar energy forecasting and site adjustment with machine learning techniques

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ABSTRACT

Estimation of solar radiation is a key task in optimizing the operation of power systems incorporating high levels of photovoltaic (PV) generation. This paper discusses the application of machine learning techniques, namely extreme gradient boosting (XGBT) and random forest (RF), to improve accuracy in the forecasting of solar radiation while adapting for different sites. Utilizing datasets such as meteorological and solar radiation data, the suggested models demonstrate the enhancement of forecasting accuracy by 39% from traditionally applied statistical practices. Along with this, this study also encompasses how endogenous and exogenous factors could be involved in better predictions of solar energy availability. From our findings, XGBT, as well as other machine learning techniques, do enjoy superior performance levels when it comes to the forecasting of solar radiation, which in turn promotes efficient management and potential adaptation of solar energy systems. This study demonstrates how this last generation of algorithms could be applied to noticeably improve the efficiency of solar power forecasting and thereby contribute to more sustainable and reliable energy systems as a byproduct of that.

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1. INTRODUCTION

One of the most abundant renewable sources is solar energy, attracting a lot of attention at every chance to be a tool to combat climate change and abate the use of fossil fuels. Photovoltaic (PV) technology has been developed to become ever more accessible, efficient, and cheaper with the preservation of solar power supply. Yet, variability in solar radiation may be caused by weather conditions or the location of installation-readily poses challenges for power system operators [1]-[3]. Accurate forecasts of solar radiation are important for optimizing solar power generation in the interest of ensuring grid stability and maximizing the integration of renewable energy sources into the electrical grid. Traditionally, most forecasting methods for solar radiation rely on purely statistical models that use historical data to describe the future availability of solar energy. Despite their popularity, these methods have limited applicability because they generally cannot account for intricate environmental factors influencing solar radiation [4], [5]. However, machine learning techniques provide a highly dynamic and accurate solution by processing large datasets that can bring out the patterns missed by other models. This enables the ML algorithm to improve forecasting significantly as well as adapt better than traditional models. This paper discusses a methodology to improve solar radiation forecasting using machine learning techniques such as extreme gradient boosting (XGBoost) and random forest (RF). The endogenous integration of endogenous/exogenous data inputs is used for optimization of forecast accuracy and site adaptation of solar energy systems [6].

The rest of the paper is presented in the following way. In section 2 describes the methodology: data collection, preprocessing, and implementation of ML models. In section 3 refers to the results and discusses the performance of XGBT and RF models. Conclusions based on findings and directions for further research are provided in the final section.

2. PROPOSED METHODOLOGY

The following components make up the solar radiation forecasting method, which is depicted in Figure 1. The automatic weather stations situated at ground level next to the solar power plants gather meteorological data such as clouds, speed of the wind, sunshine duration, and pressure in the atmosphere. First, a legit and appropriate set of data is gained from it, which has solar radiation as data. Second: keeping in mind the representation of data, data inputs, and data analysis [7], [8]. Next is a stage for data pre-processing, which includes outliers and missing data removal. Normalization is accomplished for this purpose: to eliminate the extremes without in any way detracting from their importance. Next, we move to feature selection. Subsequently, the data should be placed into training, validation, and testing datasets, and the data will become varied algorithm types. Therefore, XGBoost and RF models are used to measure the precision of the solar radiation prediction algorithms [9].

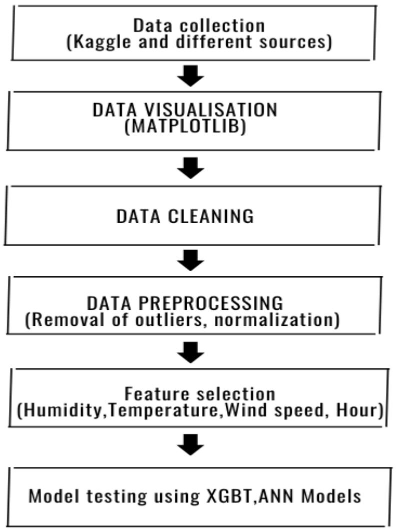

Figure 1. Flowchart of the proposed methodology

2.1. Data analysis and data preprocessing

Here in this section, the results of the research are illustrated, and a comprehensive discussion is also done [10]. Results are presented in the form of graphs, figures, tables, and others that facilitate easy understanding by the reader. The discussion is done in numerous sub-sections. The proper initiating step of the solar radiation forecasting model through accurate pre-processing protocols is important. Data cleaning is the first step [11]. It includes the formation of the coefficient from different scales of measurement. In research on solar light, only those are considered that are made during the day [12]. If the data from the entire series were employed, nearly all observed values would be zero, and the forecast values would also be approximated to zero, leading the model to overestimate the error in prediction and the forecasting performance [13]-[15]. The IQR method is used to detect outliers in data once it is ordered, where each quartile contains 25 percent of the total data. Three sets are created from the historical dataset: training, validation, and testing. The training data set is the basis for which ML models are required [16], [17]. This comes with the required input and output. However, the testing set is used as the model performance estimator on data not involved in the training process. 70% of the data is covered by the training set, 10% of the data is with the validation set, and 20% is with the test set parameters. Hyperparameter tuning is essential and crucial to the algorithm’s performance.

2.2. Machine learning algorithms
Various kinds of machine learning approaches are used for solar energy forecasting, namely: XGBoost, artificial neural network (ANN), and RF. These algorithms use historical weather and solar radiation data, together with other important parameters, to help forecast solar energy production. With the application of our proposed methodology, the selection of ML algorithms is assessed in terms of their capability toward the production of solar radiation by evaluating their performance. Predicting solar radiation and site adaptation techniques is done by artificial intelligence, or, in technical terms, the XGBT model.

2.3. XGBT
An effective and recognized machine learning technique built on the gradient boosting framework is called XGBoost [18]. The XGBoost algorithm uses a tree ensemble model to predict the output [19]. When boosting, trees are constructed one after the other so that each one learns from and reduces the mistakes of the one before it [20]. An algorithm that uses gradient descent is used to minimize the errors when new models are added. The XGBoost model uses a parallel running process to enhance the training time [21], [22].

2.4. RF model
A useful tree-learning method is the RF algorithm. In the training stage, it results in many decision trees [23], [24]. Every tree is built utilizing an arbitrary subgroup of the data set to assess a random subset of qualities in each partition. When predicting, the algorithm averages or votes on the output of each tree [25], [26]. The results of this collective decision-making process, which is aided by the insights of several trees, are compatible and precise. Each of these trees represents a different expert with a focus on a definite area of the data [27], [28]. Essentially, they perform separately, minimizing the possibility that the subtleties of a single tree will have an inappropriate impact on the model. A key component of RF's training access is bagging, which involves taking numerous bootstrap samples from the original data and using them to sample replacement instances. In conclusion, a distinct subset of data is used for each decision tree, which adds diversity to the training process and fortifies the model [29], [30].

3. RESULTS AND DISCUSSION
In this section, two main tasks are performed: presenting the findings (results) and interpreting their significance (discussion). Overall, the XGBoost model demonstrates robust performance, with key features driving its predictive power. While accuracy is generally high, addressing outliers and improving temporal alignment can further optimize the model's reliability and precision. The RF model shows strong predictive performance, with key features driving its accuracy. While the model generally predicts well, addressing outliers and periods of discrepancy can further enhance its reliability and precision.

Figure 2 represents the scatter plot between true and expected values for the solar radiation forecasting model using the XGBoost model. Every plot point indicates a data point. Every point's X coordinate indicates the actual solar radiation value (ground truth) for that data point. The y-coordinate represents the predicted solar radiation value generated by the XGBoost model for the same data point. Figure 3 represents the feature importance plot using different parameters such as temperature, wind speed, and others vs. their F scores. A feature importance plot using an XGBoost model illustrates the significance of many attributes in forecasting the desired variable. Each vertical bar represents a feature (or variable) used in the XGBoost model. Features with taller bars are considered more important because they have a bigger impact on the model's predictions. The importance of each feature is quantified by a numerical score, which is known as the F score. Figure 4 shows actual versus expected values over time for an XGBoost model. The blue line represents the actual values over Unix time, whereas the orange line represents the predicted values over Unix time. Figure 5 represents the graph that predicts the accuracy of the model. The X-axis represents density, and the Y-axis shows how the actual and expected values differ from each other. Figure 6 shows the actual versus expected values of a RF model. A visual representation measures how well the true values match the model's predictions. Each plot point indicates a data point. Every data point's x-coordinate indicates its real value, while the RF model's predicted value for the same data point is represented by the y-coordinate. Figure 7 shows the actual versus expected values over time for a RF. The X-axis shows the Unix time, while the Y-axis shows the values of the target variable that the RF model is predicting. The target variable's actual values are represented as data points on the graph. The target variable predicted values produced by the RF model are also plotted on the graph. The distribution of differences between actual and expected values for a RF model is shown in Figure 8, which provides insights into the errors made by the model across various predictions. The discrepancy between the actual and expected values for each data point is displayed on the horizontal axis. This discrepancy is computed as the actual value minus the predicted value and is commonly referred to as the residual or prediction error. Usually, the density of data points with a specific difference between actual and anticipated values is shown by the vertical axis.

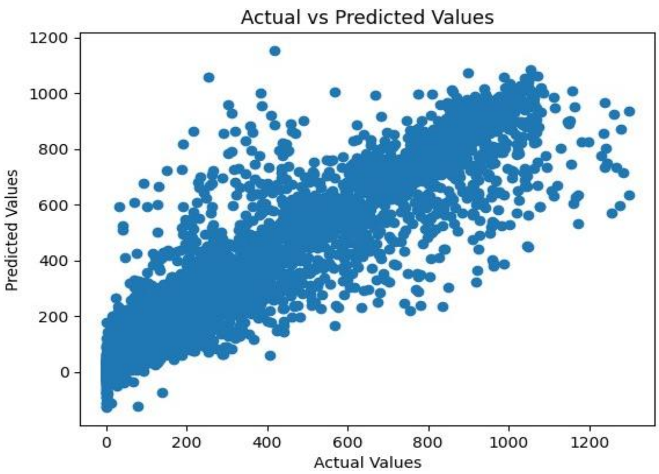

Figure 2. Scatter plot between actual and predicted values

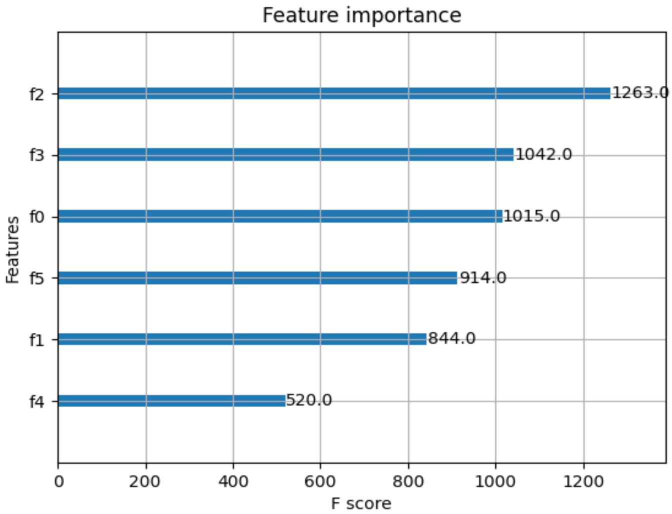

Figure 3. Feature importance of XGBT model

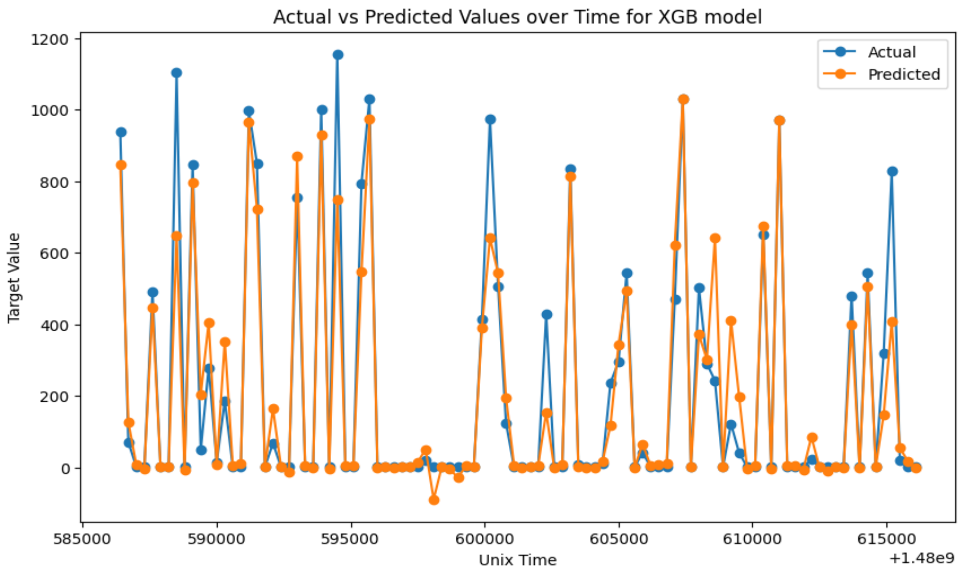

Figure 4. Graph showing actual vs. predicted values over time for the XGBoost model

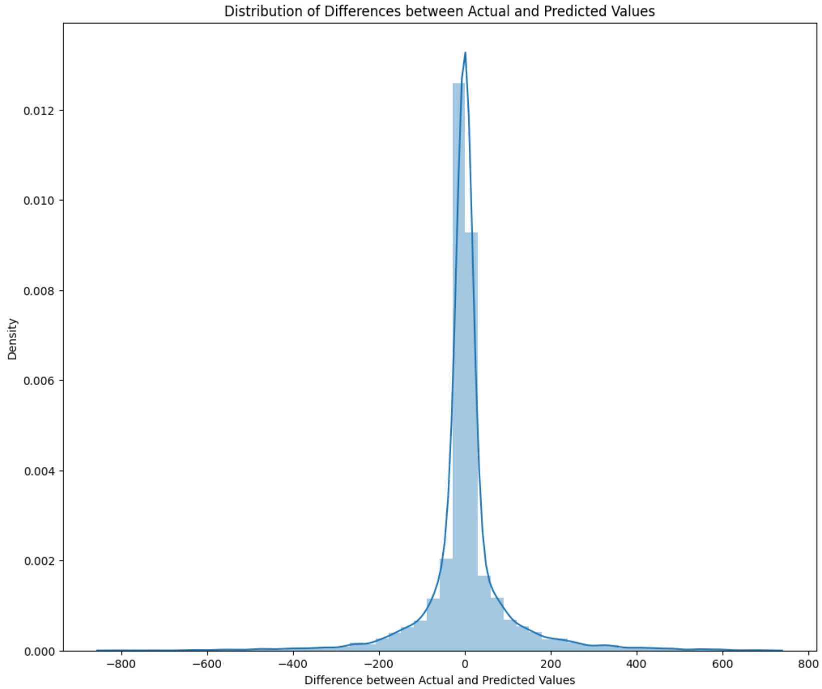

Figure 5. Graph showing the distribution of differences between actual and predicted values

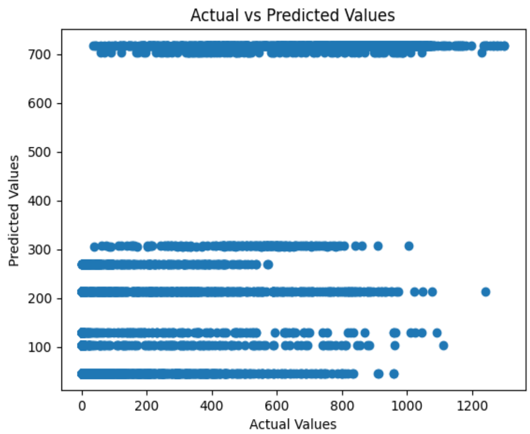

Figure 6. Scatter plot of actual vs. predicted values of RF model

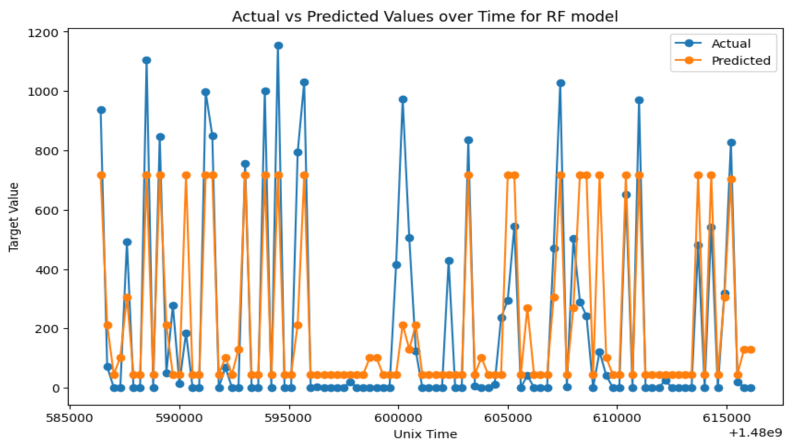

Figure 7. Graph showing Actual vs. predicted Values over time of RF Model

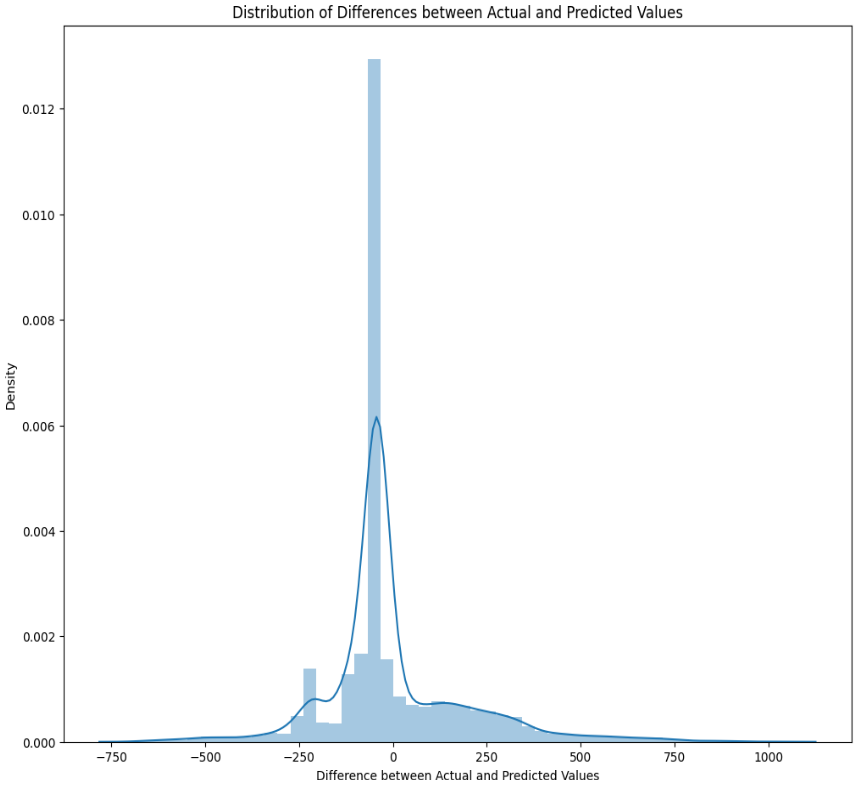

Figure 8. Graph showing the distribution of differences between actual and predicted values of the RF model

When we discuss RMSE to machine learning, we are mostly discussing its use as a performance metric for prediction- or forecasting-based algorithms. A basic building block in statistical analysis and machine learning, the root mean square error provides a straightforward but useful measure of prediction error. On the other hand, a larger RMSE indicates a larger difference between the expected and observed results. As mentioned in Table 1, the RMSE value of the XGBoost was calculated and found to be 101.5818, whereas the RMSE value of the RF model was found to be 190.21. As mentioned above, lower the RMSE value, and the model can predict more accurately. So XGBoost model predictions are more accurate, and it gives a correct estimate of the average deviation between the expected and actual values in the dataset.

Table 1. Statistical evaluation indices

Models	Mean squared error (MSE)	Root mean squared error (RMSE)
XGBoost model	10318.8769	101.5818
Random forest	190.2149	190.2149

4. CONCLUSIONS

The proposed research strives to determine the efficiency of forecasting solar radiation by XGBoost, RF machine learning algorithms. XGBT outperformed the classical methods with an improvement rate of 39% and gave better results with lower RMSE compared to traditional methods, hence establishing superior forecasting capability. It can also be inferred from the analysis that an RF model also proved to give good results. However, this is not as accurate as that provided by XGBT. Such results indicate the prospects in which machine learning can optimize solar energy forecasting and site adaptation to integrate solar energy into power grids effectively. Further making use of large datasets as well as advanced algorithms, predictions are eventually generated that turn out more reliable. Further steps could then focus on real-time data inclusion and introduce new machine-learning techniques for the further improvement of accuracy across different regions.

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AUTHOR CONTRIBUTIONS STATEMENT

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Jayanta Kumar Sahu		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓		✓
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This article does not contain any studies with human participants or animal studies performed by any of the authors.

DATA AVAILABILITY

The datasets used and/or analyzed during the current study available from the corresponding author [SRS], on reasonable requests.

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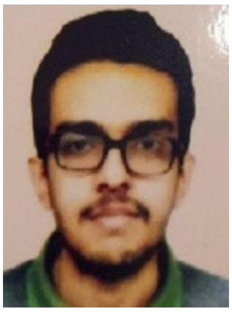

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