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Power PV Forecasting using Machine Learning Algorithms Based on Weather Data in Semi-Arid Climate

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Abstract. As the energy demand continues to rise, renewable energy sources such as photovoltaic (PV) systems are becoming increasingly popular. PV systems convert solar radiation into electricity, making them an attractive option for reducing reliance on traditional electricity sources and decreasing carbon emissions. To optimize the usage of PV systems, intelligent forecasting algorithms are essential. They enable better decision-making regarding cost and energy efficiency, reliability, power optimization, and economic smart grid operations. Machine learning algorithms have proven to be effective in estimating the power of PV systems, improving accuracy by allowing models to understand complex relationships between parameters and evaluate the output power performance of photovoltaic cells. This work presents a study on the use of machine learning algorithms Catboost, LightGBM, XGboost and Random Forest to improve prediction. The study results indicate that using machine learning algorithms LightGBM can improve the accuracy of PV power prediction, which can have significant implications for optimizing energy usage. In addition to reducing uncertainty, machine learning algorithms improve PV systems' efficiency, reliability, and economic viability, making them more attractive as renewable energy sources.

1 Introduction

In the 2020s, energy strategies have been focusing on ensuring that power systems are sustainable, reliable, and adaptable. The European Union's energy strategy places a significant emphasis on the role of PV technology in achieving climate objectives [1]. However, the rapid increase in PV installations, due to its dependency on weather conditions, presents grid management challenges for operators [2]. This has made the advancement of precise solar forecasting techniques a critical area of research, matching the importance and volume of studies.

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Forecasting methods of PV power output can be categorized into statistical methods and machine learning approaches. Statistical methods have become popular due to their simplicity in implementation, minimal data requirements, and lower computational costs compared to traditional methods. Initially, forecasting models for solar PV power relied exclusively on historical solar irradiance data, operating under the assumption that solar irradiance was the sole factor that influences PV system performance[3,4]. However, Recent interest has grown in using machine learning (ML) methods to predict PV power production. A thorough inspection of the literature reveals that various models that the use of ML have been applied for this purpose. For instance, Scott et al.in [5] present a comprehensive analysis of the utilization of machine learning algorithms for forecasting the power output of PV systems. The authors perform a detailed evaluation of several machine learning approaches, employing techniques such as Random Forest, Support Vector Machines, Neural Networks, and Linear Regression, to determine their efficacy in predicting the energy production of a PV system. Additionally, Markovics et al. [6] conduct a detailed comparison of 24 ML algorithms for PV power forecasting, highlighting the importance of predictor selection and hyperparameter tuning in achieving optimal forecasting accuracy. Cabezon et al. [7] have investigated the application of ML for short-term power forecasting in photovoltaic production facilities. Focusing on a Scottish solar farm. Their study finds that the XGB tree based model yields highest accuracy in forecasting power demand for the upcoming hour. In Mystakidis et al. [8], explore the use of both ML and deep learning (DL) algorithms for forecasting energy generation from time-series data. The study uses various metrics to assess the predictive capabilities of these models and concludes that an ensemble method, which combines several ML and DL algorithms, achieves the highest accuracy.

One of the most significant and valuable responsibilities is to accurately anticipate PV production. AI is increasingly being used in this field, as evidenced by several advances, techniques, and research [9-14].

The studies have several limitations, including a primary focus on application-ready machine learning (ML) models, insufficient exploration of probabilistic forecasting, and inadequate investigation of hybrid models. Additionally, there may be concerns regarding the generalizability of the findings. Furthermore, the studies do not adequately consider the influence of varying weather patterns, and there is minimal research employing PV forecasting in semi-arid regions.

This study aims to evaluate ML algorithms for forecasting the performance of a localized PV system situated in a semi-arid climate, utilizing real data gathered from a precise meteorological station. The effectiveness of ML in predicting PV system outputs hinges on selecting the appropriate ML methodology. To this end, this research presents a comprehensive comparison of actual results derived from various ML techniques, identifying the most accurate and reliable method for forecasting PV power production in environments characterized by semi-arid climates. This comparison is critical for optimizing the application of ML in enhancing the predictability and efficiency of PV systems under such specific geographical and climatic conditions within PV systems.

The subsections of this paper are organised as outlined- Section 2 introduces an experimental study on PV power and methodologies; Section 3 discusses the outcomes of machine learning algorithms; Section 4 concludes the complete work.

2 Materials and Methods

2.1 Experimental setup

This study is carried out at Green Energy Park (GEP), research facility research in Benguerir, utilizing a 2.3kWp PV system comprising 7 polycrystalline panels, each with a capacity of 335Wp, connected in series (see Table 1). To capture the system's power output, a datalogger device was employed, with its findings illustrated in Fig.1. The panels were maintained through a stringent manual cleaning regimen, rigorously implemented every two days. This meticulous maintenance protocol was informed by the discerning findings presented in the research conducted by Aljaghoub et al.[15] Their study explored deeply into the effects of various photovoltaic panel cleaning methodologies on Sustainable Development Goals (SDGs), employing the sophisticated TOPSIS method -a multi-criteria decision-making technique- for meticulous analysis. The findings underscored the paramount importance of manual cleaning in optimizing the panels' performance while aligning with broader sustainability objectives.

Meteorological data were collected over the course of one year (from January 1, 2022, to December 31, 2022) from the meteorological station situated at GEP, Morocco. This station is equipped to measure various meteorological parameters, including temperature, precipitation, humidity, Direct Normal Irradiation (DNI), Diffuse Horizontal Irradiation (DHI), Global Horizontal Irradiation (GHI), as well as wind speed and direction. These measurements are captured at three-second intervals by high-precision sensors. The recorded data can be presented in a variety of formats to suit specific requirements, such as one-minute, ten-minute, hourly, or monthly intervals. Additionally, other customized intervals can be configured based on the particular needs of the analysis or study.

Fig2 provides a visual representation of the meteorological station situated at the GEP research facility, illustrating its layout and equipment setup. This case study employed high-resolution data collection, with measurements taken every hour of each day. After data collection, an extensive analysis was performed using Python 3.9. This analysis included an Exploratory Data Analysis (EDA) to visually interpret the collected data, detailed in section 2.2, allowing for deeper insights and understanding of the meteorological patterns and trends observed during the specified period.

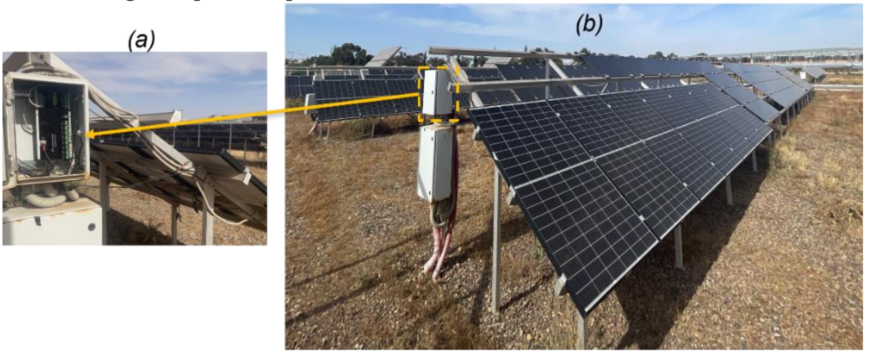

Fig.1. Experimental setup (a) Datalogger device, (b) the PV System

Fig.2. The meteorological station in GEP Benguerir site.

Table 1. Solar panel specifications.

Electrical data	Values
Power Output P_{MAX} (W)	335
Maximum Power Voltage-U_{MPP} (V)	34.0
Maximum Power Current-I_{MPP} (A)	9.85
Open Circuit Voltage-U_{OC} (V)	40.7
Short Circuit Current-I_{SC} (A)	10.5

2.2 Methodology

To forecast photovoltaic (PV) power generation with machine learning models, the essential data processing steps are presented in Fig.3.

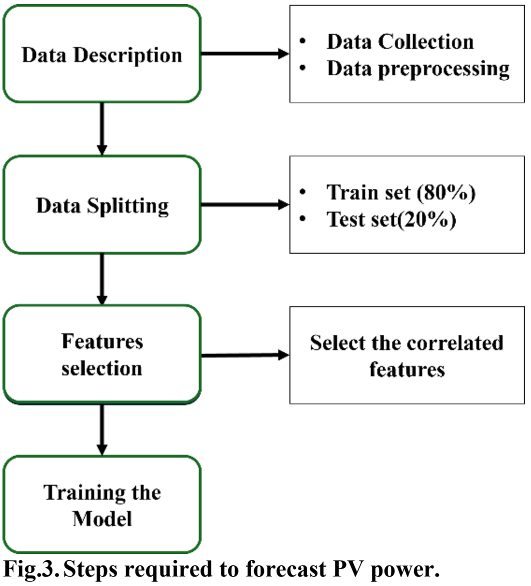

Fig.3. Steps required to forecast PV power.

To ensure that accurate estimates of solar electricity are made, a methodical process must be followed as outlined in Fig.3. Following is a list of these essential actions:

- **Data Description**: This study used the GEP dataset for Benguerir, Morocco. This weather station provides high-quality meteorological data on temperature, precipitation, humidity, solar irradiance and wind speed and direction for the year 2022. Pre-processing and cleaning of the dataset imputed any missing or incorrect data.
- **Data processing:** To ensure the accuracy and prevent errors in the machine learning models, the dataset underwent a rigorous cleaning process. This included addressing missing data points, which can significantly impact model performance. Notably, all missing values represented by "NaN" (Not a Number) were imputed using a suitable method[16,17].
- **Data splitting**: Following this cleaning process, the dataset was strategically divided into two distinct sets: a training set and a testing set. The training set, comprising 80% of the data, served to train the ML models. The remaining 20% constituted the testing set, used to evaluate the models' performance. This 80/20 split helped mitigate the risk of overfitting, where the models simply memorize the training data instead of learning generalizable patterns.
- **Feature selection:** is a critical data preprocessing technique that reduces the number of features in a dataset. This method involves searching the entire feature space to identify an optimal set of features that are free from redundancy and irrelevance. By diminishing the dataset's dimensionality through the removal of unnecessary features, feature selection plays a crucial role in enhancing the performance—specifically the accuracy—of inductive learning algorithms and in constructing simpler models[18]. Therefore, feature selection is an essential aspect of machine learning. This study utilizes various input variables, including Air Temperature (Air_Temp), Atmospheric Pressure (Pressure), Relative Humidity (RH), Wind Speed (Wind_speed), Wind Direction (Wind_dir), Wind Gust (Wind_gust), Rainfall (Rain), Hour, Day, and Month. Fig.4 illustrates the correlation between these inputs and the output variables, showcasing the relationship's intensity and direction. The forecasting models applied in this study, namely CatBoost, XGBoost, LightGBM, and Random Forest, are meticulously chosen for their proven effectiveness in handling such predictive tasks, offering insights into the dynamic nature of solar power generation.

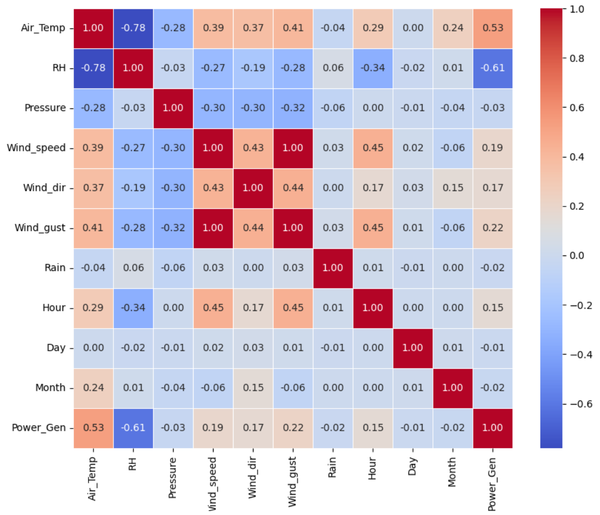

Fig.4. Correlation matrix displaying the strength of association between observed weather variables and power output.

2.3 Machine learning algorithms

Solar power is an important source of renewable energy that helps meet global energy needs while reducing greenhouse gas emissions. A precise forecast is necessary for the integration of solar power into the power grid and for the efficient management of energy. Machine learning models are increasingly favoured for predicting solar power outcomes because of their proficiency in identifying intricate patterns and non-linear correlations within data on solar power generation. This paper present four machine learning models for forecasting power generation

2.3.1 Random Forest (RF)

Random Forest is an effective ensemble learning strategy that aggregates the predictions from various decision trees to create a more accurate result than any single tree could achieve. It works by dividing the data into subsets and using these to train individual trees, effectively creating a 'forest' of decision trees. The algorithm makes its final decision based on the aggregated results of these trees[19].

2.3.2 Extreme Gradient Boosting

XGBoost is a collective of machine learning methods that produces a combination of models that is superior to any individual model in the combination. Typically, the core models are decision trees, so gradient boosting is considered a way of generalizing these. All things considered; gradient boosting algorithms create decisions trees that are added together. Importantly, each decision tree is interdependent, designed to address the inaccuracies of the forecasts made by preceding trees, ensuring that every new tree enhances the accuracy of its predecessors. The models are suitable for any differentiable loss function and optimization algorithm that relies on gradients. This is the basis for the name "gradient boosting," since the model reduces the loss gradient as it is developed, akin to how a neural network functions [20].

2.3.3 CatBoost

Catboost is an open source model developed by Dorogush and it successfully combines categorical features that have the least amount of information loss[21]. Catboost is different from other gradient-based boosting. First, it employs ordered boosting, a specialized form of gradient boosting that overcomes the issue of target leaking. Second, this algorithm is beneficial on small datasets. Third, Catboost is capable of dealing with categorical traits. This procedure is typically completed during the preprocessing phase, and it involves replacing the original categorical variables with a single or multiple numerical values.

2.3.4 Light Gradient Boosting Machine

LightGBM is an advanced implementation of gradient boosting decision trees designed for speed and efficiency. Originating from Microsoft Research, it introduces innovative techniques such as Exclusive Feature Bundling (EFB) and Gradient-based One-Side Sampling (GOSS) to enhance training speed and reduce memory usage, all without compromising accuracy.. GOSS selectively uses instances with large gradients, which are more informative for learning, thus reducing the data size needed for accurate information gain estimation. EFB efficiently bundles mutually exclusive features (those rarely non-zero simultaneously) to decrease the feature dimensionality, tackling challenges posed by high-dimensional data. These methodologies enable LightGBM to outperform existing implementations significantly, achieving up to 20 times faster training speeds while maintaining competitive accuracy, even on large datasets with high feature dimensionality[22].

2.3.5 Hyperparameter tuning

Machine learning models are defined by both parameters and hyperparameters. Parameters are determined during training and establish the relationship between inputs and outputs, while hyperparameters, set during the model initialization, dictate the model's structure, and control the training process. The selection and optimization of hyperparameters, known as tuning, are crucial as they influence the model's training convergence and accuracy. Although many machine learning libraries, such as scikit-learn, provide default hyperparameter settings that yield satisfactory accuracy for general applications, fine-tuning these hyperparameters is essential to fully realize a model's capabilities and achieve the highest accuracy tailored to specific problems. In this study, we employed grid search with a larger set of hyperparameters. We then selected the best hyperparameters for each model, as shown in Table 2.

Table 2. hyperparameters tuning of algorithms

Models		**Values**
XGboost Model	Learning_rate	0.3
	Max_depth	6
	Min_child_weight	1
	N_estimators	100
	Colsample_bytree	1
Random Forest	Learning_rate	0.1
	max_depth	10
	max_features	auto
	Iterations	100
C a	Learning_rate	0.1

	Min_data_in_leaf	1
	subsample	0.8
	iterations	100
LightGBM	Learning_rate	0.1
	Max_depth	8
	Min_child_weight	1
	N_estimators	100
	Colsample_bytree	1

2.4 Evaluation metrics

After training the model, its effectiveness is measured using the test data through various metrics. These metrics typically encompass Mean Absolute Root Mean Square Error (RMSE), Error (MAE), and the Correlation Coefficient.

2.4.1 Mean absolute error

MAE is a metric used to assess the accuracy of a regression model. It calculates the average magnitude of errors between pairs of actual and predicted values, without considering their direction. MAE is determined as the average of the absolute differences between predicted and actual values across all observations in the dataset. [23].

2.4.2 Root mean square error

RMSE quantifies how predicted values differ from actual observed values. It measures by squaring the errors (to remove any negative signs), averaging these squares over all observations, and then calculating the square root of the average [24].

2.4.3 Correlation coefficient

The correlation coefficient serves as a quantitative indicator of the linear association between real and predicted values. It assesses the degree to which forecasted values align with the underlying trend exhibited by the actual data.
A correlation coefficient approaching 1 suggests a strong, positive linear correlation. To put it more straightforwardly, the estimated values tend to increase or decrease along with the actual values. Conversely, a value near -1 suggests a strong, negative linear relationship. This indicates that an increase in one variable is usually accompanied by a decrease in the other, and the opposite is equally valid.

3 Results and discussions

PV power prediction processing involves numerous phases in order to effectively anticipate future PV power generation. These processes might involve data collection, data processing, model selection, training, and evaluation. The flow chart of the developed algorithms is illustrated in Fig.5.

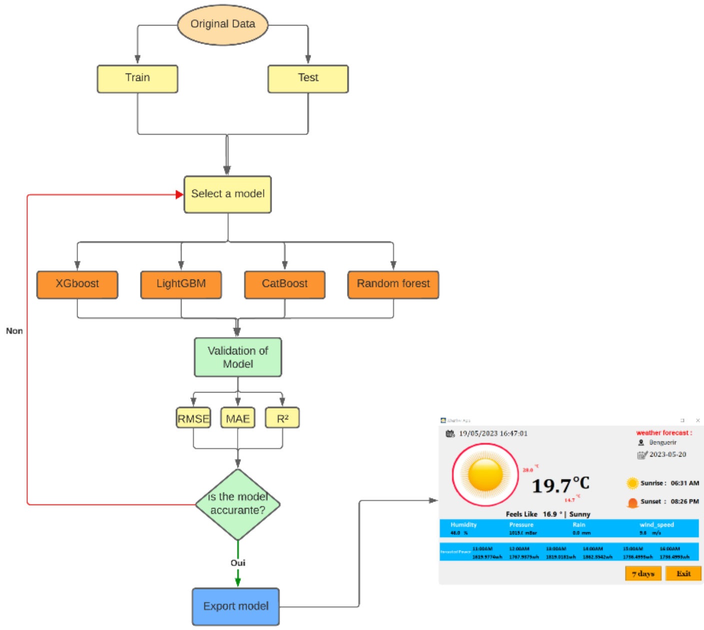

Fig.5. Algorithms Process.

The study used four machine learning algorithms to forecast solar energy: Catboost, lightGBM, XGboost and Random Forest. The models were assessed using a variety of measures, including MAE, RMSE, R^2. The evaluation findings are described in Fig.5.

Giving Table 3, the ML models selected for this study are classified based on their gradient-based methods. The results present that all chosen ML algorithms foarcast PV power generation with considerable accuracy, as evidenced by the high R_squared values and low MAE and RMSE values. Specifically, the LightGBM model outperformed the others, achieving the lowest RMSE and the highest R^2 values. Additionally, the LightGBM exhibited an RMSE of 231.9, and MAE=119.6 the lowest among the models, and an R^2 value of 0.87, indicating very high accuracy. A lower RMSE value signifies a smaller deviation of predicted values from actual values, and a higher R^2 value denotes a more accurate fit to the data in comparison with other models. Fig.6.a compares the performance of various forecasting algorithms in predicting photovoltaic (PV) power generation for the test data. As shown in Fig.6.b, all algorithms manage to capture the overall trends in power generation, even on days with significant fluctuations. To further analyze their performance under more stable conditions, Fig.6.c focuses on how these algorithms perform on typical days with less variation in power generation.

Table 3. The evaluation of the performance of the algorithms

Model	MAE	RMSE	R^2
XGBoost	148.8	251.91	0.85
CatBoost	127	239.64	0.86
LightGBM	**119.6**	**231.9**	**0.87**
Random Forest	119.22	238.89	0.86

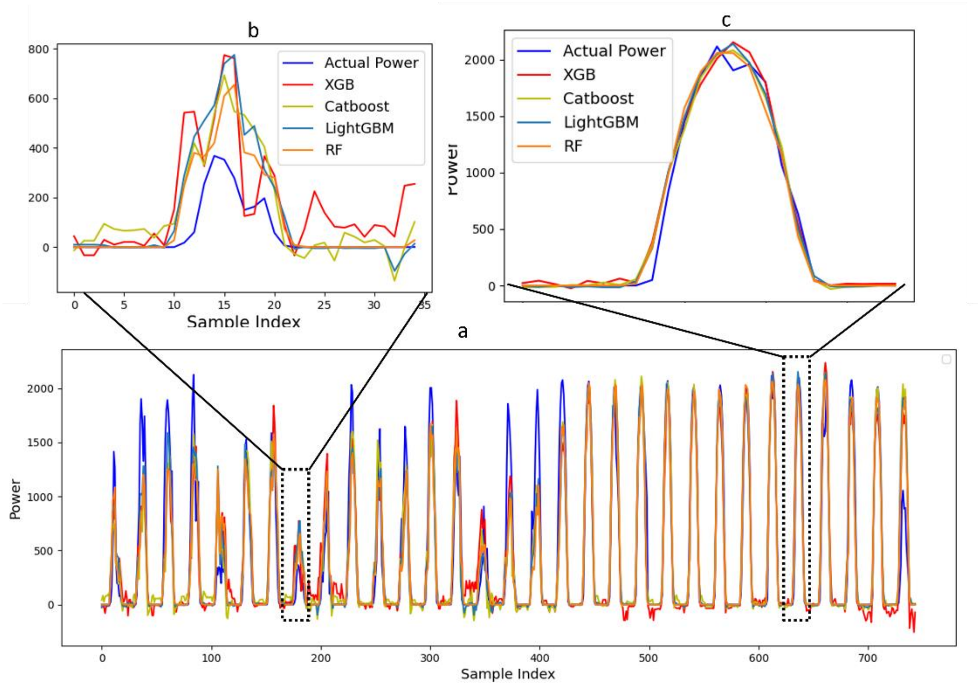

Fig.6. (a) Comparison of the performance of each model against actual PV power generation. (b) Comparison of fluctuations in power generation. (c) Comparison on a typical day.

4 Conclusion

The paper provides a detailed comparison of machine learning algorithms aimed at improving the accuracy of photovoltaic (PV) power forecasting. It focuses on four algorithms: CatBoost, LightGBM, XGBoost, and Random Forest, utilizing data collected from an experimental setup at GEP Benguerir. This study underscores the potential of these techniques in refining PV power predictions, which is crucial for optimizing energy management and facilitating smoother grid integration. Results showed that LightGBM had the highest R^2=0.87, lowest RMSE=231.5 and lowest MAE=119.6, demonstrating a small but noticeable advantage over other algorithms in terms of accuracy and error metrics.

Regular surveillance and modification of the forecasting model are vital for adapting to shifting weather scenarios and data configurations, maintaining the precision and trustworthiness of solar energy forecasts over time. Employing AI technologies in the forecasting of solar power is instrumental in boosting solar energy output and its assimilation into the international energy framework. Utilizing precise forecasts allows decision-makers to make well-informed decisions, fostering more effective energy management and paving the way toward a more sustainable and environmentally friendly future.

However, it's important to consider that this study's data is limited to Benguerir, Morocco, for a specific timeframe and region (Semi-Arid). The models might perform differently elsewhere or under different weather conditions. Future research could investigate this by testing the models in various locations and weather scenarios. This would reveal how well the models generalize and how robust they are. Additionally, exploring how data pre-processing techniques affect the models' performance could be valuable. By comparing

different pre-processing methods, researchers could improve the performance and reliability of PV power predictions.
This paper represents a significant contribution in the field of solar power forecasting, underscoring the potential of AI models to improve forecasting precision and support the integration of renewable energy resources. With the ongoing development and incorporation of AI methods into solar energy forecasting systems, they are poised to become a key factor in moving towards a more sustainable and environmentally friendly energy paradigm.

References

[1] W. House and C. Street, 'Industrial Innovation: Pathways to deep decarbonisation of Industry.Part 2: Scenario analysis and pathways todeep decarbonisation', (2019).
[2] 'IEA – International Energy Agency'. Accessed: (Mar. 21, 2024). [Online]. Available: https://www.iea.org/
[3] N. Sharma, P. Sharma, D. Irwin, and P. Shenoy, 'Predicting solar generation from weather forecasts using machine learning', in *2011 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, (2011), pp. 528–533. doi: 10.1109/SmartGridComm.2011.6102379.
[4] M. G. De Giorgi, P. M. Congedo, and M. Malvoni, 'Photovoltaic power forecasting using statistical methods: impact of weather data', *IET Science, Measurement & Technology*, vol. **8**, no. 3, pp. 90–97, (2014), doi: 10.1049/iet-smt.2013.0135.
[5] C. Scott, M. Ahsan, and A. Albarbar, 'Machine learning for forecasting a photovoltaic (PV) generation system', *Energy*, vol. **278**, p. 127807, Sep. (2023), doi: 10.1016/j.energy.2023.127807.
[6] D. Markovics and M. J. Mayer, 'Comparison of machine learning methods for photovoltaic power forecasting based on numerical weather prediction', *Renewable and Sustainable Energy Reviews*, vol. **161**, p. 112364, Jun. (2022), doi: 10.1016/j.rser.2022.112364.
[7] L. Cabezón, L. G. B. Ruiz, D. Criado-Ramón, E. J. Gago, and M. C. Pegalajar, 'Photovoltaic Energy Production Forecasting through Machine Learning Methods: A Scottish Solar Farm Case Study', *Energies*, vol. **15**, no. 22, Art. no. 22, Jan. (2022), doi: 10.3390/en15228732.
[8] A. Mystakidis *et al.*, 'Energy generation forecasting: elevating performance with machine and deep learning', *Computing*, vol. **105**, no. 8, pp. 1623–1645, Aug. (2023), doi: 10.1007/s00607-023-01164-y.
[9] E. Sarmas, E. Spiliotis, E. Stamatopoulos, V. Marinakis, and H. Doukas, 'Short-term photovoltaic power forecasting using meta-learning and numerical weather prediction independent Long Short-Term Memory models', *Renewable Energy*, vol. **216**, p. 118997, Nov. 2023, doi: 10.1016/j.renene.(2023).118997.
[10] S. mahdi Miraftabzadeh, M. Longo, and F. Foiadelli, 'A-Day-Ahead Photovoltaic Power Prediction Based on Long Short Term Memory Algorithm', in (*2020) International Conference on Smart Energy Systems and Technologies (SEST)*, Sep. 2020, pp. 1–6. doi: 10.1109/SEST48500.2020.9203481.
[11] M. AlShafeey and C. Csáki, 'Evaluating neural network and linear regression photovoltaic power forecasting models based on different input methods', *Energy Reports*, vol. **7**, pp. 7601–7614, Nov. 2021, doi: 10.1016/j.egyr.(2021).10.125.
[12] W. VanDeventer *et al.*, 'Short-term PV power forecasting using hybrid GASVM technique', *Renewable Energy*, vol. **140**, pp. 367–379, Sep. (2019), doi: 10.1016/j.renene.2019.02.087.

[13] S. Cantillo-Luna, R. Moreno-Chuquen, D. Celeita, and G. Anders, ‘Deep and Machine Learning Models to Forecast Photovoltaic Power Generation’, *Energies*, vol. **16**, no. 10, Art. no. 10, Jan. (2023), doi: 10.3390/en16104097.
[14] P. Gupta and R. Singh, ‘PV power forecasting based on data-driven models: a review’, *International Journal of Sustainable Engineering*, vol. **14**, no. 6, pp. 1733–1755, Nov. (2021), doi: 10.1080/19397038.2021.1986590.
[15] H. Aljaghoub, F. Abumadi, M. N. AlMallahi, K. Obaideen, and A. H. Alami, ‘Solar PV cleaning techniques contribute to Sustainable Development Goals (SDGs) using Multi-criteria decision-making (MCDM): Assessment and review’, *International Journal of Thermofluids*, vol. **16**, p. 100233, (2022).
[16] T.-T.-H. Phan, ‘Machine Learning for Univariate Time Series Imputation’, in (*2020) International Conference on Multimedia Analysis and Pattern Recognition (MAPR)*, Ha Noi, Vietnam: IEEE, Oct. 2020, pp. 1–6. doi: 10.1109/MAPR49794.2020.9237768.
[17] S. M. Mostafa, ‘Missing data imputation by the aid of features similarities’, *International Journal of Big Data Management*, vol. **1**, p. 81, Jan. 2020, doi: 10.1504/IJBDM.(2020).106883.
[18] M. BÜYÜKKEÇECİ and M. Okur, ‘A Comprehensive Review of Feature Selection and Feature Selection Stability in Machine Learning’, *GAZI UNIVERSITY JOURNAL OF SCIENCE*, vol. **36**, Sep. (2022), doi: 10.35378/gujs.993763.
[19] L. Breiman, ‘Random Forests’, *Machine Learning*, vol. **45**, no. 1, pp. 5–32, Oct. (2001), doi: https://doi.org/10.1023/A:1010933404324.
[20] G. Surribas Sayago, J. D. Fernández-Rodríguez, and E. Dominguez, ‘Photovoltaic Energy Prediction Using Machine Learning Techniques’, in *Advances in Computational Intelligence*, I. Rojas, G. Joya, and A. Catala, Eds., Cham: Springer Nature Switzerland, (2023), pp. 577–587. doi: 10.1007/978-3-031-43085-5_46.
[21] A. V. Dorogush, V. Ershov, and A. Gulin, ‘CatBoost: gradient boosting with categorical features support’, *CoRR*, vol. **abs**/1810.11363, (2018)(, doi: http://arxiv.org/abs/1810.11363.
[22] G. Ke *et al.*, ‘LightGBM: A Highly Efficient Gradient Boosting Decision Tree’, in *Neural Information Processing Systems*,(2017).
[23] C. J. Willmott and K. Matsuura, ‘Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance’, *Climate Research*, vol. **30**, no. 1, pp. 79–82, Dec. (2005), doi: 10.3354/cr030079.
[24] T. Chai and R. R. Draxler, ‘Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature’, *Geoscientific Model Development*, vol. **7**, no. 3, pp. 1247–1250, Jun. (2014), doi: 10.5194/gmd-7-1247-2014.