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ENVIRONMENTAL RADIATION PREDICTION WITH ATMOSPHERIC FACTORS USING MACHINE LEARNING

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Abstract: Environmental radiation, originating from the Sun, atmosphere, and Earth's surface, encompasses various electromagnetic waves like visible light, ultraviolet, infrared, radio waves, X-rays, and gamma rays, influencing heat transfer processes. Monitoring involves gathering data on parameters such as date, location, time, temperature, atmospheric pressure, humidity, wind, and solar phenomena. Machine learning techniques, including classification and regression models, support radiation forecasting. Performance metrics assess modelefficiency, aiding to radiation's environmental and climatic changes. These insights can be displayed through a web application utilizing the framework in Python.

Keywords: Solar, Radiation, Atmosphere, Sun.

I. INTRODUCTION:

Environmental radiation prediction, leveraging atmospheric factors through machine learning, is pivotal for understanding and mitigating the impact of radiation on ecosystems and human health. By harnessing advanced algorithms, such as regression and classification models, and integrating atmospheric variables like temperature, humidity, wind patterns, and solar events, predictive systems aim to forecast radiation. This predictive capability enables proactive measures to manage radiation exposure, assess health risks, and safeguard environmental integrity. Through comprehensive data analysis, model refinement, and continuous evaluation, machine learning empowers decision-makers with insights into radiation dynamics, facilitatinginformed strategies for environmental protection and climate resilience. As the importance of renewable energy grows, accurate radiation prediction becomes indispensable for optimizing energy production and ensuring sustainable development in harmony with our natural surroundings.

Solar radiation, essential for Earth's energy balance, facilitates heat transfer crucial for climate dynamics. Current prediction systems utilize machine learning, integrating classificationalgorithms and weather data to forecast radiation levels. However, model accuracy falls short of optimal performance. Enhancing these models is imperative for deeper comprehension andeffective management of solar radiation's influence on climate and environmental processes.

II. LITERATURE SURVEY:

This paper provides a comprehensive review of photovoltaic (PV) forecasting methods, focusing on multi-temporal and multi-spatial scales[1]. It emphasizes the reliance on numerical weather prediction (NWP) models for solar irradiance forecasts beyond a few hours. The review delineates the structure and configuration of operational NWP models commonly employed for this purpose[2]. Additionally, it examines the use of Artificial Neural Network (ANN) based techniques for solar radiation prediction, aiming to identify suitable methods and research gaps. Furthermore, the paper discusses the adoption of hybrid models and ensemble forecast approaches to enhance prediction performance[5]. This analysis offers valuable insights into the advancements and challenges in PV forecasting, crucial for ensuring the stability and economic operation of power systems reliant on solar energy resources[8].

III. PROPOSED SYSTEM:

Solar radiation, comprising electromagnetic waves from the Sun, significantly influences atmospheric and climatological dynamics. The proposed system integrates various features likedate, location, time, temperature, atmospheric pressure, humidity, wind direction, speed, sunrise and sunset times, and radiation for comprehensive analysis. Through steps including data Preprocessing, feature engineering, model selection, training, and evaluation, this approach enhances machine learning models' efficiency in predicting solar radiation patterns. Such robust predictions facilitate the optimal utilization of renewable energy resources.

3.1 Flow Chart:

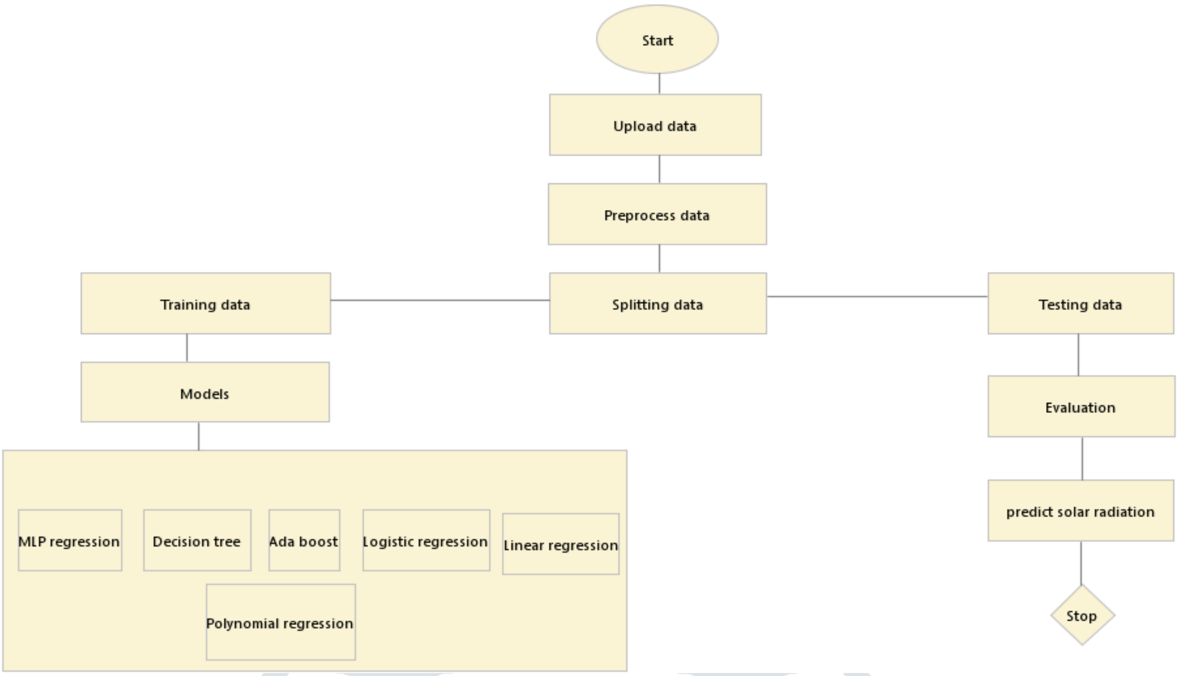


Figure-1 Flow chart for the proposed system

IV. METHODOLOGY:

This method employs machine learning techniques to predict radiation using input features and delivers output through a web application built with the Framework in Python.

4.1 STEP-BY-STEP PROCEDURE:

Data is gathered from diverse sources like Kaggle and subjected to preprocessing techniques. It's then split into training and testing sets as needed. Various machine learning models such asADA boost, Decision Tree, Multi-layer Perceptron Regression, Logistic Regression, Linear Regression, and Polynomial Regression are utilized for training. In the testing phase, these models undergo evaluation via metrics to identify the most effective one based on accuracy and error values. Ultimately, the top-performing model is integrated into a web application using a Python framework to forecast radiation based on input data.

4.2 ALGORITHMS:

4.2.1 MLP REGRESSION:

The Multilayer Perceptron (MLP) Regression classifier algorithm predicts environmental radiation considering atmospheric parameters like date, time, location, temperature, humidity,wind direction, speed, sunrise and sunset times, and radiation presence. Performance metrics gauge its accuracy, precision, recall, and F1 score, ensuring reliable predictions for environmental radiation dynamics.

4.2.2 DECISION TREE:

The decision tree classifier algorithm is employed to predict environmental radiation based onatmospheric conditions. Features such as date, time, location, temperature, humidity, wind direction, speed, sunrise time, sunset time, and radiation presence are utilized. Performance metrics assess the model's accuracy, precision, recall, and F1 score aiding in effective environmental radiation forecasting and management.

4.2.3 ADA BOOST:

The ADA Boost classifier algorithm is employed to predict environmental radiation based on atmospheric conditions. Features such as date, time, location, temperature, humidity, wind direction, speed, sunrise, sunset, and radiation presence are utilized. Performance metrics assess model accuracy, precision, recall, and F1 score aiding in effective radiation forecastingand management.

4.2.4 LOGISTIC REGRESSION:

The logistic regression classifier algorithm predicts environmental radiation based on atmospheric conditions. Features include the date, time, location, temperature, humidity, winddirection, speed, sunrise, sunset, and radiation presence. Performance metrics assess its accuracy, precision, recall, and F1 score, aiding in evaluating the model's effectiveness in radiation prediction.

4.2.5 LINEAR REGRESSION:

In environmental radiation prediction, linear regression utilizes features like date, time, location, temperature, humidity, wind direction and speed, sunrise and sunset times, and radiation presence. This algorithm aims to model relationships between atmospheric conditions and radiation levels to predict radiance accurately, allowing for error analysis and metric evaluation.

4.2.6 POLYNOMIAL REGRESSION:

The polynomial regression algorithm is applied to predict environmental radiation considering atmospheric conditions. Features such as date, time, location, temperature, humidity, wind direction, speed, sunrise time, sunset time, and radiation presence are forecasted. This approach aims to identify errors in metrics and refine radiation forecasting accuracy.

- Among these algorithms, MLP Regression exhibits the highest accuracy, which is pivotal for deploying machine learning applications. Leveraging this algorithm, we'vedeveloped a web application using a Python framework. This system accurately predicts radiation based on provided data, ensuring reliable outcomes for users.

V. OUTPUT GRAPHS:

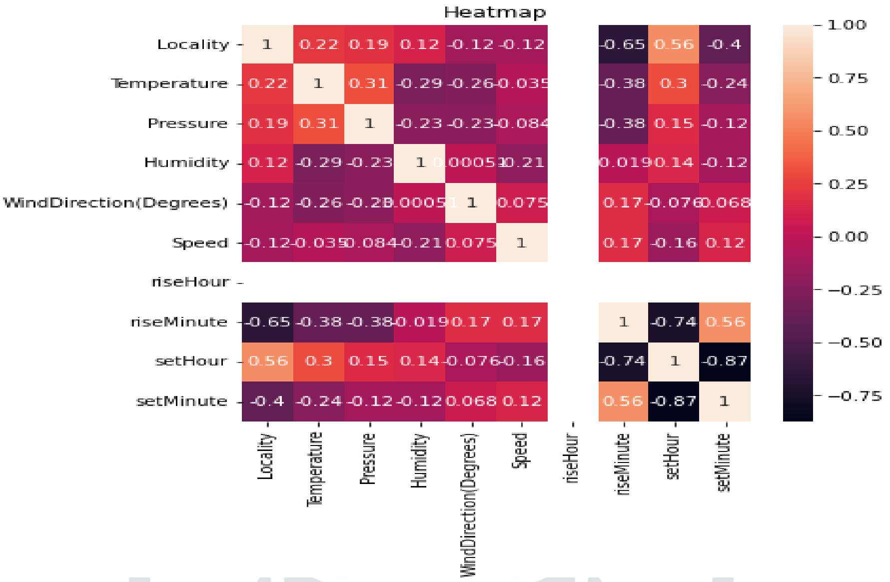


Figure 2: Heat Map for Input Features visualizes the volume of features within the dataset.

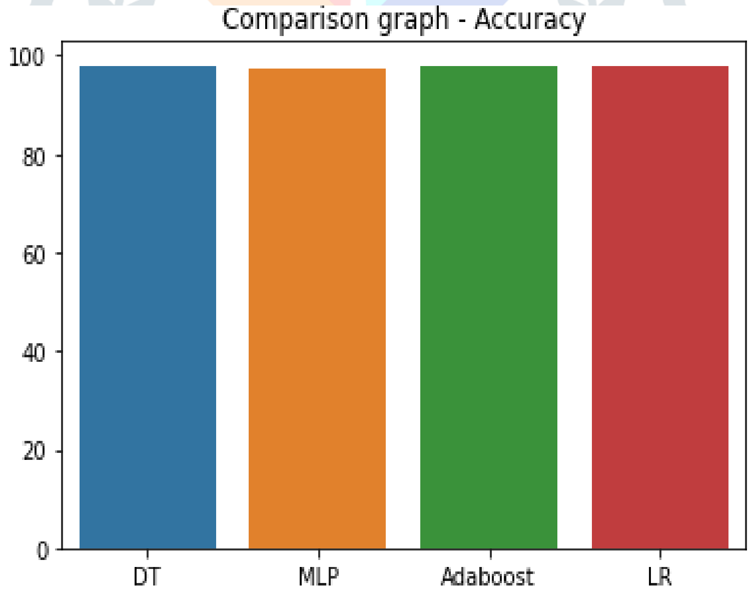


Figure 3: Comparison Graph for Algorithms Accuracy

It ensures that data meets reliability so that it can support various applications.

X-axis=Algorithms

Y-axis=Accuracy

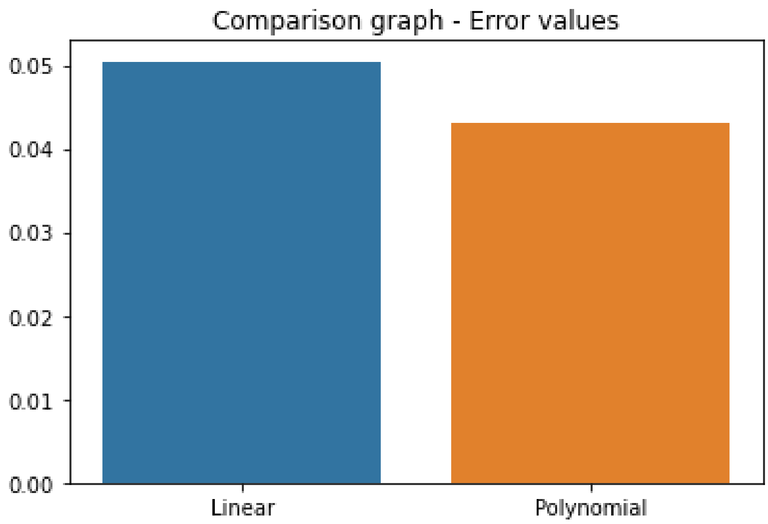


Figure-4 Comparison Graph for Linear and Polynomial Regression Error Values

To check prediction values and how they learn data.

X-axis=Algorithms

Y-axis=Error Values

VI. METRIC FORMULAS:

1. $Accuracy = \frac{Correct\ predictions}{Total\ predictions}$

Where accuracy is used to know the performance of the machine learning models and deploy a model. This can be done based on the accuracy score.

VII. ERROR FORMULAS:

1. The mean square error (MSE) uses the squared of the difference between observed and predicted values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2$$

Where MSE-Mean Square Error

n- Number of observations

2. The mean absolute error (MAE) is appropriate for applications with linear cost functions, i.e., where the costs resulting from a poor forecast are proportional to the forecast error:

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right|$$

Where MAE-Mean Absolute Error

n- Number of observations

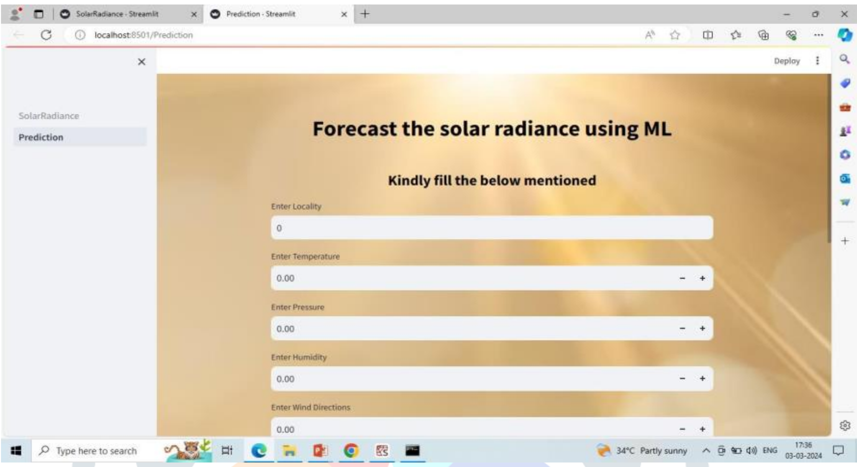
3. The root mean square error (RMSE) is more sensitive to big forecast errors. It hence is suitable for applications where small errors are more tolerable and larger errors cause disproportionately high costs, for example in the case of utility applications. It is probably the reliability factor that is most appreciated and used:

$$RMSE = \sqrt{\sum_{k=1}^{n}\frac{1}{n}}\langle y_k - \widehat{y_k}\rangle^2$$

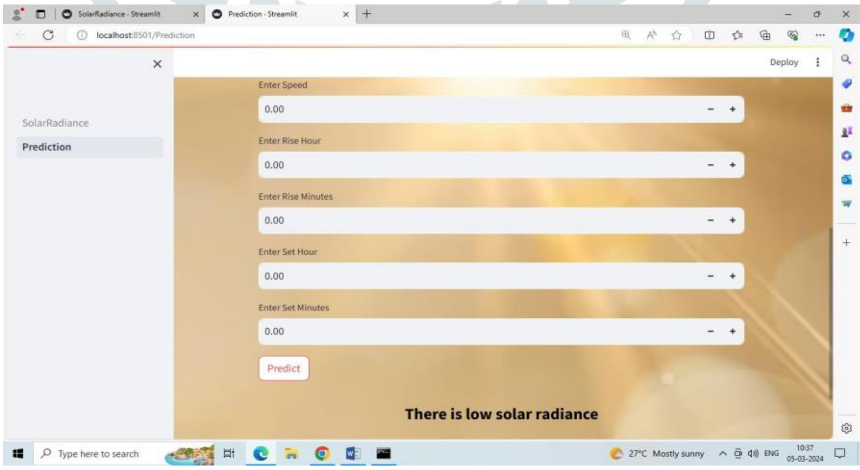
Where RMSE-Root Mean Squared Error

n- Number of observations

VIII. WEB APPLICATION OUTPUT SCREENSHOTS:



Screenshot-1 This gives radiation output using the given data



Screenshot-2 This shows radiation output based on input data according to ranges

IX. ACKNOWLEDGEMENT:

Lastly, I express my gratitude to all the authors and developers whose work laid the foundation for this project. Their contributions to the fields of Machine learning and data Resources have been used in shaping this research endeavor. Thank you to everyone who has played a part, no matter how small, in bringing this project to fruition.

X. CONCLUSION:

In employing machine learning techniques for environmental radiation prediction, considering atmospheric factors offers significant promise. Predictive models can better forecast radiation by incorporating features such as date, time, pressure, humidity, wind patterns, and solar events. Despite ongoing challenges in achieving optimal accuracy, continuous refinement of these models through data preprocessing, feature engineering, and rigorous evaluation holds potential. Such advancements facilitate proactive mitigation strategies and promote the sustainable management of environmental radiation, ensuring a safer and healthier future.

REFERENCES:

[1]. Liu, C.; Li, M.; Yu, Y.; Wu, Z.; Gong, H.; Cheng, F. A Review of Multi-temporal and Multi-spatial Scales Photovoltaic Forecasting Methods.

[2]. Larson, V.E. Forecasting Solar Irradiance with Numerical Weather Prediction Models In Solar Energy Forecasting and Resource Assessment; Academic Press: Boston, MA, USA,2013; pp. 299–318.

[3]. Colak, I.; Yesilbudak, M.; Genc, N.; Bayindir, R. Multi-Period Prediction of Solar Radiation Using ARMA and ARIMA Models. In Proceedings of the 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA), IEEE, Miami, FL, USA, 9–11 December 2015; pp. 1045–1049.

[4]. Huang, J.; Korolkiewicz, M.; Agrawal, M.; Boland, J. Forecasting Solar Radiation on an Hourly Time Scale Using a Coupled Auto-Regressive and Dynamical System (CARDS) Model. Solar Energy 2013, 87, 136–149.

[5]. Yadav, A.K.; Chandel, S.S. Solar Radiation Prediction Using Artificial Neural Network Techniques: A Review. Renew. Sustain. Energy Rev. 2014, 33, 772–781.

[6]. Kumar, R.; Aggarwal, R.K.; Sharma, J.D. Comparison of Regression and Artificial Neural Network Models for Estimation of Global Solar Radiations. Renew. Sustain. Energy Rev. 2015, 52, 1294–1299.

[7]. Dong, Z.; Yang, D.; Reindl, T.; Walsh, W.M. A Novel Hybrid Approach Based On Self Organizing Maps, Support Vector Regression and Particle Swarm Optimization to Forecast Solar Irradiance. Energy 2015, 82, 570–577.

[8]. Voyant, C.; Notton, G.; Kalogirou, S.; Nivet, M.-L.; Paoli, C.; Motte, F.; Fouilloy, A.Machine Learning Methods for Solar Radiation Forecasting: A Review. Renew. Energy2017, 105, 569–582.