Solar Radiation Prediction Using Machine Learning

A final year project dissertation
submitted in partial fulfillment of the requirements
for the award of the degree of

Bachelor of Technology
in
Electrical Engineering

by

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Candidate's Declaration

We affirm the authenticity and originality of our project titled **"Solar Radiation Prediction Using Machine Learning"** This project is presented as a partial fulfillment of the requirements for the degree of **Bachelor of Technology in Electrical Engineering at National Institute of Technology Srinagar**.

Under the guidance of **Dr Hailiya Ahsan and Dr. Shoeb Hussain**, We have undertaken this project work independently. We hereby declare that this dissertation has not been submitted for the attainment of any other degree in this or any other academic institution.

Throughout this academic pursuit, We have diligently respected the intellectual property rights of others and have acknowledged their contributions accordingly. We are fully aware that any infringement of copyright or intellectual property rights, whether in part or in whole, will solely be my responsibility, and We understand that my Supervisor, Head of the Department, or the Institute shall not be held accountable in any manner, even after the conferral of my degree.

Date: 26-06-2024
Place: Srinagar

Anurudra Yadav (2020BELE077)
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Certificate

This is to certify that the project titled **"Solar Radiation Prediction Using Machine Learning"** submitted by **Mr. Anurudra Yadav, Mr.Dhruv Sharma, Mr. Kaushinder**, under **Enroll No. 2020BELE024, 2020BELE077 and 2020BELE099 respectively**, is a result of their diligent efforts and academic pursuits. That has been conducted under my guidance and supervision in partial fulfillment of the requirements for the degree of **Bachelor of Technology in Electrical Engineering** at **National Institute of Technology Srinagar**.

To the best of my knowledge, the content presented in this project represents their original work and has not been previously submitted to this or any other Institute/University for the purpose of obtaining any degree.

Date: 26-06-2024 **Dr. Hailiya Ahsan**

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Approved for evaluation and award of degree.

Date: 26-06-2024 **Dr.Shekh Javed Iqbal**

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(Dhruv Sharma, Anurudra Yadav & Kaushinder)

Abstract

Solar radiation prediction is crucial for optimizing the efficiency and effectiveness of solar energy systems. Traditional methods of predicting solar radiation often rely on complex physical models and historical data, which can be time-consuming and less accurate. In recent years, artificial intelligence (AI) techniques, such as machine learning (ML) and deep learning (DL), have shown promising results in predicting solar radiation with higher accuracy and efficiency.

This Project Report presents a comprehensive review of AI-based approaches for solar radiation prediction. It explores the use of ML and DL algorithms, such as Linear Regression, Decision Tree Regresor and random forests in predicting solar radiation. The paper discusses the advantages and limitations of these algorithms and compares their performance.

Furthermore, the paper examines the various factors that affect solar radiation prediction, such as weather conditions, geographical location, and time of day. It also discusses the importance of feature selection and data preprocessing in improving the accuracy of solar radiation prediction models.

The study evaluates the performance of AI-based models using real-world solar radiation data and compares their accuracy with traditional methods. The results show that AI-based approaches outperform traditional methods in terms of accuracy and computational efficiency. Additionally, the project Report discusses the challenges and future directions of AI-based solar radiation prediction, such as the need for more comprehensive and diverse datasets, and the integration of AI models.

In conclusion, this paper highlights the potential of AI techniques in improving solar radiation prediction and emphasizes the importance of further research in this area to harness the full potential of solar energy.

Contents

List of Figures

List of Abbreviations

ANN	Artificial Neural Network
DT	Decision Tree
K-NN	K-Nearest Neighbour
LR	Linear Regression
MLP	Multi-Layer Perceptron
NB	Naïve Bayesian
Pred	Prediction
SQL	Structured Query Language
SVM	Support Vector Machine
NISE	The National Institute of Solar Energy
NSM	National Solar Mission
NDCs	Nationally Determined Contributions
RMSE	Root mean square error
MAE	Mean absolute error

Chapter 1

Introduction

Overview

The prediction of solar radiation is a critical component in the development and management of solar energy systems. Accurate solar radiation forecasting can significantly enhance the efficiency and reliability of solar power generation, thereby contributing to sustainable energy solutions and reducing dependence on fossil fuels. This project aims to explore the application of machine learning models in predicting solar radiation levels, leveraging various meteorological and environmental factors to achieve precise and reliable forecasts.

1.1 Background and Motivation

Solar energy is one of the most promising renewable energy sources due to its abundance and environmental benefits. However, its variability and dependence on weather conditions pose challenges for consistent energy generation. Traditional methods of solar radiation prediction often rely on physical models and empirical formulas, which can be limited by their complexity and data requirements. The advent of machine learning offers a powerful alternative, enabling the analysis of large datasets and the discovery of complex patterns that can enhance prediction accuracy.

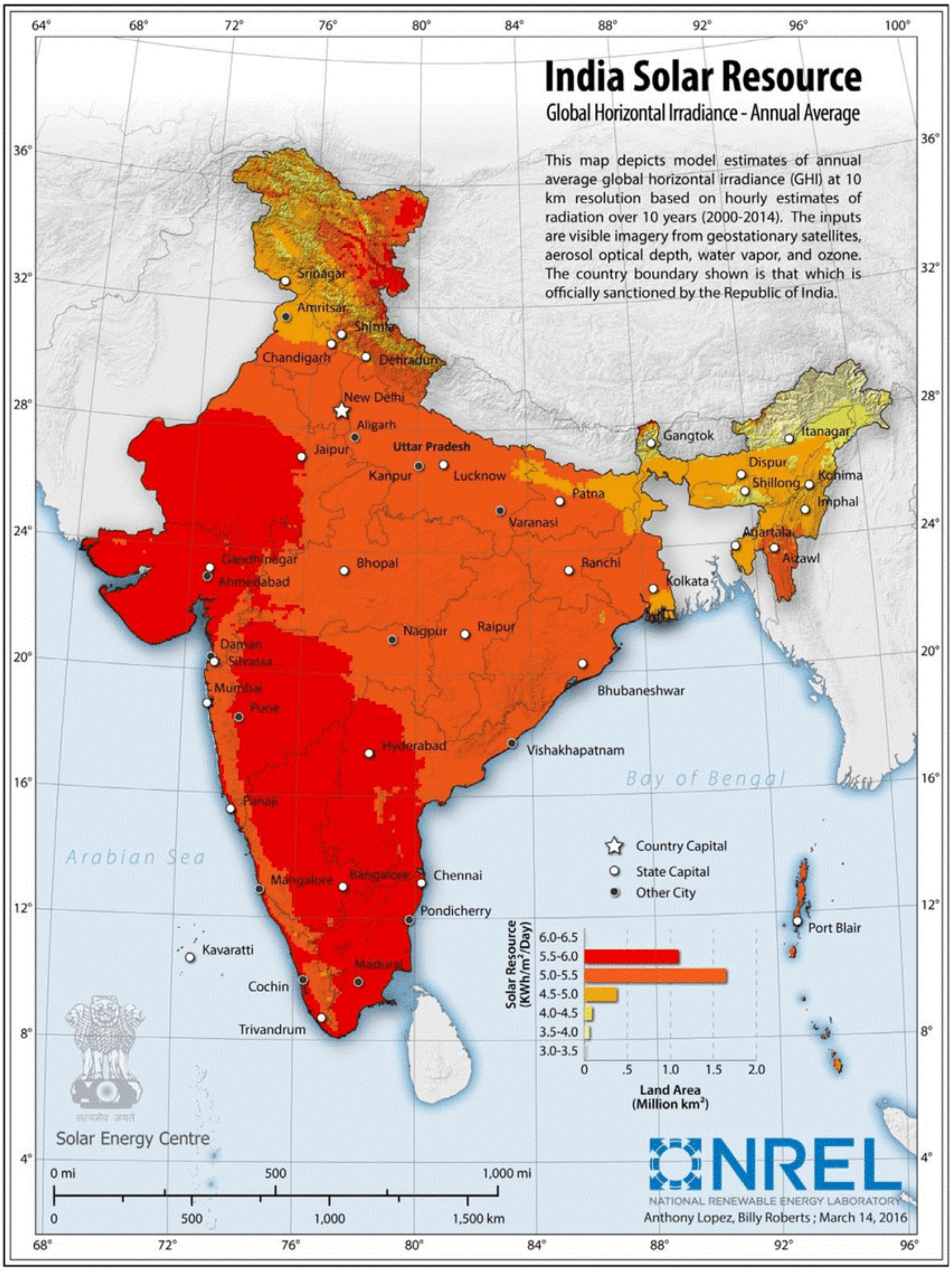


Figure 1.1: Annual Average Golbal Solar Radiation in India

1.2 Objectives

The primary objective of this project is to develop and evaluate machine learning models capable of predicting solar radiation with high accuracy. Specific objectives include:

1. Data Collection and Preprocessing: Gather historical solar radiation data along with relevant meteorological variables such as temperature, humidity, cloud cover, and wind speed. Clean and preprocess the data to ensure its suitability for model training.

2. Feature Selection and Engineering: Identify key features that influence solar radiation and perform feature engineering to enhance the predictive power of the models.

3. Model Development: Implement and train various machine learning models, including but not limited to linear regression, decision trees, random forests, support vector machines, and neural networks.

4. Model Evaluation: Assess the performance of the developed models using appropriate metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). Compare the results to identify the most effective model for solar radiation prediction.

5. Deployment and Application: Discuss the potential application of the best-performing model in real-world scenarios, such as optimizing solar panel placement, managing energy storage systems, and integrating with smart grid technologies.

1.3 Significance and Impact

The successful implementation of machine learning models for solar radiation prediction can have profound implications for the renewable energy sector. By improving forecast accuracy, energy providers can optimize the operation of solar power plants, enhance grid stability, and reduce the reliance on supplementary fossil fuel-based power generation. Additionally, accurate solar radiation predictions can aid in the planning and deployment of solar energy projects, making them more economically viable and environmentally friendly.

1.4 Structure of the Report

This report is structured as follows:

1. Literature Review: An overview of existing methods and research in solar radiation prediction.

2. Methodology: Detailed description of the data collection, preprocessing, feature selection, and model development processes.

3. Results and Discussion: Presentation and analysis of the model performance results.

4. Conclusion and Future Work: Summary of findings, implications for the renewable energy sector, and potential directions for future research.

Through this project, we aim to demonstrate the potential of machine learning in advancing solar radiation prediction, thereby contributing to the broader goal of sustainable energy development.

Chapter 2

Literature Review

Overview of Solar Radiation Prediction Methods

Solar radiation prediction has long been a subject of extensive research, given its critical importance in the design and operation of solar energy systems. Traditional methods for predicting solar radiation have typically relied on physical models, empirical approaches, or a combination of both. These methods, while useful, often come with limitations such as the need for detailed site-specific data and complex calculations that can be computationally intensive.

2.1 Traditional Methods

Physical Models: Physical models for solar radiation prediction are based on understanding the physical processes that govern solar radiation's interaction with the Earth's atmosphere. These models often include parameters such as solar angles, atmospheric conditions, and geographic location. Examples of physical models include the ASHRAE Clear Sky Model and the Bird Clear Sky Model. While these models can be highly accurate, they require extensive and precise input data, which can be a barrier to their widespread application.

Empirical Models: Empirical models use historical solar radiation data to establish statistical relationships between solar radiation and other meteorological variables. Common empirical models include the Angstrom-Prescott model, which relates solar radiation to sunshine duration, and models that correlate solar radiation with temperature and cloud cover. These models are generally simpler to implement than physical models but can be less accurate when applied to locations or conditions that differ significantly from those used to develop the models.

2.2 Machine Learning Approaches

The advent of machine learning has introduced new possibilities for solar radiation prediction. Machine learning models can analyze large and complex datasets, uncovering patterns and relationships that may not be apparent through traditional methods. These models can adapt to new data, potentially offering more accurate and robust predictions.

Types of Machine Learning Models

1. Linear Regression

Linear regression models predict solar radiation based on the linear relationship between the dependent variable (solar radiation) and one or more independent variables (e.g., temperature, humidity). While simple and interpretable, linear regression may not capture the nonlinear relationships often present in meteorological data.

2. Decision Trees and Random Forests

Decision trees split the data into subsets based on the values of the input variables, leading to a tree-like model of decisions. Random forests, an ensemble method, combine multiple decision trees to improve prediction accuracy and reduce overfitting. These models can handle both linear and nonlinear relationships and are relatively robust to outliers.

3. Support Vector Machines (SVM)

SVMs are effective in high-dimensional spaces and are used for regression and classification tasks. They work by finding the hyperplane that best separates the data into classes or predicts continuous values. SVMs are powerful but can be computationally intensive and require careful tuning of parameters.

4. Neural Networks

Neural networks, especially deep learning models, have gained popularity for their ability to model complex, nonlinear relationships. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are particularly useful for handling spatial and temporal data, respectively. Neural networks require large datasets and significant computational resources but can provide high prediction accuracy.

2.3 Comparative Studies

Several studies have compared the performance of different machine learning models in predicting solar radiation. For instance, Voyant et al. (2017) evaluated various models, including linear regression, decision trees, SVMs, and neural networks, finding that ensemble methods like random forests and deep learning models generally outperformed simpler models in terms of accuracy and robustness. Similarly, a study by Wang et al. (2019) demonstrated that deep learning approaches, particularly long short-term memory (LSTM) networks, excelled in capturing the temporal dependencies in solar radiation data, leading to more accurate predictions.

2.4 Hybrid Models

Hybrid models combine traditional methods with machine learning techniques to leverage the strengths of both approaches. For example, a hybrid model might use a physical model to generate initial predictions and then apply machine learning algorithms to refine these predictions based on additional meteorological data. Such approaches can improve prediction accuracy while maintaining the interpretability and robustness of physical models.

2.5 Challenges and Future Directions

Despite the advancements, several challenges remain in the field of solar radiation prediction. These include the need for high-quality, comprehensive datasets, the computational complexity of advanced machine learning models, and the difficulty in interpreting complex models. Future research may focus on developing more efficient algorithms, improving data collection methods, and integrating multiple data sources to enhance prediction accuracy.

Conclusion

The literature indicates a clear shift towards the use of machine learning models in solar radiation prediction, driven by their ability to handle large datasets and model complex relationships. While traditional methods provide a solid foundation, machine learning approaches offer significant improvements in accuracy and adaptability. As the field progresses, hybrid models and advancements in data science are likely to play a crucial role in overcoming existing challenges and further enhancing the reliability of solar radiation forecasts.

Chapter 3

Importance of Solar Radiation Prediction

Solar resource forecasting is very important for the operation and management of solar power plants. Solar radiation is highly variable because it is driven mainly by synoptic and local weather patterns. This high variability presents challenges to meeting power production and demand curves, notably in the case of photovoltaic (PV) power plants, which have little or no storage capacity. For concentrating solar power (CSP) plants, variability issues are partially mitigated by the thermal inertia of the plant, including its heat transfer fluid, heat exchangers, turbines and, potentially, coupling with a heat storage facility; however, temporally and spatially varying irradiance introduces thermal stress in critical system components and plant management issues that can result in the degradation of the overall system's performance and reduction of the plant's lifetime. Solar radiation prediction is a crucial component of renewable energy planning, grid management, and climate research. Its importance stems from its role in optimizing energy production, improving grid stability, reducing costs, advancing climate understanding, and aiding in urban planning and agriculture

1. Optimizing Energy Production: Solar radiation prediction enables solar power plants to optimize their energy production. By forecasting sunlight availability, these plants can adjust their operations, such as tilting solar panels or managing energy storage, to maximize energy output. This optimization leads to increased efficiency and a more stable energy supply.

2. Grid Management: Solar radiation prediction is essential for grid operators to manage the integration of solar energy into the grid. Accurate predictions allow operators to anticipate fluctuations in solar power generation and balance supply and demand accordingly. This helps prevent overloading the grid during periods of high solar generation and ensures a reliable energy supply.
3. Cost Reduction: Accurate solar radiation prediction can lead to cost reductions in several ways. By optimizing energy production, solar power plants can reduce their operating costs and improve their profitability. Additionally, grid operators can avoid costly grid upgrades by efficiently managing solar energy integration, leading to overall cost savings for energy consumers.
4. Climate Research: Solar radiation data is crucial for climate research and modeling. It provides insights into the Earth's energy balance, which is essential for understanding climate patterns and trends. Solar radiation prediction helps researchers study the impact of solar variability on the climate and improve climate change predictions.
5. Urban Planning and Agriculture: Solar radiation prediction has practical applications in urban planning and agriculture. In urban areas, accurate predictions can help architects and city planners design buildings and infrastructure that maximize natural lighting and energy efficiency. In agriculture, solar radiation data can assist farmers in planning crop planting and harvesting times, leading to improved yields and resource management. Overall, solar radiation prediction is a critical tool for maximizing the benefits of solar energy while minimizing its impact on the environment. By improving our ability to forecast solar radiation, we can increase the reliability and efficiency of solar energy systems, contributing to a more sustainable future.

3.1 Current Methods and Challenges

3.1.1 Current Methods

1. Satellite Data: Satellites provide a wide range of data for solar radiation prediction, including direct measurements of solar radiation and indirect measurements such as cloud cover and atmospheric conditions. These data are used in models to estimate solar radiation levels at different locations on Earth. While satellite data offer broad coverage, they can be limited by factors such as cloud cover, which can obscure the view of the sun and affect the accuracy of the predictions.

2. Ground-Based Sensors: Ground-based sensors directly measure solar radiation at specific locations. These sensors provide real-time data, allowing for more immediate adjustments to solar energy production and grid management. However, their coverage is limited to the areas where the sensors are installed, making it challenging to obtain comprehensive data for large regions.

3. Numerical Models: Numerical models simulate the interactions of sunlight with the Earth's atmosphere and surface to predict solar radiation levels. These models incorporate data from satellite observations, ground-based measurements, and atmospheric models to estimate solar radiation under different conditions. While numerical models can provide valuable insights into solar radiation patterns, they can be computationally intensive and require accurate input data to produce reliable predictions.

3.1.2 Challenges

1.Cloud Cover: Cloud cover is a major challenge in solar radiation prediction, as clouds can block or scatter sunlight, significantly affecting the amount of solar radiation that reaches the Earth's surface. Predicting cloud cover and its impact on solar radiation is complex due to the variability of cloud formations and movements.

2.Atmospheric Conditions: Changes in atmospheric conditions, such as aerosol concentrations and water vapor content, can alter the path of sunlight and affect solar radiation levels. These changes are challenging to predict accurately, particularly in regions with complex terrain or weather patterns.

3. Data Accuracy: Ensuring the accuracy of input data is crucial for reliable solar radiation prediction. Errors or inaccuracies in satellite data, ground-based measurements, or atmospheric models can lead to inaccuracies in the predictions. Calibration and validation of data sources are essential to improving prediction accuracy.

4. Resolution: Achieving high spatial and temporal resolution in solar radiation prediction is important for applications such as solar energy planning and grid management. However, obtaining high-resolution data can be challenging, particularly in remote or inaccessible areas.

5.Model Complexity: Modeling sunlight interactions with the Earth's atmosphere and surface requires complex algorithms and computational resources. Improving the accuracy and efficiency of these models is an ongoing challenge in solar radiation prediction. Addressing these challenges requires ongoing research and development in areas such as remote sensing, atmospheric modeling, and data assimilation. Advances in technology and data availability are essential for improving the accuracy and reliability of solar radiation prediction models.

3.2 The UV Index and Effects of Sun on Skin

Humans are exposed to UV radiation, especially UVA and UVB radiation, which can be dangerous to their skin. One of the ways we have to measure the negative consequences of this type of radiation on people is the global solar UV index (UVI). This index ranges from one to eleven and the higher the index, the greater the likelihood of skin and eye damage. Among other consequences, it increases the chances of

Figure 3.1: Pyranometer

sunburn, premature ageing and even skin cancer, especially in people with a lighter phototype. For this reason, the IUV is an important and differential element in raising public awareness of the risks of excessive exposure, warning of the imminent need to adopt protective measures to minimise the risks.

Staying out of the sun in the middle of the day and, if there is no alternative, staying in the shade and drinking plenty of water.

Wearing protective clothing, like hats, caps or carrying parasols to protect the eyes, face and neck, and light garments. Wear good quality sunglasses, in other words those with certified lenses and, if possible, with a wraparound design and with side panels.

Use sun protection cream with a sun protection factor higher than 15, although it is advisable to choose according to the skin phototype, half an hour before exposure. Apply generously and repeat as often as necessary.

Chapter 4

Methodology

4.1 Approach

Our approach to solar radiation prediction involves a detailed methodology that integrates advanced machine learning algorithms with high-resolution satellite data. Here's a comprehensive overview of our approach

1. Data Collection: We collect a diverse range of data sources, including: Historical solar radiation data from ground-based stations or satellite observations. High resolution satellite imagery to capture cloud cover, atmospheric conditions, and surface reflectance. Weather data from ground-based stations, including temperature, humidity, wind speed, and precipitation. Atmospheric conditions data, such as air pressure, moisture content, and aerosol levels. This comprehensive dataset provides the foundation for our solar radiation prediction model.

2. Data Preprocessing: The collected data undergoes preprocessing to ensure its quality and suitability for analysis. This includes cleaning the data to remove noise, correcting errors, and standardizing formats. We also perform data normalization and transformation to prepare it for input into our machine learning models.

3. Feature Selection: We use feature selection techniques to identify the most relevant features for predicting solar radiation levels. These features may include variables such as time of day, day of year, solar zenith angle, cloud cover, and atmospheric conditions. Feature selection helps reduce the dimensionality of the data and improve the efficiency of our models.

4. Model Selection: We select machine learning algorithms based on their suitability for solar radiation prediction. Commonly used algorithms include regression models (e.g., linear regression, support vector regression), decision trees (e.g., random forests), and neural networks. We also consider ensemble methods, such as bagging and boosting, to combine multiple models for improved accuracy.

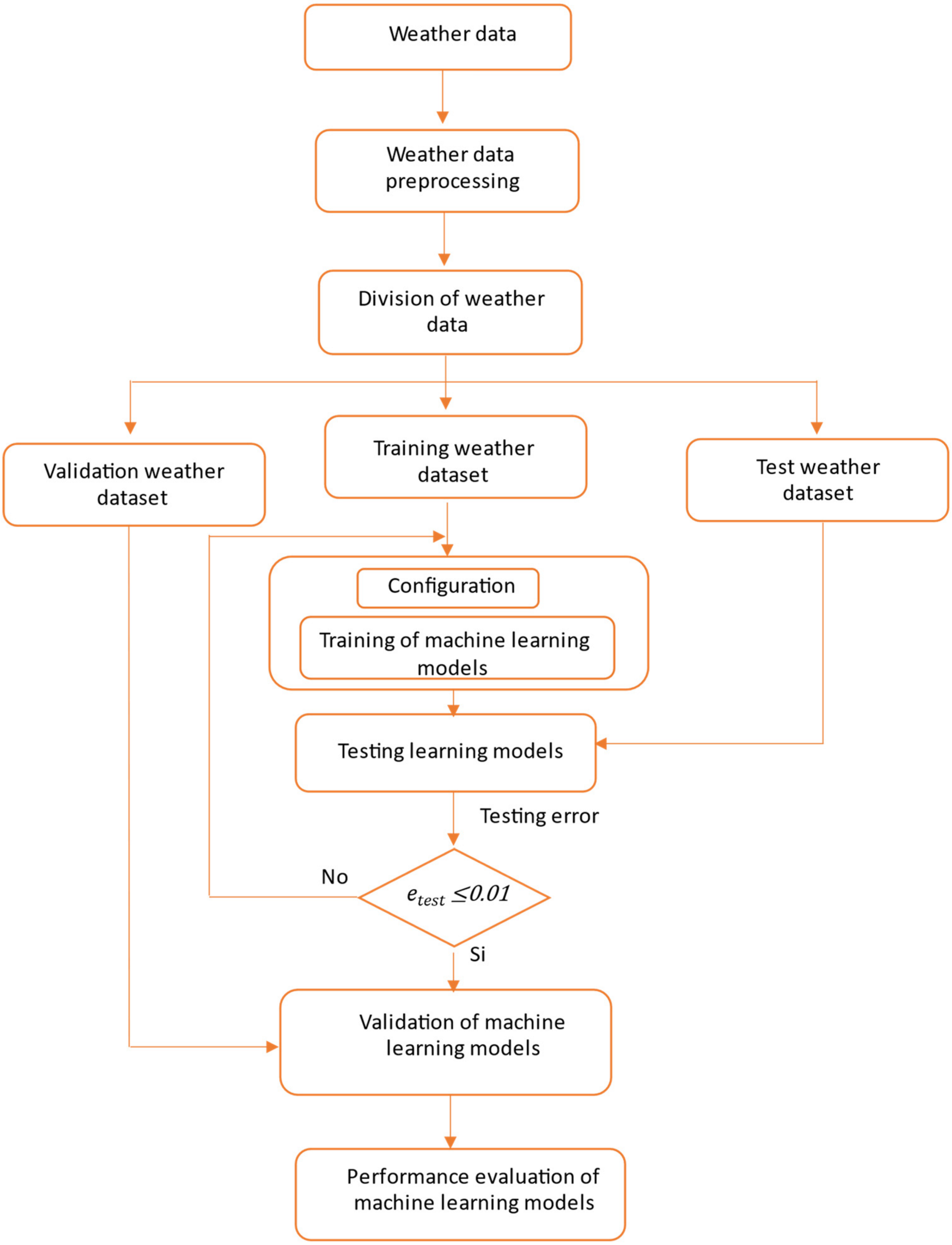


Figure 4.1: Testing of figure

5. Model Training: The selected models are trained using the pre-processed data and selected features. We use techniques like cross-validation to split the data into training and validation sets, optimizing the model hyperparameters to prevent over-fitting. Training the model involves iteratively adjusting the model parameters to minimize the prediction error.

6. Model Evaluation: We evaluate the trained models using validation data to assess their performance. Common evaluation metrics include mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R-squared). We compare the performance of our models with baseline models or existing methods to validate their effectiveness.

7. Prediction Generation: Once trained and validated, the models are used to generate solar radiation predictions. These predictions are based on current weather conditions, satellite imagery, and other relevant factors, providing real-time or near real-time estimates of solar radiation levels.

8. Model Deployment: The trained models are deployed for real-world use, such as in solar energy planning, grid management, or climate research. We continuously monitor the performance of the models and update them as needed to ensure their accuracy and reliability.

4.2 Objectives

The primary objectives of solar radiation prediction are to optimize the design and placement of solar energy systems for maximum efficiency, improve energy management by balancing supply and demand, and achieve economic benefits by reducing operational costs and enhancing the return on investment for solar projects. Accurate predictions support the development of sustainable energy policies and maximize the potential of solar energy.

1. Develop a Robust Prediction Model: Utilize advanced machine learning algorithms, such as deep learning and ensemble methods, to develop a prediction model. Incorporate diverse datasets, including historical solar radiation data, satellite imagery, weather data, and atmospheric conditions, to improve prediction accuracy. Implement feature selection techniques to identify the most relevant features for predicting solar radiation levels.

2. Improve Renewable Energy Planning: Provide accurate and reliable solar radiation predictions to support the planning and operation of solar power plants. Optimize energy production forecasts to maximize the efficiency of solar power generation. Enhance grid integration of solar energy by providing real-time or near real-time solar radiation predictions to grid operators.

3. Enhance Grid Management: Develop tools and models to help grid operators manage the variability of solar energy generation. Provide insights and recommendations for balancing supply and demand, maintaining grid stability, and optimizing energy distribution.

4. Advance Climate Research: Contribute to climate research by providing high quality solar radiation data for studying climate patterns and trends. Improve understanding of solar variability and its impact on the Earth's climate system.

5. Support Sustainable Development: Promote the use of renewable energy sources, such as solar energy, to reduce reliance on fossil fuels and mitigate climate change. Support sustainable development goals by providing reliable and actionable information for energy planning and decision-making.

6. Enable Data-Driven Decision Making: Provide stakeholders with reliable and up to-date information based on data-driven predictions. Enable informed decision making regarding energy planning, grid management, and climate adaptation.

7. Facilitate Integration of Renewable Energy: Support the integration of renewable energy sources into existing energy systems by providing accurate solar radiation predictions. Optimize the use of solar energy and reduce dependence on non renewable energy sources.

By achieving these objectives, our project aims to contribute to the advancement of renewable energy technologies, improve the efficiency and reliability of solar energy systems, and support sustainable development practices.

4.3 Data Collection

Our approach to data collection for solar radiation prediction involves gathering diverse datasets from multiple sources. Here's a detailed outline of our data collection process:

1. Historical Solar Radiation Data: Collect historical solar radiation data from ground-based stations or satellite observations. Include data on solar radiation levels at regular intervals (e.g., hourly or daily averages) over an extended period (e.g., several years). Ensure data quality by performing quality control checks and correcting any anomalies or errors.

2. Satellite Imagery: Obtain high-resolution satellite imagery from sources such as NASA or commercial satellite providers. Use satellite imagery to capture cloud cover, atmospheric conditions, and surface reflectance, which are critical factors influencing solar radiation levels. Ensure timely access to satellite data to provide up-to-date information for solar radiation prediction.

3. Weather Data: Gather weather data from ground-based stations, including temperature, humidity, wind speed, and precipitation. Use weather data to account for local weather conditions that can impact solar radiation levels, such as cloud cover and atmospheric stability. Ensure the accuracy and reliability of weather data by calibrating and validating against other sources.

4. Atmospheric Conditions Data: Collect data on atmospheric conditions, such as air pressure, moisture content, and aerosol levels. Use atmospheric data to account for the effects of atmospheric composition and conditions on solar radiation levels. Ensure the availability of atmospheric data for the target region and time period of interest.

5. Data Preprocessing: Preprocess the collected data to remove outliers, correct errors, and standardize formats. Perform data normalization and transformation to prepare the data for input into machine learning models. Ensure that the preprocessed data is clean and suitable for analysis.

6. Data Integration: Integrate the various datasets (e.g., solar radiation data, satellite imagery, weather data) to create a comprehensive dataset for solar radiation prediction. Use data integration techniques to combine data from different sources and formats into a unified dataset.By following this detailed data collection process, we aim to gather the necessary data for training our machine learning models and improving the accuracy of solar radiation prediction.

Chapter 5

Technical Approach

The technical approach in a solar radiation prediction project involves collecting data from sensors, weather stations, and satellites, followed by preprocessing to clean and integrate the data. Advanced machine learning and statistical models are then used to predict solar radiation patterns. These models are validated and tested for reliability, and the predictions are integrated into solar energy management systems to optimize energy production and usage.

5.1 Reading the dataset

```
import numpy as np
import pandas as pd
import seaborn as sns
from datetime import date
import matplotlib.pyplot as plt
from collections import defaultdict
import matplotlib.lines as mlines
import matplotlib.transforms as mtransforms
```

```
df = pd.read_csv('C:/Users/singh/OneDrive/Desktop/Solar
    project/SolarPrediction.csv')
display(df)
```

	UNIXTime	Date	Time	Radiation	Temperature	Pressure	Humidity	WindDirection	Speed	TimeSunRise	TimeSunSet
0	1475229326	9/29/2016 12:00:00 AM	23:55:26	1.21	48	30.46	59	177.39	5.62	06:13:00	18:13:00
1	1475229023	9/29/2016 12:00:00 AM	23:50:23	1.21	48	30.46	58	176.78	3.37	06:13:00	18:13:00
2	1475228726	9/29/2016 12:00:00 AM	23:45:26	1.23	48	30.46	57	158.75	3.37	06:13:00	18:13:00
3	1475228421	9/29/2016 12:00:00 AM	23:40:21	1.21	48	30.46	60	137.71	3.37	06:13:00	18:13:00
4	1475228124	9/29/2016 12:00:00 AM	23:35:24	1.17	48	30.46	62	104.95	5.62	06:13:00	18:13:00
...	...	...	...	...	...	...	...	...	...	...	...
32681	1480587604	12/1/2016 12:00:00 AM	00:20:04	1.22	44	30.43	102	145.42	6.75	06:41:00	17:42:00
32682	1480587301	12/1/2016 12:00:00 AM	00:15:01	1.17	44	30.42	102	117.78	6.75	06:41:00	17:42:00
32683	1480587001	12/1/2016 12:00:00 AM	00:10:01	1.20	44	30.42	102	145.19	9.00	06:41:00	17:42:00
32684	1480586702	12/1/2016 12:00:00 AM	00:05:02	1.23	44	30.42	101	164.19	7.87	06:41:00	17:42:00
32685	1480586402	12/1/2016 12:00:00 AM	00:00:02	1.20	44	30.43	101	83.59	3.37	06:41:00	17:42:00

32686 rows × 11 columns

Figure 5.1: Description of Dataset

5.2 Data Cleaning

```python
def func_date(data):
    data = data.split()
    data = data[0]
    data = data.split('/')

    day = int(data[1])
    month = int(data[0])
    year = int(data[2])

    date1 = date(year-1, 12, 31)
    date2 = date(year, month, day)
    diff = date2 - date1
    diff = str(diff)
    diff = diff.split(' ')

    return int(diff[0])

def func_time(data):
    data = data.split(':')
    time = int(data[0])*3600 + int(data[1])*60 + int(data[2])
    return time
```

```python
df['Date'] = df['Date'].apply(func_date)
df['Time'] = df['Time'].apply(func_time)
df['TimeSunRise'] = df['TimeSunRise'].apply(func_time)
df['TimeSunSet'] = df['TimeSunSet'].apply(func_time)
display(df)
```

	Date	Time	Radiation	Temperature	Pressure	Humidity	WindDirection	Speed	TimeSunRise	TimeSunSet
0	273	86126	1.21	48	30.46	59	177.39	5.62	22380	65580
1	273	85823	1.21	48	30.46	58	176.78	3.37	22380	65580
2	273	85526	1.23	48	30.46	57	158.75	3.37	22380	65580
3	273	85221	1.21	48	30.46	60	137.71	3.37	22380	65580
4	273	84924	1.17	48	30.46	62	104.95	5.62	22380	65580
...	...	...	...	...	...	...	...	...	...	...
32681	336	1204	1.22	44	30.43	102	145.42	6.75	24060	63720
32682	336	901	1.17	44	30.42	102	117.78	6.75	24060	63720
32683	336	601	1.20	44	30.42	102	145.19	9.00	24060	63720
32684	336	302	1.23	44	30.42	101	164.19	7.87	24060	63720
32685	336	2	1.20	44	30.43	101	83.59	3.37	24060	63720

32686 rows × 10 columns

Figure 5.2: Clean Dataset

5.3 Summarizing Dataset

```python
df.describe()
```

	Date	Time	Radiation	Temperature	Pressure	Humidity	WindDirection	Speed	TimeSunRise	TimeSunSet
count	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000
mean	306.110965	43277.574068	207.124697	51.103255	30.422879	75.016307	143.489821	6.243869	23258.431133	64691.463624
std	34.781367	24900.749819	315.916387	6.201157	0.054673	25.990219	83.167500	3.490474	931.122823	995.053346
min	245.000000	1.000000	1.110000	34.000000	30.190000	8.000000	0.090000	0.000000	22020.000000	63720.000000
25%	277.000000	21617.000000	1.230000	46.000000	30.400000	56.000000	82.227500	3.370000	22440.000000	63900.000000
50%	306.000000	43230.000000	2.660000	50.000000	30.430000	85.000000	147.700000	5.620000	23040.000000	64260.000000
75%	334.000000	64849.000000	354.235000	55.000000	30.460000	97.000000	179.310000	7.870000	24000.000000	65340.000000
max	366.000000	86185.000000	1601.260000	71.000000	30.560000	103.000000	359.950000	40.500000	25020.000000	67080.000000

Figure 5.3: Summarize Dataset

```python
plt.rcParams["font.size"] = 14
df.hist(figsize=(12,12))
plt.tight_layout()
```

```
plt.show()
```

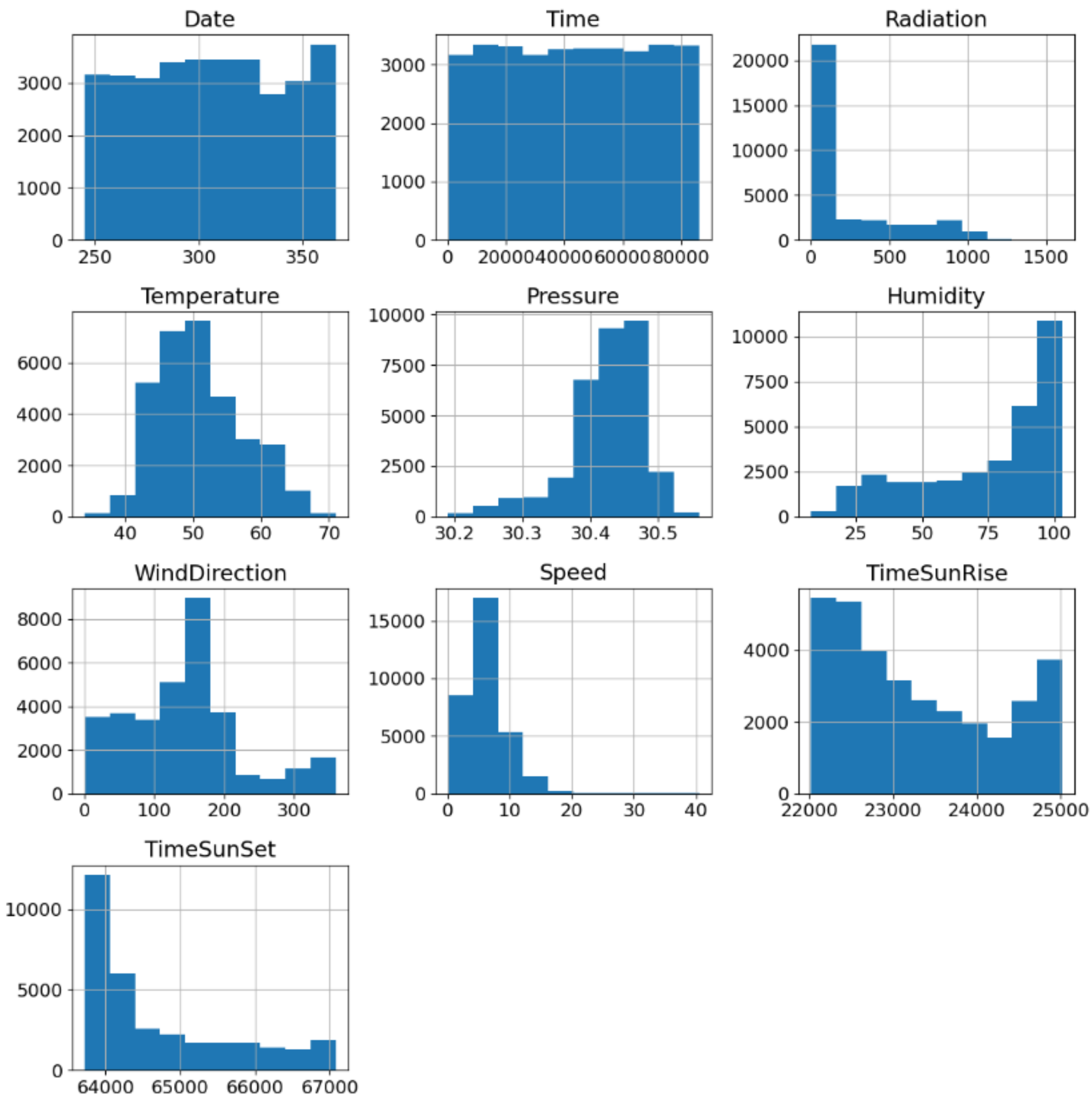


Figure 5.4: Histogram map of attributes

5.3.1 Hourly Average Plots

```
plt.rcParams["figure.figsize"] = (22, 12)


columns = ['Temperature', 'Pressure', 'Humidity', 'Speed']


hourlyY1 = defaultdict(list)
for index, row in df.iterrows():
```

```
  hourlyY1[row['Time']//3600].append(row['Radiation'])

hour = list(hourlyY1.keys())
Y1 = []
for hr in hour:
  Y1.append(sum(hourlyY1[hr])/len(hourlyY1[hr]))

for ind, ylabel in enumerate(columns):

  hourlyY2 = defaultdict(list)
  for index, row in df.iterrows():
    hourlyY2[row['Time']//3600].append(row[ylabel])

  hour = list(hourlyY2.keys())
  Y2 = []
  for hr in hour:
    Y2.append(sum(hourlyY2[hr])/len(hourlyY2[hr]))

  ax1 = plt.subplot(2, 2, ind+1)

  color = 'tab:red'
  ax1.set_xlabel('Time (hr)', labelpad=15)
  ax1.set_ylabel('Radiation', color=color, labelpad=15)
  ax1.plot(hour, Y1, color=color, linewidth=2, label='Radiation')
  ax1.tick_params(axis='y', labelcolor=color)
  ax1.legend(loc='upper left')

  ax2 = ax1.twinx()

  color = 'tab:blue'
  ax2.set_ylabel(ylabel, color=color, labelpad=15)
  ax2.plot(hour, Y2, color=color, linewidth=2, label=ylabel)
  ax2.tick_params(axis='y', labelcolor=color)
  ax2.legend(loc='upper right')
```

```
plt.tight_layout()
```

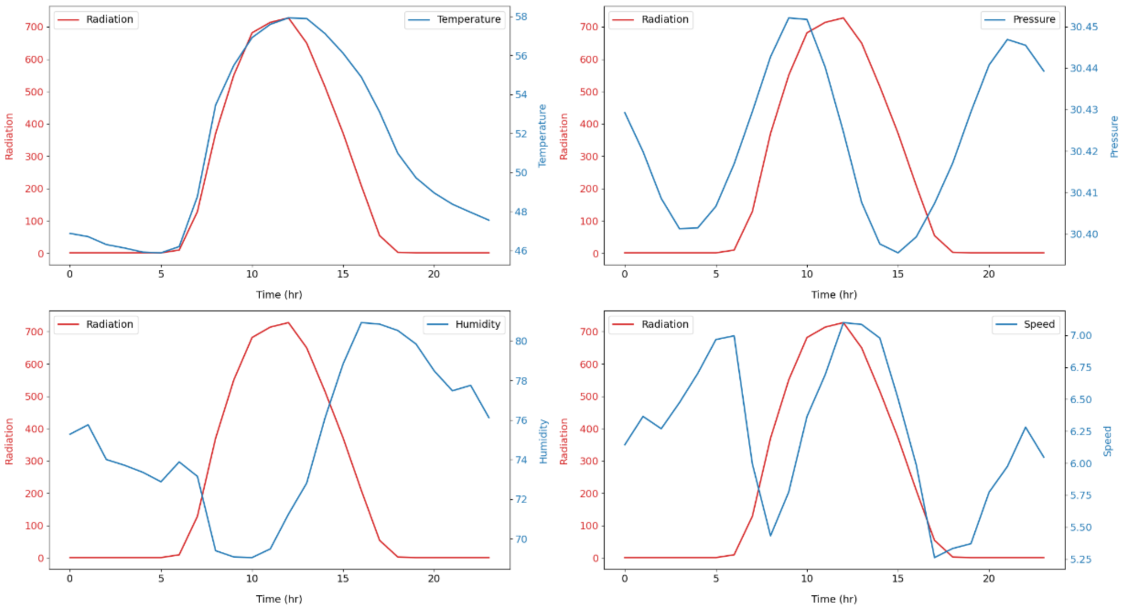


Figure 5.5: Hourly Solar radiation Graph

5.4 Feature Selection

5.4.1 correlation Matrix

```
display(df.corr(method='pearson'))
```

	Date	Time	Radiation	Temperature	Pressure	Humidity	WindDirection	Speed	TimeSunRise	TimeSunSet
count	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000	32686.000000
mean	306.110965	43277.574068	207.124697	51.103255	30.422879	75.016307	143.489821	6.243869	23258.431133	64691.463624
std	34.781367	24900.749819	315.916387	6.201157	0.054673	25.990219	83.167500	3.490474	931.122823	995.053346
min	245.000000	1.000000	1.110000	34.000000	30.190000	8.000000	0.090000	0.000000	22020.000000	63720.000000
25%	277.000000	21617.000000	1.230000	46.000000	30.400000	56.000000	82.227500	3.370000	22440.000000	63900.000000
50%	306.000000	43230.000000	2.660000	50.000000	30.430000	85.000000	147.700000	5.620000	23040.000000	64260.000000
75%	334.000000	64849.000000	354.235000	55.000000	30.460000	97.000000	179.310000	7.870000	24000.000000	65340.000000
max	366.000000	86185.000000	1601.260000	71.000000	30.560000	103.000000	359.950000	40.500000	25020.000000	67080.000000

Figure 5.6: Correlation Matrix

5.4.2 Correlation Heatmap

```
plt.rcParams["font.size"] = 14
df.hist(figsize=(12,12))
plt.tight_layout()
plt.show()
```

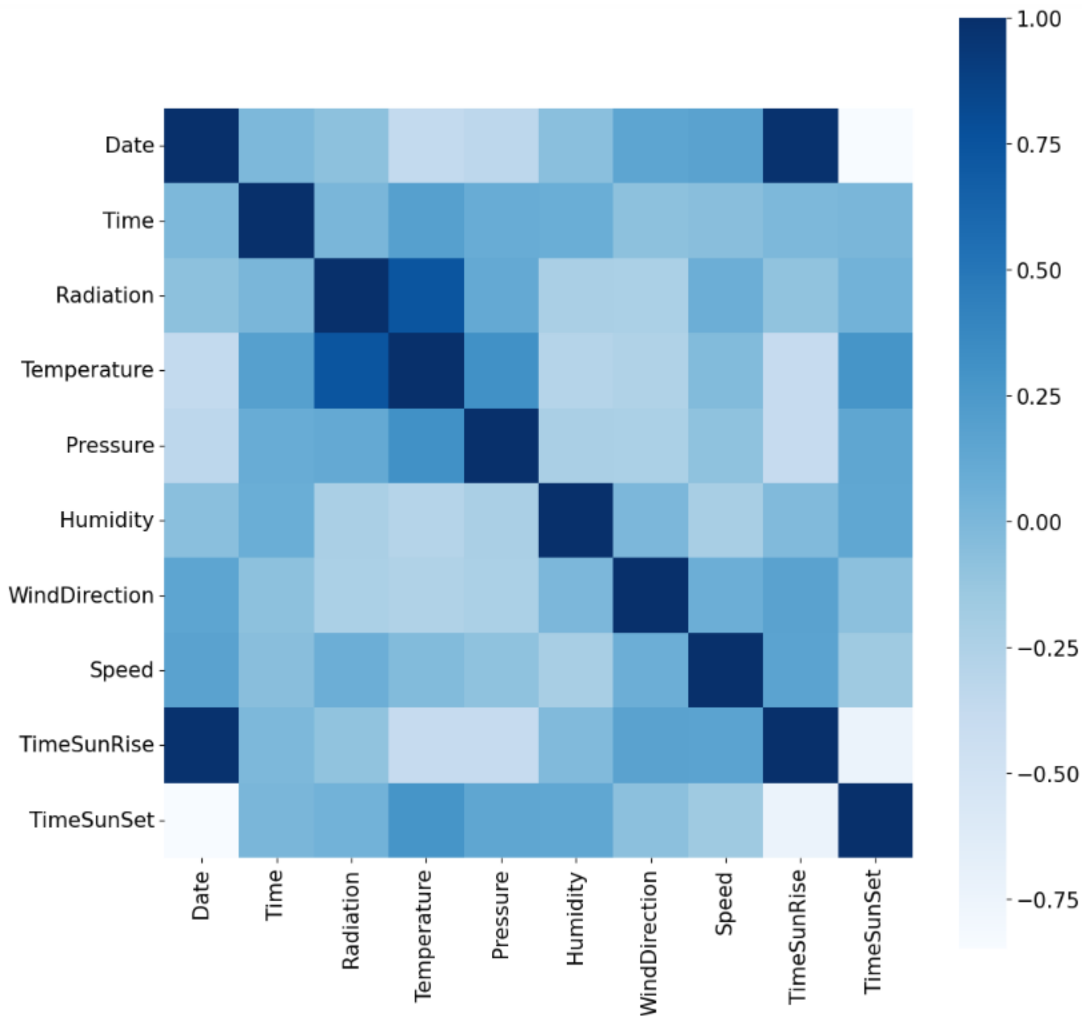


Figure 5.7: Correlation Heatmap

```
plt.rcParams["figure.figsize"] = (14, 14)
plt.rcParams["font.size"] = 14

ylabel = 'Radiation'
columns = ['Date', 'Time', 'Temperature', 'Pressure', 'Humidity',
    'WindDirection', 'Speed', 'TimeSunRise', 'TimeSunSet']
```

```
for index, xlabel in enumerate(columns):
  plt.subplot(3, 3, index+1)
  plt.scatter(df[xlabel],
      df[ylabel],color='blue',marker='+',linewidth=0.5)
  plt.xlabel(xlabel)
  plt.ylabel(ylabel)
  plt.title(ylabel + ' vs ' + xlabel)

plt.tight_layout()
```

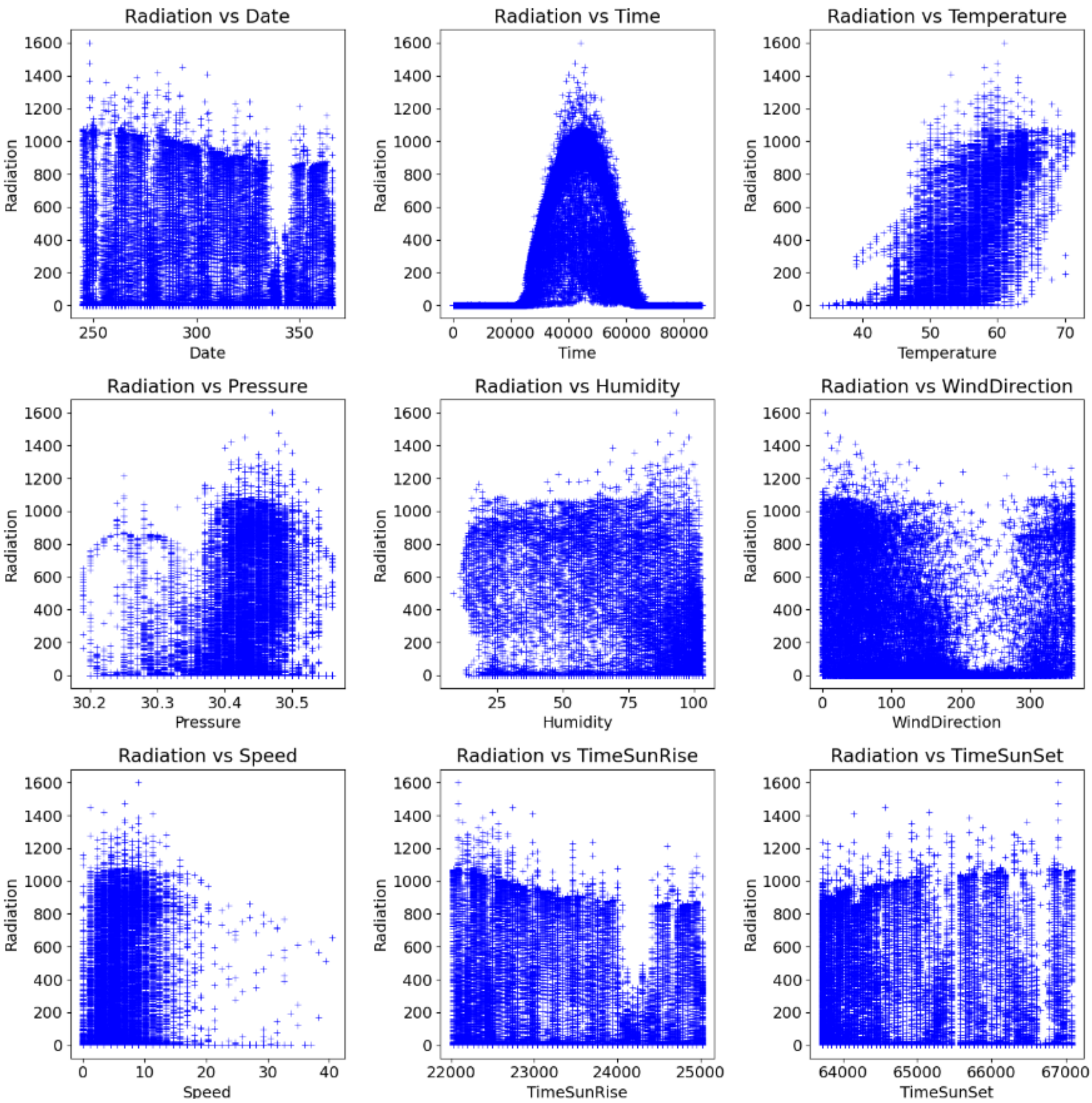


Figure 5.8: Scatter plot of Radiation vs Attributes

5.5 Training and Testing the models

```
from sklearn.model_selection import train_test_split

Y = df['Radiation'].values

df.drop(['Radiation'], axis=1, inplace=True)

X = df.values

RS = 1811

X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.2,
random_state=RS)
```

Chapter 6

Models

6.1 Linear Regression Model

Overview

A linear regression model predicts the relationship between a dependent variable and one or more independent variables by fitting a straight line through the data points. It works by minimizing the differences between the observed values and the predicted values. This model is widely used due to its simplicity, interpretability, and effectiveness in identifying trends and making predictions across various fields, such as economics, biology, engineering, and social sciences.

6.1.1 Approach Behind Linear Regression

Linear regression predicts the relationship between two variables by assuming they have a straight-line connection. It finds the best line that minimizes the differences between predicted and actual values. Used in fields like economics and finance, it helps analyze and forecast data trends. Linear regression can also involve several variables (multiple linear regression) or be adapted for yes/no questions (logistic regression).

Simple Linear Regression

There is one independent variable and one dependent variable. The model estimates the slope and intercept of the line of best fit, which represents the relationship between the variables. The slope represents the change in the dependent variable for each unit change in the independent variable, while the intercept represents the predicted value of the dependent variable when the independent variable is zero.

Linear regression is a quiet and the simplest statistical regression technique used for predictive analysis in machine learning. Linear regression shows the linear relationship between the independent(predictor) variable i.e. X-axis and the dependent (output) variable i.e. Y-axis, called linear regression. If there is a single input variable X (independent variable), such linear regression is simple linear regression.

Simple Linear Regression The graph above presents the linear relationship between

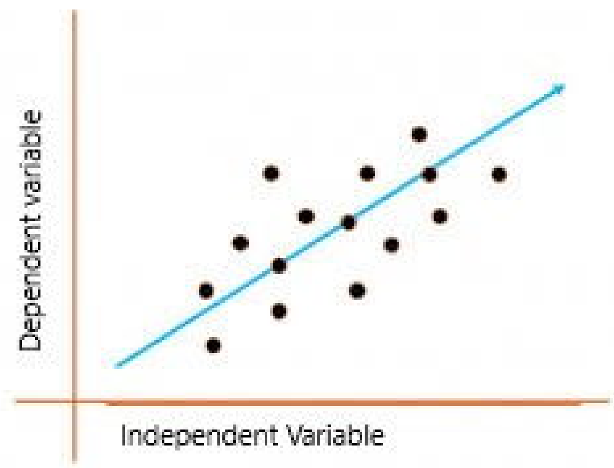


Figure 6.1: Simple Linear Regression

the output(y) and predictor(X) variables. The blue line is referred to as the best-fit straight line. Based on the given data points, we attempt to plot a line that fits the points the best.

Simple Regression Calculation

To calculate best-fit line linear regression uses a traditional slope-intercept form which is given below,

The goal of the linear regression algorithm is to get the best values for B 0 and B 1 to find the best-fit line. The best-fit line is a line that has the least error which means the error between predicted values and actual values should be minimum. Simple Linear Regression explanation But how the linear regression finds out which is the best fit line?

The goal of the linear regression algorithm is to get the best values for B0 and B1 to find the best fit line. The best fit line is a line that has the least error which means the error between predicted values and actual values should be minimum.

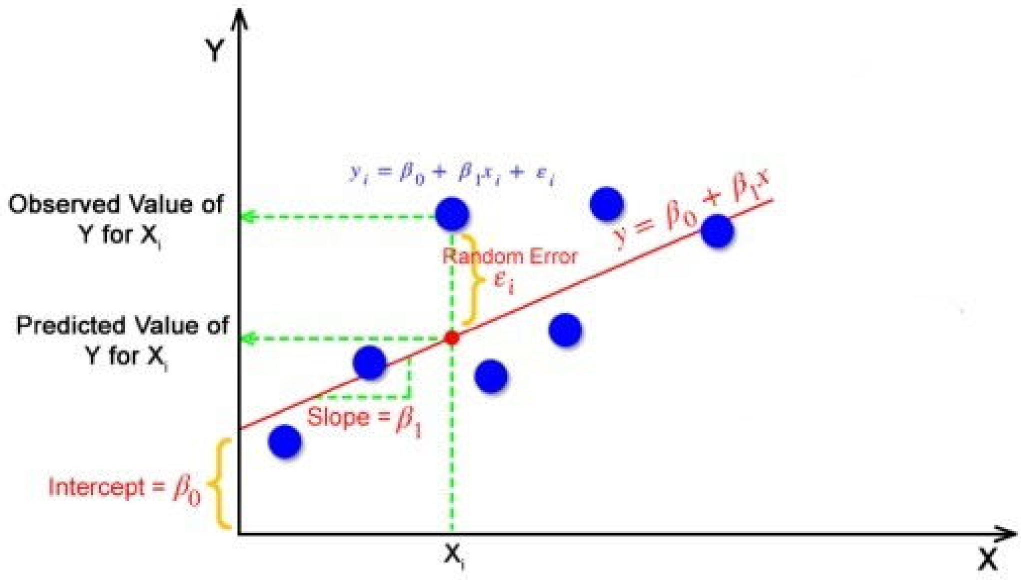


Figure 6.2: Linear Regression Calcultion Graph

6.1.2 Code

```
!pip install xgboost==1.5.0
from sklearn.svm import SVR
from xgboost import XGBRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
```

6.1.3 Prediction Using Linear Regression Model

```
lr=LinearRegression()
lr.fit(X_train, Y_train)
pred=lr.predict(X_test)


m=lr.coef_
m
```

array([1.98104301e+00, -2.07962649e-03, 4.38422669e+01, -3.59256338e+02, 5.47659755e-01, -2.74759504e-01, 5.44636736e+00])

```
c=lr.intercept_
c
```

8343.381813532798

6.1.4 Result

```
print("Accuracy for Train data sets")
print( lr.score(X_train, Y_train)*100,'%')
print("Accuracy for Test data sets")
print( lr.score(X_test, Y_test)*100,'%')
```

Accuracy for Train data sets

61.90414543792242 %

Accuracy for Test data sets

62.5918994079995 %

6.2 Decision Tree Regressor

Overview

A decision tree is a machine learning algorithm used for both classification and regression tasks. It works by recursively splitting the data into subsets based on the values of input features, creating a tree-like model of decisions. Each internal node represents a feature, each branch represents a decision rule, and each leaf node represents an outcome. Decision trees are intuitive and easy to interpret, as they mimic human decision-making processes. They can handle both numerical and categorical data and are robust to outliers. However, they can be prone to overfitting, which can be mitigated by techniques like pruning, setting a maximum depth, or using ensemble methods such as random forests.

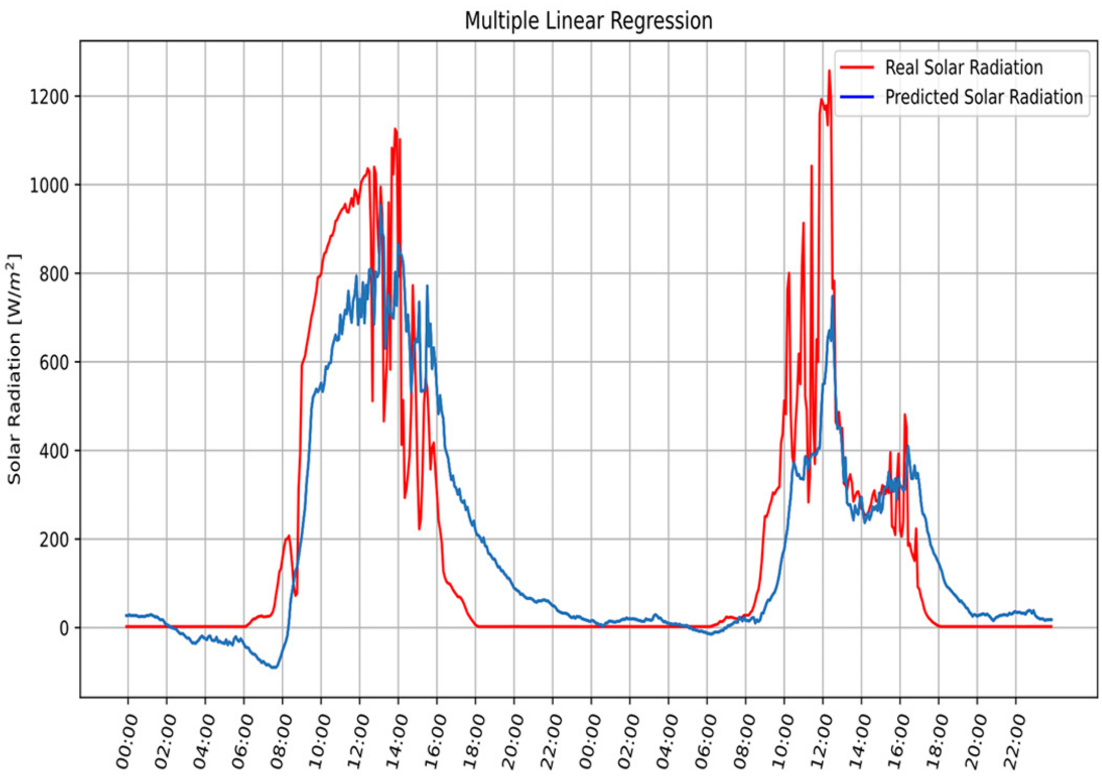


Figure 6.3: Linear Regression Real vs Predicted

6.2.1 Approach behind Decision Tree

A decision tree is a hierarchical model used in decision support that depicts decisions and their potential outcomes, incorporating chance events, resource expenses, and utility. This algorithmic model utilizes conditional control statements and is non-parametric, supervised learning, useful for both classification and regression tasks. The tree structure is comprised of a root node, branches, internal nodes, and leaf nodes, forming a hierarchical, tree-like structure.

Decision trees can be used for classification as well as regression problems. The name itself suggests that it uses a flowchart like a tree structure to show the predictions that result from a series of feature-based splits. It starts with a root node and ends with a decision made by leaves. **Decision Tree algorithm works in simpler steps:**

Starting at the Root: The algorithm begins at the top, called the "root node," representing the entire dataset. Asking the Best Questions: It looks for the most important feature or question that splits the data into the most distinct groups. This is like asking a question at a fork in the tree. Branching Out: Based on the answer to

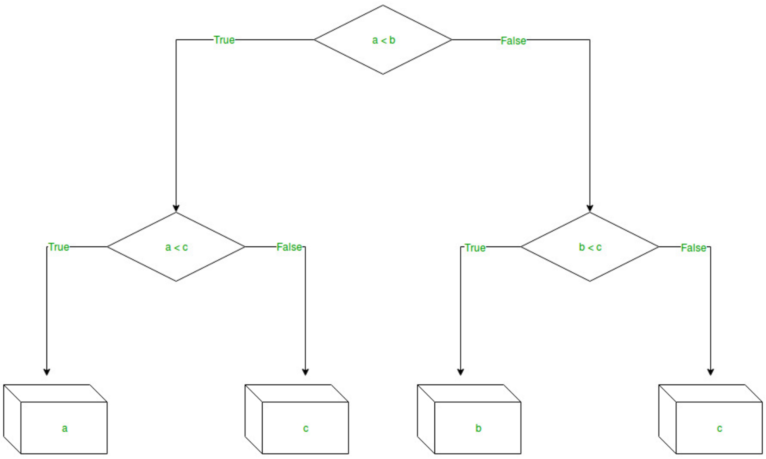


Figure 6.4: Decion Tree flow Chart

that question, it divides the data into smaller subsets, creating new branches. Each branch represents a possible route through the tree. Repeating the Process: The algorithm continues asking questions and splitting the data at each branch until it reaches the final "leaf nodes," representing the predicted outcomes or classifications.

6.2.2 Code

```
!pip install xgboost==1.5.0
from sklearn.svm import SVR
from xgboost import XGBRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
```

6.2.3 Prediction Using Decision Tree Regressor

```
from sklearn.tree import DecisionTreeRegressor
dtr = DecisionTreeRegressor(random_state=RS)
dtr.fit(X_train, Y_train)
```

6.2.4 Result

```
print("Accuracy for Train data sets")
print('train', dtr.score(X_train, Y_train))
print("Accuracy for Test data sets")
print('test', dtr.score(X_test, Y_test))
```

Accuracy for Train data sets

train 1.0

Accuracy for Test data sets

test 0.8748831378034979

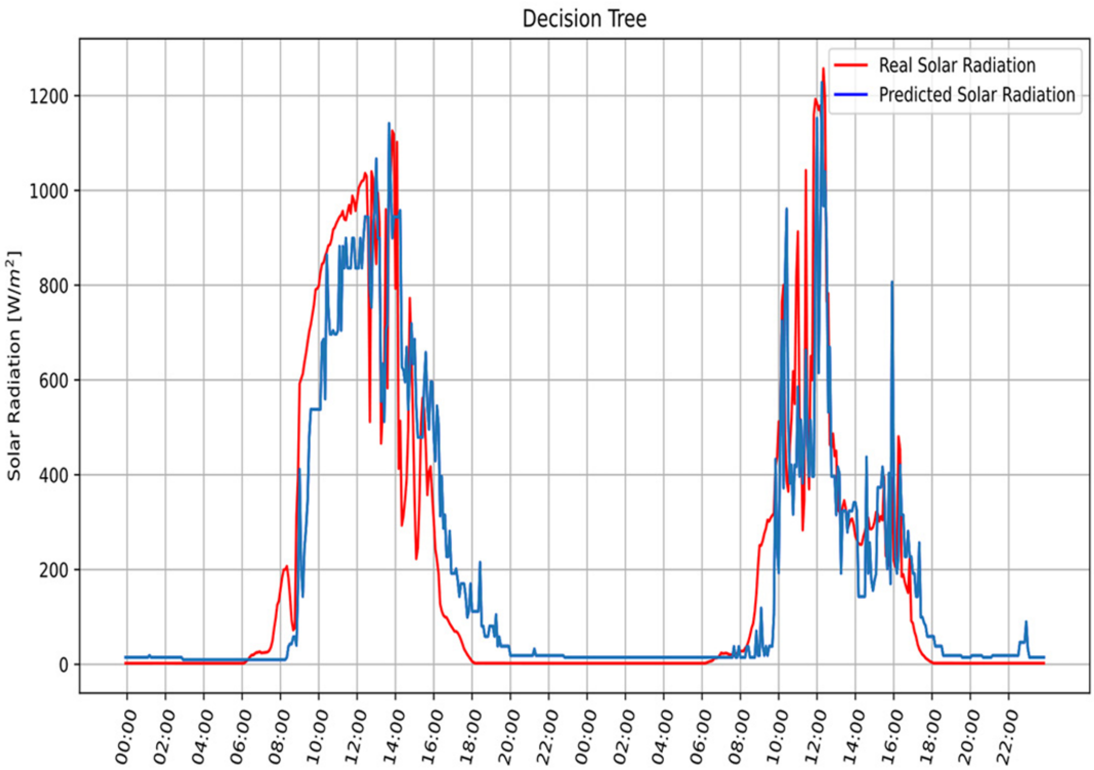


Figure 6.5: decision Tree Real vs Predicted values

6.3 Random Forest Regressor

Overview

The random forest model is a machine learning algorithm that builds multiple decision trees during training and outputs the average prediction (for regression) or mode of predictions (for classification) of the individual trees. It reduces overfitting by using subsets of the training data and random feature selection. Random forests handle large datasets with high dimensionality, maintain accuracy with missing data, and provide estimates of feature importance. They are widely used in finance, healthcare, and marketing for their robustness and flexibility.

6.3.1 Approach behind Random Forest Regressor

Random forest, a popular machine learning algorithm developed by Leo Breiman and Adele Cutler, merges the outputs of numerous decision trees to produce a single outcome. Its popularity stems from its user-friendliness and versatility, making it suitable for both classification and regression tasks.

Its widespread popularity stems from its user-friendly nature and adaptability, enabling it to tackle both classification and regression problems effectively. The algorithm's strength lies in its ability to handle complex datasets and mitigate over fitting, making it a valuable tool for various predictive tasks in machine learning.

One of the most important features of the Random Forest Algorithm is that it can handle the data set containing continuous variables, as in the case of regression, and categorical variables, as in the case of classification. It performs better for classification and regression tasks. In this tutorial, we will understand the working of random forest and implement random forest on a classification task. **Steps Involved in Random Forest Algorithm**

Step 1: In the Random forest model, a subset of data points and a subset of features is selected for constructing each decision tree. Simply put, n random records and m features are taken from the data set having k number of records.
Step 2: Individual decision trees are constructed for each sample.
Step 3: Each decision tree will generate an output.
Step 4: Final output is considered based on Majority Voting or Averaging for Classification and regression, respectively.

6.3.2 Code

```
!pip install xgboost==1.5.0
```

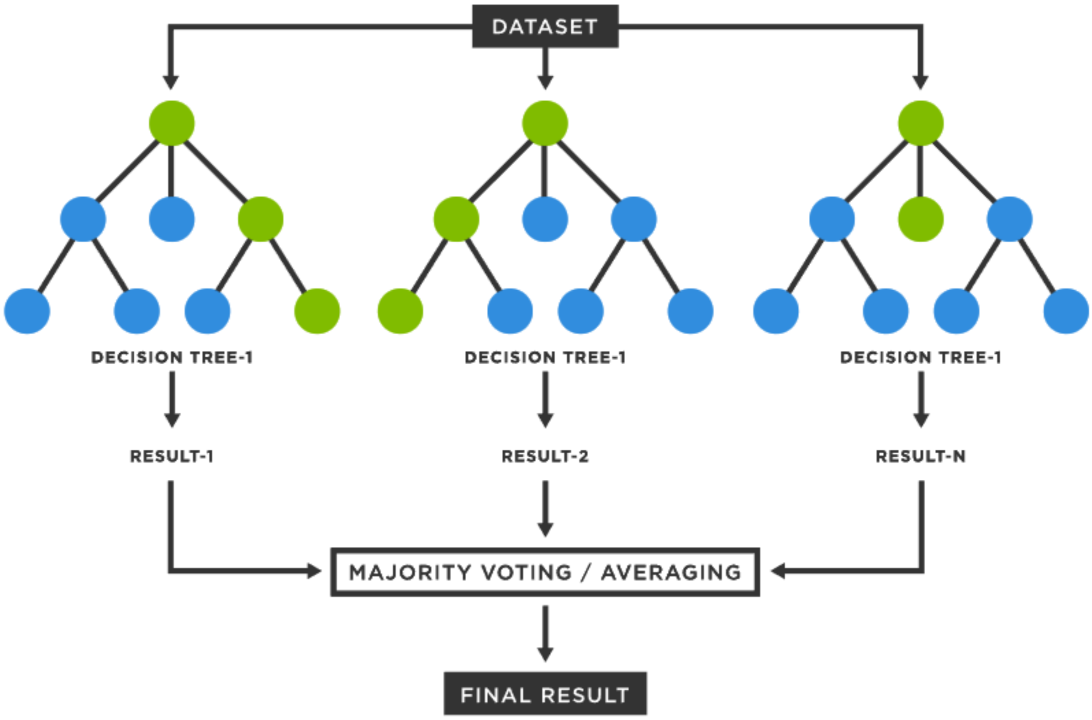


Figure 6.6: Random Forest Flow Chart

```
from sklearn.svm import SVR
from xgboost import XGBRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
```

6.3.3 Prediction Using Random Forest Regressor

```
from sklearn.ensemble import RandomForestRegressor
rfr = RandomForestRegressor(random_state=RS)
rfr.fit(X_train, Y_train)
```

6.3.4 Result

```
print("Accuracy for Train data sets")
```

```
print('train', dtr.score(X_train, Y_train))
print("Accuracy for Test data sets")
print('test', dtr.score(X_test, Y_test))
```

Accuracy for Train data sets

train 0.990636239140551

Accuracy for Test data sets

test 0.938671525993316

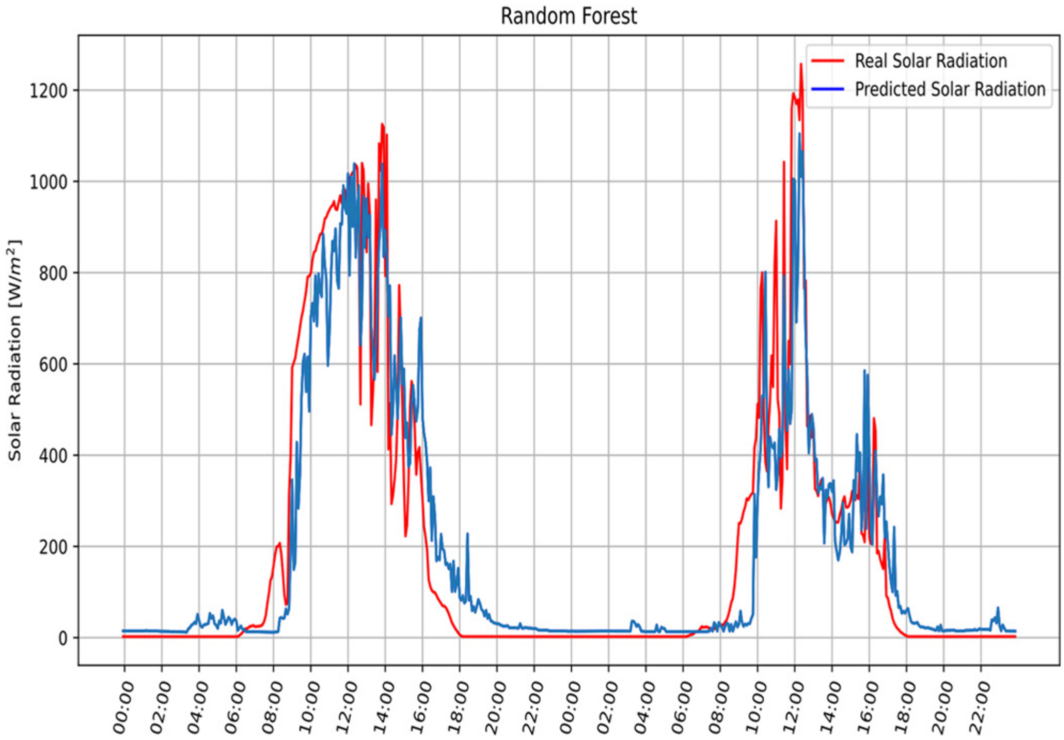


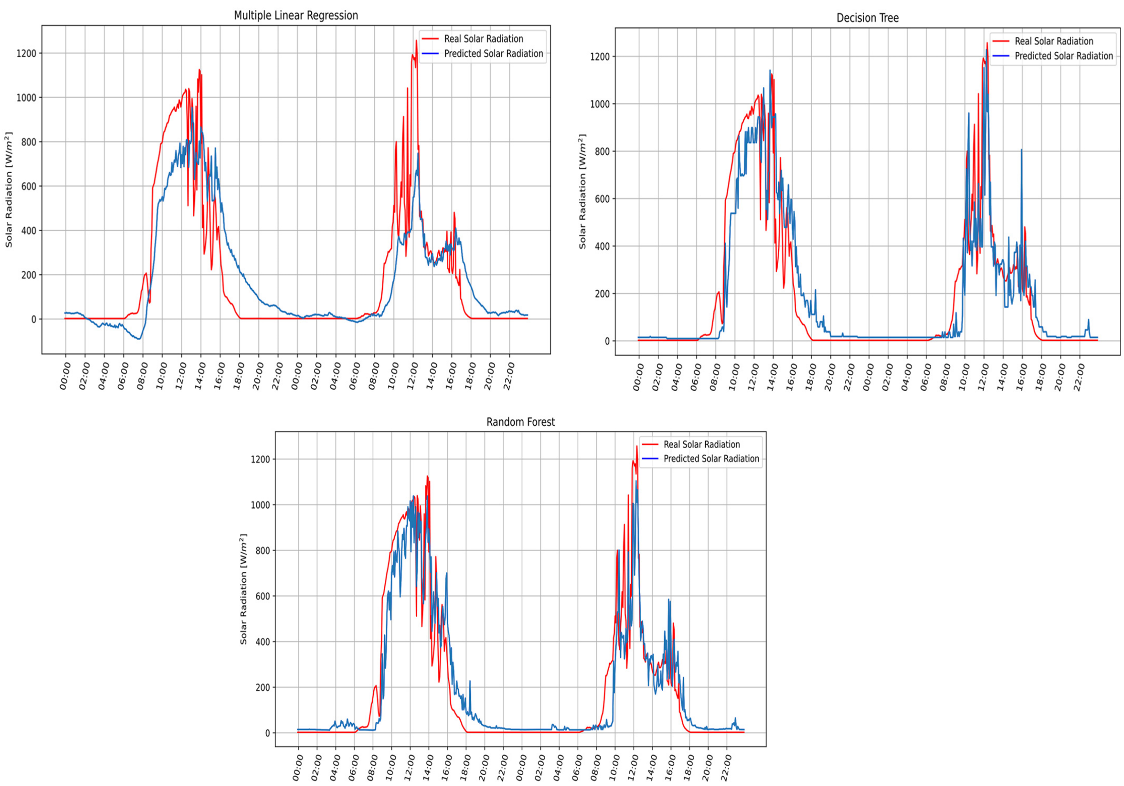
Figure 6.7: Random Forest Real vs Predicted values

Chapter 7

Comparison of Models

S.NO	MODEL-NAME	TRAIN DATASET ACCURACY	TEST DATASET ACCURACY
1	Multiple Linear Regression	61.90414	62.591899
2	Decision Tree Regressor	1	87.488313
3	Random Forest Regressor	99.0623	93.867152

Figure 7.1: Comparision of models



Chapter 8

Application of Solar Radiation Prediction

Solar radiation prediction has numerous applications across various industries and fields. Here are some key applications:

1. Renewable Energy Planning: Solar radiation prediction is crucial for planning and optimizing the operation of solar power plants. By forecasting solar radiation levels, energy producers can schedule the generation of solar energy more efficiently, thereby maximizing energy output and reducing costs.

2. Grid Integration: Solar radiation prediction helps grid operators manage the integration of solar energy into the grid. By accurately predicting solar radiation levels, grid operators can anticipate fluctuations in solar power generation and adjust grid operations accordingly to maintain grid stability.

3. Energy Storage Management: Solar radiation prediction is essential for managing energy storage systems, such as batteries. By forecasting solar radiation levels, energy storage systems can be charged or discharged at optimal times, maximizing the use of stored energy.

4. Climate Research: Solar radiation prediction plays a crucial role in climate research. By providing data on solar radiation levels, researchers can better understand the Earth's energy balance, climate patterns, and the impact of solar variability on the climate.

5. Agriculture: Solar radiation prediction is valuable for agricultural planning. By forecasting solar radiation levels, farmers can optimize crop planting and harvesting times, leading to improved yields and resource management.

6. Urban Planning: Solar radiation prediction can inform urban planning efforts, particularly in designing energy-efficient buildings and infrastructure. By considering solar radiation levels, planners can optimize building orientation and design to maximize natural lighting and reduce energy consumption.

7. Disaster Management: Solar radiation prediction can be useful in disaster management scenarios, such as predicting solar radiation levels in areas affected by natural disasters. This information can help emergency responders plan relief efforts and mitigate the impact of disasters.

Overall, solar radiation prediction has a wide range of applications that contribute to energy efficiency, sustainability, and climate resilience.

Chapter 9

Future Work of Solar Radiation Prediction

The future of solar radiation prediction is promising, with ongoing advancements in technology and research contributing to improved accuracy and reliability. Here are some key trends and developments shaping the future of solar radiation prediction:

1. Advanced Machine Learning Techniques: The use of advanced machine learning techniques, such as deep learning and ensemble methods, is expected to improve the accuracy of solar radiation prediction models. These techniques can better capture complex patterns in solar radiation data and enhance prediction capabilities.

2. Integration of Satellite Data: Continued advancements in satellite technology are enabling the collection of high-resolution data on solar radiation and atmospheric conditions. Integrating this data into prediction models can improve the spatial and temporal resolution of predictions.

3. Big Data Analytics: The increasing availability of big data analytics tools and platforms allows for the analysis of large and diverse datasets. This enables more comprehensive and accurate solar radiation predictions by incorporating a wide range of relevant data sources.

4. Integration with Renewable Energy Systems: Solar radiation prediction models are increasingly being integrated into renewable energy systems, such as solar power plants and grid management systems. This integration enables real-time optimization of energy production and grid operations based on predicted solar radiation levels.

5. Climate Change Adaptation: Solar radiation prediction is becoming increasingly important for climate change adaptation efforts. By providing insights into future solar radiation patterns, these predictions can help policymakers and planners develop strategies to mitigate the impacts of climate change.

6. Cross-Disciplinary Collaboration: Collaboration between researchers from different disciplines, such as meteorology, climatology, and data science, is expected to drive innovation in solar radiation prediction. This collaboration can lead to the development of more holistic and accurate prediction models.

7. Increased Accessibility: As solar energy continues to play a larger role in the global energy mix, there is a growing demand for accessible and reliable solar radiation prediction tools. Efforts to make these tools more user-friendly and accessible to a wider audience are expected to continue.

Overall, the future of solar radiation prediction is characterized by advancements in technology, increased integration with renewable energy systems, and a focus on addressing the challenges of climate change. These developments are expected to improve the accuracy and reliability of solar radiation predictions, ultimately supporting the growth of solar energy and sustainable development.

Conclusion

In detailed conclusion, solar radiation prediction stands as a crucial pillar supporting the transition towards sustainable energy practices and climate resilience. Through the accurate estimation of solar radiation levels, this field enables optimized energy production, grid stability, cost reduction, climate research, and sustainable urban planning.

The future of solar radiation prediction is marked by advancements in technology, particularly in machine learning and satellite imagery, which promise to enhance prediction accuracy and spatial-temporal resolution. Moreover, the integration of prediction models with renewable energy systems and climate change adaptation strategies will further solidify the importance of this field in addressing global challenges.

Collaboration across disciplines and sectors will continue to drive innovation in solar radiation prediction, ensuring that it remains at the forefront of renewable energy research and application. By leveraging these advancements, solar radiation prediction will play an increasingly pivotal role in shaping a sustainable and climate-resilient future for generations to come.

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