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SOLAR POWER GENERATION PREDICTION USING MACHINE LEARNING

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Abstract*:* It presents a machine learning based approach for predicting solar power generation. The approach includes data collection, preprocessing, feature selection, training, selection, evaluation, model and deployment. High-quality data from multiple sources, including weather data, and historical solar power generation data, are collected and pre-processed to remove outliers, handle missing values, and normalize the data. Relevant features such as temperature, humidity, wind speed, and solar irradiance are selected for model training. Additionally, the model may consider time-related features such as time of day, day of the week, and seasonal variations. This project leverages advanced machine learning techniques, specifically Random Forest Regression and Gradient Boosting models, to predict solar power output. These models are chosen for their robustness in handling non-linear relationships and their ability to manage large datasets with numerous features. By integrating weather data, historical solar power generation records, and other relevant environmental parameters, the models aim to provide accurate short-term and long-term forecasts of solar energy production. The methodology involves data preprocessing, feature selection, model training, and validation. The performance of the Random Forest Regression and Gradient Boosting models is evaluated using metrics such as Mean Absolute Error (MAE) and R squared. The results demonstrate that machine learning models can significantly enhance the accuracy of solar power generation forecasts.

KEYWORDS

Machine learning, Random Forest Regression, Gradient Boosting model, Mean Absolute Error (MAE), R squared, Voting Regressor approach

I INTRODUCTION

1.1EXISTING SYSTEM:

The model combines two key components: Support Vector Regression (SVR) and Particle Swarm Optimization (PSO). SVR is employed to create a forecasting model based on influential historical data collected from an actual PV power station. PSO optimizes the SVR model parameters, enhancing its performance. A novel data preparation algorithm is developed to create a solar irradiance pattern. This pattern is based on weather conditions and the percentage of cloud cover obtained from online weather forecast reports. It provides valuable guidance for accurate PV output power forecasting in practical applications.

1.1.1CHALLENGES:

- Accuracy: The existed system of solar power generation Forecasting yields 86% accuracy.
- Dependency on External Data: The model relies heavily on online weather reports, making it vulnerable to inaccuracies or delays in data collection or reporting.
- Data Quality Issues: The accuracy of the forecasting model depends on the availability and quality of online weather reports, which may suffer from issues such as missing data or sensor errors.

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1.2PROPOSED SYSTEM:

The proposed system for solar power generation prediction using Random Forest Regression and Gradient Boosting models is designed to provide accurate and reliable forecasts of solar energy production. The Random Forest Regression model is an ensemble learning method that operates by constructing a multitude of decision trees during training time and outputting the mean prediction of the individual trees. This model is particularly effective for handling complex datasets with high dimensionality and can capture non-linear relationships between features and the target variable.

On the other hand, the Gradient Boosting model is another powerful ensemble technique that builds the model in a stage-wise fashion. It constructs new models that predict the residuals or errors of prior models and then combines them to produce the final prediction. This approach allows for the optimization of arbitrary differentiable loss functions, making it highly flexible and suitable for a wide range of predictive modeling tasks.

In the context of solar power generation prediction, these models would utilize historical data on solar radiation, temperature, humidity, and other relevant meteorological parameters. The Random Forest model would identify the most important features affecting solar power output, while the Gradient Boosting model would iteratively improve the predictions by focusing on the hardest to predict instances. By combining the strengths of both models, the proposed system aims to minimize prediction errors and provide a robust tool for solar power forecasting, which is crucial for efficient energy management and grid integration.

1.2.1 ADVANTAGES:

- Accuracy: The proposed system of solar power generation yields 95% accuracy.
- Robustness to Overfitting: Random Forest Regression naturally guards against overfitting, a common issue in complex datasets. By aggregating multiple decision trees and considering only a subset of features at each node, it reduces the risk of fitting noise in the data, resulting in more robust predictions.
- Scalability: Random Forest Regression can handle large datasets and is parallelizable, making it suitable for applications where computational efficiency is essential. It can be trained on distributed computing frameworks, enabling scalability to massive datasets.

II LITERATURE REVIEW

Solar energy prediction has become increasingly important as the demand for renewable energy sources grows. Accurate forecasting of solar irradiance and energy production can significantly enhance the efficiency and stability of power grids. Traditional methods of solar prediction, such as statistical models and physical simulations, have laid the groundwork for forecasting techniques. However, recent advances in machine learning (ML) have brought new possibilities for improving prediction accuracy and operational efficiency.

Machine learning has emerged as a powerful tool for solar prediction, offering techniques that adapt and learn from data rather than relying solely on predefined physical models. Among the various ML approaches, supervised learning methods such as neural networks, support vector machines, and ensemble methods have shown considerable promise. Neural networks, particularly deep learning models, excel in capturing complex, non-linear relationships in historical solar irradiance data. Studies like those by L. S. Vasconcelos et al. (2019) demonstrate that deep neural networks can effectively model intricate patterns in solar irradiance and enhance short-term forecasting accuracy. Similarly, support vector machines have been employed to improve prediction by classifying and regressing solar radiation data with high precision (Mousazadeh et al., 2006).

In addition to supervised learning, unsupervised learning techniques have been utilized to analyze and cluster solar data. Techniques such as k-means clustering and principal component analysis (PCA) help in understanding patterns and reducing dimensionality in solar data, making it easier to handle large datasets and improve forecasting models (Ming et al., 2021). These methods are particularly useful for identifying hidden structures in data and enhancing the performance of predictive models by preprocessing and feature extraction.

Hybrid models that combine machine learning with traditional statistical and physical models offer a promising approach to solar prediction. These models integrate the strengths of both methodologies to refine predictions and address limitations inherent in individual approaches. For example, combining numerical weather prediction (NWP) models with machine learning techniques allows for the incorporation of atmospheric data and improves the reliability of forecasts (Luo et al., 2020). This integration enables more accurate short-term and long-term solar irradiance predictions by leveraging historical data and real-time weather information.

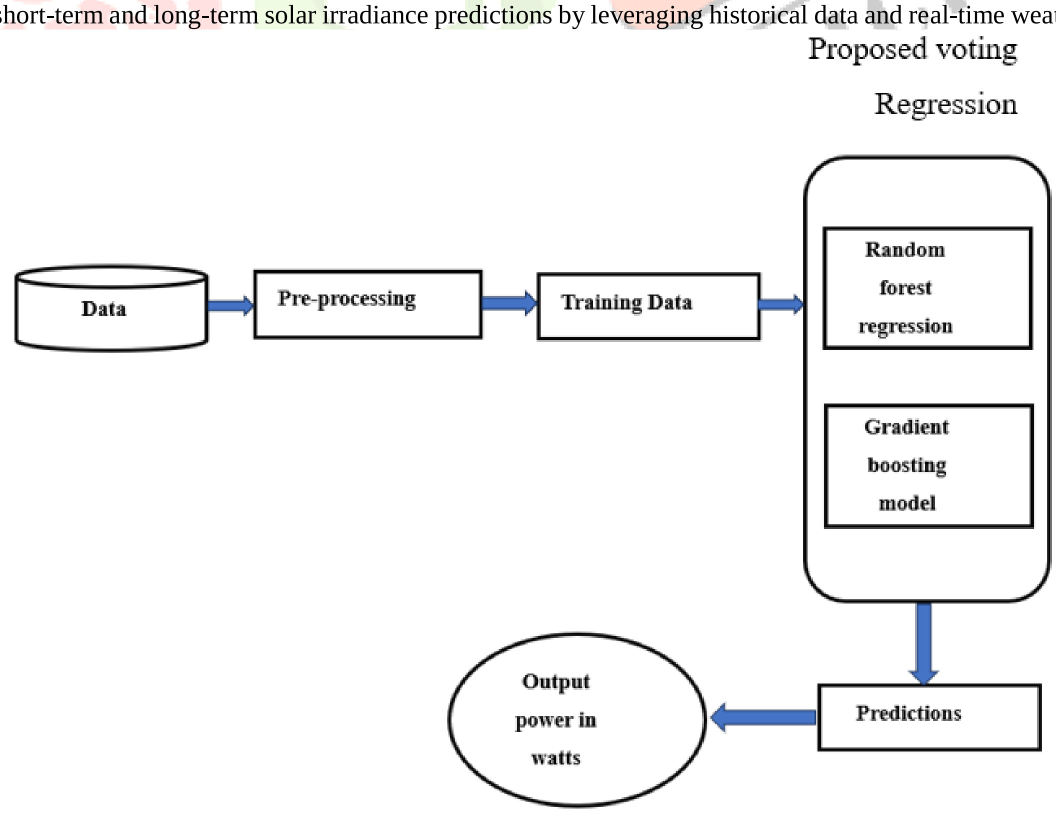


Fig.1 Architecture of System

III METHODOLOGY

3.1 INPUT

The input design is the link between the information system and the user. It comprises the developing specification and procedures for data preparation and those steps 28 are necessary to put transaction data in to a usable form for processing can be achieved by inspecting the computer to read data from a written or printed document or it can occur by having people keying the data directly into the system. The design of input focuses on controlling the amount of input required, controlling the errors, avoiding delay, avoiding extra steps and keeping the process simple. The input is designed in such a way so that it provides security and ease of use with retaining the privacy.

input design is crucial for training an effective model. Historical weather data, encompassing variables like solar irradiance, temperature, humidity, wind speed, and cloud cover, serves as the primary input. Additionally, data on actual solar power generation, alongside timestamps, provides essential context for model training and validation. Preprocessing steps involve feature engineering to extract meaningful insights from raw data, normalization to ensure uniformity, and handling missing values. Integrating data from various sources and splitting it into training and testing sets ensures the model's accuracy and robustness. Through thoughtful input design, the Random Forest Regression model can harness historical data to generate accurate predictions, contributing to efficient solar energy utilization.

3.2 OUTPUT

A quality output is one, which meets the requirements of the end user and presents the information clearly. In any system results of processing are communicated to the users and to other system through outputs. In output design it is determined how the information is to be displaced for immediate need and also the hard copy output. It is the most important direct source information to the user. Efficient and intelligent output design improves the system’s relationship to help user decision-making.

The output design focuses on presenting forecasted solar energy output in an accessible and informative manner. This involves generating clear visualizations, such as line graphs or time series plots, to illustrate predicted power generation trends over various time intervals. Additionally, summary statistics like mean forecasted power and confidence intervals enhance the understanding of forecast accuracy and reliability. Overall, the output design emphasizes clarity, accuracy, and accessibility to facilitate effective utilization of solar energy predictions for sustainable energy planning and management.

```
[1]: import pandas as pd
     import numpy as np
     import seaborn as sns
     import matplotlib.pyplot as plt
     %matplotlib inline
     from sklearn.metrics import accuracy_score

     import warnings
     warnings.filterwarnings("ignore")

[2]: pd.set_option('display.max_columns',None)
     pd.set_option('display.max_rows',None)
     #pd.set_option('precision',3)

[3]: #Importing Power Generation & Weather Sensor Data
     generation_data = pd.read_csv(r"C:\Users\donga\Downloads\GENERATION.csv")

[4]: weather_data = pd.read_csv(r"C:\Users\donga\Downloads\Plant_2_Weather_Sensor_Data.csv")
```

Fig.2 Packages and Dataset

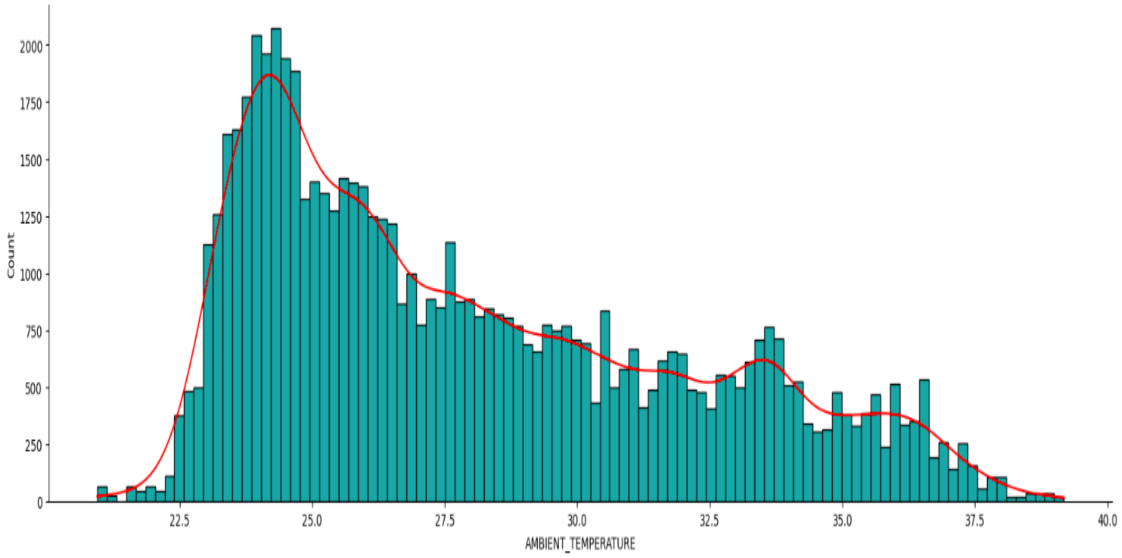
In the above image importing the required packages and read the data sets.

```
[10]: df_solar.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 67698 entries, 0 to 67697
Data columns (total 17 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   DATE_TIME            67698 non-null  datetime64[ns]
 1   SOURCE_KEY           67698 non-null  object
 2   DC_POWER             67698 non-null  float64
 3   AC_POWER             67698 non-null  float64
 4   DAILY_YIELD          67698 non-null  float64
 5   TOTAL_YIELD          67698 non-null  float64
 6   AMBIENT_TEMPERATURE  67698 non-null  float64
 7   MODULE_TEMPERATURE   67698 non-null  float64
 8   IRRADIATION          67698 non-null  float64
 9   DATE                 67698 non-null  object
 10  TIME                 67698 non-null  object
 11  DAY                  67698 non-null  int32
 12  MONTH                67698 non-null  int32
```

Fig .3 Displaying Columns and Its Types

```
[14]: #Data Visualization
      sns.displot(data=df_solar, x="AMBIENT_TEMPERATURE", kde=True, bins = 100,color = "red", facecolor = "#3F7F7F",height = 5, aspect = 3.5);
```




```
[15]: df_solar['DATE'].nunique()

[15]: 34
```

Fig.4 Data of Ambient Temperature

In the above image presents the Data visualization of solar AMBIENT TEMPERATURE of 34 days.

```
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, VotingRegressor
from sklearn.metrics import r2_score
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

# Define the Random Forest pipeline
pipeline_rfr = Pipeline([
    ('scaler', StandardScaler()),
    ('regressor', RandomForestRegressor())
])

# Define the Gradient Boosting pipeline
pipeline_gbr = Pipeline([
    ('scaler', StandardScaler()),
    ('regressor', GradientBoostingRegressor())
])

# Define the Voting Regressor combining both pipelines
voting_regressor = VotingRegressor([
    ('rfr', pipeline_rfr),
    ('gbr', pipeline_gbr)
])

# Train the Voting Regressor on the training data
voting_regressor.fit(X_train, y_train)

# Predict with the Voting Regressor on the test data
y_pred_voting = voting_regressor.predict(X_test)

# Calculate the R2 score for the Voting Regressor
R2_Score_voting = round(r2_score(y_test, y_pred_voting) * 100, 2)
print("Voting Regressor R2 Score: ", R2_Score_voting, "%")

Voting Regressor R2 Score:  95.38 %
```

Fig.5 Defining and Evaluating

In the above image represents the splitting of dataset into test set and train set.

We propose our algorithm which is used to evaluate by using evaluation metrics like Mean square error (MSA), Root mean square error (RMSA)and R-squared (R^2) and our proposed system got 95%.

```
import pickle
pickle.dump(voting_regressor, open('model.pkl','wb'))
```

```
import pickle

# Load the model from the pickle file
model = pickle.load(open('model.pkl', 'rb'))

# Input data (ensure it matches the format of your training data)
input_data = [[0.933333,    1.816953e+08,    24.544685,  24.077230,  0.012962,    15.746667]]

# Predict the output
pred = model.predict(input_data)

# Convert the prediction to watts (if the model outputs in a different unit)
# Assuming the prediction is already in watts
predicted_power_in_watts = pred

# Print the predicted power
print("Predicted Power in Watts:", predicted_power_in_watts)
```

```
Predicted Power in Watts: [15.26916933]
```

```
predicted_power_in_watts = pred[0]
print("Predicted Power in AC Watts:", predicted_power_in_watts)
```

```
Predicted Power in AC Watts: 15.269169333066714
```

Fig.6 Output Prediction

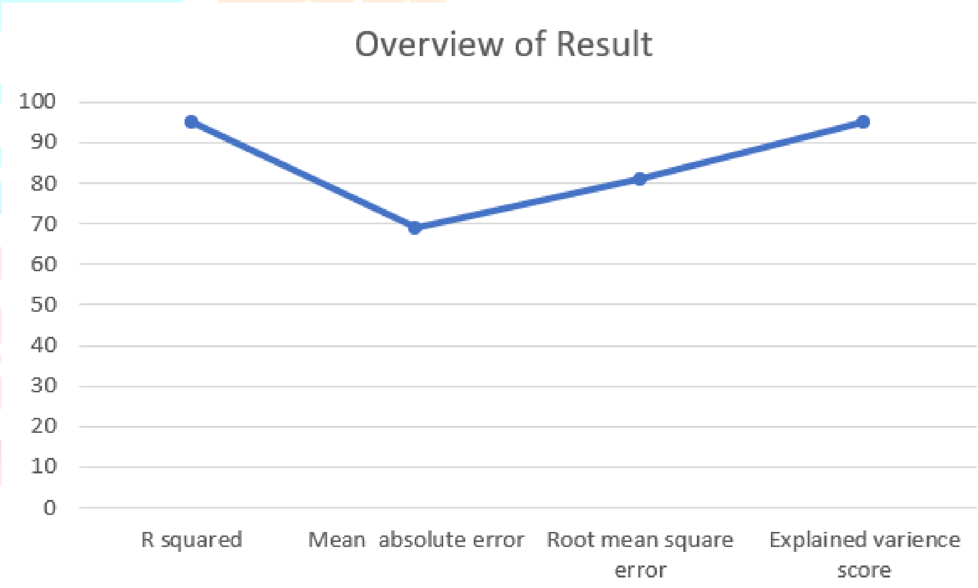


Fig.7 Overview of Result

IV RESULTS

Generating solar power generation predictions using machine learning involves several steps, including data collection, preprocessing, feature selection, model training, and evaluation. Here's a detailed outline of the process, particularly focusing on using Random Forest Regression and Gradient Boosting Model combined through Voting Regression:

1. Data Collection:

Historical Solar Power Data: Collect historical data on solar power generation from solar panels.

Weather Data: Gather historical and forecasted weather data, including parameters like temperature, humidity, wind speed, cloud cover, and solar irradiance.

Time Data: Include time-related features such as time of day, day of the week, and season.

2. Data Preprocessing

Handling Missing Values: Fill or interpolate missing values in the dataset.

Normalization/Scaling: Normalize or scale the data to bring all features to a similar range, which is essential for some machine learning models.

Feature Engineering: Create additional relevant features such as moving averages, rolling statistics, or lagged variables.

3. Feature Selection

Correlation Analysis: Use correlation analysis to identify and select features that have a strong relationship with the target variable (solar power generation).

Feature Importance: Employ methods like feature importance from tree-based models to determine which features contribute most to the model.

4. Model Training

Split Data: Divide the dataset into training and testing sets.

Random Forest Regression:

Train a Random Forest Regressor on the training set. This model operates by constructing multiple decision trees during training and outputting the mean prediction of the individual trees.

Gradient Boosting Model:

Train a Gradient Boosting Regressor on the training set. This model builds an ensemble of trees sequentially, where each tree corrects the errors of the previous one.

5. Model Combination Using Voting Regressor:

Combine the predictions of Random Forest and Gradient Boosting using a Voting Regressor. Voting can be either hard voting (based on the mode of the predictions) or soft voting (based on the average of the predicted values).

In this case, we use soft voting to average the predictions from both models.

6. Evaluation

Metrics: Evaluate the combined model using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) to assess performance.

Cross-Validation: Perform k-fold cross-validation to ensure the model's robustness and generalizability.

V DISCUSSION

In the realm of solar power generation prediction using machine learning, particularly through random forest regression, the future holds promising avenues for advancement. Firstly, there is a significant scope for enhancing the performance of predictive models. Researchers can focus on refining feature selection methodologies and optimizing model hyperparameters to achieve higher accuracy and reliability in solar power generation forecasts. Moreover, exploring advanced machine learning techniques beyond random forest regression, such as gradient boosting or deep learning architectures, could potentially unlock new insights and improve predictive capabilities.

Another compelling area for future exploration involves the integration of additional data sources into predictive models. By incorporating diverse datasets such as satellite imagery for cloud cover prediction, historical energy production data from various renewable sources, or socio-economic indicators, researchers can develop more comprehensive models that capture a broader range of factors influencing solar power generation. This expansion of data sources not only enriches the predictive model but also enhances its applicability across different geographical regions and environmental conditions.

Furthermore, the future scope encompasses real-time prediction and forecasting of solar power generation, enabling timely adjustments to energy management strategies in response to changing environmental conditions. Implementing streaming data processing techniques and adaptive model updating mechanisms can facilitate the development of dynamic prediction models that provide accurate forecasts for short-term energy planning and grid management. Integration with energy management systems and smart grid technologies will be crucial in leveraging these forecasts to optimize energy scheduling, demand response, and grid stability management.

In addition to technical advancements, there is a growing emphasis on the interdisciplinary nature of solar energy research. Collaborations between experts from fields such as machine learning, renewable energy, environmental science, and policy analysis can lead to holistic solutions that address technical, environmental, and socio-economic challenges in solar power generation. This interdisciplinary approach is essential for developing sustainable energy policies, fostering innovation, and promoting renewable energy adoption on a global scale. Overall, the future of solar power generation prediction using machine learning is bright, with ample opportunities for innovation, collaboration, and positive impact on the transition towards a sustainable energy future.

VI CONCLUSION

The solar power generation prediction project utilizing Random Forest Regression and gradient boosting model demonstrates the potential of machine learning techniques to enhance renewable energy utilization and management. Through the integration of historical weather data and solar power generation records, the developed model offers valuable insights into forecasted solar energy output.

VII FUTURE SCOPE

The future of solar power generation prediction using machine learning is poised for transformative advancements that will significantly enhance the efficiency and reliability of solar energy systems. As machine learning algorithms become increasingly sophisticated, they will offer improved accuracy in both short-term and long-term forecasts by incorporating complex data sources such as satellite imagery, real-time weather data, and Internet of Things (IoT) sensor inputs. This will enable more precise predictions of solar irradiance and power output, allowing for dynamic adjustments to solar panel configurations and optimized energy storage management. The integration of these predictive models with smart grids and hybrid energy systems will facilitate better energy management, balancing solar power with other renewable and non-renewable sources to ensure grid stability. Additionally, machine learning will aid in predictive maintenance, reducing downtime and operational costs by forecasting equipment failures before they occur. The economic benefits will be substantial, as enhanced predictions will lead to more accurate cost-benefit analyses and investment decisions. Moreover, the ability to personalize recommendations for solar system configurations based on local conditions and user preferences will drive increased adoption. As the technology evolves, machine learning will also address the challenges posed by climate change by adapting to variable weather patterns and integrating with broader smart city frameworks, thereby promoting sustainability and optimizing energy use in urban environments. Overall, the convergence of advanced machine learning techniques with solar power generation will pave the way for a more reliable, efficient, and economically viable renewable energy future.

VIII ACKNOWLEDGEMENT

Ms. M. Tarani is an Assistant Professor in the Master of Computer Applications (MCA) program at Sankethika Vidya Parishad Engineering College in Visakhapatnam, Andhra Pradesh. She has one year of experience as an Automation Test Engineer at Stigentech IT Services Private Limited. She is also a member of the ACNG, and the institution is accredited by NAAC. Her areas of interest include C, Java, Data Structures, Web Technologies, Python, and Software Engineering.

Ms. K. Nandini is currently in her final semester of the MCA program at Sankethika Vidya Parishad Engineering College, which is accredited with an A grade by NAAC, affiliated with Andhra University, and approved by AICTE. With a keen interest in Python and Machine Learning Ms. Nandini has undertaken her postgraduate project on "Solar power Generation Prediction Using Machine Learning". She has also published a paper related to this project under the guidance of Ms. M. Tarani, an Assistant professor at SVPEC.

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