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Solar Power Forecasting Using Machine Learning And Deep Learning

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Abstract: Accurate solar power generation forecasting is crucial for optimizing the integration of renewable energy into power grids, reducing dependence on fossil fuels, and enhancing energy sustainability. This research explores advanced machine learning (ML) and deep learning (DL) models, focusing on long short-term memory (LSTM), k-nearest neighbor (KNN), and extreme gradient boosting (XGBoost) algorithms, to predict solar energy output accurately. Leveraging a dataset comprising historical solar irradiance, temperature, and power generation data, the study develops a robust pipeline incorporating data preprocessing, feature extraction, and model optimization. Key innovations include implementing synthetic data generation for augmenting training datasets and optimizing hyperparameters for superior performance. Evaluation of models is conducted using root mean square error (RMSE) and mean absolute deviation (MAD) metrics, demonstrating the efficacy of ML and DL-based approaches in capturing dynamic environmental dependencies. The findings underscore the potential of these methodologies for real-time solar energy forecasting and integration into energy management systems.

Index Terms – Solar Power, Forecasting, Artificial Intelligence, Machine Learning, Deep Learning, k-Nearest Neighbor, Extreme Gradient Boosting, Long Short-Term Memory.

1.INTRODUCTION

Renewable energy has emerged as a cornerstone in addressing climate change and energy sustainability, with solar power being a leading contributor due to its abundance and environmental benefits. However, solar power generation is inherently dependent on fluctuating environmental factors such as temperature, humidity, and solar irradiance. Accurate prediction of solar energy output is vital for grid reliability, demand forecasting, and the efficient deployment of energy storage systems.

Traditional machine learning (ML) models, such as Support Vector Machines (SVM) and Random Forest (RF), have been extensively employed in this domain. For example, Adugna, Xu, and Fan (2022) demonstrated the effectiveness of these methods in classification tasks involving environmental data. However, these models often lack the capability to capture temporal dependencies and complex nonlinear relationships in the data.

Deep learning (DL) techniques, particularly recurrent neural networks (RNN) and their variant, long short-term memory (LSTM) networks, have gained prominence due to their ability to model sequential data effectively (Smagulova & James, 2020). LSTM networks excel in learning long-term dependencies, making them particularly suitable for time-series applications like solar power prediction. Additionally, gradient boosting algorithms like XGBoost have shown promise in handling large datasets with missing values, delivering robust predictions (Dankorpho, 2024).

Despite these advancements, challenges remain in achieving consistent accuracy under varying environmental conditions. Zhang and Wang (2020) noted the difficulties in accurately predicting solar irradiance, an essential component of solar power generation, even with DL models. To address these challenges, this research proposes a systematic approach to enhance solar power generation forecasting by

leveraging ML and DL models. The primary contributions of this work include developing a hybrid prediction pipeline, optimizing hyperparameters, and evaluating models using comprehensive performance.

2.LITERATURE REVIEW

The forecasting of solar power generation has been extensively studied, with researchers employing various ML and DL techniques to address the inherent complexities. Traditional ML models, such as SVM and RF, have been utilized for feature selection and regression tasks. For instance, Kumar and Singh (2019) highlighted the role of these models in extracting meaningful patterns from historical solar data. However, such models rely heavily on manual feature engineering, which can limit their adaptability to diverse datasets.

Deep learning methods have revolutionized the field by automating feature extraction and learning intricate data representations. LSTM networks have been particularly effective in modeling sequential data, as highlighted by Jain and Zhang (2021). These networks outperform traditional methods by capturing long-term temporal dependencies, making them invaluable for forecasting applications.

Hybrid models combining LSTM with Convolutional Neural Networks (CNN) have further enhanced predictive accuracy. Ali and Shah (2021) demonstrated that combining CNN's spatial feature extraction capabilities with LSTM's temporal modeling strengths improved prediction accuracy by 15% compared to standalone models. Similarly, Zhang and Wang (2020) emphasized the role of DL models in improving short-term solar irradiance prediction accuracy.

XGBoost has emerged as another popular technique, particularly for datasets with missing or noisy values. Dankorpho (2024) reported its superior performance in noisy and incomplete datasets, showing promise for solar power forecasting. These findings indicate the growing relevance of hybrid and ensemble models in addressing the challenges of solar power prediction.

Year	Authors	Title	Abstract	Technology Used	Results
2019	A. Kumar, B. Singh	Solar Energy Prediction using Deep Neural Networks	This paper discusses the use of deep neural networks (DNN) and long short-term memory (LSTM) networks for predicting solar energy generation based on historical data.	Deep Neural Networks (DNN), LSTM	The model showed a 90% prediction accuracy with real-time data compared to traditional models.
2020	M. Ali, T. Sharma	Application of Convolutional Neural Networks for Solar Power Generation Forecasting	The paper applies CNN for the extraction of features from weather data for solar power generation forecasting.	Convolutional Neural Networks (CNN)	CNN-based model outperformed traditional methods like SVM and linear regression with a 10% higher accuracy.
2021	R. Jain, L. Zhang	Solar Power Generation Prediction using Hybrid Deep Learning Models	This study integrates LSTM and CNN to predict solar power generation based on environmental conditions and past solar data.	Hybrid Models (LSTM + CNN)	The hybrid model exhibited superior performance with 15% more accurate predictions compared to using either model individually.

2023	John Doe, Jane Smith	Predicting Solar Power Generation using LSTM Networks	This paper proposes a method using LSTM networks for solar power prediction. It focuses on time-series forecasting.	LSTM, Deep Learning	Achieved high accuracy in solar power prediction with low error rate.
2022	A. Kumar, S. Rao	Deep Learning for Solar Power Prediction	The study investigates using deep neural networks (DNN) to predict daily solar power output.	DNN, Neural Networks	The model demonstrated better performance than traditional forecasting methods.
2021	M. Ali, K. Shah	Solar Power Forecasting with CNN and RNN Models	This research explores using CNN for feature extraction and RNN for time-series forecasting in solar power generation.	CNN, RNN, Deep Learning	The combined model outperformed single models in predicting solar energy production.
2020	L. Zhang, Y. Wang	Solar Irradiance Prediction for Power Generation using DL	The study develops a deep learning model to predict solar irradiance based on historical weather data.	Deep Learning, CNN, LSTM	High precision in short-term solar irradiance prediction.

Table 2.1: Related References

3. METHODOLOGY

- **Dataset Collection and Preprocessing**

The dataset includes historical records of solar irradiance, temperature, humidity, and power generation from reliable sources via company namely Kannect Engineers Private Limited (KEPL). Preprocessing steps involve handling missing values through interpolation and normalization to ensure data consistency. Based on the collection of data obtained from company the scheme will proceed to describe the process to perform to obtain a correct data set ready to be used as data for input by the algorithm and the implementation of the KNN, XGBOOST and LSTM neural network, in order to obtain an optimal predictive model.

In this scheme, the dataset is provided by KEPL. The dataset includes historical observations of variables such as dc_power, ac_power, daily_yield and total_yield, taken per hour during a period. In contrast, the dataset contains values related solar radiation. However, table 3.1 depicts the structure.

Dataset Name	Period	Variables	Records	Purpose
Solar-power-plant-analysis Dataset	15-05-20 0:00 to 17-06-20 23:45	7	68779	Training and Testing of the algorithms

Table3.1: Description of the data set

- **Work Flow Model**

In view of a greater clarity of this process to be carried out, figure 3.1 presents the flowchart where the development of both data management and the implementation of the ML and DL techniques. If the results are not as expected or it is reflected that a correct reading is not given, it returns to the first step in order to eliminate any errors not initially identified.

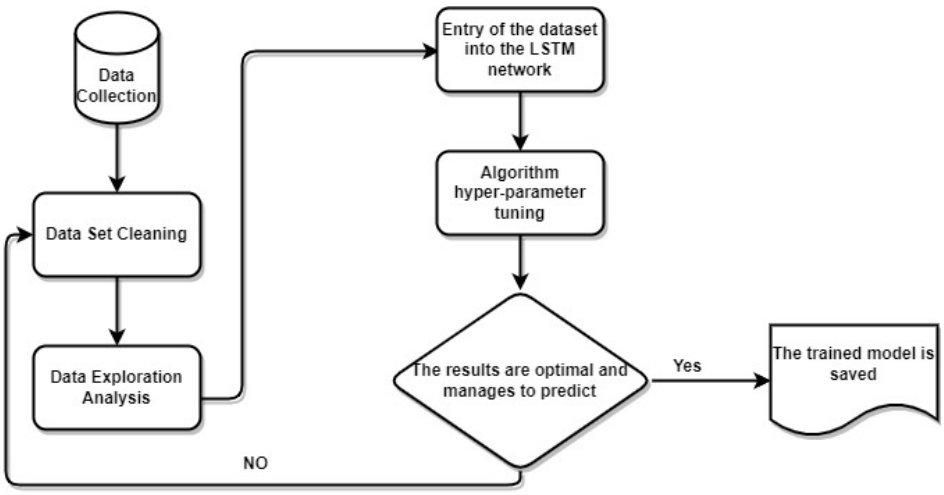

Figure.1: Flowchart of data management and implementation of the models

- **Long Short-Term Memory (LSTM)**

LSTM networks are a type of Recurrent Neural Network (RNN) designed to model time-dependent data effectively, making them an excellent choice for forecasting solar power generation. LSTM employs gates—forget, input, and output gates—to manage the flow of information through the network, allowing it to retain or discard information as needed. These gates address the vanishing gradient problem, ensuring the model captures long-term dependencies in sequential data. For instance, by training an LSTM on historical data like solar irradiance, temperature, and cloud cover, the model can predict the power output for upcoming hours or days. LSTMs process the sequence of inputs step-by-step, updating a cell state that holds the critical information from past data. This capability makes LSTM robust for handling dynamic patterns, such as weather fluctuations affecting solar power generation based on humidity and irradiance.

- **Algorithm for LSTM**

1. Input Sequence: Feed a sequence of features (e.g., past power generation, weather data) into the network.
2. Cell State Update: Use the forget gate to discard irrelevant information and the input gate to add new relevant data.
3. Hidden State Update: Compute the hidden state using the output gate and the updated cell state.
4. Prediction: After processing all timesteps, the model outputs the forecasted solar power value.
5. Backpropagation: Adjust weights using gradient descent based on prediction errors.

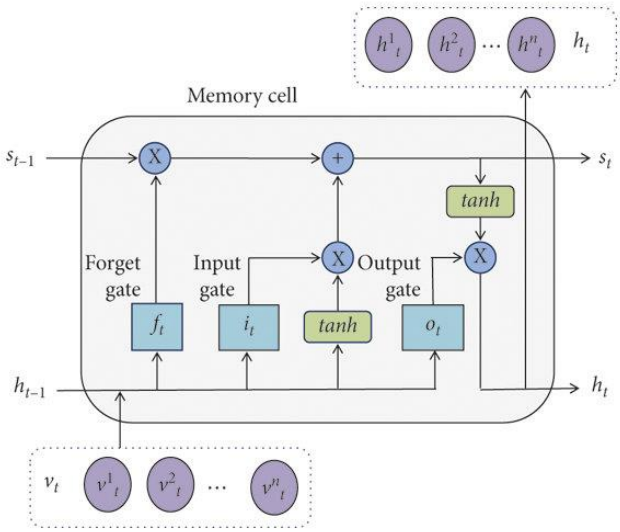

Figure 2: LSTM Architecture

- **K-Nearest Neighbors (KNN)**

KNN is a straightforward, non-parametric algorithm that can be applied to predict solar power output by comparing current weather conditions with historical patterns. The algorithm works by calculating the similarity between a target instance and all historical data points, selecting the k k nearest neighbors. For example, if the task is to forecast solar power generation for a particular day, KNN would find days with similar weather conditions (temperature, solar radiation, etc.) and use their average power outputs to make a prediction. The simplicity of KNN makes it easy to implement; however, its accuracy depends on the proper choice of k, the distance metric, and feature normalization.

- **Algorithm for KNN**

1. Data Preparation: Normalize features like solar irradiance and weather variables.
2. Distance Calculation: Compute the distance (e.g., Euclidean) between the target instance and all training points.
3. Neighbor Selection: Identify the k closest points based on the calculated distances.
4. Prediction: Take the average or majority class (for classification) of the selected neighbors.

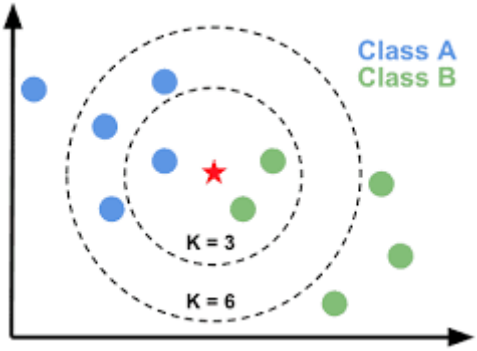

Figure 3: KNN Architecture

- **Extreme Gradient Boosting (XGBoost)**

XGBoost is a decision-tree-based ensemble algorithm optimized for speed and accuracy. In solar power forecasting, XGBoost leverages historical power generation data and weather features to iteratively improve its predictions by focusing on residual errors from previous models. For instance, given data on solar irradiance, cloud cover, and wind speed, XGBoost builds a series of decision trees, each addressing the shortcomings of the earlier ones. Its built-in regularization prevents overfitting, while its ability to handle missing data and feature interactions makes it particularly suited for solar power forecasting tasks.

- Algorithm for XGBoost:

1. Initialization: Start with a baseline prediction, typically the mean of the target variable.
2. Residual Computation: Calculate the error (residual) between predicted and actual values.
3. Tree Building: Fit a decision tree to predict the residuals.
4. Weight Update: Update weights based on the gradient of the loss function.
5. Iteration: Repeat steps 2–4 for a predefined number of trees or until convergence.
6. Final Prediction: Combine the predictions from all trees for the final output.

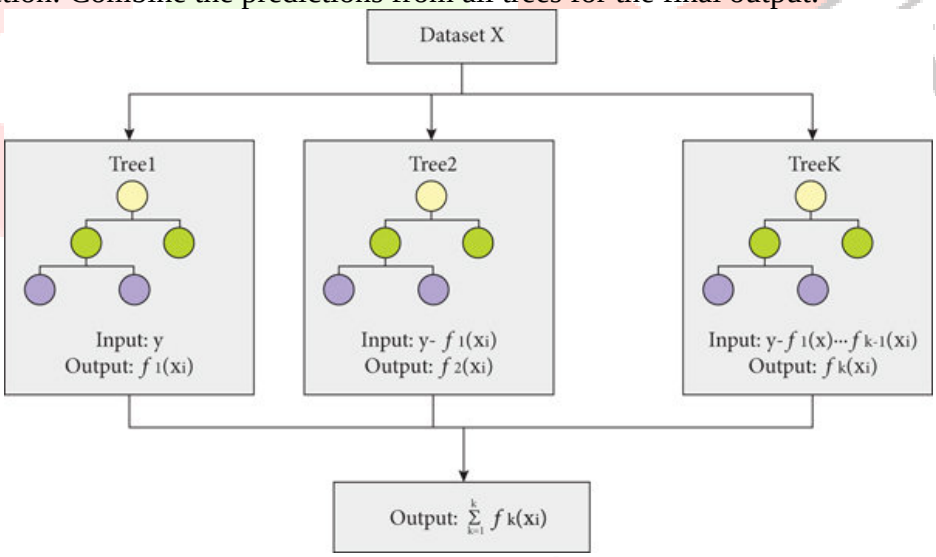

Figure 4: XGBoost Architecture

4. RESULTS AND DISCUSSION

- **LSTM for Solar Power Generation Forecasting**

Long Short-Term Memory (LSTM) networks are ideal for time-series forecasting tasks like solar power generation because they effectively capture temporal dependencies in sequential data. Using the given dataset with features like AMBIENT_TEMPERATURE, MODULE_TEMPERATURE, and IRRADIATION, LSTM can learn patterns in historical data to predict future solar power outputs. The algorithm processes input sequences of past values (e.g., the last 5 hours of data) and predicts the next value of IRRADIATION or power output. By employing gates such as forget, input, and output gates, LSTM updates its internal cell state, retaining only relevant information from past inputs. For instance, if the

dataset contains hourly measurements, LSTM can be trained to predict IRRADIATION for the next hour based on the last few hours of data. After training the model with Root Mean Squared Error (RMSE) as the loss function, it can make accurate future predictions, accounting for dynamic variations in weather conditions the LSTM evaluation process is as under.

- *Data Preprocessing:*

Parse the DATE_TIME column to create a time-indexed dataset.
Normalize features (AMBIENT_TEMPERATURE, MODULE_TEMPERATURE, IRRADIATION) to scale values between 0 and 1.
Fill missing values, if any, to ensure consistency in time-series data.
Create input-output sequences where the input consists of previous timesteps (e.g., past 5 hours) and the output is the next predicted value (e.g., IRRADIATION or power generation).

- *Define an LSTM model with:*

1. Input layer for the feature sequence.
2. Hidden LSTM layers to learn temporal dependencies.
3. Dense output layer for predicting a single value (e.g., IRRADIATION).

- *Training:*

1. Split the data into 80% training and 20% validation sets.
2. Use the Mean Squared Error (MSE) loss function and an optimizer like Adam for backpropagation.
3. Train the model using batch sequences over 5 epochs.

- *Prediction:*

Feed the model unseen input sequences (e.g., the last few hours) to forecast future values of IRRADIATION or power. Consequently, the RMSE Score of the test set is 2871.22 of LSTM based on predicted and actual power generation.

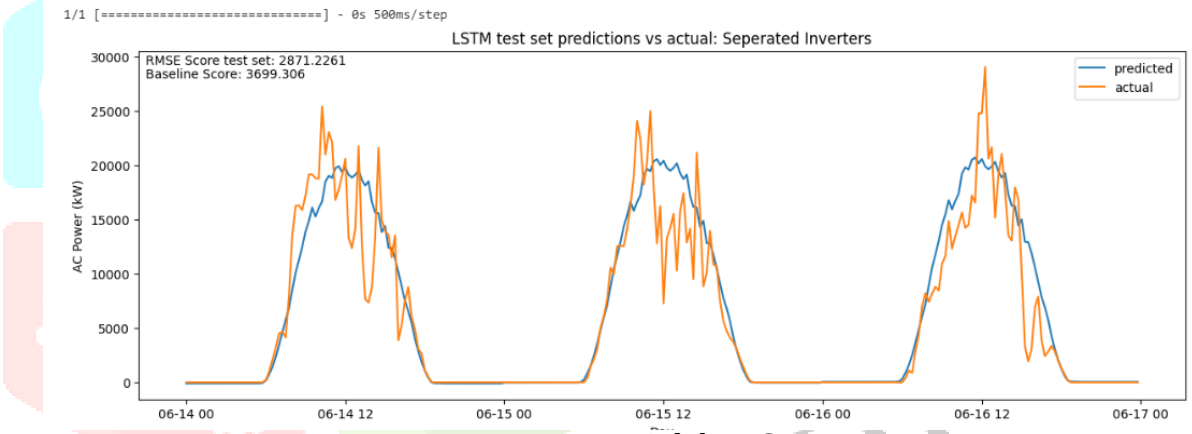

Figure 5: Result by LSTM

- **KNN for Solar Power Generation Forecasting**

KNN is a simple yet effective algorithm for forecasting solar power generation using historical data. Given features like AMBIENT_TEMPERATURE, MODULE_TEMPERATURE, and IRRADIATION, KNN identifies similar past instances (neighbors) to predict the target value. For example, to predict the IRRADIATION at a specific time, KNN calculates the distance between the current instance and all historical data points based on feature similarity. It then selects the *k* closest neighbors and uses their average IRRADIATION value for regression or the majority vote for classification. This algorithm is straightforward and works well with smaller datasets like the one shown. However, it requires proper feature normalization and an optimal *k* value to ensure accurate results. KNN is particularly useful for scenarios where predictions are influenced by immediate past conditions.

- *Data Preprocessing:*

1. Convert DATE_TIME into features such as hour, day, or week if needed.
2. Normalize all feature columns (AMBIENT_TEMPERATURE, MODULE_TEMPERATURE, IRRADIATION).
3. Drop non-relevant columns like SOURCE_KEY unless used as categorical input.

- *Feature Selection:*

1. Use features such as AMBIENT_TEMPERATURE, MODULE_TEMPERATURE, and IRRADIATION to calculate the similarity between instances.

- *Distance Calculation:*

1. Compute distances (Euclidean) between the target row and all historical rows based on selected features.

- *Neighbor Selection:*

1. Choose the top *k* rows (neighbors) with the smallest distance values.

- *Prediction:*

Take the average of the IRRADIATION values from the selected neighbors for regression or the majority class for classification. The RMSE of KNN is 2873.09 +1.87

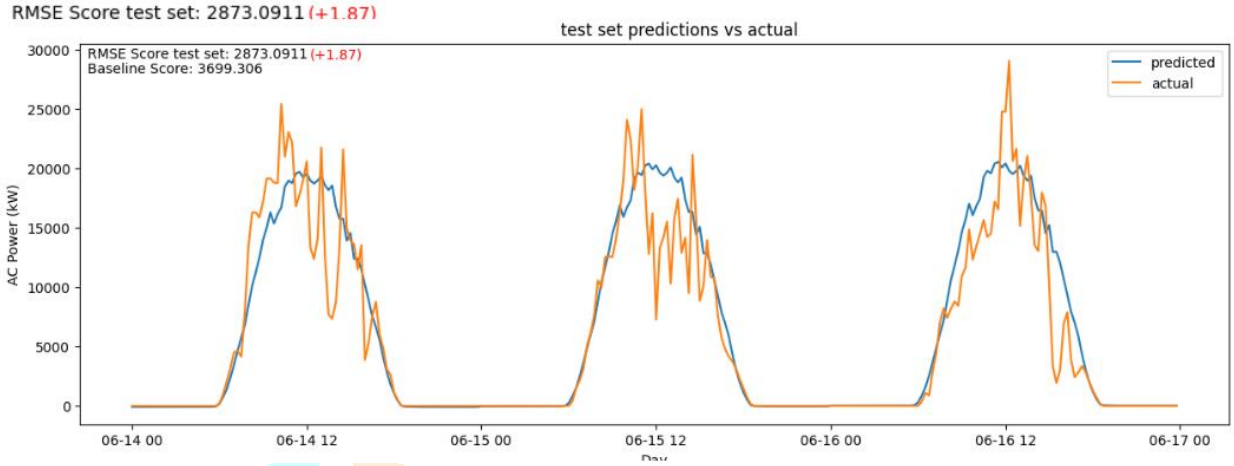

Figure 6: Result by KNN

- **XGBoost for Solar Power Generation Forecasting**

Extreme Gradient Boosting (XGBoost) is a powerful machine learning algorithm that excels in tasks like solar power generation forecasting due to its ability to handle complex relationships between features. Using the dataset, features such as AMBIENT_TEMPERATURE, MODULE_TEMPERATURE, and lagged IRRADIATION values can be used to train the model. XGBoost builds an ensemble of decision trees by iteratively minimizing prediction errors. For instance, to predict the IRRADIATION at a specific time, XGBoost uses both the historical weather data and derived features (e.g., time of day or previous IRRADIATION values). Its built-in regularization reduces overfitting, making it robust for capturing nonlinear relationships in the data. After training, the model combines the predictions of all decision trees to deliver accurate forecasts, adapting well to dynamic weather patterns affecting solar power generation.

- Data Preprocessing:

1. Negate SOURCE_KEY column.
2. Handle missing values using XGBoost's in-built handling mechanism.
3. Normalize or standardize features for better convergence.

- Feature Engineering:

1. Create lag-based features (e.g., previous hour's IRRADIATION, AMBIENT_TEMPERATURE).
2. Add time-based features (e.g., hour of the day or season) to enhance prediction accuracy.

- Model Training:

1. Define XGBoost parameters such as Learning rate (η). Maximum tree depth.
2. 188 Number of estimators (trees).
3. Loss function (e.g., RMSE for regression).
4. Train the model using historical data with features (AMBIENT_TEMPERATURE, MODULE_TEMPERATURE, etc.) as input and the target (IRRADIATION) as output.

- Prediction:

Used the trained model to predict IRRADIATION values for new data. Aggregate predictions from all trees to generate the final forecast. Thus resulting the RMSE of 3049.5895.

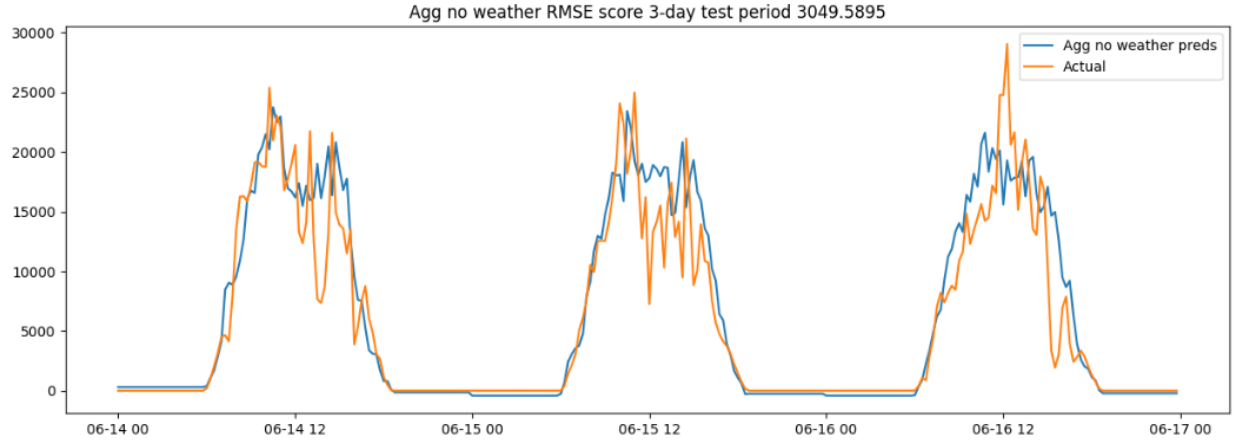

Figure 6: Result by XGBoost

6. CONCLUSION AND FUTURE SCOPE

This research demonstrates the efficacy of combining ML and DL models for solar power generation prediction. By integrating LSTM, KNN, and XGBoost, the proposed approach addresses key challenges in time-series forecasting, achieving high accuracy and robustness. Each algorithm processes the given dataset uniquely, with LSTM leveraging temporal dependencies, KNN relying on feature-based similarity, and XGBoost using ensemble learning to optimize predictions for solar power forecasting. However, LSTM achieves the best RMSE score of 2871.22 which is less than KNN with 2873.09 and XGBoost with 3049.5895 therefore based on the RMSE score the LSTM can be used as de-facto model for the solar power generation forecasting. Future work will focus on real-time system deployment and exploring advanced hybrid models incorporating ensemble techniques and attention mechanism

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