SOLAR POWER PREDICTION USING CLOUD MOTION ESTIMATION

A
Project Seminar Report
Submitted in partial fulfillment of the
Requirements for the award of the Degree of

BACHELOR OF ENGINEERING

IN

INFORMATION TECHNOLOGY

By

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DECLARATION BY THE CANDIDATE

We, **T. Devi Srujana, D. Lalitha Sowjanya** and **R. Sai Sathvik** bearing hall ticket number, **1602-20-737-011, 1602-20-737-019** and **1602-20-737-035** hereby declare that the project report entitled "**SOLAR POWER PREDICTION USING CLOUD MOTION ESTIMATION"** under the guidance of **Mrs. S. Aruna**, **Associate Professor**, Department of **Information Technology**, Vasavi College of Engineering, Hyderabad, is submitted in partial fulfillment of the requirement for the award of the degree of **Bachelor of Engineering** in **Information Technology.**

This is a record of bonafide work carried out by us and the results embodied in this project report have not been submitted to any other university or institute for the award of any other degree or diploma.

T. Devi Srujana (1602-20-737-011)
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BONAFIDE CERTIFICATE

This is to certify that the project entitled **"SOLAR POWER PREDICTION USING CLOUD MOTION ESTIMATION"** being submitted by **T. Devi Srujana**, **D. Lalitha Sowjanya** and **R. Sai Sathvik** bearing **1602-20-737-011**, **1602-20-737-019, 1602-20-737-035** in partial fulfillment of the requirements for the award of the degree of Bachelor of Engineering in Information Technology is a record of bonafide work carried out by them under my guidance.

Mrs. S. Aruna		**Dr. K. Ram Mohan Rao**
Associate Professor		**Professor,**
Internal Guide	**External Examiner**	**HOD, IT**

ACKNOWLEDGEMENT

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ABSTRACT

To relieve the global environment crisis, developing solar power generation technology is an efficient approach. But solar energy is an energy source with strong uncertainty because of the effect of climatic changes like rainfall, cloud movements e.t.c which restricts large scale photovoltaic (PV) applications until accurate solar energy predictions can be achieved. PV power forecasting methods have been widely researched based on existing predictions of satellite-derived solar irradiance, whereas modelling cloud motion directly from satellite images is still a tough task. In this project an end-to-end short term forecasting model is developed to take previous PV values as inputs, and it can learn the cloud motion characteristics from stacked optical flow maps. To reduce the huge size of measurements, static regions of interest (ROIs) are scoped based on historical cloud velocities. With its well-designed deep learning architecture, the proposed model can output multi-step-ahead prediction results. According to comparisons with related studies, the proposed model outperforms persistence and derived methods. The model can be applied to PV plants or arrays in different areas, suitable for forecast horizons within three hours.

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LIST OF ABBREVIATIONS

1. LSTM – Long Short Term Memory
2. DL - Deep Learning
3. CMV – Cloud Motion Vectors
4. RMSE – Root Mean Squared Error
5. MLP - Multilayer Perceptron
6. CNN - Convolution Neural Network

1. INTRODUCTION:

1.1. Problem Statement

Accurate predictions of solar energy are essential for the successful operation of large-scale photovoltaic (PV) applications. The power output of PV farms can fluctuate significantly due to the variability in cloud motions. To address this challenge, the problem statement for solar power prediction using cloud motion estimation focuses on developing a system that can effectively compensate for the impact of cloud movements on solar irradiance in advance. By accurately estimating cloud motion through innovative techniques like deep learning models, cloud-tracking methodologies, and cloud motion vectors from ground sensors, the goal is to enhance the precision of short-term solar irradiance forecasts within a few minutes. This approach involves leveraging technologies such as total sky imagers, sky-facing cameras to detect cloud movements, estimate future cloud positions over solar panels, and predict solar irradiance fluctuations caused by cloud transients. By integrating cloud motion estimation into solar power prediction models, this research aims to improve the reliability and efficiency of solar energy production, enabling grid operators to proactively manage solar power variability and optimize energy generation from PV systems.

1.2. Proposed Method

The Multi-Step PV Power Generation Framework with Long-Short Term Memory (LSTM) method involves utilizing LSTM-based models to predict solar power generation by integrating past and present photovoltaic (PV) values with cloud motion estimated values. This approach aims to enhance the accuracy of short-term solar power forecasting by considering both historical PV data and real-time cloud motion information. By leveraging LSTM neural networks, which are well-suited for sequence prediction tasks, the framework can effectively capture the complex relationships between PV power generation, cloud movements, and other relevant variables.

Specifically, the LSTM model processes sequential data, such as historical PV power outputs and cloud motion patterns, to learn patterns and dependencies over time. By training the LSTM network on a combination of past PV values and cloud motion estimates, the model can predict future solar power generation levels based on the evolving cloud cover and atmospheric conditions. This integration allows for a more dynamic and responsive prediction system that can adapt to changing weather patterns and cloud movements.

Overall, the Multi-Step PV Power Generation Framework with LSTM method offers a sophisticated approach to solar power prediction by fusing historical PV data with real-time cloud motion estimations. This integration enables more accurate and reliable forecasts of solar energy generation, essential for optimizing the efficiency and stability of PV systems in the presence of variable cloud cover and changing weather conditions.

1.3. Scope & objectives of the proposed work

The proposed framework aims to leverage Deep Learning and Convolutional Neural Network (CNN) techniques to estimate solar power by integrating modules for cloud motion estimation and solar power prediction. By utilizing advanced deep learning algorithms like Long Short-Term Memory (LSTM) and CNN-LSTM architectures, this framework seeks to enhance the accuracy of solar power forecasting by considering the dynamic nature of cloud movements and their impact on solar irradiance. The integration of cloud motion estimation allows for real-time adjustments in solar power predictions, enabling more precise and responsive forecasting.

The results generated from this framework can be valuable for weather predictors and educational institutions. Weather forecasters can benefit from improved solar power predictions to enhance their understanding of solar energy generation patterns and optimize energy planning. Educational institutions can utilize the framework to teach students about the intricate relationship between cloud dynamics and solar power generation, fostering knowledge and innovation in renewable energy technologies.

Moreover, the scalability and adaptability of the proposed framework offer the potential for further expansion and implementation in various settings. By continuously refining the deep learning models and incorporating new data sources, the framework can evolve to accommodate changing environmental conditions and technological advancements. This adaptability makes the framework a versatile tool for enhancing solar power prediction accuracy and supporting advancements in renewable energy research and applications.

1.4 ORGANIZATION OF REPORT

Introduction: The introduction sets the stage for the report by offering background information about the project, outlining its scope, and clearly stating the objectives and research questions that will be addressed.

Literature Survey: In this section, a comprehensive summary and evaluation of existing research and literature relevant to the project are provided. It serves to establish the context and theoretical framework for the study.

Proposed Work: The proposed work section details the research methods and procedures that will be employed throughout the project. It outlines the approach that will be taken to address the research questions and achieve the project objectives.

Experimental Study: This part of the report delves into the specifics of each dataset pre-processing. It explains the steps taken to prepare the data for analysis, ensuring transparency and reproducibility in the research process.

Summary and Future Scope: The summary and future scope section encapsulates the key findings and conclusions drawn from the project. It offers a concise overview of the outcomes and implications of the research while also suggesting potential avenues for future exploration and development.

References: The references section is a crucial component of the report, providing a comprehensive list of all sources cited throughout the document. It follows a consistent citation style to ensure proper credit is given to the original authors and to enable readers to locate the referenced material easily.

2. LITERATURE SURVEY:

The prediction of short-term photovoltaic (PV) power generation involves three primary methodologies: statistical, numerical weather prediction (NWP), and image-derived approaches, each tailored for specific forecast horizons. NWP is particularly effective for longer-term predictions, while statistical and image-derived methods are more suitable for intraday forecasts. Statistical methods rely on historical data, sometimes combined with real-time weather measurements.

On the other hand, image-derived techniques, which heavily depend on weather inputs, notably enhance accuracy within a few hours. One of the challenges faced is cloud motion prediction, leading to the emergence of methods incorporating cloud motion vectors (CMVs). Existing studies often concentrate on data inputs, sometimes overlooking temporal cloud motion. While convolutional neural networks (CNNs) enhance image-based methods, they may encounter difficulties with temporal learning. To address this, multi-frame image learning models are essential, yet research in this area remains limited.

Extracting cloud motion from derived inputs poses challenges, highlighting the necessity for models capable of handling multiple frames and effectively utilizing extensive data. Research gaps persist in understanding the effects of image size on cloud recognition and the complexities associated with managing large datasets. Moreover, incorporating imagery introduces additional complexities like data pre-processing, cloud cover correction, and spectral band selection, which require further exploration and optimization in forecasting short-term PV power generation accurately.

One of the key challenges in this field is the effective utilization of cloud motion information for short-term PV power forecasting. While convolutional neural networks (CNNs) have shown promise in image-based methods, they may struggle with capturing temporal dynamics. To address this, multi-frame image learning models are essential, yet research in this area remains limited.

Overall, the prediction of short-term PV power generation is a complex task that requires a combination of statistical, NWP, and image-derived approaches, each with its own strengths and limitations. Ongoing research aims to address the challenges posed by cloud motion prediction, data management, and the integration of multi-frame image learning models to enhance the accuracy and reliability of short-term PV power forecasting.

3. PROPOSED WORK:

The proposed work in the paper proposes a framework for data-driven solar energy estimation. The algorithm for solar energy prediction using cloud motion estimation with LSTM includes the following steps:

- Estimate cloud movement using TSI images.
- Select relevant features for prediction.
- Train an LSTM model on preprocessed data.
- Evaluation of model performance.
- Monitor and update the model over time.

Cloud Development Estimation: This step includes assessing cloud development in sky utilizing methods such as spatio-temporal relationship investigation of irradiance information or lackey symbolism. This data is utilized to foresee the future position of clouds and their impact on sun based radiation.

Feature determination: Recognize significant highlights that have a noteworthy effect on solar vitality generation, such as cloud movement vectors, sun powered radiation, and meteorological conditions. Utilize space information and factual procedures to select the most instructive highlights for the LSTM show. Consider, including intelligent and potential non-linear connections to move forward forecast accuracy.

Model Preparing: Plan an LSTM engineering with fitting input and yield layers, covered up units, and actuation capacities. Part the information into preparing and approval sets for demonstrate preparing and assessment. Prepare an LSTM demonstrate utilizing back propagation in time (BPTT) to learn transient designs in the information and optimize demonstrate parameters.

Model Assessment: Model demonstrates execution utilizing assessment measurements such as RMSE, R-squared, or precision depending on the expectation errand. Compare anticipated values with real perceptions to confirm demonstrate precision and generalizability. Perform cross-validation or time-series approval to guarantee the strength and unwavering quality of the demonstrate beneath distinctive scenarios.

Model Checking and Upgrades: Make a checking framework to screen demonstrate execution measurements and distinguish deviations or floats in forecasts. Execute input circle that occasionally overhauls the demonstrate with modern information and retrains it to move forward forecast precision.

3.1. ALGORITHM:

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture that is particularly effective in handling long-range dependencies and capturing patterns in sequential data. It has gained popularity in various fields, including time series prediction, natural language processing, solar power prediction.

LSTM Overview:

It involves 3 stages:

1. Recurrent Neural Networks (RNNs):

   - Traditional neural networks lack the ability to consider previous inputs when processing the current one. RNNs were introduced to address this issue by maintaining a hidden state that captures information about past inputs.

2. Vanishing Gradient Problem:

   - RNNs, however, suffer from the vanishing gradient problem, which makes it challenging for them to learn long-range dependencies.

3. LSTM Architecture:

- LSTMs were designed to overcome the vanishing gradient problem. They have a more complex structure, including a memory cell and various gates (input gate, forget gate, output gate).
- The memory cell allows information to be stored or removed, and the gates regulate the flow of information.

3.2. BLOCK DIAGRAM:

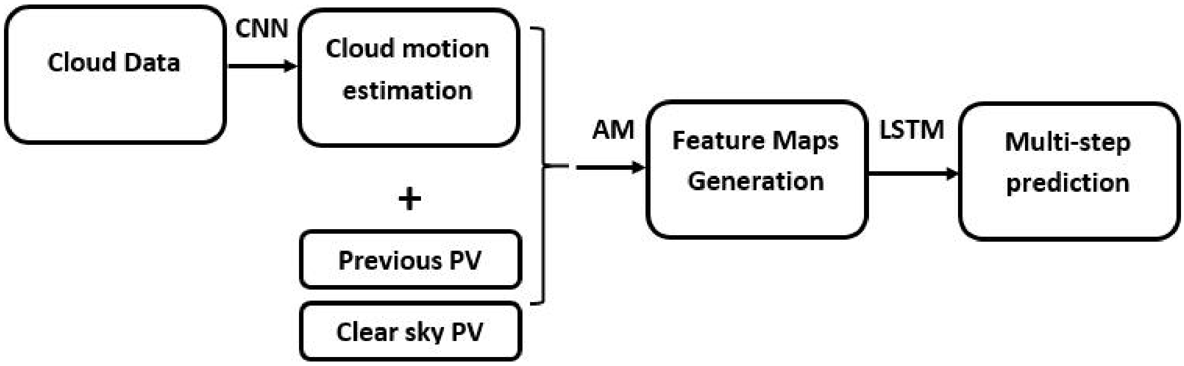

Figure 1. Block diagram

The above figure 1 depicts the working of the proposed LSTM model. The cloud motion estimation is done based on the collected cloud data combined with the previous and clear sky PV values to form feature maps. These feature maps capture essential features from the input to aid the LSTM network in predicting PV values.

4. EXPERIMENTAL SETUP:

4.1. DATASET:

Collection of dataset:

The proposed system for solar vitality forecast utilizing cloud movement estimation was assessed on the dataset. The table 1 dataset includes 21 distinctive variables such as temperature, wind speed, cloud cover, solar azimuth, etc. The components were handled utilizing the proposed systemto get real-time gauges of PV values.

distance-to-solar-noon	temperature	wind-direction	wind-speed	sky-cover	visibility	humidity	average-wind-speed-(period)	average-pressure-(period)	power-generated
0.859897172	69	28	7.5	0	10	75	8	29.82	0
0.628534704	69	28	7.5	0	10	77	5	29.85	0
0.397172237	69	28	7.5	0	10	70	0	29.89	5418
0.165809769	69	28	7.5	0	10	33	0	29.91	25477
0.065552699	69	28	7.5	0	10	21	3	29.89	30069
0.296915167	69	28	7.5	0	10	20	23	29.85	16280
0.528277635	69	28	7.5	0	10	36	15	29.83	515
0.759640103	69	28	7.5	0	10	49	6	29.86	0
0.862113402	72	29	6.8	0	10	67	6	29.86	0
0.630154639	72	29	6.8	0	10	49	0	29.87	0
0.398195876	72	29	6.8	0	10	54	0	29.9	4939
0.166237113	72	29	6.8	0	10	64	0	29.92	24335
0.065721649	72	29	6.8	0	10	23	9	29.88	29025
0.297680412	72	29	6.8	0	10	30	18	29.84	15408
0.529639175	72	29	6.8	0	10	65	11	29.84	491
0.761597938	72	29	6.8	0	10	75	5	29.85	0
0.86545925	73	29	7.9	0	10	72	6	29.84	0
0.632600259	73	29	7.9	0	10	78	6	29.86	0
0.399741268	73	29	7.9	0	10	63	0	29.88	4854
0.166882277	73	29	7.9	0	10	69	3	29.88	23855

Table 1. Dataset

LINK: https://www.neuraldesigner.com/learning/examples/solar-power-generation/

4.2. SOFTWARE REQUIREMENTS

• Python

• Keras

• Pandas

• Jupyter

4.3. PREPROCESSING:

The raw data had the following issues:

• No datetime index

• Some negative values (such as -99999) for features that should only have positive values

• Some outliers

• Missing data

• Unneeded columns

To get the data into usable form, Steps followed:

• custom function to convert existing time features to a datetime object.

• Set negative values to 0.

• Remove and impute outliers.

• Drop unneeded columns

4.4 RESULTS

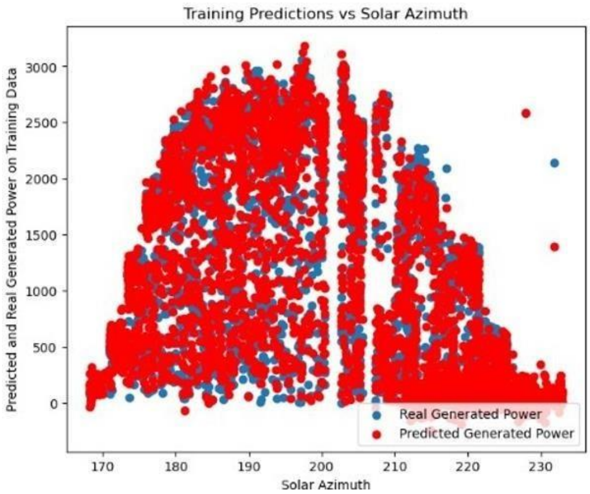

Figure 2. Training predictions vs solar azimuth using LSTM

The figure 2 shows training predictions vs. solar azimuth in solar power prediction using cloud motion estimation illustrates the performance of the model during the training phase in predicting the solar azimuth. Solar azimuth refers to the horizontal angle between the sun's position and the north direction, which is crucial for optimizing the orientation of solar panels to maximize energy production. In this context, the graph likely displays the comparison between the actual solar azimuth values and the predicted values generated by the model during the training process.

The training predictions vs. solar azimuth graph provides a visual representation of how well the model captures the relationship between cloud motion, solar irradiance, and the resulting solar azimuth. It showcases the accuracy of the model in predicting the solar azimuth based on the estimated cloud movement derived from Total Sky Imager (TSI) images and other relevant features selected for prediction.

The graph's trendline or data points may indicate the degree of alignment between the predicted solar azimuth values and the actual values observed during the training period. A close match between the training predictions and the actual solar azimuth values would suggest that the model has successfully learned and generalized the patterns associated with cloud motion and solar energy generation.

By analyzing the graph showing training predictions vs. solar azimuth, researchers and practitioners can assess the model's performance in capturing the complex dynamics of cloud movement and its impact on solar energy production. This evaluation is essential for refining the model, enhancing its predictive capabilities, and ultimately improving the accuracy of short-term solar power forecasts based on cloud motion estimation.

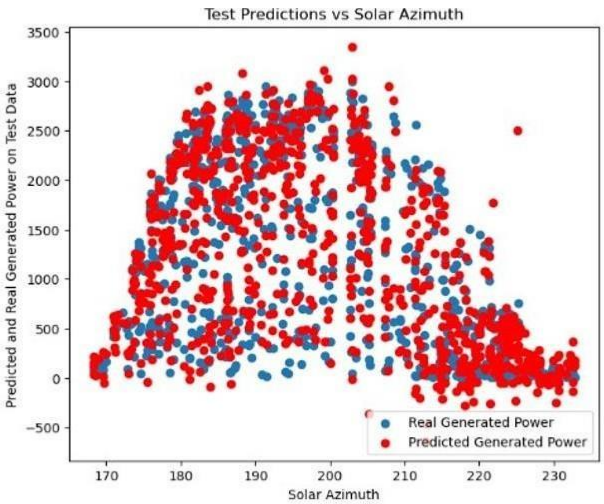

Figure 3. Test predictions vs solar azimuth using LSTM

The figure 3 shows test predictions vs. solar azimuth in solar power prediction using cloud motion estimation illustrates the model's performance during the testing phase in predicting the solar azimuth. Solar azimuth, which represents the horizontal angle between the sun's position and the north direction, is a critical factor in optimizing solar panel orientation for efficient energy production. In this context, the graph would display the comparison between the actual solar azimuth values and the predicted values generated by the model during the testing period.

This graph provides a visual representation of how accurately the model can forecast the solar azimuth based on cloud motion estimation and other relevant features. It demonstrates the model's ability to predict the solar azimuth under real-world conditions, reflecting its effectiveness in capturing the dynamics of cloud movement and its impact on solar energy generation.

The trendline or data points on the graph may indicate the level of agreement between the predicted solar azimuth values and the actual values observed during the testing phase. A close alignment between the test predictions and the true solar azimuth values would suggest that the model has successfully generalized its learning from the training phase to make accurate predictions on unseen data.

By analyzing the graph showing test predictions vs. solar azimuth, researchers and practitioners can evaluate the model's performance in predicting solar azimuth values outside the training data. This evaluation is crucial for assessing the model's robustness, reliability, and generalizability in forecasting solar energy production based on cloud motion estimation, ultimately contributing to the optimization of solar energy systems for enhanced efficiency and performance.

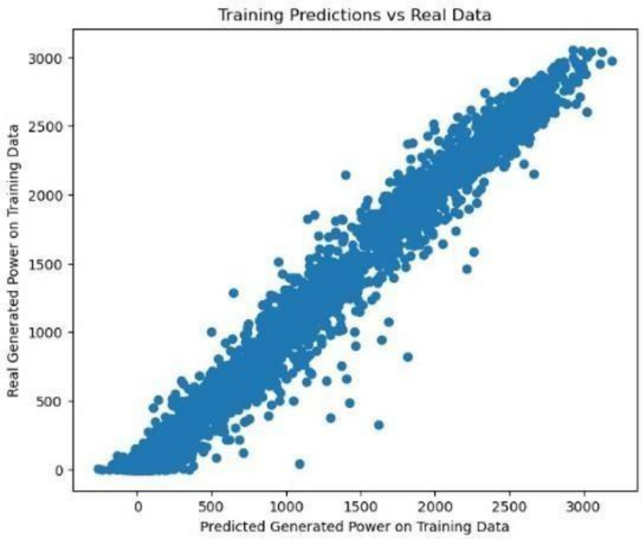

Figure 4. Training predictions vs Real data using LSTM

The figure 4 shows training predictions vs. real values of solar power in solar power prediction using cloud motion estimation illustrates the model's performance during the training phase in predicting solar power output based on cloud motion estimation. In this context, the graph displays the comparison between the predicted solar power values generated by the model and the actual observed values during the training period.

This graph provides a visual representation of how well the model can forecast solar power generation by incorporating cloud motion estimation and other relevant features. It demonstrates the accuracy of the model in predicting solar power output under simulated conditions, reflecting its ability to capture the complex relationships between cloud movement, solar irradiance, and energy production.

The trendline or data points on the graph may indicate the level of agreement between the predicted solar power values and the actual values recorded during the training phase. A close alignment between the training predictions and the real solar power values would suggest that the model has successfully learned and generalized the patterns associated with cloud motion and its impact on solar energy generation.

By analyzing the graph showing training predictions vs. real values of solar power, researchers and practitioners can evaluate the model's performance in forecasting solar power output based on cloud motion estimation. This evaluation is crucial for refining the model, improving its predictive capabilities, and ultimately enhancing the accuracy and reliability of short-term solar power forecasts, contributing to the efficient management and integration of solar energy systems.

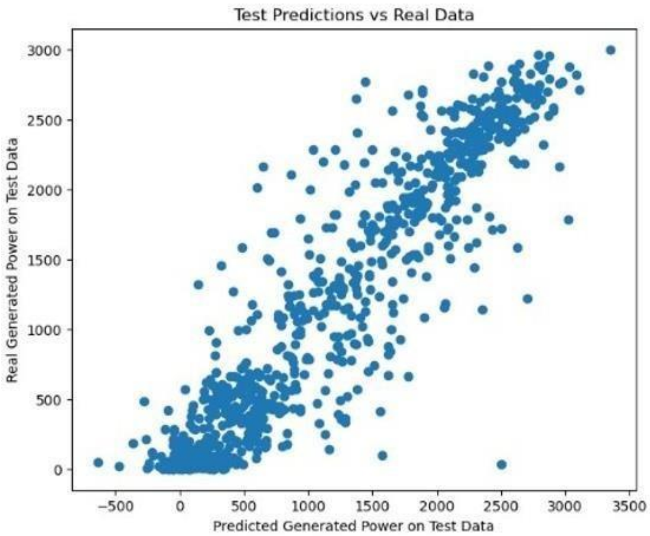

Figure 5. Test predictions vs Real data using LSTM

The figure 5 shows test predictions vs. real values of solar power in solar power prediction using cloud motion estimation likely illustrates the model's performance during the testing phase in predicting solar power output based on cloud motion estimation. This graph would display the comparison between the predicted solar power values generated by the model and the actual observed values during the testing period.

In this context, the graph provides a visual representation of how accurately the model can forecast solar power generation under real-world conditions, incorporating cloud motion estimation and other relevant features. It demonstrates the model's ability to predict solar power output outside the training data, reflecting its effectiveness in capturing the dynamics of cloud movement and its impact on solar energy generation.

The trendline or data points on the graph may indicate the level of agreement between the predicted solar power values and the actual values recorded during the testing phase. A close alignment between the test predictions and the real solar power values would suggest that the model has successfully generalized its learning from the training phase to make accurate predictions on unseen data, showcasing the model's reliability and generalizability.

By analyzing the graph showing test predictions vs. real values of solar power, researchers and practitioners can evaluate the model's performance in forecasting solar power output based on cloud motion estimation beyond the training data. This evaluation is crucial for assessing the model's robustness, reliability, and accuracy in predicting solar energy production, contributing to the optimization and efficiency of solar energy systems.

	Real Solar Power Produced	Predicted Solar Power
1	1,159.14	862.61
2	1,798.44	1,961.02
3	2,196.65	1,119.86
4	86.92	178.92
5	380.08	537.78
6	876.92	1,226.14
7	2,464.53	2,392.53
8	1,766.89	1,702.31
9	2,127.15	2,004.11
10	359.65	651.27

Table 2. Real solar power vs Predicted solar power

The table 2 shows the real and predicted values of solar power in solar power prediction using cloud motion estimation likely presents a comparison between the actual solar power measurements and the model's forecasted solar power output.

This table provides a quantitative evaluation of the model's performance in predicting solar power generation based on the estimated cloud motion and other relevant features. The table may include columns for the actual (or "real") solar power values and the corresponding predicted values generated by the model.

By comparing the real and predicted solar power values, the table allows researchers and practitioners to assess the accuracy and reliability of the solar power prediction model. Key metrics that may be included in the table are:

1. Actual/Real Solar Power: The observed or measured solar power values, which serve as the ground truth for evaluating the model's predictions.

2. Predicted Solar Power: The solar power values forecasted by the model using the cloud motion estimation and other input features.

3. Absolute Error: The difference between the actual and predicted solar power values, which indicates the magnitude of the prediction error.

4. Relative Error: The absolute error expressed as a percentage of the actual solar power value, providing a measure of the prediction accuracy.

5. Statistical Metrics: Depending on the study, the table may also include performance metrics such as Root Mean Squared Error (RMSE), R-squared, or Mean Absolute Percentage Error (MAPE) to quantify the overall model accuracy.

Comparison with SPFNet:

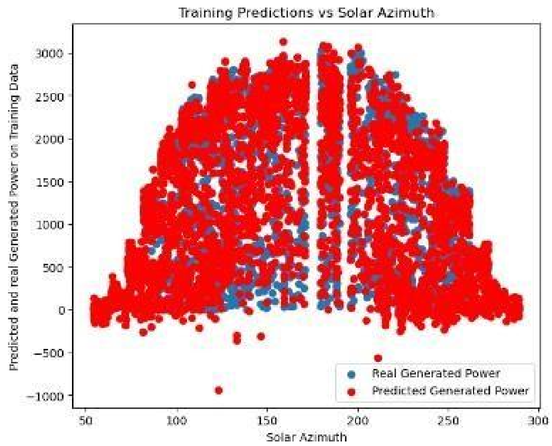

Figure 6. Training predictions vs solar azimuth using SPFNet

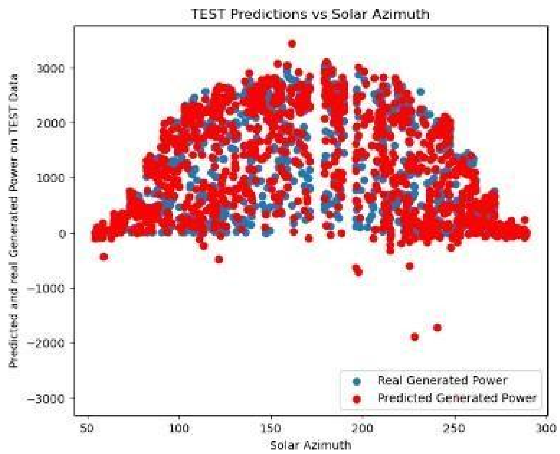

Figure 7. Test predictions vs solar azimuth using SPFNet

The above figures figure 6 and figure 7 illustrates the training and test predictions vs solar azimuth for the SPFNet model. These figures provide a visual representation of the accuracy of the models in predicting the solar azimuth, which is a critical factor affecting solar energy production.

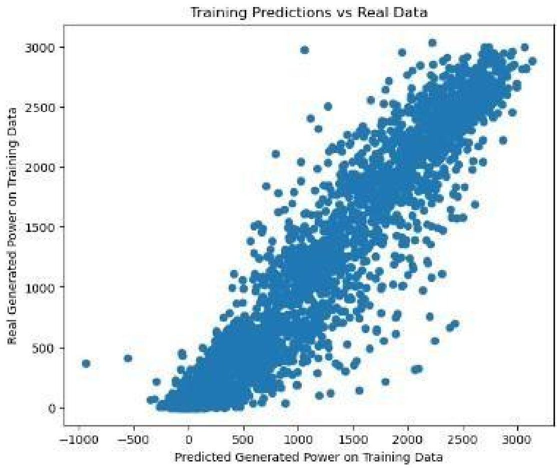

Figure 8. Training predictions vs Real data using SPFNet

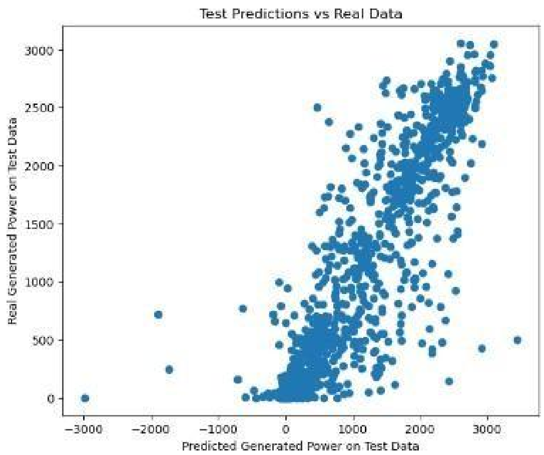

Figure 9. Test predictions vs Real data using SPFNet

The above figures figure 8 and figure 9 illustrates the training and test predictions vs Real Data for the SPFNet model, with predicted PV values plotted on the x-axis and real PV values on the y-axis.

	Real Solar Power Produced	Predicted Solar Power
7	2,497.53	2,508.76
8	514.65	604.34
9	916.92	1,102.97
10	1,911.95	1,884.42
11	35.15	321.71
12	2,449.04	2,508.14
13	38.84	948.87
14	823.41	2,121.19
15	2,274.65	2,222.83
16	1,123.40	1,151.78
17	946.53	1,341.53

Table 3. Real vs Predicted solar power using SPFNet Model

The table 3 in the study presents a comparison of the actual and predicted solar power values obtained from the proposed SPFNet model. The table includes columns for the actual solar power values, the predicted solar power values.

4.5 ANALYSIS:

Evaluation of the Solar Power Prediction Model

A modified LSTM model was trained and tested on the dataset to obtain the following results. The R2 score, Mean, Standard Deviation, Relative Standard Deviation were calculated. R2 score, Mean, Standard Deviation, Relative Standard Deviation are commonly used metrics to evaluate the performance of a machine learning model. Accuracy measures the proportion of correctly predicted labels out of all the labels. Mean measures the average of predicted values. A high accuracy, Standard Deviation, R2 Score indicate a well-performing model. Training metrics are calculated during the training phase of the model, where the model is trained on a portion of the available data. The purpose of training metrics is to evaluate the performance of the model on the training set and to monitor the progress of the model during training. Training metrics are used to adjust the model's parameters to minimize the error on the training set. Validation metrics, on the other hand, are calculated on a separate validation set that is not used during training. The purpose of validation metrics is to evaluate the model's performance on unseen data and to detect overfitting. Validation metrics are used to adjust the model's hyperparameters to optimize its performance on the validation set. The training and validation metrics are shown in the table below.

Evaluation metrics

	Value
R2 Score of Training Set	0.973996
R2 Score of Test Set	0.842314
Mean of Test Set	1206.380737
Standard Deviation pf Test Set	920.220032
Relative Standard Deviation	0.762794

Table 4. Evaluation metrics

The table 4 displays primary evaluation metrics used in the study to assess the accuracy of the model which include the R-Squared score, the mean of the test data, standard deviation, and relative standard deviation. These metrics are used to evaluate the performance of the model inpredicting solar radiation.

5. CONCLUSION & FUTURE SCOPE:

Cloud development estimation is a basic figure in sun based execution determining since it specifically influences the steadiness of sun based control era. Utilizing Add up to Sky Imager (TSI) symbolism to identify cloud developments and appraise future cloud positions over sun powered boards has appeared promising comes in the improvement of cloud development estimation adequate for lattice administrators to take sun oriented moderation measures the execution instability. LSTM models have been appeared to be compelling in foreseeing short-term sun powered radiation, with considers illustrating their capacity to altogether move forward the quality of cloud movement prediction. The proposed LSTM model in this study beated other models such as Variety Optical-flow (VOF), Gated Repetitive Unit (GRU) and Convolutional Long Short-term Memory (ConvLSTM) in anticipating short-term cloud movement. The utilization of LSTM-based models in sun based control determining has been appeared to progress the solidness of control era, encourage the advancement of commercially practical PV frameworks, and increment the competitiveness of sun powered PV assets. Be that as it may, there are still issues in cloud movement estimation methods, such as ceaseless changes in cloud shape, numerous cloud layers with distinctive speeds and headings, and misfortune of data in TSI pictures due to trailing arm, shadow band, and edge of circular pictures.

The future scope for the proposed model includes:

Integrate different information sources: Investigate the integration of other information sources such as meteorological information, adherent symbolism, and ground sensors to increment the exactness of sun-based control estimates. Investigate the effect of joining diverse information streams on the execution of an LSTM model in sun-based vitality forecasting.

Improved cloud movement estimation: Create progressed cloud movement estimation calculations that can capture complex cloud elements, numerous cloud layers, and quick cloud shape changes to move forward the precision of sun-oriented vitality figures. Actualize real-time cloud following procedures that can adjust to distinctive cloud designs and developments for more precise forecasts.

Long-Term Determining: Amplify the determining skyline past short-term figures to incorporate long-term estimates that span a few days, empowering utilities and lattice administrators to arrange for broader sun-oriented integration. Investigate the achievability of LSTM models for long-term sun-based vitality estimating and assess their execution in capturing regular changes and expanded climate patterns.

Model optimization and assessment: Optimize the LSTM design by testing with diverse organize arrangements, hyperparameters, and preparing methodologies to move forward the prescient capabilities of the demonstrate. Perform a comprehensive assessment of LSTM show execution utilizing different assessment measurements and approval strategies to guarantee the strength and unwavering quality of sun-oriented vitality predictions.

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APPENDIX

Code:

```
# Training data scatter plot

plt.subplot(1, 2, 1)

plt.scatter(x_axis_train, y_train_orig, label='Real Generated Power')

plt.scatter(x_axis_train, train_pred_orig, c='red', label='Predicted Generated
Power')

plt.ylabel('Predicted and Real Generated Power on Training Data')

plt.xlabel('Solar Azimuth')

plt.title('Training Predictions vs Solar Azimuth')

plt.legend(loc='lower right')


# Testing data scatter plot

plt.subplot(1, 2, 2)

plt.scatter(x_axis_test, y_test_orig, label='Real Generated Power')

plt.scatter(x_axis_test, y_pred_orig, c='red', label='Predicted Generated Power')
```

```
plt.ylabel('Predicted and Real Generated Power on Test Data')

plt.xlabel('Solar Azimuth')

plt.title('Test Predictions vs Solar Azimuth')

plt.legend(loc='lower right')

plt.show()

results = np.concatenate((y_test_orig, y_pred_orig), 1)

results = pd.DataFrame(data=results)

results.columns = ['Real Solar Power Produced', 'Predicted Solar Power']

#results = results.sort_values(by=['Real Solar Power Produced'])

pd.options.display.float_format = "{:,.2f}".format

#results[800:820]


results[1:14]

df_results = pd.DataFrame.from_dict({

    'R2 Score of Training Set': r2_score(train_pred_orig, y_train_orig),
```

```
    'R2 Score of Test Set': r2_score(y_pred_orig, y_test_orig),

 'Mean of Test Set': np.mean(y_pred_orig),

    'Standard Deviation pf Test Set': np.std(y_pred_orig),

'Relative Standard Deviation': np.std(y_pred_orig) / np.mean(y_pred_orig),

},orient='index', columns=['Value'])

display(df_results.style.background_gradient(cmap='afmhot', axis=0))
```

SOLAR POWER PREDICTION USING CLOUD MOTION ESTIMATION

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Abstract— Solar energy prediction is a crucial aspect of solar energy production, as the presence of clouds can significantly affect the amount of electricity produced by solar photovoltaic (PV) systems. Cloud motion estimation is a promising approach to predict solar radiation and the resulting solar output. This method involves analyzing the movements of clouds and estimating their future position above the solar panels in order to predict fluctuations in solar radiation. Cloud motion estimation is a promising approach to predict solar radiation and solar output. Recent studies have shown the potential of deep learning and machine learning techniques for solar predictions, with the algorithms achieving high levels of accuracy. Ground-based camera systems such as simple web cameras can also be used for short-term cloud motion prediction, achieving predicted results with an accuracy of up to 97.51% compared to actual results. Cloud-based motion estimation enables grid operators to manage energy production and demand, ensure grid stability, and prevent voltage fluctuation problems caused by solar radiation fluctuations.

Keywords— Deep learning, Cloud motion estimation, Solar power prediction, LSTM, Recurrent neural networks.

1. Introduction

The prediction of solar energy is essential for the integrating solar energy into the energy grid, as the presence of clouds can significantly affect the amount of electricity produced by solar photovoltaic (PV) systems. Cloud motion estimation is a promising approach to predict solar radiation and solar output. The detection of cloud movements from Total Sky Imager (TSI) images helps in the estimation of future positions of the clouds above solar panels, allowing the prediction of solar radiation fluctuations caused by transient clouds.

Deep learning techniques such as the Long Short-Term Memory (LSTM) algorithm have shown the potential to improve the cloud motion estimation quality for grid operators in a time window to take measures to mitigate solar power fluctuations. LSTM models can learn to predict long-term cloud movement for cloud motion estimation, including video image prediction, human motion prediction, and many other applications along with solar energy prediction.

The LSTM algorithm was used in solar power forecasting, achieving a high level of accuracy in solar irradiance and power forecasting. The use of LSTM models in solar energy prediction has been shown to improve the stability of power generation, facilitate the development of commercially viable PV systems, and increase the competitiveness of solar PV resources.

In this context, the combination of cloud motion estimation and LSTM algorithms represents a cutting-edge approach to solar energy prediction that offers a path to better prediction accuracy, better grid management, and increased utilization of solar energy resources. By leveraging the power of advanced machine learning techniques such as LSTM in conjunction with cloud motion estimation, the potential for more accurate and reliable solar energy predictions is increasingly achievable, paving the way for a more sustainable energy future.

In conclusion, cloud motion estimation using LSTM models has the potential to significantly improve solar power prediction, enable grid operators to manage power generation, ensure grid stability, and prevent voltage variability problems caused by solar radiation fluctuations.

2. Related Work

Cloud motion estimation for short-term solar radiation forecast Hao Huang et al. (2013) [1]: This research introduces a solar power forecasting system that identifies cloud motion from Total Sky Imager (TSI) pictures and projects forthcoming cloud positions on solar panel installations.

Photovoltaic System Performance Forecasting Using LSTM Neural Networks [2]: This thesis project investigates methods for forecasting photovoltaic (PV) system performance using LSTM convolutional neural networks. It highlights the superior performance of LSTM models compared to other proposed models for PV system performance prediction.

Short-term solar radiation forecasting [3]: This paper discusses the importance of cloud movement estimation for short-term solar radiation forecasting and related challenges. It highlights the need for cost-effective solutions that do not require any expensive equipment and at the same time meet the requirements for accuracy and performance.

Short-term solar radiation prediction using hybrid deep residual learning [4]: This study investigates hourly solar radiation predictions using LSTM models. The proposed LSTM model uses a hybrid deep residual learning approach to improve the accuracy of short-term solar radiation forecasting.

Advances in Solar Forecasting using Computer Vision with Deep Learning [5]: This article discusses the use of computer vision and deep learning for solar forecasting. Besides the potential of traditional models such as climate prediction models, it also demonstrates the advantages of deep learning models in predicting the future impact of climate change on solar energy production.

A comparative study of deep learning models for short-term solar energy forecasting [6]: This study compares the performance of deep learning models, including LSTM, in short-term solar forecasting. The results show that the LSTM model outperforms other models in terms of accuracy and robustness.

Deep Learning for Intra-hour Solar Power Forecasting Review [7]: This review article provides a comprehensive overview of deep learning techniques for hourly solar power forecasting. It discusses the use of LSTM models for solar energy prediction based on historical data and cloud motion estimation. The review also highlights challenges and future research directions in this area.

3. Methodology

The proposed work in the paper proposes a framework for data-driven solar energy estimation. The algorithm for solar energy prediction using cloud motion estimation with LSTM includes the following steps:

- Estimate cloud movement using TSI images.
- Collect and pre-process historical data.
- Select relevant features for prediction.
- Train an LSTM model on preprocessed data.
- Evaluation of model performance.
- Monitor and update the model over time.

Cloud Development Estimation: This step includes assessing cloud development in sky utilizing methods such as spatio-temporal relationship investigation of irradiance information or lackey symbolism. This data is utilized to foresee the future position of clouds and their impact on sun based radiation.

Data collection: Collect chronicled information from different sources such as climate stations, ground sensors such as lost values, exceptions, and information irregularities. Clean the information by expelling exceptions, rectifying mistakes, and taking care of lost values utilizing ascription or addition. Normalize the information to guarantee that all highlights are on a comparative scale, anticipating certain factors from overwhelming the preparation of the show. Change the information into arrangements reasonable for LSTM input with regard to time steps and window sizes to capture worldly dependencies.

distance-to-solar-noon	temperature	wind-direction	wind-speed	sky-cover	visibility	humidity	average-wind-speed-(period)	average-pressure-(period)	power-generated
0.859897172	69	28	7.5	0	10	75	8	29.82	0
0.628534704	69	28	7.5	0	10	77	5	29.85	0
0.397172237	69	28	7.5	0	10	70	0	29.89	5418
0.165809769	69	28	7.5	0	10	33	0	29.91	25477
0.065552699	69	28	7.5	0	10	21	3	29.89	30069
0.296915167	69	28	7.5	0	10	20	23	29.85	16280
0.528277635	69	28	7.5	0	10	36	15	29.83	515
0.759640103	69	28	7.5	0	10	49	6	29.86	0
0.862113402	72	29	6.8	0	10	67	6	29.86	0
0.630154639	72	29	6.8	0	10	49	0	29.87	0
0.398195876	72	29	6.8	0	10	54	0	29.9	4939
0.166237113	72	29	6.8	0	10	64	0	29.92	24335
0.065721649	72	29	6.8	0	10	23	9	29.88	29025
0.297680412	72	29	6.8	0	10	30	18	29.84	15408
0.529639175	72	29	6.8	0	10	65	11	29.84	491
0.761597938	72	29	6.8	0	10	75	5	29.85	0
0.86545925	73	29	7.9	0	10	72	6	29.84	0
0.632600259	73	29	7.9	0	10	78	6	29.86	0
0.399741268	73	29	7.9	0	10	63	0	29.88	4854
0.166882277	73	29	7.9	0	10	69	3	29.88	23855

Table 3.1

The above table 3.1 depicts the data used for training and testing the model, which includes various factors such as temperature, pressure, cloud coverage, wind speed, humidity, and solar azimuth that affect solar power radiation generation. These factors are essential for predicting solar power radiation accurately and efficiently.

Feature determination: Recognize significant highlights that have a noteworthy effect on solar vitality generation, such as cloud movement vectors, sun powered radiation, and meteorological conditions. Utilize space information and factual procedures to select the most instructive highlights for the LSTM show. Consider, including intelligent and potential non-linear connections to move forward forecast accuracy.

Model Preparing: Plan an LSTM engineering with fitting input and yield layers, covered up units, and actuation capacities. Part the information into preparing and approval sets for demonstrate preparing and assessment. Prepare an LSTM demonstrate utilizing back propagation in time (BPTT) to learn transient designs in the information and optimize demonstrate parameters.

Model Assessment: Model demonstrates execution utilizing assessment measurements such as RMSE, MAE, R-squared, or precision depending on the expectation errand. Compare anticipated values with real perceptions to confirm demonstrate precision and generalizability. Perform cross-validation or time-series approval to guarantee the strength and unwavering quality of the demonstrate beneath distinctive scenarios.

Model Checking and Upgrades: Make a checking framework to screen demonstrate execution measurements and distinguish deviations or floats in forecasts. Execute input circle that occasionally overhauls the demonstrate with modern information and retrains it to move forward forecast precision. Ceaselessly assess the demonstrate execution against pre-defined benchmarks and alter the expectation prepare for ideal results.

3.1 Proposed Model:

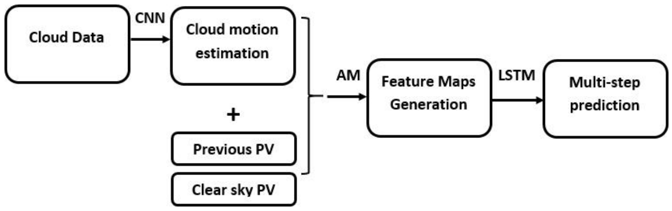

Figure 3.1.1

The above figure 3.1.1 depicts the working of the proposed LSTM model. The cloud motion estimation is done based on the collected cloud data combined with the previous and clear sky PV values to form feature maps. These feature maps capture essential features from the input to aid the LSTM network in predicting PV values.

4. Results

The proposed system for solar vitality forecast utilizing cloud movement estimation was assessed on the dataset. The dataset included 21 distinctive variables such as temperature, wind speed, cloud cover, solar azimuth, etc. The components were handled utilizing the proposed system to get real-time gauges of PV values. The proposed LSTM model's accuracy on the training dataset is 97.39% and 84.23% on the test dataset, which is a significant improvement compared to other models like SPFNet. The high accuracy of the proposed model demonstrates its effectiveness in predicting short-term solar radiation, which is crucial for optimizing the performance of solar power systems. The model's accuracy on the test dataset is also higher than other models, indicating its generalization ability and reliability in real-world applications. The study highlights the importance of cloud motion estimation in improving the accuracy of short-term solar radiation forecasting.

4.1. Comparison with the other prevalent demonstrate SPFNet

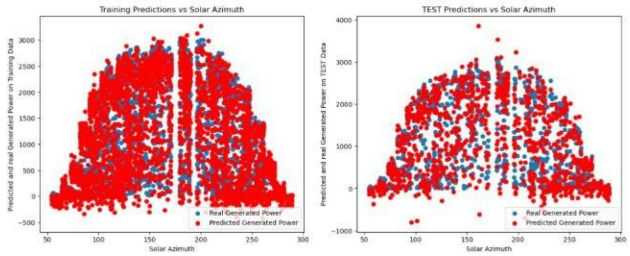

Figure 4.1.1 Results of solar power forecast using SPFNet.

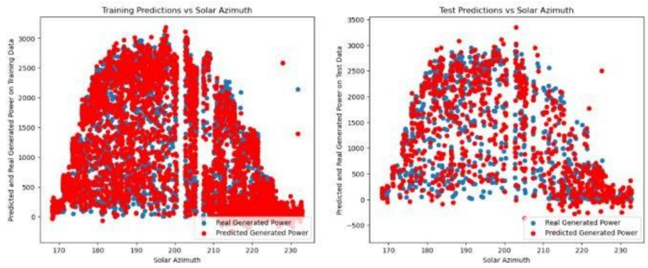

Figure 4.1.2 Results of solar power forecast using LSTM.

The figures 4.1.1 and 4.1.2 illustrates the comparison between the training and test predictions of solar azimuth for the LSTM and SPFNet models. These figures provide a visual representation of the accuracy of the models in predicting the solar azimuth, which is a critical factor affecting solar energy production.

4.2. Training data vs Testing data results

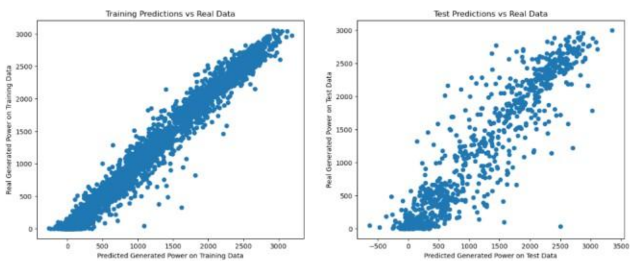

Figure 4.2.1

The above figure 4.2.1 illustrates the comparison between training and test predictions against actual PV values, with predicted PV values plotted on the x-axis and real PV values on the y-axis. This visualization provides a clear representation of the model's performance in forecasting photovoltaic (PV) system output, showcasing how well the predicted values align with the actual values.

4.3. Evaluation Metrics

	Value
R2 Score of Training Set	0.973996
R2 Score of Test Set	0.842314
Mean of Test Set	1206.380737
Standard Deviation pf Test Set	920.220032
Relative Standard Deviation	0.762794

Table 4.3.1

The above table 4.3.1 displays primary evaluation metrics used in the study to assess the accuracy of the model which include the R-Squared score, the mean of the test data, standard deviation, and relative standard deviation. These metrics are used to evaluate the performance of the model in predicting solar radiation.

4.4. Real vs Predicted Solar power values

	Real Solar Power Produced	Predicted Solar Power
1	1,159.14	862.61
2	1,798.44	1,961.02
3	2,196.65	1,119.86
4	86.92	178.92
5	380.08	537.78
6	876.92	1,226.14
7	2,464.53	2,392.53
8	1,766.89	1,702.31
9	2,127.15	2,004.11
10	359.65	651.27
11	1,827.95	1,774.06

Table 4.4.1

The above table 4.4.1 in the study presents a comparison of the actual and predicted solar power values obtained from the proposed LSTM model. The table includes columns for the actual solar power values, the predicted solar power values.

5. Future Work

Integrate different information sources: Investigate the integration of other information sources such as meteorological information, adherent symbolism, and ground sensors to increment the exactness of sun-based control estimates. Investigate the effect of joining diverse information streams on the execution of an LSTM model in sun-based vitality forecasting.

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6. Conclusion

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The utilization of LSTM-based models in sun based control determining has been appeared to progress the solidness of control era, encourage the advancement of commercially practical PV frameworks, and increment the competitiveness of sun powered PV assets. Be that as it may, there are still issues in cloud movement estimation methods, such as ceaseless changes in cloud shape, numerous cloud layers with distinctive speeds and headings, and misfortune of data in TSI pictures due to trailing arm, shadow band, and edge of circular pictures.

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