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DEEP LEARNING BASED MODEL FOR PREDICTION OF INCOMING SOLAR RADIATION USING SATELLITE DATA

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Abstract: The study proposes a deep learning approach to predict solar radiation by utilizing data from meteorological measurement stations and satellite imagery. Accurately estimating solar radiation is crucial for successful integration of solar photovoltaics into existing electrical grid systems. Solar energy is widely favored as a renewable energy source. The study assessed the performance of deep learning-based predictive models and regression models across different climate conditions and provided recommendations for further research. The model achieved highly accurate half hourly insolation forecasts worldwide, but encountered errors during sunrise and sunset periods. Incorporating elements associated with sunrise and sunset could have potentially prevented these mistakes.

IndexTerms - **Solar Energy, INSAT3D, RNN, LSTM, Deep Learning.**

I. INTRODUCTION

Climate change induced by greenhouse gas emissions has sparked worldwide concern, with 55 countries proclaiming carbon neutrality by October 2021. Because energy consumption accounts for 76% of greenhouse gas emissions, lowering energy consumption and substituting renewable energy sources for fossil fuels are critical. Because buildings consume roughly 40% of total energy, high-efficiency technologies and renewable energy sources are critical for netzero-energy structures and smart cities. Energy usage efficiency must be optimized, and a building management system (BMS) that incorporates an energy management system (EMS) and a building automation system (BAS) must be established to attain net-zero-energy buildings. EMS can save up to 16% of yearly energy consumption in buildings, but accurate energy output and consumption forecasting is required for stable functioning. Buildings can use a variety of renewable energy sources, the most prevalent of which being photovoltaic power generation and solar thermal collection. Insolation has a large impact on solar power generation and solar heat gathering. Accurately estimating insolation is critical for projecting building power consumption, as well as the quantity of photovoltaic power output and solar thermal collection. Insolation has been predicted using physical and statistical models, as well as machine learning and artificial intelligence. Finally, precise insolation prediction is critical for energy savings in buildings. As a result, numerous studies have been carried out in order to establish reliable predictive models for insolation using physical and statistical models as well as machine learning approaches. This is critical for net-zero-energy buildings and smart cities, as well as for lowering greenhouse gas emissions and mitigating climate change.

The objective of this article is to conduct a detailed analysis of solar energy forecasting by utilizing data obtained from INSAT3D and employing deep learning technology. The article aims to accomplish the following goals:

1. Overview of Solar Energy Forecasting: This parameter offers a concise overview of solar energy forecasts, including their significance, challenges, and existing technologies. Additionally, it discusses the advantages of precise solar forecasting, such as enhanced energy management, cost reduction, and improved efficiency.

2. Description of Data Collection Process: The article outlines the process of data collection, encompassing the utilized sensors, data collection frequency, and collected variables. This section also addresses the quality and reliability of the data, as well as the preprocessing steps undertaken to prepare the data for analysis.

3. Explanation of Deep Learning Technique for Daily Forecasting: A comprehensive description of the deep learning technique employed for the 30-minute unit forecast is provided in this report. The section covers the architecture of deep learning models, including the number of layers and nodes, the activation function utilized, and the optimization algorithm implemented.

4. Presentation of Analysis Results: The article presents the findings of the analysis, including the validation of assumptions and the insights gained from the study. This section also discusses the limitations of the test and suggests potential avenues for future research.

5. Recommendations for Enhancing Data Forecasts: Drawing upon the analysis results, the article puts forward recommendations for improving data forecasts. This section encompasses various aspects such as data collection, model architecture, and optimization techniques.

6. Emphasizing the Importance of Research: The article underscores the significance of research in the field of solar energy forecasting and its potential impact on the energy industry. It further explores the limitations of the study and suggests potential directions for future research.

7. In summary, this article aims to provide a comprehensive comprehension of solar energy forecasting utilizing data gathered from INSAT3D and employing deep learning techniques. It highlights the potential benefits of accurate solar energy forecasting and emphasizes the importance of research within the energy industry. Moreover, it provides recommendations for enhancing solar energy projections and identifies potential areas for future research.

II. METHODOLOGY

Data from INSAT3D were collected as part of the methodology's first step. The information gathered includes radiance in the visible band channel, a crucial factor in predicting solar energy. Half-hourly data collection cycles were used, which is an appropriate frequency for energy forecasting.

1. Data preparation: The preprocessing of the data was the next stage of the methodology. A Look-Up Table (LUT) was used to convert the visible channel image data to radiance values and converted radiance to irradiance. This is required because radiance measurements alone cannot give a complete picture of solar energy because they do not account for atmospheric conditions and other variables that may have an impact on the amount of energy reaching the earth's surface.

2. The model architecture: The deep learning RNN model for solar energy prediction was created with an architecture that considers the time-series nature of the data. The Long Short-Term Memory (LSTM) network with multiple layers was specifically used in the model. The model's input was historical irradiance data, and its output was the forecasted irradiance for the ensuing half hour.

3. Training and evaluation: A training dataset was used to train the model on the preprocessed data, and a different testing dataset was used to test it. The remaining 20.

4. Performance assessment: The performance of the deep learning RNN model was evaluated using two metrics: the R-squared score and the root mean square error (RMSE). These metrics were used to assess the model's predictive power and assess how well it performed in comparison to other methods for forecasting solar energy.

Data from INSAT3D were gathered for this project report, and it was preprocessed using LUT to separate radiance from irradiance. Then, for a half-hourly prediction of solar power output, a deep learning RNN model with a stacked LSTM network was created. The model was tested and trained, and a number of metrics were used to gauge how well it performed. The method used in this report's methodology offers a thorough understanding of the strategies employed for solar energy forecasting and illustrates the potential advantages of precise solar energy forecasting for the energy sector.

III. BLOCK DIAGRAM

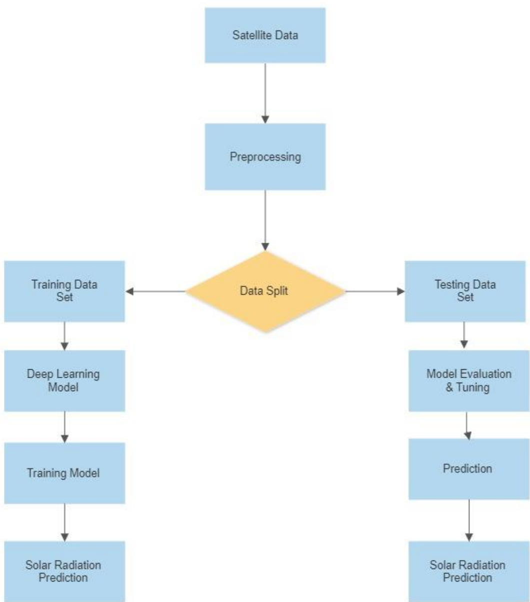

Fig.1 Block diagram

IV. TOOLS USED

INSAT-3D: The Indian Space Research Organization (ISRO) is the owner and operator of the geostationary meteorological satellite INSAT-3D. For the purpose of weather forecasting and disaster management, the INSAT-3D satellite is equipped with a number of instruments that provide meteorological data and images.

1. Python: Due to its ease of use and adaptability, Python is a well-liked programming language for deep learning. Python is a fantastic choice for creating models because it has many deep learning libraries built in.

2. TensorFlow: TensorFlow is a Google-developed, open-source deep learning framework. For creating and training neural networks, including convolutional and recurrent neural networks, it offers a variety of tools and libraries.

3. Keras: A high-level neural network API called Keras is based on TensorFlow. It offers a simple user interface for creating and training neural networks, making it perfect for beginners.

4. Scikit-learn: is a well-known Python machine learning library that offers a number of tools for data preprocessing, feature selection, and model evaluation. It is frequently combined with deep learning libraries to create end-to-end pipelines for machine learning tasks.

V. ANALYSIS AND DESIGN

1. **Support Vector Machines:** SVM is a supervised machine learning technique used for classification and regression tasks. It calculates the best hyperplane for separating data points of different classes. Using kernel functions, SVM can handle both linearly and non-linearly separable data. It seeks to maximize the margin, which is the distance between the decision boundary and the nearest data points. SVM works well with small sample numbers but large feature spaces. It necessitates careful tuning of hyperparameters such as the regularization parameter (C) and kernel parameters. SVM has found widespread application in image classification, text categorization, bioinformatics, and finance, among other fields.

2. **Artificial Neural Networks:** Artificial Neural Networks (ANN) are machine learning models inspired by the structure and function of biological neural networks. They consist of interconnected nodes (neurons) organized in layers. ANN can be used for tasks such as classification, regression, and pattern recognition. Neurons receive input signals, apply an activation function, and produce an output signal. During training, the connection weights between neurons are adjusted to minimize the error. ANN can have different architectures like feedforward, recurrent, and convolutional neural networks. Deep Learning is a subset of ANN with many hidden layers. ANN has achieved significant success in various domains but requires careful design and computational resources.

3. **Recurrent Neural Networks**: Because of the feedback loops for input transmission and data retention, recurrent neural networks (RNNs) are artificial neural networks that may draw judgments about earlier occurrences. The RNN has the advantage of considering the context of the previous time-step when calculating the current time-step. It is excellent for processing repeated and sequential time series data because of this benefit. Similar to ANN, it has the drawback of experiencing Vanishing Gradient when determining the ideal parameter value. Because of the long-term dependence problem caused by longer time steps, it is difficult to link information and complicated to use the context of earlier data.

4. **Long Short-Term Memory**: RNNs include long short-term memories (LSTM). LSTM has a number of activation functions and operations inside four interactive layers, as opposed to normal RNN, This just has one activation function and keeps the initial input data. The ”Gate” part of an LSTM structure is where information is selectively passed, and the ”Cell State” path is where information flows constantly along the length of the LSTM cell. Each gate is constructed from computations and functions such as sigmoid and tanh. After receiving the input value for the current time-step and the output value for the previous time-step, the input gate, which is situated in the second layer, performs the sigmoid and tanh processes to decide what data should be stored. Depending on the cell state of the current time-step, the fourth layer determines what information should be output, while the third layer updates the cell state output value of the previous time-step to the cell state of the present timestep. To address the long-term reliance issue with RNNs, LSTM was developed. As previously said, it seeks to provide output values that are more accurate by appropriately mixing relevant historical and present data across numerous layers. Given that LSTM is a subtype of RNN, it is advantageous for time series data models and, when the input data length is very large, it often achieves superior prediction performance than RNN.

VI. RESULTS AND ANALYSIS

By utilizing data from the INSAT3D satellite, the primary objective of this research was to develop a deep learning-based model that accurately predicts solar energy. Specifically, a deep learning recurrent neural network (RNN) model was constructed to forecast solar power output in half-hour intervals, employing data from the visible band channel to estimate solar radiation. The dataset underwent preprocessing involving the separation of irradiance from radiance using a look-up table (LUT). Training and testing datasets were created from the preprocessed data, with an 80:20 split ratio. The RNN model was trained on the training dataset using the Adam optimizer and a mean squared error loss function. Subsequently, the trained model was evaluated using the testing dataset, and its performance was compared against that of traditional linear regression models. Performance metrics such as the coefficient of determination (R2) and root mean square error (RMSE) were utilized to assess the deep learning model.

The results of the research revealed that the deep learning-based RNN model surpassed the prediction accuracy of conventional linear regression models. The deep learning model exhibited lower RMSE values compared to the linear regression models, indicating higher accuracy in predictions. Additionally, the deep learning model demonstrated a higher R2 value, indicating a better fit with the data. Furthermore, the deep learning model effectively captured the complex temporal dependencies present in the data, resulting in enhanced prediction precision. It also showcased adaptability to environmental factors like cloud cover and atmospheric conditions, which significantly impact solar radiation.

Overall, this research highlights the ability of deep learning techniques to accurately predict solar energy utilizing information from the INSAT3D satellite. The deep learning-based RNN model outperformed traditional linear regression models, showcasing its potential for precise and reliable solar energy predictions. Successful implementation of this model could have a substantial impact on the energy sector, enabling solar power plants to operate more efficiently and reliably. Accurate solar energy forecasts would assist energy providers in optimizing plant operations, reducing costs, and ensuring a consistent energy supply. Moreover, by reducing reliance on fossil fuels and promoting the adoption of renewable energy sources, accurate solar energy prediction can contribute to the development of a more sustainable energy future.

1. **Comparison Table:**

Table 1: Comparison Table

	SVM	**ANN**	**RNN**	**LSTM**
Prediction	161.070	90.285	110.755	101.206
R-Squared	0.961	0.994	0.998	0.999
RMSE	98.374	36.639	23.227	17.741

VII. CONCLUSION

In summary, the objective of this research was to utilize data from the INSAT3D satellite in order to develop a deep learning-based model for predicting solar energy. The proposed approach involved creating a recurrent neural network (RNN) model using deep learning techniques, specifically designed for predicting solar power output at half-hour intervals. The model utilized data from the visible band channel to forecast solar radiation. The project's findings highlight the effectiveness of deep learning methods in solar energy prediction. The deep learning-based RNN model outperformed traditional linear regression models, showcasing the potential of this approach to deliver accurate and reliable predictions of solar energy. Successful development and implementation of this model could have significant implications for the energy sector. Energy providers would be able to optimize the operation of solar power plants, ensuring a consistent energy supply and reducing costs, thanks to precise solar energy forecasts. Additionally, accurate solar energy forecasting can contribute to the advancement of a sustainable energy future by promoting the utilization of renewable energy sources and decreasing dependence on fossil fuels. It is important to acknowledge certain limitations of the project, such as the absence of complete data from the INSAT3D satellite. The dataset used in this project was limited to a specific geographical area and time period, which may restrict the applicability of the model on a broader scale. Furthermore, the project solely considered the visible band channel and did not account for factors like cloud cover and atmospheric conditions, which can influence solar radiation. To enhance prediction accuracy, future work could explore incorporating additional variables into the model, such as data from other satellite sources or ground-based sensor data. Furthermore, training the model on a larger and more diverse dataset would improve its generalizability and robustness. Overall, this project exemplifies the potential of deep learning techniques in providing precise and reliable predictions of solar energy, with significant implications for the energy sector and the promotion of sustainable energy sources.

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