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CNN-BiLSTM-Attention Solar Energy Forecasting using Cloud Motion Vectors

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Supervised by Dr Happy Nkanta Monday

Abstract

Solar energy prediction is crucial for optimizing the grid connection of renewable energy, but due to the complexity and dynamics of solar radiation patterns, solar energy prediction faces significant challenges. Traditional prediction methods often struggle with accuracy, especially when it comes to capturing the inherent complex spatial and temporal dependencies in solar data. Although the advancement of machine learning has enhanced the predictive ability, the inaccuracy of solar motion vector prediction remains a persistent problem. This project utilizes deep learning to enhance prediction accuracy by developing a new hybrid model, known as BiLSTM, combined with a dual-path architecture. This innovative model combines the advantages of BiLSTM in capturing time dependencies, enabling it to focus on both spatial and temporal granularities simultaneously while maintaining the computational efficiency of accurate solar motion vector predictions.

Dataset

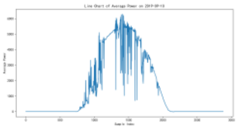

Figure 1 Examples of Power measurements

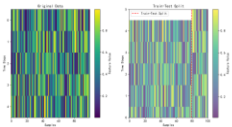

Figure 2 Illustration of dataset splitting and reshaping

The training set, test set are divided in the ratio of 8:2.

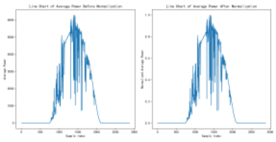

Figure 3 Comparison before and after normalization

The dataset underwent a rigorous preprocessing pipeline, including temporal alignment, missing value removal, normalization, sequence slicing, and input reshaping. These procedures ensured the integrity of the temporal data and facilitated accurate forecasting in subsequent model development.

Ensemble models

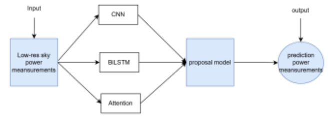

Figure 4 Ensemble model

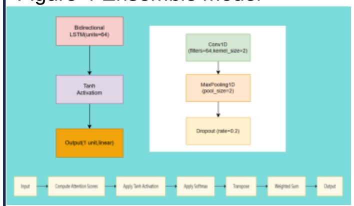

Figure 5 The various blocks of Ensemble Modelling.

CNN Layer: Extracts local features.

BiLSTM Layer: Captures bidirectional temporal dependencies.

Attention Mechanism: Highlights crucial time steps.

Fully Connected Layers: Produces the final prediction.

This hybrid deep learning model effectively balances local feature extraction, sequential modeling, and adaptive attention, making it well-suited for time-series forecasting tasks.

Model evaluation

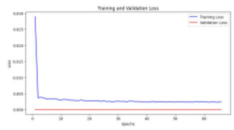

Figure 6 Loss variation curves on the validation and Training set

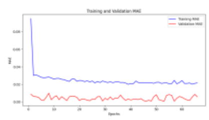

Figure 7 MAE variation curves on the validation and Training set

Figure 8 MAPE variation curves on the validation and Training set

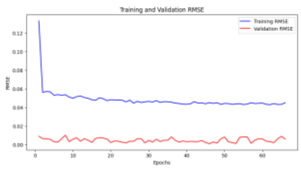

Figure 9 RMSE variation curves on the validation and Training set

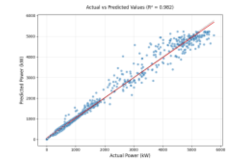

Figure 10 R^2 variation curves on the validation and Training set

The above figure shows the prediction task of the solar motion vector for this experiment using CNN,BiLSTM, and Attention

Interpretability and significance analysis of the model

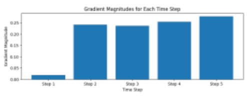

Figure 11 Gradient Magnitudes

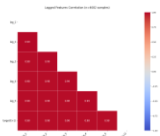

Figure 12 Lagged Futures Correlation Heatmap

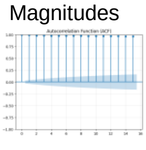

Figure 12 *ACF*

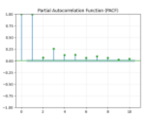

Figure 13 PACF

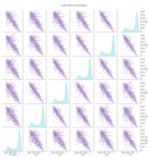

Figure 14 Lagged Features Scatter Matrix

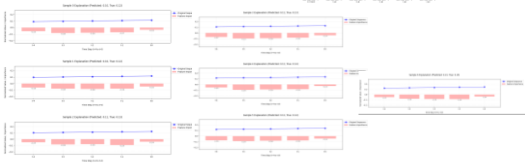

Figure 15,16,17 *LIME Interpretability Analysis*

Decomposability analysis aims to explain the decision-making process of the model and help understand why the model makes specific predictions. On the other hand, significance analysis focuses on the regions or features that have the greatest impact on the model's prediction in the prediction task, helping to understand the model's focus and decision-making basis.

WEB APPLICATION DEVELOPMENT

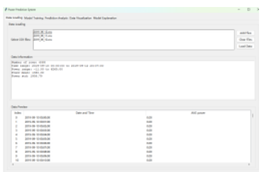

Figure18 System Main Interface

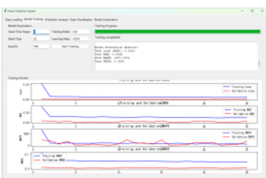

Figure19 Model training

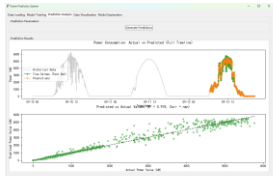

Figure 20 Prediction Analysis

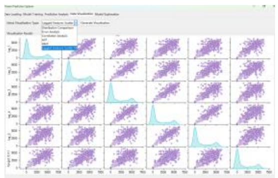

Figure 21 Data Visualization

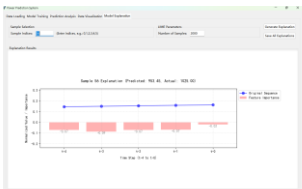

Figure 22 Model Explanation

The Tkinter - based GUI offers a user - friendly interface for operations like data loading and model setting, yet model training and prediction are executed locally in Python.

Future work

1. Exploring advanced architectures
2. Deploying the system as a cloud-based API using frameworks
3. Validating the model on multi-regional datasets with varied climatic conditions
4. Integrating the model with energy management systems