

Chengdu University of Technology, Oxford Brookes Graduate Project Poster

The growing global demand for clean energy has positioned solar power as a key component of sustainable development. However, accurate solar forecasting remains challenging due to rapid weather fluctuations, especially cloud cover dynamics, which traditional methods struggle to predict in real time. Recent advances in deep learning and sky image analysis enable real-time solar radiation prediction by detecting cloud properties, outperforming conventional approaches. Yet, model reliability depends on high-quality, diverse datasets, which are currently limited in coverage and standardization. Our work leverages deep learning and sky imagery to enhance solar forecasting accuracy, supporting grid stability and efficient energy management with real-time, scalable solutions. This approach promises significant technological innovation for solar energy applications. The project open-source the datasets and model for future research at [***https://github.com/Aura8998/solar-prediction***](https://github.com/Aura8998/solar-prediction).

Figure 1: Project Overview

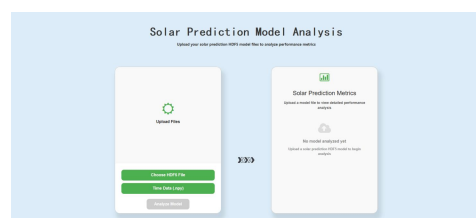
- ***Enhanced Solar Forecasting with Attention Mechanisms.*** This study introduces a deep learning framework combining CNNs with Squeeze-and-Excitation (SE) attention to improve short-term solar energy prediction. The SE-attention model outperformed baseline architectures, reducing RMSE and MAE while increasing R^2 , demonstrating superior adaptability to dynamic cloud movements.
- ***Interpretable and Meteorologically Relevant AI.*** Through Grad-CAM analysis, the research reveals distinct attention patterns in sunny vs. cloudy conditions, ensuring model decisions align with real-world meteorological dynamics.
- ***Deployable Web-Based Tool for Real-World Application.*** The framework was implemented in an interactive web-based GUI, enabling real-time solar potential simulations for energy operators. This deployment enhances accessibility and usability, transforming research into a practical tool for improving grid stability and renewable energy integration.

Figure 2: Sunny and Cloudy samples of the sky images, and PV power distribution across datasets

This study utilizes two high-resolution sky image datasets for solar forecasting. The SKIPPD dataset (Stanford) includes 2048x2048 pixel fisheye images captured at 1-minute intervals, synchronized with nearby PV power data. The second dataset similarly provides ultra-HD sky videos (20 fps) and solar measurements at 60-second resolution. Both datasets enable precise correlation between cloud dynamics and PV output, supporting short-term forecasting under varying weather conditions.

Raw sky images were resized to 64×64 pixels while preserving aspect ratios, with pixel values normalized to [0,1] for model compatibility. RGB color fidelity was maintained to enhance cloud feature detection by attention mechanisms. For evaluation, data was partitioned into daily solar cycles, shuffled while preserving intra-day sequences, and split using k-fold cross-validation to ensure temporal consistency and diverse weather exposure. This approach balanced computational efficiency with robust performance assessment.

- Home Page shows the source of solar prediction including introduction, dataset, codes, functions
- Data display page shows the details of dataset
- Upload the dataset and time data and click "analyze model" to get the solar prediction metrics and model explainability



Model Prediction
Page

Figure 7: Deployment on Web

Evaluation Metrics: The study developed three CNN variants (baseline, SE-attention, spatial-attention) and deployed an interactive GUI, integrating technical execution with real-world usability.

Results: The SE-attention model achieved optimal accuracy, validated by RMSE/MAE metrics and Grad-CAM interpretability, proving effective for solar forecasting under dynamic weather.

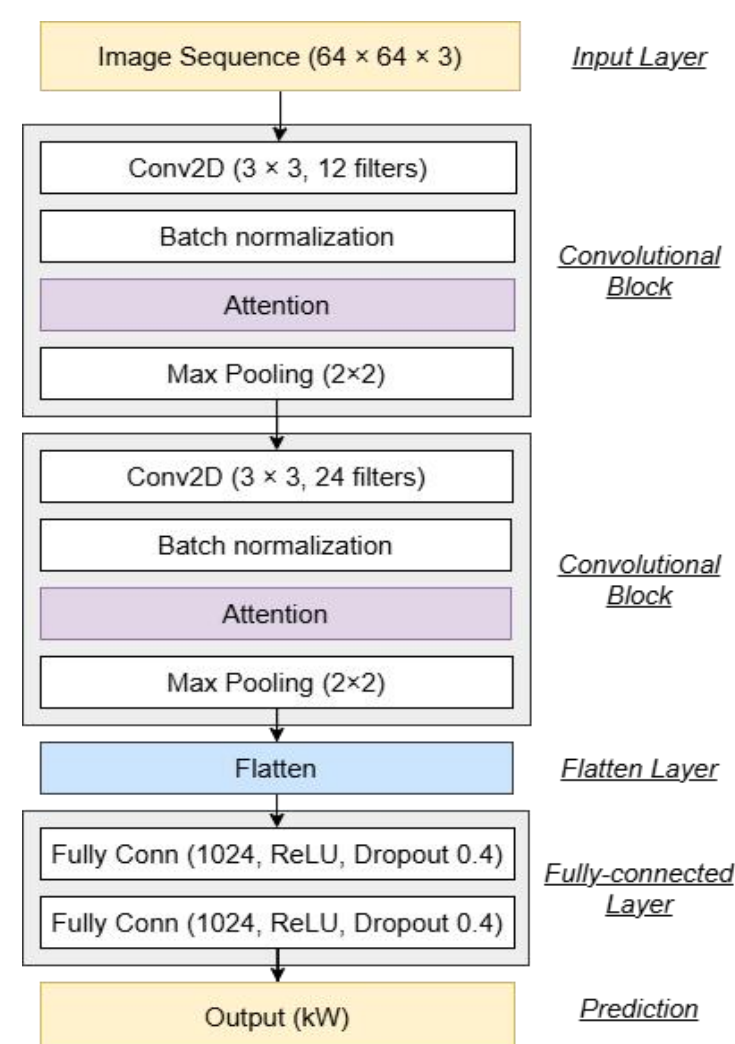


Figure 3: Proposed Model

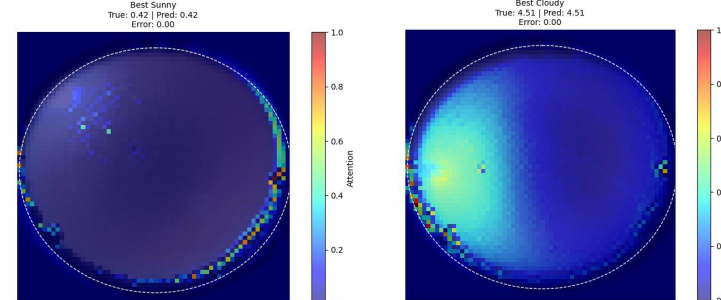


Figure 6: Best Sunny and Cloudy days in Grad-CAM

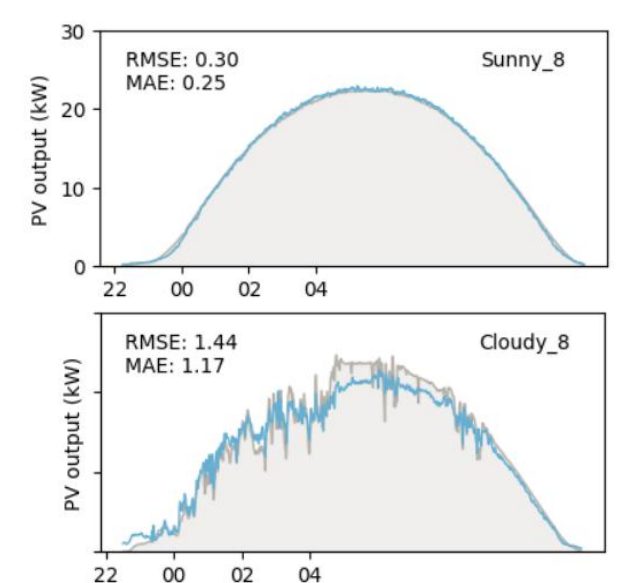


Figure 4: Visualization of CNN+SE-Attention model

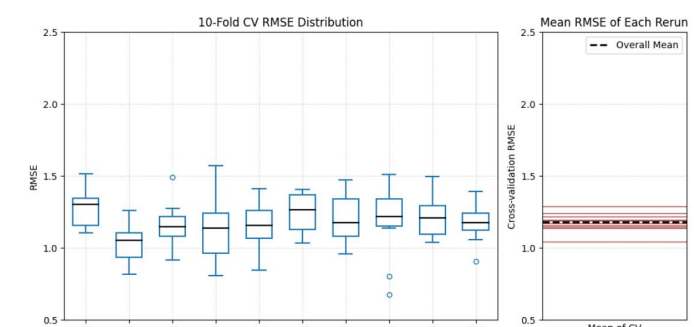


Figure 5:
RMSE distribution across 10-fold

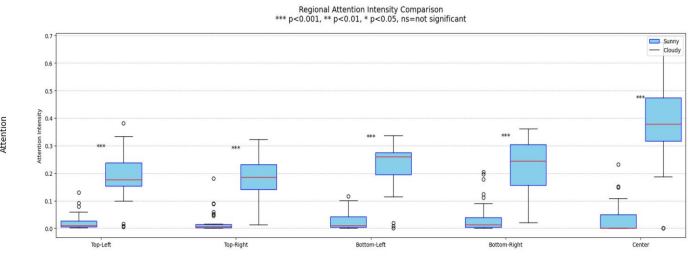


Figure 7: Regional Attention intensity comparison

- Developed CNN+SE-Attention; Grad-CAM reveals weather attention patterns; Deployable GUI for solar forecasting
- Limited to single station, low resolution, high GPU dependency
- Future works: Multi-angle camera arrays, lightweight design, transfer learning for real-world adaptation