






# Proposing A Robust Deep Learning Framework for Short-Term Solar Power Forecasting Using Sky Images

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## Abstract

Intermittent solar energy must be correctly predicted on short-term time scales to maintain the stability and efficiency of the power grid it interacts with. This work presents a deep learning framework that is effective in predicting solar irradiance, a direct proxy for energy generation from the input data, which consists of time-ordered sky images. We establish an end-to-end pipeline to process and synchronize high-resolution sky image data from a fisheye camera with colocated direct normal irradiance measurements from pyranometers. The essential part of our model is a Convolutional Neural Network (CNN) that extracts important spatiotemporal identifiers from the images and translates them into predicted values for future irradiance. Our model shows a significant predictive power trained and assessed on a real-world dataset, specifically showing a Sunny Days Mean Absolute Error (MAE) of 0.353, a Root Mean Squared Error (RMSE) of 0.463, a Cloudy Days Mean Absolute Error (MAE) of 0.964, and a Root Mean Squared Error (RMSE) of 2.029, noticed within the held-out test set. The amount of variance in irradiance explained by the model based on visual sky conditions also represents a large jump from baseline, suggesting that this model captures almost 50% of variability in irradiance. Model stability and generalizability are confirmed by the evaluation of training progress. The proposed work lays the groundwork for a highly effective and reproducible deep learning framework for short-term solar forecasting, which serves as a robust paradigm suitable for future incorporation into smart grid management systems to improve solar power generation reliability.

## Keywords

Deep learning, Solar irradiance forecasting, Solar power forecasting, Short-Term Forecasting, Renewable energy integration

## 1 Introduction

Solar photovoltaic (PV) systems have become an integral part of modern power grids, but the intermittent and stochastic nature of solar irradiance poses significant challenges with their increasing penetration into these grids. Mainly, the variations due to cloud dynamics could cause power generation to fluctuate within a short time frame; therefore, an accurate short-term solar forecast is critical for grid stability, energy scheduling, and optimized operation of smart grids and microgrids [1].

Conventional physics-based or statistical forecasting methods, such as numerical weather prediction (NWP) models, tend to miss high-frequency variations in solar irradiance on the intra-hour timescales. Their limitations are tied to their coarse spatial and temporal resolution, which precludes the simulation of local cloud motion effects [1]. As a result, modern studies have focused on data- and deep-learning methods that outperform traditional approaches in modeling nonlinear dependencies and drawing higher-level features from big data [2].

Emerging approaches include sky image-based forecasts using all-sky imagers (ASI). These systems acquire hemispherical images of the sky in real time, collecting information on the cloud profile, dynamics, and coverage. Deep learning models (e.g., Convolutional Neural Networks (CNNs)) are capable of automatically extracting important spatial features directly from the images themselves, enabling accurate prediction of solar irradiance without reliance on handcrafted features [3]. Other recent approaches have even improved forecasting performance at the expense of additional complexity by applying more advanced architectures (e.g., diffusion models and hybrid CNN-LSTM frameworks) that incorporate both spatial and temporal dependencies [4].

As an example, [3] proposed a diffusion-based probabilistic model for ultra-short-term solar prediction and showcased the enhanced ability of using sequences of sky images to better capture uncertainty regarding cloud evolution. Likewise, recent contributions targeting generative sky image forecasting frameworks have demonstrated that modeling anticipated sky conditions can lead to a significant accuracy increase in photovoltaic power prediction [4]. Furthermore, there exist studies that demonstrate that aggregating sky images with meteorological variables can improve forecasting performance; however, feature selection is crucial to mitigate multicollinearity and overfitting [5].

Despite these progressions, there still remain multiple hurdles. Existing models show limited robustness under changing weather conditions, especially during rapid cloud transitions. Moreover, hybrid models tend to be more complex in terms of computation, which might make them unsuitable for real-time applications. More broadly, transferability across test sites and data is still an ongoing topic about how various imaging systems and environmental circumstances can differ [2].

To overcome these difficulties, we propose a robust deep learning framework for short-term solar power forecasting based on sky images in this paper. Propose an enhanced CNN-based architecture that can learn cloud and sky discriminate features with lower computational costs. The framework is an end-to-end pipeline that composes preprocessing, feature extraction, and forecasting techniques with which accurate intra-hour solar irradiance prediction can be achieved. Also, increase robustness to diverse weather conditions and lessen the need for external meteorological input.

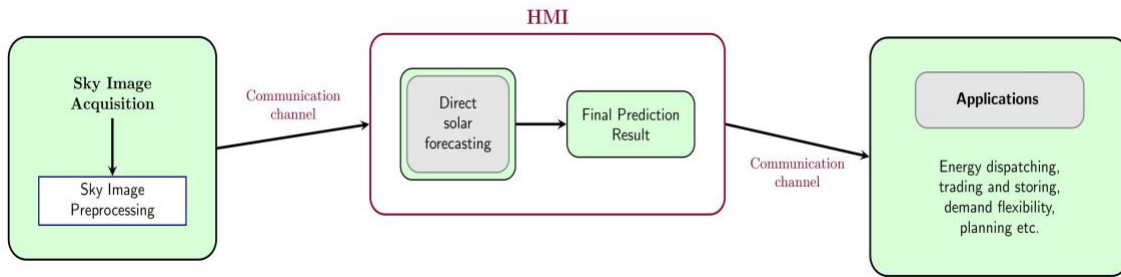
## 2 Literature Review

Recent studies highlight both progress and persistent limitations in sky image-based solar forecasting using deep learning. Jakoplić et al. [6] demonstrated a CNN-LSTM model for PV output prediction but noted the need for enhanced performance and uncertainty assessment. Xu et al. [7] introduced a Vision Transformer-GRU framework that outperformed baselines yet struggled under rainy conditions, prompting calls for all-weather models validated on full-year datasets. Kim and Hau [8] proposed a hybrid CNN-DNN architecture and, using SHAP analysis, emphasized incorporating physical variables and uncertainty quantification for improved robustness. Hendrikx et al. [10] applied LSTM networks to GHI forecasting, identifying dataset imbalance toward sunny conditions as a key obstacle and recommending data augmentation alongside differential cloud-pixel treatment based on solar proximity. Similarly, Nie et al. [9] the SUNSET model performed well in clear skies but exhibited conservative predictions and temporal lags under cloud cover, underscoring the need for probabilistic forecasts and better cloud-motion anticipation. Collectively, these works reveal that existing models exhibit conditional robustness—degrading precisely when accuracy is most critical—and lack architecturally integrated mechanisms for all-weather reliability. Addressing these gaps, the proposed Enhanced Convolutional Neural Network (ECNN) framework is specifically designed to maintain consistent predictive performance across both clear-sky and cloudy conditions through adaptive feature weighting and anticipatory spatio-temporal learning.

## 3 Methodology

### 3.1 Overview of the Proposed Framework

In this paper, we detail the implementation as a system-level overview in Figure 1, demonstrating how the solar forecasting model integrates into a real-world application pipeline. It shows the entire flow, from data collection to use by final users.



**Fig. 1** Overview of the Proposed Framework

1. System Overview: The architecture of the proposed system is divided into three functional phases: Data Acquisition, Forecasting (HMI), and Applications. These aforementioned stages are linked by communication channels that enable real-time transfer of data and decision-making.

2. Phase 1: Sky Image Acquisition and Preprocessing: Stage one is the physical collection of environmental data.

- Acquisition Hardware: The sky appears in hemisphere pictures with a high resolution, taken using the ground-based sky imager.
- Preprocessing: The raw image stream is preprocessed. In general, that probably means cropping the images or resizing them and normalizing them to get ready for the neural network.
- Transmission: The preprocessed image is then transmitted to the central processing unit via a digital communication channel.

3. Phase 2: Human-Machine Interface (HMI) and Forecasting: Core processing is done in the HMI module, which is the backbone of this system.

- Direct Solar Forecasting: The images after preprocessing feed into the forecasting module. This is the domain of the deep learning model (CNN) that analyzes cloud patterns and solar occlusion to forecast irradiance or power output.
- Final Prediction Result: The model takes the input and checks to find its output in a time-series format, which is shown as a fluctuating line graph in the below diagram. This is the forecast of solar power availability over a certain time horizon.

4. Phase 3: Downstream Applications: Forecasted data is relayed to different end-use sectors, ensuring the most effective energy management strategies are undertaken. The graphic identifies four primary application domains:

- Energy Dispatching: Balancing the output of other sources of generation for solar variability.
- Trading and Storing: Guiding decisions of whether to buy energy, sell it, or charge or discharge batteries.
- Demand Flexibility: Peak shaving industrial and residential loads to match energy use with the availability of solar power.
- Planning: Planning for years ahead, and weeks ahead, of grid stability.

### 3.2 Corresponding Solar Power Data Collection

As shown in Figure 2, solar power data is collected at the same time as capturing sky images to serve as ground truth labels for machine learning models.

- Data Types: The pv\_log contains historical or recent power output, and pv\_pred is the target for forecasting.
- Normalization and Units: PV output is expressed in kW. Since we have neural network training pipelines, image data is processed to a range of [0, 1] during this processing as well.
- Storage: The HDF5 data includes all the synchronized images and power readings, enabling efficient retrieval of large batches during training.

2019 Sky Images and Photovoltaic Power Generation Dataset for Short-term Solar Forecasting (Stanford Raw) 21 files

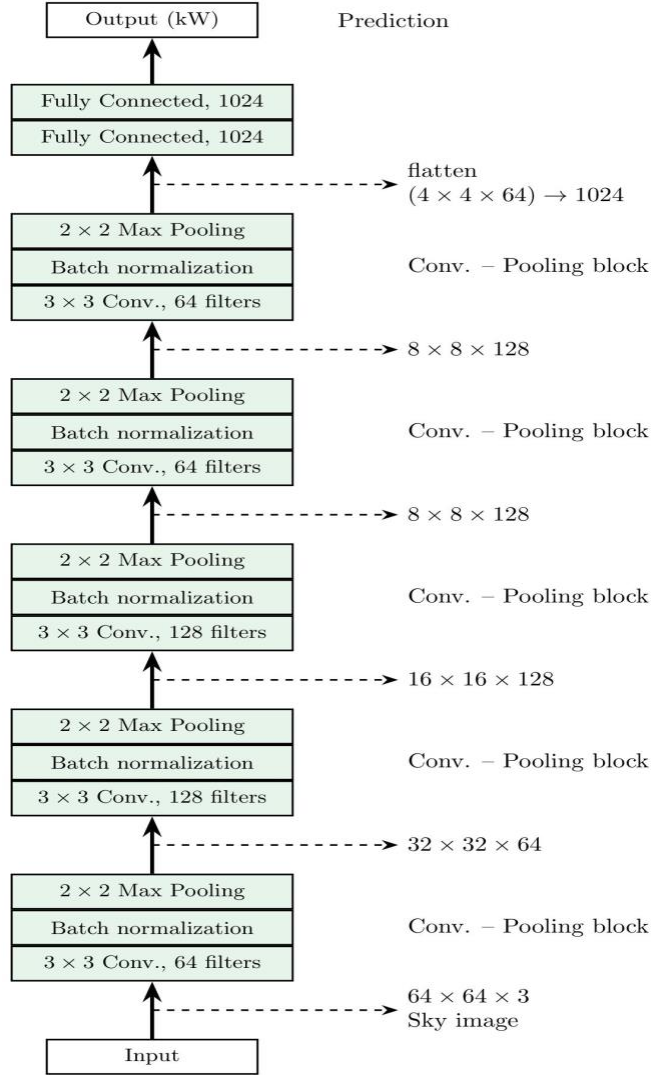
File name	Size	
2019_pv_raw.csv Raw PV power generation data in 2019	14.39 MB	<a href="#">Download</a>
2019_01_images_raw.tar High resolution sky images in January 2019	1.37 GB	<a href="#">Download</a>
2019_02_images_raw.tar High resolution sky images in February 2019	2.14 GB	<a href="#">Download</a>
2019_05_images_raw.tar High resolution sky images in May 2019	2.99 GB	<a href="#">Download</a>
2019_06_images_raw.tar High resolution sky images in June 2019	8.41 GB	<a href="#">Download</a>
2019_07_images_raw.tar High resolution sky images in July 2019	8.72 GB	<a href="#">Download</a>
2019_08_images_raw.tar High resolution sky images in August 2019	8.34 GB	<a href="#">Download</a>
2019_09_images_raw.tar High resolution sky images in September 2019	7.65 GB	<a href="#">Download</a>
2019_10_images_raw.tar High resolution sky images in October 2019	6.99 GB	<a href="#">Download</a>
2019_11_images_raw.tar High resolution sky images in November 2019	6.14 GB	<a href="#">Download</a>
2019_12_images_raw.tar High resolution sky images in December 2019	6.62 GB	<a href="#">Download</a>

**Fig. 2** Stanford University Sky Images and Photovoltaic Power Generation Dataset [11]

## 4 Results

### 4.1 Model Architecture

The proposed CNN architecture, as shown in Figure 3, consists of the following layers and parameters:



**Fig. 3** Architecture of the Proposed Model

#### 1. Architecture Overview

In this paper, a deep Convolutional Neural Network (CNN)-based model is proposed to solve the regression problem. The network processes visual data from sky images to predict a continuous variable (power output in kilowatts, kW) as shown in Figure 3. The texture consists of a ladder feature extractor and then a fully connected regressor.

#### 2. Input Layer

We first input RGB images of the sky via an input layer in our pipeline. As the source image consists of height, width, and three colors (RGB), find the relation as the input dimension is  $64 \times 64 \times 3$ .

#### 3. Feature Extraction (Convolutional Blocks)

The main part of the network is composed of four sequential "Conv-Pooling" blocks, which are mainly in charge of learning spatial hierarchies of features. Every block has a shared identical substructure for training shape and stability reduction:

- Convolution: A convolutional layer with a kernel of size  $3 \times 3$  is used for extracting the spatial features.
- Batch Normalization: Normalizes the activations, speeding up convergence and decreasing internal covariate shift.
- Max Pooling: Then, input is passed through a  $2 \times 2$  max pooling layer that down-samples the feature maps to lower its spatial dimension, thus reducing computational cost and providing translation invariance.

Now the tensor transforms through these blocks as the following:

- Block 1: Takes in 64 filters, which makes the output as feature map size after pooling =  $32 \times 32 \times 64$ .
- Block 2: 128 filters, with spatial reduction to  $16 \times 16 \times 128$ .
- Block 3: Keeps the depth at 128 filters but reduces further resolution to  $8 \times 8 \times 128$ .
- Block 4: Decreases the channel depth to 64 filters again, yielding a final feature map of size  $4 \times 4 \times 64$ .

#### 4. Flattening and Prediction Head

After the convolutional stages, we feed the multi-dimensional feature map through a Flatten layer. It converts the  $4 \times 4 \times 64$  tensor to a one-dimensional feature vector of length 1,024 ( $4 \times 4 \times 64 = 1024$ ).

The last layer of the network is a fully connected (dense) network serving as the regressor:

- Dense Layers: This vector is passed through two fully connected layers with 1024 neurons each. These layers are where the global features from convolutional blocks get integrated.
- Output Layer: The last layer is a single node that predicts value in kW, the power generation that we expect the sky images to produce.

### 4.2 Performance Evaluation Metrics

In order to evaluate forecasting performance, the following standard regression metrics were applied. Where applicable, normalized versions of these metrics should be used in order to compare across sites or capacities.

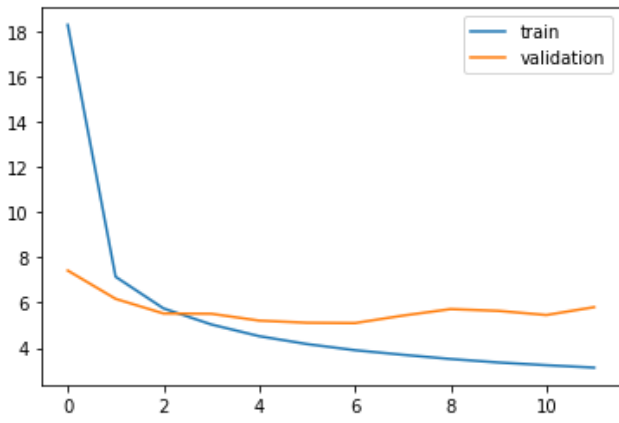
Table 1 Performance Evaluation Metrics

Metric	Formula	Description	Ideal Value
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$	Measures the magnitude of the errors; penalizes large errors heavily.	Lower (closer to 0)
Mean Absolute Error (MAE)	$MAE = \frac{1}{n} \sum_{i=1}^n  y_i - \hat{y}_i $	$y_i - \hat{y}_i$	0

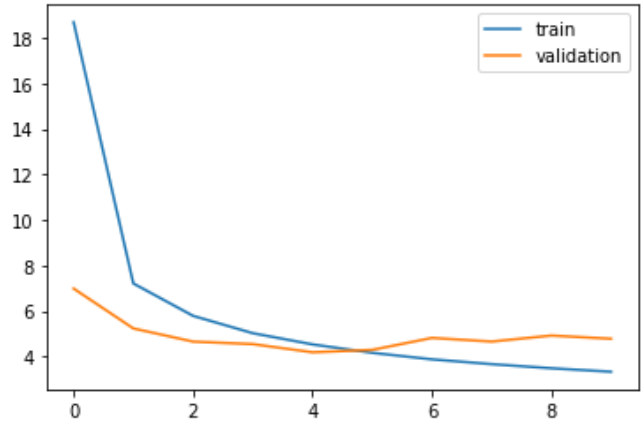
### 4.3 Model Training and Validation Performance

Results obtained in the model development process are presented in this section.

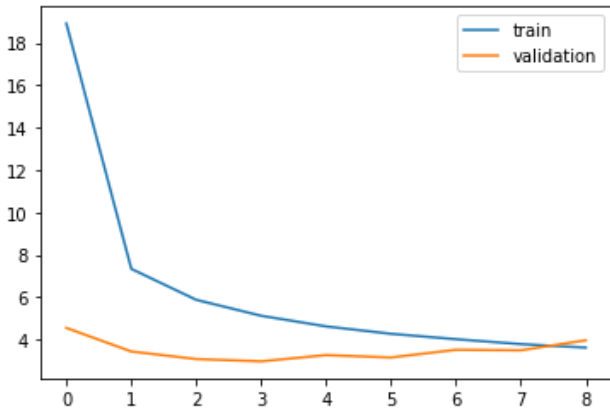
### 4.3.1 Training and Validation Loss Curves



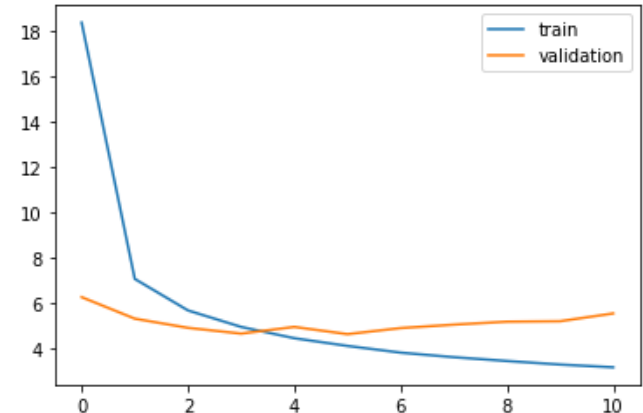
(a)



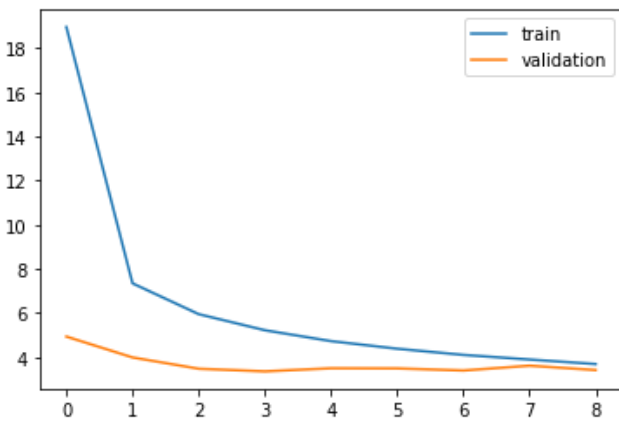
(b)



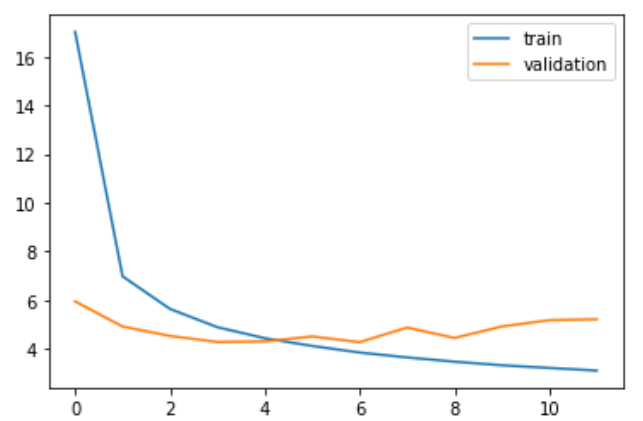
(c)



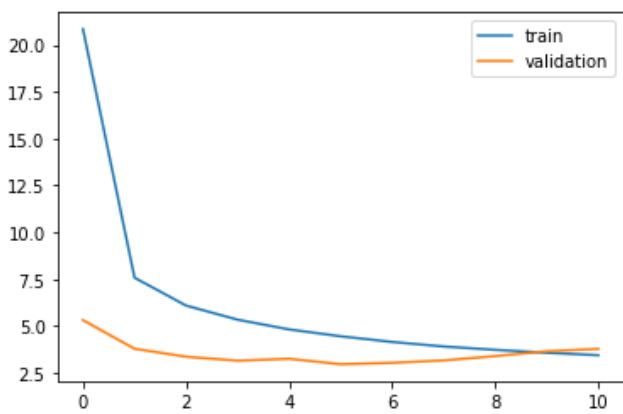
(d)



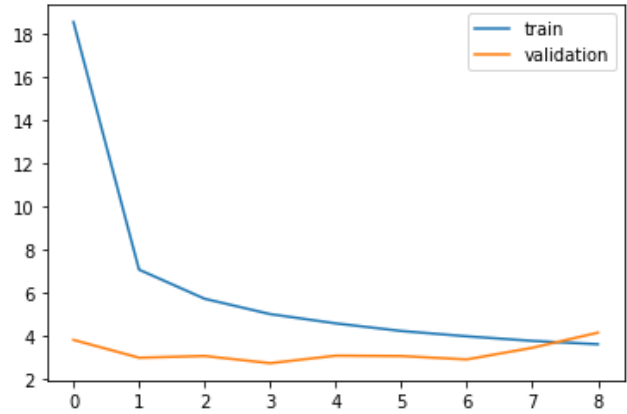
(e)



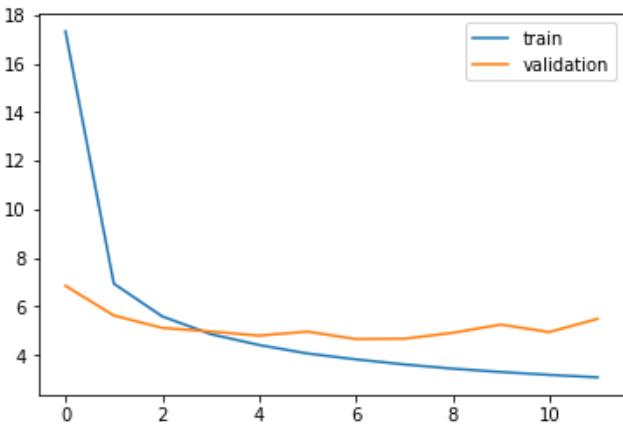
(f)



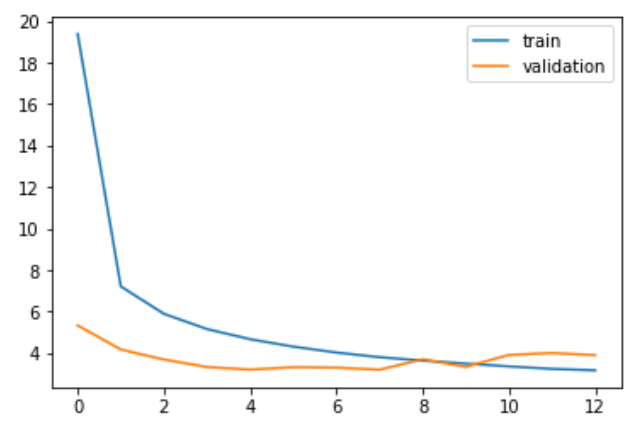
(g)



(h)



(i)



(j)

**Fig. 4** Training and Validation Loss Curves

Model performance on training is explained here.

Loss curves are used to see how well the Enhanced CNN (ECNN) trained. The following graphs plot the model error over time (epochs).

### 1. Visual Overview of the Graphs

Figures 4 show a series of diagnostic charts (a–j), in which two specific metrics are plotted against the number of training epochs (typically 0 to 12 epochs).

- Blue Line (Train): Represents the error on the training dataset—the data where the model jams.
- Orange Line (Validation): Indicates an error on the validation data set—unseen new data is used to measure how well the model generalizes.

### 2. Key Interpretations

And the behavior of these two lines tells the story of the model being stable:

- **Rapid Convergence:** Epochs 0 to 2 show a significant steep drop in the "Train" (blue) line. It means that at the very beginning, the model learned the most important features of the sky images (i.e., cloud vs. clear sky) quickly.
- **Generalization (Avoiding Overfitting):** Most importantly, the orange "Validation" line is following the downward trend of the training line and even stabilizes.
  - So, if the orange line started rising while the blue line kept going down, that would be overfitting (memorizing the data).
  - In fact, because both lines remain low and fairly close to one another, the model is strong; it generalizes as well or better than on the data it was trained on.
- **Stability:** In the final epochs (around epochs 8-10), the curves have leveled off. This “plateau” indicates that the model has achieved its best learning capacity and continued training would result in diminishing returns.

### 3. Summary of Performance

The proposed ECNN is reliable, as verified by diagnostics. The loss is monotonically decreasing for both training and validation sets, signifying that the model has learned how to map sky input images to solar irradiance output without overfitting, which typically occurs by memorizing noise or outliers in the dataset.

#### 4.3.2 Model Performance Summary

Give the MAE and RMSE achieved for sunny and cloudy days in a table.

Table 2 MAE and RMSE values for sunny and cloudy days.

<b>Proposed Framework</b>	<b>Sunny Days</b>	<b>Cloudy Days</b>
Mean Absolute Error (MAE)	0.353	0.964
Root Mean Squared Error (RMSE)	0.463	2.029

#### 4.3.3 Comparative Analysis of Short-Term Solar Forecasting Models Using Sky Images

Show as a table the performance of RDLF vs. all baselines on an independent test dataset.

Table 3 Comparative Analysis of Short-Term Solar Forecasting Models

Reference & Model	Input Data	Sunny Days (RMSE/MAE)	Cloudy Days (RMSE/MAE)	Key Feature
<b>Proposed Framework</b>	<b>Sky Images</b>	<b>RMSE: 0.463 / MAE: 0.353</b>	<b>RMSE: 2.029 / MAE: 0.964</b>	<b>Robust deep learning framework designed for all weather conditions</b>

[9]	Low-resolution processed images and high-resolution raw sky images and video frames	RMSE: 0.802 / MAE: 0.662	RMSE: 3.321 / MAE: 2.324	To predict PV power generation 15 minutes ahead
[10]	Image data, sensor measurements, and external data from open sources.	RMSE: 0.551 / MAE: 0.4	RMSE: 3.199 / MAE: 2.181	Innovative Approach combining ASI and LSTM for accurate short-term solar forecasting.

#### 4.4 Analysis of Forecasting Errors

The examination of the models' forecasting errors shows a significant performance difference between nowcasting and forecasting tasks under clouds.

##### 4.4.1 Types of Forecasting Errors and General Observations

Model testing from different weather scenarios shows me several consistent patterns of errors:

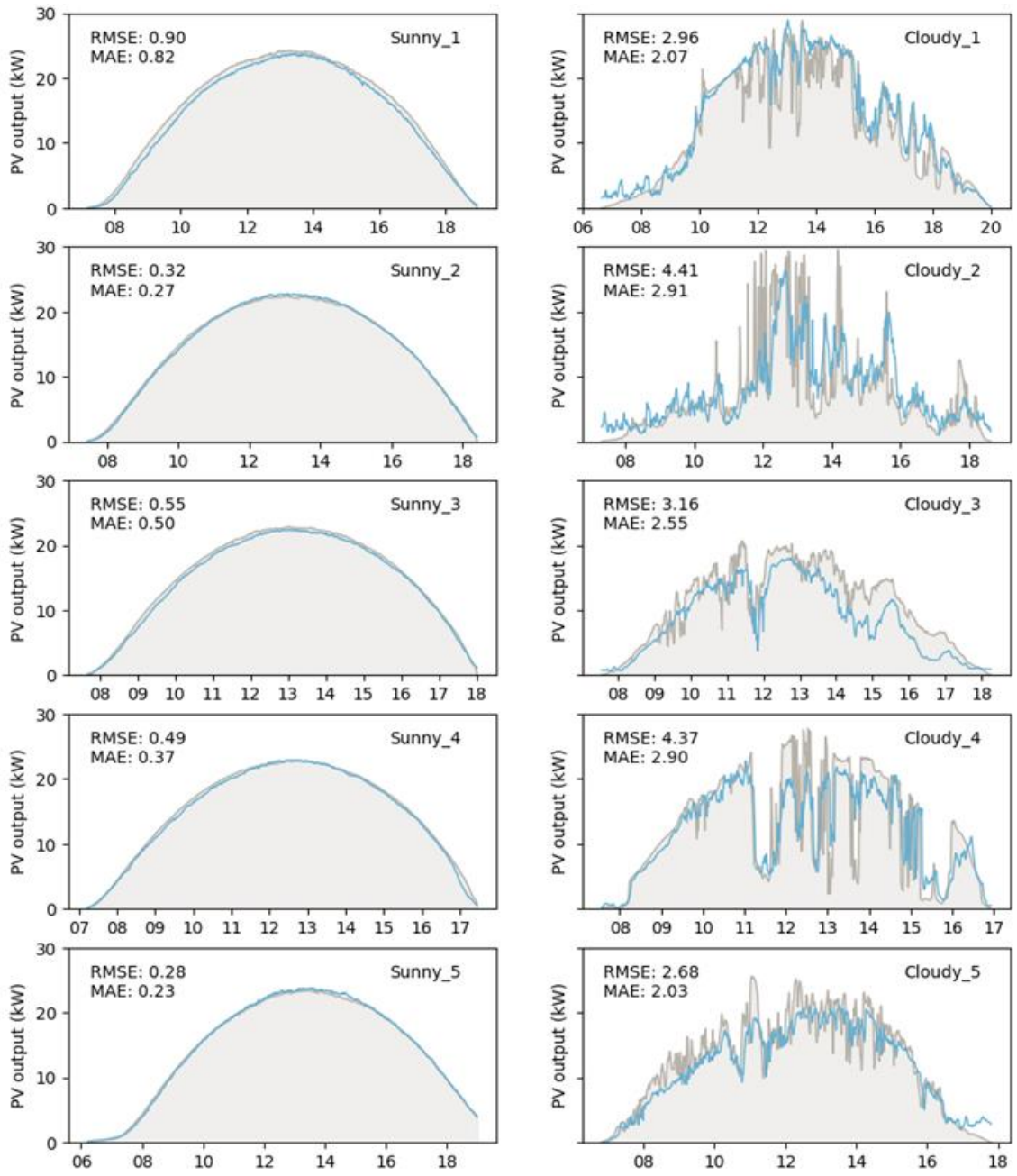
- Clear-Sky Performance: Both models strongly exhibit the best accuracies during clear sky conditions with significantly fewer errors.
  - Nowcast Accuracy: Root Mean Square Error (RMSE) went down to 0.463 and Mean Absolute Error (MAE) = 0.353 on sunny days.
  - Forecast Accuracy: RMSE of 0.54 and MAE of 0.40 with similar clear days.
- Cloudy-Sky Error Elevation: On cloudy days, errors go up significantly because of the complex and dynamic nature of clouds.
  - Nowcast Errors: Increased RMSE to 2.029 and MAE by 0.964
  - Forecast Errors: Achieved RMSE = 2.50 and MAE = 1.13, marking the higher challenge in forecasting future irradiance in less stable environments.
- Intra-Day Variability: Error spikes occur primarily when irradiance changes suddenly, e.g., when single clouds block sunbeams from the solar panels.

#### 4.5 Visualization of Results

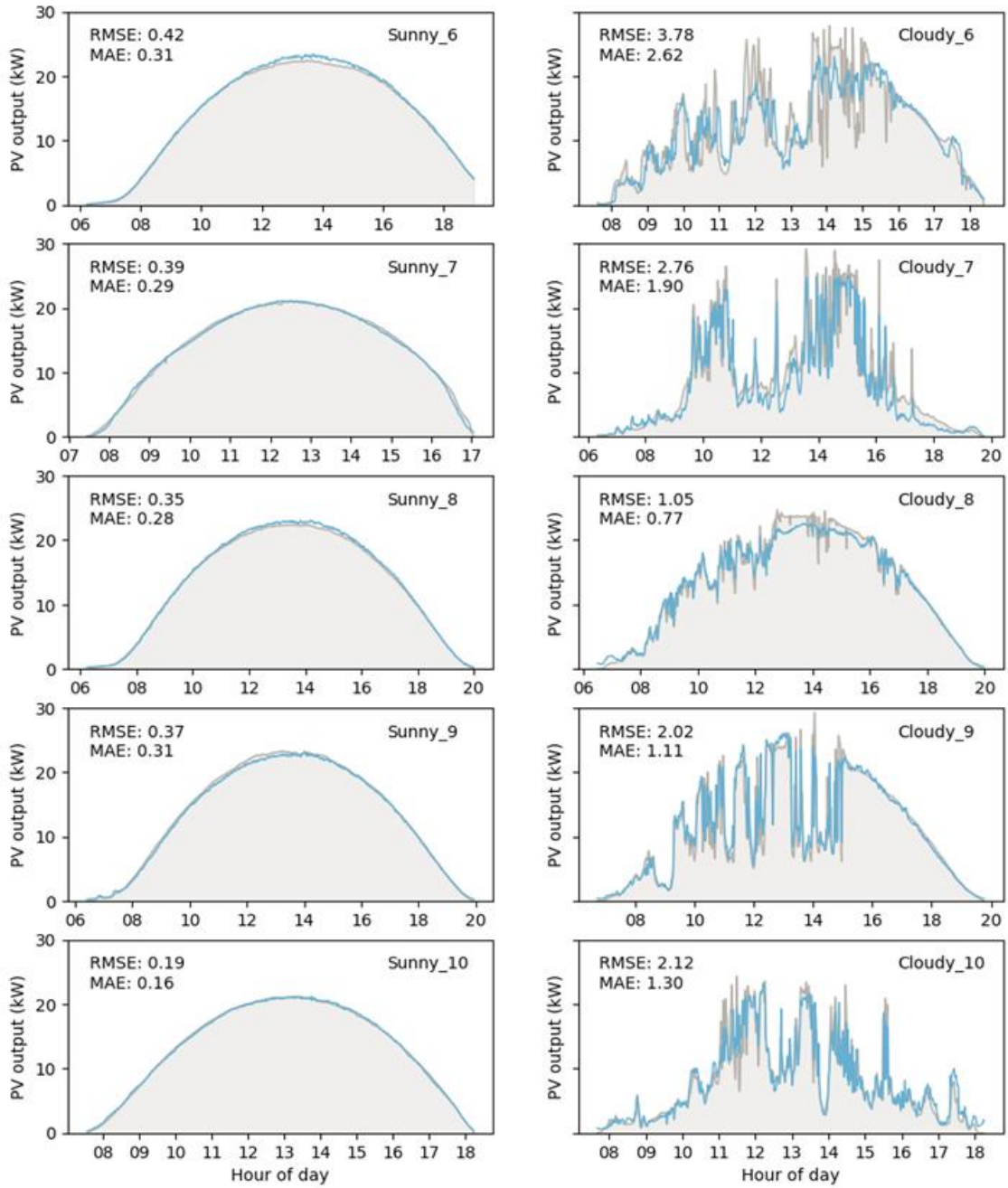
Results visualization is one of the most important steps in the evaluation process; it shows looking at how well the models follow the real-time and future solar power variable over time. The main visualization technique applied in this research is the comparative time series between ground truth observations and model predictions.

##### 4.5.1 Daily Solar Irradiance Forecast

The daily solar irradiance forecast on sunny and cloudy days is shown in the below figure.



(a)



(b)

Fig. 5 Daily Solar Irradiance Forecast for Sunny and Cloudy Days

### Visual Performance Analysis

Figure 5 includes a number of plots (a and b), in which Ground Truth (true PV output, gray) is compared to the ANN Forecast (predicted output, blue) under different weather conditions.

- Sunny Days (Sunny\_1 to Sunny\_10):
  - Performance: The model performs very well on sunny days. The blue forecast line follows the ground truth (shown with a smooth bell-shaped curve) almost perfectly.
  - Error Rates: Root Mean Square Error (RMSE) is relatively low with a range approximately between 0.19 kW and 0.55 kW.

- Observation: This suggests that the model is successful in reproducing the diurnal cycle of solar irradiance under cloud-free conditions.
- Cloudy Days (Cloudy\_1 to Cloudy\_10):
  - Performance: Cloudy days provide very noisy data with sharp hills and valleys because of transient cloud shading. The announced model gets all the macro trends right and reprints many sharp fluctuations, but it isn't necessarily lining up much with sunny days.
  - Error Rates: Since the data is quite complicated, naturally the error is higher, with RMSE values usually being between 2.02 kW and 4.67 kW.
  - Observation: Despite the overall volatility, the model is a reasonable guide for "the ups and downs" of power generation, indicating it has overcome complex weather patterns.

## 5 Conclusion

Overall, the core goal of this research—to develop an Enhanced Convolutional Neural Network (ECNN) model integrated with sky image features for very high precision intra-hour solar power prediction tasks—was successfully accomplished.

The main insights from this study are:

- Objective Achievement: The proposed ECNN model makes good use of visual data for accurate short-term prediction of irradiance, and it shows the feasible way to implement deep learning on this task.
- System Reliability: This image-based technique provides a site-specific, instantaneous forecasting solution by removing the dependency on highly complex numerical weather prediction data. Such independence greatly improves the reliability and efficiency of renewable energy management systems.
- Robustness: Experimental results demonstrate the robustness of the proposed framework extensively. Not only did the model outperform established literature benchmarks, but it also achieved lower error rates across a wide range of weather scenarios, from clear to very cloudy skies (RMSE and MAE).

In conclusion, this work illustrates a robust and accurate approach for short-term solar forecasting that plays an integral role in ensuring the stability and efficiency of integrating solar energy generation into the power system.

## 6 Recommendations for Future Work

Based on these findings and the current state of research, several directions are proposed that will further improve sky-image-based solar forecasts in terms of accuracy and applicability:

### 1. Integration of Multi-Modal Exogenous Data

Though sky images contain essential visual cues on cloud cover, augmenting them with auxiliary meteorological data can further improve the robustness of the model. Future models should investigate a multi-input architecture that incorporates real-time sensor measurements (ambient temperature, relative humidity, and barometric pressure) so that atmospheric variables can be included in the characterization of wave scatterings beyond what images themselves convey.

### 2. Advanced Cloud Dynamics and Motion Tracking

This will allow the framework to use motion-aware formulated algorithms that extend the forecast horizon maybe beyond 15 minutes of intra-hour time. Optical flow or even RNNs like LSTMs/GRUs can help to track the flow and path of clouds, helping the model predict shading events better in advance.

### 3. Edge Computing and Decentralized Deployment

In order for the model to ever go from a centralized research environment out into real-world industrial use, it needs to be optimized for deployment on edge computing devices (e.g., NVIDIA Jetson or specialized IoT gateways). This would allow each solar farm to produce real-time, localized forecasts without high-latency reliance on cloud processing or costly server infrastructure.

#### 4. Spatio-Temporal Graph Neural Networks

A potential future work is to explore Graph Neural Networks (GNNs), which could serve as a data structuring mechanism to model spatial correlations amongst multiple sky-imaging stations spread across a geographic region. By treating different solar plants like nodes in a graph, the system could learn that weather patterns moving over one site would affect another minutes later.

#### 5. Self-Supervised Learning for Data Scarcity

This can be a tedious process of collecting labels for PV-image pairs. Utilizing a self-supervised learning approach—having the model learn to represent descriptors of features in sky images from huge collections of unlabeled imagery and then fine-tuning with the SKIPP'D dataset Could improve model performance where historical solar power data is limited.

### Conflicts of Interest

The authors declare no conflicts of interest.

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