VERY SHORT-TERM SOLAR RADIATION FORECASTING WITH ALL-SKY IMAGES AND METEOROLOGICAL DATA

Trinh Trung Hieu, Nguyen Binh Nam*, Duong Minh Quan, Nguyen Van Tan, Tran Anh Tuan

The University of Danang - University of Science and Technology, Vietnam

*Corresponding author: nbnam@dut.udn.vn

(Received: May 11, 2025; Revised: June 15, 2025; Accepted: June 20, 2025)

DOI: 10.31130/ud-jst.2025.23(9D).577E

Abstract - The ability to forecast solar radiation accurately on a very short time scale is essential for optimizing the performance and reliability of solar power systems. This work introduces a deep learning approach based solely on Convolutional Neural Networks (CNNs) to predict solar radiation over a 5-minute horizon. By processing sequences of infrared all-sky images alongside meteorological variables, the proposed model captures intricate spatial patterns and relevant environmental factors influencing solar irradiance. Experimental evaluation reveals that the proposed approach achieves a forecast skill improvement of 8.67% over the persistence model, with a root mean square error (RMSE) of 87.53 W/m² compared to 95.84 W/m², and a mean absolute error (MAE) of 42.48 W/m² versus 44.50 W/m². These results highlight the capability of CNN-based models to enhance the reliability of very short-term solar radiation forecasting and support the advancement of intelligent renewable energy management systems.

Key words - Renewable energy; all-sky image; convolution neural networks; long short-term memory; very short-term forecasting

1. Introduction

The growing integration of renewable energy sources into modern power grids has heightened the need for precise and dependable forecasting techniques to maintain grid stability and optimize energy management. Solar energy, in particular, has emerged as a leading renewable resource due to its abundance and sustainability. Nevertheless, the inherent intermittency and variability of solar irradiation present significant challenges for its effective deployment [1], [2]. Achieving accurate very short-term solar irradiation forecasts - on the order of minutes to hours - is essential for maximizing the efficiency of solar energy systems, enhancing grid reliability, and supporting real-time energy trading

Conventional forecasting approaches, such as Numerical Weather Prediction (NWP) models and statistical methods, often struggle to capture the rapid and localized fluctuations in solar irradiation caused by transient cloud cover and dynamic atmospheric conditions [3]. Recent advances in deep learning have paved the way for substantial improvements in forecasting accuracy by enabling the extraction of complex patterns from large and heterogeneous datasets. In particular, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image analysis and spatial feature extraction, making them highly suitable for solar forecasting tasks that rely on visual data [4].

This paper presents a deep learning-based approach for very short-term solar irradiation forecasting, leveraging the power of CNNs to process all-sky images and meteorological measurements. All-sky images offer rich information about cloud formations and atmospheric dynamics, which are critical for understanding short-term changes in solar irradiance. When combined with meteorological data, such as temperature, humidity, and wind speed, these visual cues provide a comprehensive view of the factors influencing solar variability [5]. By integrating these diverse data sources, the proposed CNN-based model aims to deliver more accurate and robust forecasts than traditional methods.

The core of the proposed model is a CNN architecture designed to automatically extract spatial features from sequences of all-sky images, such as cloud patterns and their evolution, which are essential for predicting short-term solar irradiation changes. By learning these intricate spatial relationships, the model is well-equipped to address the challenges posed by the highly dynamic nature of solar energy generation.

The main contributions of this work are as follows: i. the development of a CNN-based deep learning model specifically tailored for very short-term solar irradiation forecasting, ii. the integration of all-sky images and meteorological data as complementary input features, and iii. a thorough evaluation of the model's performance in comparison with state-of-the-art forecasting techniques. The results highlight the effectiveness of the proposed approach in enhancing forecasting accuracy, thereby advancing the field of solar energy prediction.

2. Related works

The rapid expansion of Photovoltaic (PV) installations in power systems has underscored the importance of precise solar irradiance forecasting for maintaining grid reliability and optimizing energy dispatch. Forecasting solar radiation on very short timescales, particularly within a 30-minute window, is essential for managing the swift changes in solar output driven by cloud movement. This section provides an overview of recent progress in solar forecasting, with an emphasis on the application of All-Sky Imagers (ASI), machine learning, and deep learning methodologies.

2.1. All-Sky Imaging in Solar Forecasting

All-Sky Imagers (ASI) have become a valuable tool for short-term solar irradiance prediction, as they deliver high-resolution, real-time sky images that capture cloud behavior and atmospheric variability. Compared to traditional approaches such as Numerical Weather Prediction (NWP) and satellite-based models, ASI-based techniques have demonstrated enhanced accuracy for lead times up to 30 minutes [6].

Typical ASI-based forecasting pipelines involve extracting features from sky images - such as cloud fraction, luminance, and Cloud Motion Vectors (CMVs) - which are then used as inputs for statistical or machine learning models to estimate Global Horizontal Irradiance (GHI). Methods like optical flow and cross-correlation are frequently employed to derive CMVs, which are crucial for tracking cloud displacement and forecasting future irradiance [7]. However, the reliability of CMV-based predictions can diminish under rapidly changing cloud conditions, leading to reduced accuracy as the forecast horizon extends.

2.2. Deep Learning Approaches for Solar Irradiance Prediction

The advent of deep learning has significantly advanced the field of solar forecasting. Convolutional Neural Networks (CNNs), in particular, have shown great promise in extracting spatial features from ASI images, such as cloud morphology and distribution, which are directly linked to solar irradiance variability [8]. By leveraging large datasets, CNNs can automatically learn complex visual patterns that traditional feature engineering might overlook.

Recent studies have highlighted the effectiveness of deep learning models in solar forecasting tasks, especially when combined with meteorological data. The integration of image-based features with environmental measurements - such as temperature, humidity, and wind speed - has been shown to further improve forecast accuracy. The choice of input features and the design of the CNN architecture play a critical role in maximizing predictive performance.

2.3. Dataset Description

The dataset utilized in this research was collected at the Milan, Italy (latitude: 45.50°N, longitude: 9.16°E), spanning from October 1st, 2023, to November 30th, 2024. It comprises:

- Infrared All-Sky Images: Acquired using a thermal infrared imager, providing continuous visual monitoring of sky conditions.

- Meteorological Data: Includes numerical measurements such as global horizontal irradiance (GHI), ambient temperature, and relative humidity.

2.4. Infrared All-Sky Imager Specifications

The thermal infrared all-sky camera employed in this study is the Sky InSight™ system by Reuniwatt. This device is equipped with a long-wavelength infrared sensor, capturing images at a resolution of 640×480 pixels every minute. Mounted on a mast and utilizing a hemispherical mirror, the imager achieves a full 180° view of the sky.

Infrared ASI technology offers several advantages for solar forecasting applications [9]:

- Elimination of Sun Glare: The system avoids sun glare in the image center, ensuring clear visualization of the sun's vicinity and improving cloud detection accuracy.

- Direct Cloud Emission Detection: By sensing thermal emissions, the imager can identify cloud presence even under low-light or nighttime conditions.

- Enhanced Cloud-Sky Contrast: Infrared imaging provides superior differentiation between clouds and clear sky, facilitating more reliable cloud classification and motion analysis.

An example of an image captured by the infrared ASI is shown in Figure 1, illustrating its capability to deliver high-contrast, glare-free sky observations.

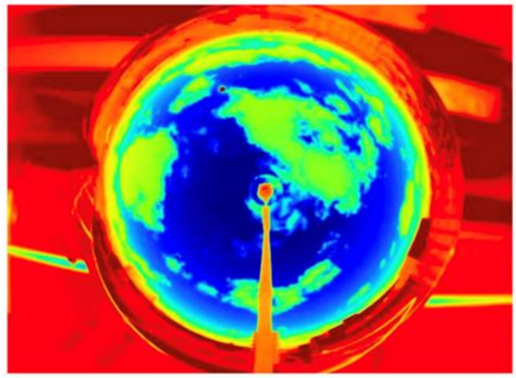

Figure 1. *All-Sky Image in infrared spectrum*

2.5. Meteorological Data Collection

Environmental measurements were obtained from a weather station at Milan, Italy (latitude: 45.50°N, longitude: 9.16°E). The station is equipped with sensors for solar irradiance, temperature, and humidity. Solar irradiance was measured using two secondary standard pyranometers, recording both horizontal and 30°-tilted global irradiance. Data was sampled every ten seconds, and for each minute, the average, maximum, minimum, and standard deviation were calculated to provide a comprehensive summary of the atmospheric conditions.

3. Proposed forecasting model

This study introduces a deep learning-based framework for ultra-short-term solar irradiance prediction, utilizing the strengths of Convolutional Neural Networks (CNNs) and leveraging data from infrared all-sky imaging and meteorological measurements. Although advanced models have shown promise in short-term forecasting, surpassing the persistence model - a simple yet robust baseline - remains a significant challenge. The following section details the methodology, including data preparation, model architecture, and evaluation strategy. The effectiveness of the proposed approach is benchmarked against the persistence method to highlight its practical benefits.

3.1. Data Preparation

Prior to model training, the dataset underwent a comprehensive cleaning and synchronization process. Meteorological records were filtered to remove anomalies and entries with physically implausible values, such as periods with zero clear-sky GHI. Infrared sky images were uniformly resized to 128×128 pixels and converted to grayscale, ensuring consistency and reducing computational complexity. To facilitate accurate pairing, both image and meteorological data streams were aligned based on their timestamps, resulting in a synchronized dataset suitable for supervised learning.

3.2. CNN-Based Deep Learning Model

The proposed Convolutional Neural Network (CNN) model is specifically designed for very short-term solar irradiance forecasting by effectively integrating both image-based and meteorological data. At each prediction instance, three consecutive all-sky images, captured at times t_0, $t_0 - \Delta t$, and $t_0 - 2\Delta t$ (with $\Delta t = 2$ minutes), are stacked along the channel dimension to form a single composite input image of size 3×28×128. This stacked image encapsulates the recent temporal evolution of sky conditions and serves as the input to the CNN feature extraction block.

The CNN feature extractor consists of three convolutional layers with kernel sizes of 3×3 and filters count of 64, 128, and 256, respectively. Each convolutional layer is followed by a ReLU activation function and a max pooling operation to progressively reduce the spatial dimensions and capture increasingly abstract representations. The output of the final max pooling layer represents the high-level spatial features extracted from the stacked sky images. The architecture of the CNN feature extraction block is detailed in Figure 3.

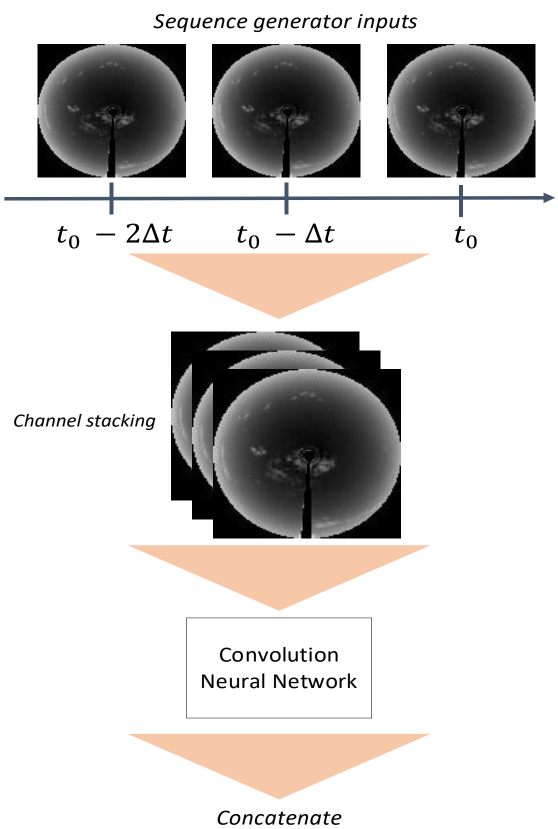

Figure 2. *Representation of CNN feature extraction pipeline*

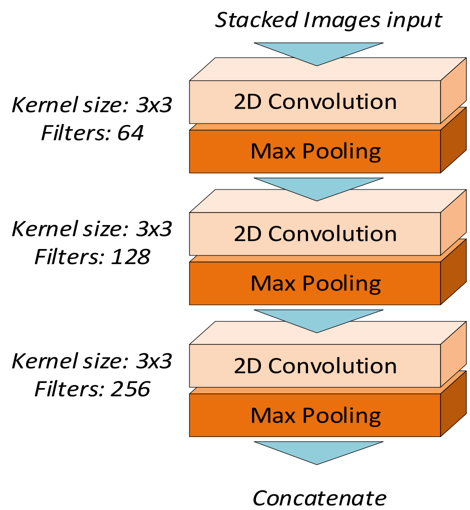

Figure 3. *CNN block structure*

In parallel, meteorological measurements, including Global Horizontal Irradiance (GHI), temperature, and humidity, are collected at the same three points (t_0, $t_0 - \Delta t$, and $t_0 - 2\Delta t$). These nine values are flattened and concatenated to form a single 1×9 feature vector, which is then merged with the CNN-extracted image features to create a unified feature representation.

This combined feature vector is subsequently passed through a fully connected neural network comprising three dense layers with 256, 128, and 64 units, respectively, each followed by a ReLU activation function. The final output layer produces the predicted GHI value for the specified forecast horizon.

The complete model architecture is summarized in Figure 4. This architecture enables the model to effectively capture both the spatial dynamics of cloud patterns and the contextual influence of recent meteorological conditions, resulting in robust and accurate very short-term solar irradiance forecasts.

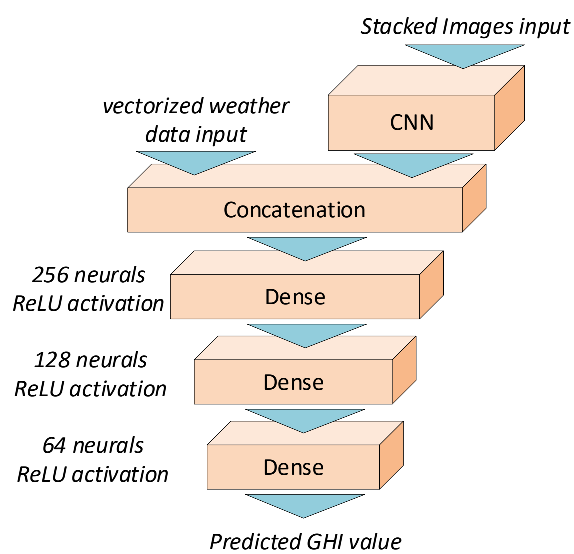

Figure 4. *Representation of proposed forecasting model*

3.3. Baseline and Evaluation Criteria

To assess the performance of the proposed CNN-based model, its predictions are compared to those of the persistence model, which assumes that the most recent observed GHI remains unchanged throughout the forecast period. This baseline is widely recognized for its simplicity and reliability in short-term solar forecasting.

Model accuracy is quantified using three standard metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Forecast Skill (FS). These metrics are defined as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (2)$$

$$FS = 1 - \frac{RMSE_{model}}{RMSE_{persistence}} \quad (3)$$

where, N is the total number of data points in the evaluation set, y_i denotes the observed value and $\hat{y}_i$ represents the predicted value at the same time step.

4. Result analysis

The CNN model was trained using data collected from 1st October 2023 to 31st July 2024. After training, the model's performance was evaluated on a separate test set spanning from 1st August 2024 to 30th November 2024. Evaluation results were visualized through plots comparing the predicted and actual GHI values, providing insights into the model's ability to capture temporal variations and assess its predictive accuracy. In this study, the model was specifically configured to generate forecasts with a 5-minute prediction horizon.

To comprehensively assess performance, the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Forecast Skill (FS) were calculated as functions of both the forecast horizon and the historical input window. These metrics were compared against those of the persistence model, which serves as a strong baseline for very short-term solar radiation forecasting. Detailed results are presented in Table 1.

Table 1. *Detailed results for the tested models*

Model	MAE (W/m^2)	RMSE (W/m^2)	FS (%)
CNN	42.48	87.53	8.67
Persistance	44.50	95.84	0.0

The results indicate that the proposed CNN model consistently outperforms the persistence model in both MAE and RMSE. Specifically, the CNN model achieves a lower MAE of 42.48 W/m² compared to 44.50 W/m² for the persistence model, reflecting improved accuracy in solar radiation prediction. Similarly, the RMSE for the CNN model is 87.53 W/m², which is notably lower than the 95.84 W/m² recorded for the persistence model. This improvement corresponds to a forecast skill of 8.67%, underscoring the model's enhanced ability to capture the spatial and contextual patterns in solar radiation dynamics. The reduction in RMSE highlights the effectiveness of the CNN architecture in leveraging both all-sky image sequences and meteorological data for very short-term forecasting.

Figure 5 presents a visual comparison of the MAE and RMSE values for both the CNN model and the persistence model, clearly illustrating the differences in their performance. The bar chart shows that the CNN model reduces errors across both metrics, with a more pronounced improvement in RMSE, which is sensitive to larger deviations caused by rapid cloud movements.

Figures 6 and 7 demonstrate the model's forecasting performance across distinct daily intervals in 2024. Figure 6 illustrates the 5-minute ahead prediction on a sunny day, where the CNN model closely tracks the actual GHI with minimal deviations, outperforming the persistence model during stable irradiance periods. In contrast, Figure 7 shows performance on a cloudy day, highlighting the CNN's robustness in handling variability; while the persistence model exhibits larger errors during sudden drops in GHI due to cloud cover, the CNN model mitigates these through its learned spatial features from all-sky images.

Overall, the analysis reveals that the CNN model's superior performance is most evident under variable weather conditions, where meteorological data integration helps in anticipating short-term fluctuations. However, the moderate FS of 8.67% suggests room for improvement, particularly in scenarios with extreme atmospheric dynamics. Factors such as image resolution and the choice of historical window (e.g., Δt=2 minutes) influence accuracy, with potential for optimization in future iterations.

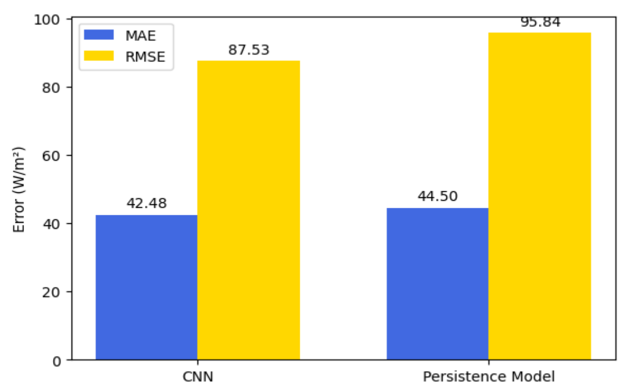

Figure 5. *MAE and RMSE comparison between CNN and Persistence Model*

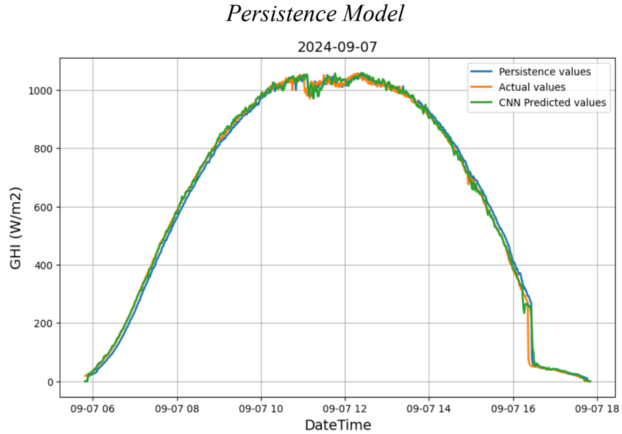

Figure 6. *5-minute ahead prediction performance of CNN and persistence models in a sunny day*

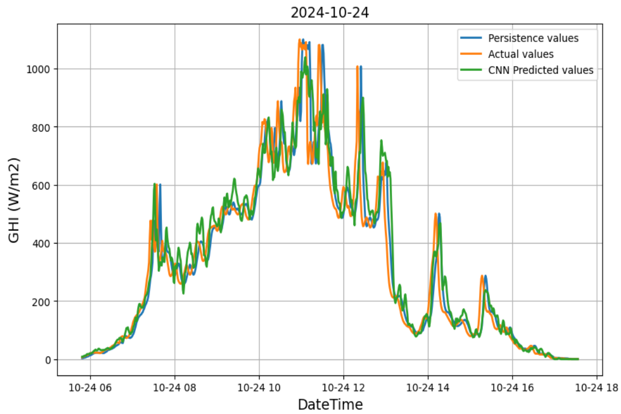

Figure 7. *5-minute ahead prediction performance of CNN and persistence models in a cloudy day*

5. Conclusion

In this study, we developed a Convolutional Neural Network (CNN) model for very short-term solar radiation forecasting with a 5-minute prediction horizon. The model was designed to extract spatial features from sequences of all-sky images, which were combined with recent meteorological measurements to enhance predictive accuracy. Training and evaluation were performed on a comprehensive dataset, and the model's performance was benchmarked against the persistence model, a widely recognized baseline in solar forecasting.

The results indicate that the CNN model consistently outperforms the persistence approach, achieving a forecast skill of 8.67%. Specifically, the CNN model attained a lower RMSE of 87.53 W/m² and an MAE of 42.48 W/m², compared to 95.84 W/m² and 44.50 W/m², respectively, for the persistence model. These findings highlight the CNN's ability to leverage both image-based and meteorological data for improved short-term solar irradiance prediction.

Despite these improvements, the overall forecast skill remains moderate, suggesting opportunities for further refinement. Future work could focus on incorporating additional atmospheric parameters, such as cloud optical properties, or experimenting with more advanced network architectures to better capture complex sky conditions. Additionally, targeted analysis during periods of rapid irradiance change could provide deeper insights into the model's robustness and practical utility. This research demonstrates the potential of CNN-based deep learning models in advancing the accuracy of renewable energy forecasting and lays the groundwork for future developments in the field.

REFERENCES

[1] C. Wan, J. Zhao, Y. Song, Z. Xu, J. Lin, and Z. Hu, "Photovoltaic and solar power forecasting for smart grid energy management”, *CSEE Journal of Power and Energy Systems*, vol. 1, no. 4, pp. 38-46, 2015.

[2] M. S. Hossain and H. Mahmood, "Short-Term Photovoltaic Power Forecasting Using an LSTM Neural Network and Synthetic Weather Forecast”, *IEEE Access*, vol. 8, pp. 172524-172533, 2020.

[3] J. Antonanzas, N. Osorio, R. Escobar, R. Urraca, F.J. Martinez-de-Pison, and F. Antonanzas-Torres, "Review of photovoltaic power forecasting”, *Solar Energy*, vol. 136, pp. 78-111, 2016.

[4] H. Kim, S. Park, H. -J. Park, H. -G. Son, and S. Kim, "Solar Radiation Forecasting Based on the Hybrid CNN-CatBoost Model”, *IEEE Access*, vol. 11, pp. 13492-13500, 2023.

[5] M. Harada and Y. Kameda, "3D Cloud Position Estimation for Solar Radiation Forecasting Using Time-Series Stereo Vision Integrated with All-Sky and Satellite Images”, in *2025 IEEE International Conference on Consumer Electronics* (ICCE), Las Vegas, NV, USA, 2025.

[6] N.Y. Hendrikx, K. Barhmi, L.R. Visser, T.A. de Bruin, M. Pó, A.A. Salah, W.G.J.H.M. van Sark, "All sky imaging-based short-term solar irradiance forecasting with Long Short-Term Memory networks”, Solar Energy, vol. 272, 2024.

[7] H. Yang *et al.*, "Solar irradiance forecasting using a ground-based sky imager developed at UC San Diego”, *Solar Energy*, vol. 103, pp. 502-524, 2014.

[8] M. Kanenobu, A. Takahashi, and M. Ito, "Determination of fluctuated threshold of input data in CNN-based Solar Irradiance Prediction Method Using All-sky Image”, in *2023 IEEE PES Innovative Smart Grid Technologies - Asia* (ISGT Asia), Auckland, New Zealand, 2023.

[9] I. R. Nijhum, M. Y. Hossain, T. Akinola, M. M. H. Rakib, and S. Dev, "A Hybrid CNN-LSTM Framework and Infrared Image Processing for Solar Irradiance Forecasting”, in *2024 17th International Congress on Image and Signal Processing, Biomedical Engineering and Informatics* (CISP-BMEI), Shanghai, China, 2024.