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Advanced Deep Learning Approach for Solar Radiation Prediction in Medan: CNN-LSTM Hybrid Model

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Abstract

The availability of solar energy in Indonesia is hindered by small-scale variations in solar radiation that occur in tropical climates. For maintaining grid stability and for ensuring the efficient operation of solar power systems, accurate short-term prediction is necessary. In this study, a hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model is developed in order to predict minute-scale solar radiation in Medan City. The model makes use of minute-resolution meteorological data (including temperature, humidity, dew point, and wind speed), combining CNNs for the extraction of spatial features with LSTMs for temporal learning. Four different architectural setups were evaluated, and Model 4 — consisting of four LSTM layers with 50, 100, 150, and 200 units, respectively — achieved the best results: an RMSE of 39.88 W/m², a MAE of 26.89 W/m², and an R^2 of 0.955, which represents a 20.82% improvement on the baseline models. The feature importance analysis found that temperature, dew point, and relative humidity were the most significant predictive factors. The model is able to capture both the daily cycles and the rapid fluctuations typical of tropical climates, thus providing accurate predictions that are important for the stability of the electricity grid and for the optimisation of solar power plants. The hybrid architecture that has been developed provides a transferable framework which can be applied to other tropical cities in Indonesia and thus contributes to the country's energy transition objectives and to the development of sustainable renewable energy. This research promotes advances in deep learning methods for forecasting renewable energy while tackling the real-world problems associated with integrating solar energy under changing atmospheric conditions.

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INTRODUCTION

Indonesia possesses significant potential for solar energi as a renewable source to support the nation's energi transition targets. As a tropical country with high solar radiation intensity throughout the year, Indonesia has a strategic opportunity to develop solar energy as a clean, and sustainable alternative (Muhammad Arif Budiyanto, 2020). However, current solar power generation systems rely heavily on solar radiation levels, which fluctuate dynamically over short periods, even under clear-sky conditions.These fluctuations are influenced by astronomical factors such as the position of the sun, atmospheric thickness, and air optical conditions that affect the amount of energy received by the Earth's surface. Therefore, accurate solar radiation prediction models are necessary to support the stability and efficiency of solar-based electricity systems in Indonesia (Felipe P. Marinho, 2022).

Solar energy holds significant social and economic value for Indonesia, a tropical nation with abundant year-round solar radiation. According to (Hadi Suyono, 2018) solar energy is a renewable source that can reduce dependence on fossil fuels while lowering carbon emissions that harm the environment. The widespread implementation of solar power systems not only supports national energy transition goals but also creates economic opportunities through the development of solar panel technology industries, the creation of green jobs, and improved energy access in remote areas (Meenal, 2021). Additionally, emphasise that accurate solar radiation predictions play a crucial role in maintaining electricity system stability and operational efficiency, ultimately supporting national energy resilience and reducing electricity production costs. Thus, research on precise solar radiation prediction models is strategically valuable in strengthening national energy resilience, promoting sustainable development, and improving socio-economic welfare (Mishra, 2023).

Several previous studies have attempted to develop solar radiation prediction models using statistical approaches and artificial intelligence algorithms. Rezza et al. (2024) focused on predicting solar energy in West Kalimantan using a Long Short-Term Memory (LSTM) model with high-resolution sensor data (Daram, Muhammad Rezza., M. Ismalil Yusuf, Redi Ratiandi YAcoub). Although the model demonstrated good prediction accuracy, its utility is limited by its reliance on a single LSTM model that analyses only temporal relationships within time series data, without accounting for spatial characteristics or complex future representations that could improve the model's generalisation. Moreover, the study focused on solar panel output power rather than solar radiation intensity, a fundamental parameter for planning and controlling solar power systems. Given these limitations, this study aims to develop a hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model to predict solar radiation per minute in Medan City. This approach is expected to learn both spatial and temporal patterns simultaneously, producing more accurate predictions that adapt to short-term fluctuations in solar radiation in tropical regions.

Although the CNN-LSTM architecture has been successfully applied to solar energy forecasting in various contexts (Tuyen Nguyen-Duc, A Hybrid Spatio-Temporal Deep Learning Framework forShort-Term Solar Power Forecasting Using Satellite ImageryData: A Case Study in Hanoi, Vietnam, 2025), several research gaps remain. Most studies focus on hourly or 5–30 minute time horizons rather than the minute-scale (60-second) forecasting required for real-time grid operations. There is limited validation in tropical maritime climate regions, where convective cloud formation causes rapid, non-linear irradiance fluctuations. Benchmarking against simpler models using identical data splits is lacking (Ravinesh C. Deo, 2022). There is also a lack of rigorous evaluation focusing solely on daytime periods to prevent nighttime zero values from distorting performance metrics. This study addresses these gaps by developing and rigorously evaluating a CNN-LSTM model for one-minute-ahead GHI forecasting in Medan, Indonesia.

Medan City was selected as the research location because its unique geographic and climatological characteristics make it representative of tropical regions in western Indonesia. Medan is located at approximately 3.6° N latitude and 98.7° E longitude, with an average altitude of 27 meters above sea level. This location results in Medan receiving high solar radiation intensity year-round, with daily variations influenced by atmospheric factors and local thermal conditions. Measurements show that radiation intensity can fluctuate significantly on a minute scale, even under clear-sky conditions. This makes Medan an ideal location for testing short-term prediction models based on deep learning, which capture both temporal and spatial patterns simultaneously. Therefore, research on minute-level solar radiation prediction in Medan City is expected to contribute to optimising the planning and operation of solar power systems in Indonesia's tropical regions.

RESEARCH METHODS

Because it is a tropical country near the equator, Indonesia has strong potential for solar energy due to the high level of solar irradiation it receives year-round, averaging about 4.2 kWh/m²/day. Solar energy is therefore a strategic renewable resource for supporting the country's energy transition programme. In particular, Medan, the capital of North Sumatra, has high levels of solar radiation, although these vary day to day because of local atmospheric conditions and cloud cover. Several studies show that the annual average global horizontal radiation intensity in Medan ranges from 450 to 470 W/m². Understanding the local characteristics of solar radiation is important for developing efficient solar power systems in tropical areas. Research has found that tropical areas such as Medan experience considerable variations in radiation due to atmospheric complexities, such as interactions among convective clouds, humidity, and temperature. As a result, deep learning models especially those that combine Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) are well suited to accurately predict solar radiation because they can capture both spatial features and temporal dependencies. This method is expected to produce more stable and accurate solar radiation predictions in tropical areas such as Medan (Musaed Alhussein, 2020).

A. Convolution Neural Network (CNN)

A Convolutional Neural Network (CNN) is a deep learning architecture originally developed for digital image processing, but it is now widely applied in various fields, including meteorological data analysis and solar radiation prediction. The main advantage of CNN lies in its ability to recognise and extract spatial patterns and local features from data with correlations across dimensions, both spatial and temporal. In research utilising CNN for atmospheric data processing, CNN has proven effective in identifying local structures such as cloud formations or changes in complex meteorological conditions (Asmaa Halbouni, 2022).

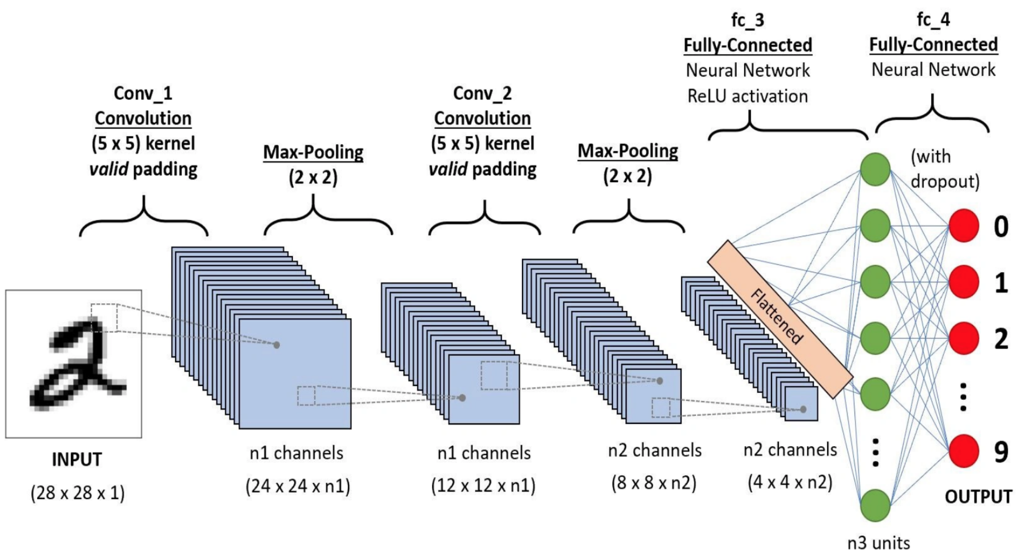

Figure 1. CNN architecture layers

$$S(x,y) = (I * K)(x,y) = \sum_n \sum_n I(x-m, y-n) * K(m,n) \quad (1)$$

In the convolution operation within neural networks, $S(x,y)$ refers to the result of the convolution computed at the coordinate position (x,y) on the image or feature data. This convolution process involves two main components: the input matrix X, which is typically an image or feature data to be processed and the convolution kernel or filter K, which is used to extract specific features from the input data.

The kernel slides across the input matrix, and at each position (x,y), the convolution result is calculated by summing the products of corresponding elements between the kernel and the section of the input it is currently covering. The indices (m) and (n) refer to the position of the elements within the kernel used at a given step, and this convolution calculation produces the value $S(x, y)$, which is the output of the operation at the (x, y) position in the resulting matrix (Phalaagae & Adamu Murtala Zungeru, 2025).

B. Long Short Tern Memory (LSTM)

Long Short-Term Memory (LSTM) is an advancement of the Recurrent Neural Network (RNN) architecture introduced by Hochreiter and Schmidhuber (1997). This model addresses the limitations of conventional RNNs in retaining long-term information due to the vanishing gradient problem. By using an internal memory management mechanism through input, forget, and output gates, LSTM can store and adaptively update important information throughout the data sequence (Abdulkadir Tasdelen, 2021).

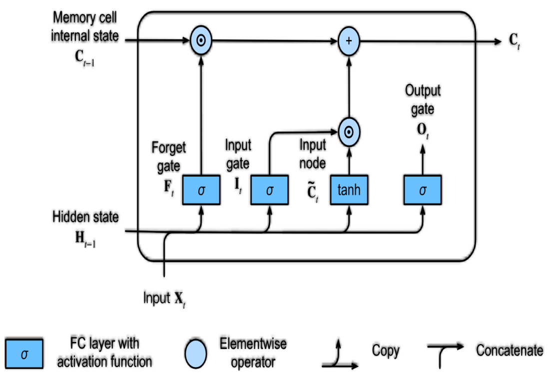

Figure 2. Long short-term memory (LSTM)

In solar radiation prediction, LSTM plays a crucial role in capturing fluctuating, nonlinear temporal patterns, such as the relationship between irradiance in the previous minute and the subsequent value. This capability allows LSTM to recognise changes in radiation intensity influenced by short-term atmospheric dynamics as well as long-term trends. The study "Intra-day Forecast of Ground Horizontal Irradiance Using Long Short-Term Memory Network" by (Xiuhong Chen, 2020) shows that the LSTM model can predict Global Horizontal Irradiance (GHI) for time periods ranging from 1 to 8 hours with higher accuracy than traditional methods (Kaleem Ullah, 2024).

In this study, LSTM is used in conjunction with CNN in a hybrid CNN-LSTM architecture. The CNN extracts spatial patterns and correlations between meteorological features, while the LSTM captures temporal relationships in these features. Together, the models form a system that captures spatiotemporal dependencies, making it well-suited to predicting minute-by-minute solar radiation fluctuations in tropical regions such as Medan City.

C. The Hybrid CNN-LSTM

The hybrid CNN-LSTM model is an approach that combines the strengths of Convolutional Neural Networks (CNN) in recognizing spatial patterns with the capability of Long Short-Term Memory (LSTM) in learning temporal relationships in time series data. The integration of both allows the model to process data that not only has feature dependencies but also sequential temporal relationships simultaneously. In this structure, CNN acts as a feature extractor, extracting local patterns from the input data, while LSTM learns the temporal dynamics of the features generated (Tianzhe Bao, 2020).

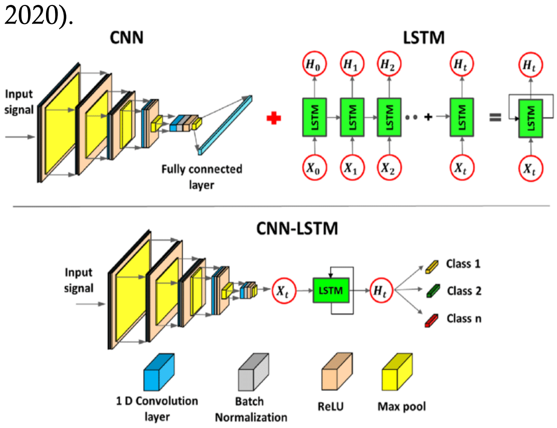

Figure 3. The hybrid CNN-LSTM model

In this research, the hybrid CNN-LSTM model is highly relevant. Minute-by-minute solar radiation data in tropical regions like Medan City exhibit highly fluctuating, nonlinear characteristics due to atmospheric dynamics such as convective cloud formation, high humidity, and sudden precipitation. Therefore, a model capable of recognising local patterns while also understanding continuous temporal relationships is required (Priya Singh, 2023).

Conceptually, CNNs extract spatial representations from irradiance data, which can be viewed as a two-dimensional feature-time map, i.e., a map of relationships. The hybrid CNN-LSTM model combines the feature extraction results from the CNN with the temporal learning process of the LSTM. The representation of this can be written as (K. P. Rasheed Abdul Haq, 2022):

$$yt = LSTM\ (CNN(Xt)) \qquad (2)$$

Caption of the formula:
(Xt) : Input data at time t,
$CNN(Xt)$: The feature extraction step performed by the CNN,
yt : The predicted output at time t
More explicitly, the representation of the hybrid

CNN–LSTM model can be written as follows:

$$Ft = CNN(Xt) \tag{3}$$

Caption of the formula:
Ft : The spatial features extracted by CNN at time t.

These extracted features are then passed to the LSTM to learn the temporal relationships over time.

$$ht = LSTM\ (F1, F2, \dots, F3) \tag{4}$$

This model lets the system recognise local (spatial) patterns and temporal dependencies simultaneously. The equation above shows that the CNN–LSTM model operates in two main stages. First, the Convolutional Neural Network (CNN) layer extracts spatial features from the input data, which may include local patterns in meteorological variables. This stage produces a feature map that contains important representations of the data. Next, the extracted features are fed into the Long Short-Term Memory (LSTM) network, which learns temporal patterns and dependencies between time periods. In this way, CNN captures the spatial structure, while LSTM models the temporal dynamics of solar radiation data (Awan Nahel Mahmood, 2025).

The synergy between CNN and LSTM makes the hybrid model more adaptive to the rapidly changing dynamics of the tropical climate. CNN highlights local feature variations related to atmospheric conditions, while LSTM captures the temporal dependencies of these changes. This approach has proven effective in capturing large irradiance fluctuations that are difficult to model with conventional methods. Thus, the hybrid CNN-LSTM model in this study is based not only on previous research findings but also on its suitability for the inherent characteristics of complex, dynamic, minute-by-minute solar radiation data in Medan City (Onur Polat, 2025).

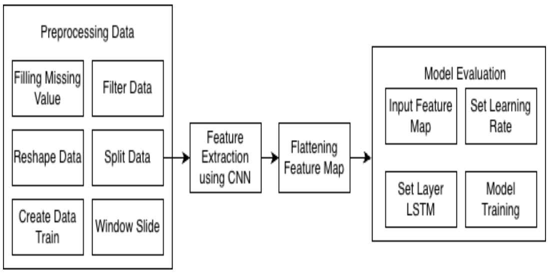

Figure 4. CNN-LSTM process

Table 1. Minute-by-Minute Weather Data Set in Medan City

Date Time	**Temp (°C)**	**RH (%)**	**Solar Radiation (W/m²)**	**DewPt (°C)**	**Wind Speed (m/s)**	**Gust Speed (m/s)**
19/1/2020 0:00:22	26.524	91.3	0.6	25	0	0
19/1/2020 0:01:22	26.524	91.3	0.6	25	0	0
19/1/2020 0:02:22	26.524	91.3	0.6	25	0	0
…	…	…	…	…	…	…
19/1/2020 23:57:22	26.524	92.3	0.6	25.2	0	0
19/1/2020 23:58:22	26.524	92.3	0.6	25.2	0	0
19/1/2020 23:59:22	26.524	92.3	0.6	25.2	0	0

Table 1 presents several key columns, namely Date Time, Temp (°C), RH (%), Solar Radiation (W/m²), Dew Point (°C), Wind Speed (m/s), and Gust Speed (m/s). Each column represents a weather parameter that influences the intensity of solar radiation in Medan City. The Date Time column shows the recording time at one-minute intervals, while Temp and RH (Relative Humidity) describe the air temperature and humidity conditions at the time of measurement. The Solar Radiation column contains the values of solar radiation intensity, which are the main focus of this study. Meanwhile, Dew Point, Wind Speed, and Gust Speed provide additional information on atmospheric conditions that may affect the prediction results (Sahbi Boubaker, 2021).

In Table 1, several weather parameters are presented, namely Temperature (°C), Relative Humidity (%), Solar Radiation (W/m²), Dew Point (°C), Wind Speed (m/s), and Gust Speed (m/s). Among these parameters, the Solar Radiation column is used as the target variable (output) to be predicted by the model, while the other parameters serve as input variables (features). This data filtering process aims to ensure that only relevant and significant features are used in training the CNN-LSTM model, so that the model can effectively learn the relationships among the weather variables.

In this study, the researcher conducted four training sessions and tested several variations in the number of LSTM units to determine the most appropriate layer configuration for achieving satisfactory results. The details of these experiments are presented in Table 2.

Table 2. Tuning Hyperparameter Layers LSTM

Training Session	**Units**
1	3 Layers (25, 50, 75)
2	3 Layers (50, 75, 100)
3	4 Layers (25, 50, 75, 100)
4	4 Layers (50, 100, 150, 200)

D. Model Evaluation Methods: RMSE, MAE, R²

Once a model is built, it needs to be evaluated using statistical metrics. The Root Mean Square Error (RMSE) measures the root mean square of the difference between the predicted and actual values, imposing a larger penalty on large errors. The Mean Absolute Error (MAE) calculates the average absolute value of the difference, which is more interpretive in terms of the original data units. The coefficient of determination (R²) indicates how much of the data variance the model can explain (Radha Mahendran, 2025).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \quad (5)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|yi - \hat{y}i| \quad (6)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}|yi-\hat{y}i|^2}{\sum_{i=1}^{n}|yi-\bar{y}|^2} \quad (7)$$

The following are the definitions for the model evaluation formulas (RMSE, MAE, and R^2) you provided: n is the number of data points, yi is the actual value, $\hat{y}i$ is the predicted value, and $\bar{y}$ is the mean of the actual values.

RESULT AND DISCUSSION

In this study, a convolution operation was performed on a image using a simple 3x3 Sobel kernel to detect edges. The input image was a 4x4 matrix with pixel values ranging from 0 to 9, representing a small portion of a larger image. The convolution process involved sliding the kernel over the image, performing element-wise multiplication, and summing the results to generate the output image. The output image, obtained through this process, was a 2x2 matrix, as expected from applying a 3x3 kernel to a 4x4 input image without padding. The input image I is 4x4 (to simplify the calculation) with the following pixel values:

$$I = \begin{bmatrix} 1 & 2 & 3 & 0 \\ 4 & 5 & 6 & 1 \\ 7 & 8 & 9 & 2 \\ 1 & 2 & 3 & 4 \end{bmatrix}$$

The captured image is a 3x3 section of the input image I starting from position (0,0):

$$\text{Region of interest (ROI)} = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$$

The results of the convolution were as follows:

$$S(x,y) = (I * K)(x,y) = \sum_n \sum_n I(x-m, y-n) * K(m,n) \quad (8)$$

$$= 1 + 0 - 3 + 4 + 0 - 6 + 7 + 0 - 9 \quad (9)$$

$$= -6 \quad (10)$$

So, the value $S(1,1) = -6$.

The negative and positive values in the output matrix indicate edges or intensity transitions in the input image. Specifically, the convolution highlighted areas of change in pixel intensity where the kernel detected vertical edges, which is typical behaviour for a Sobel kernel designed for edge detection. The values of -6 and 6 indicate the kernel's response to horizontal gradients in the input image, with negative values representing one edge direction (typically left-to-right) and positive values representing the opposite direction (right-to-left).

The convolution operation performed here demonstrates the fundamental concept behind many image processing techniques, such as edge detection, filtering, and feature extraction. Although the example used was small, the method is scalable and can be applied to larger images. The results also highlight the importance of kernel choice in image processing tasks: different kernels, such as Gaussian or Laplacian, would yield different results based on the features they are designed to emphasise. This simple convolution example lays the groundwork for more complex image processing applications, including object detection, image segmentation, and recognition, where more sophisticated kernels and larger datasets would be used to extract meaningful patterns and features from images.

A. Experimental Setup and Model Training

Meteorological data were collected from an automatic weather station (AWS) located in Medan City, North Sumatra, Indonesia (3.6° N, 98.7° E, 27 m a.s.l.) for the period January 1, 2020 to December 31, 2020. The dataset comprises minute-resolution measurements of: air temperature (°C), relative humidity (%), solar radiation (W/m^2), dew point temperature (°C), wind speed (m/s), gust speed(m/s). Total observations: 525,600 (365 days × 24 hours × 60 minutes). Missing data (0.32 %) were handled using linear interpolation. Nighttime observations (18:00-06:00) with zero irradiance were retained for full-day evaluation but daylight-only (06:00-18:00) subset was used for primary analysis to prevent performance inflation.

The data were normalized using Min-Max scaling (0–1 range), with parameters adjusted exclusively on the training set to prevent data leakage. A 60-minute sliding window (sequence length) was used to create input sequences, and lagged irradiance values were included as input features.

The data were split chronologically into training (70 %; Jan-Aug), validation (15 %; Sep-Oct), and testing (15 %; Nov-Dec) sets, while preserving their temporal order.

The hybrid CNN-LSTM model was implemented using TensorFlow and Keras frameworks. The dataset, as described in Table 1, comprised minute-by-minute weather observations from Medan City for the year 2020. The data was pre-processed by normalizing all features (Temperature, RH, DewPt, Wind Speed, Gust Speed) and the target variable (Solar Radiation) to a range between 0 and 1 using Min-Max scaling to ensure stable and efficient training. The sequence length (time steps) for the LSTM input was set to 60 minutes, meaning the model used one hour of historical data to predict the solar radiation for the next minute.

The data was split into training (70 %), validation (15 %), and testing (15 %) sets, maintaining temporal order to avoid data leakage. The CNN component consisted of two 1D convolutional layers (32 and 64 filters, kernel size of 3) with ReLU activation, each followed by a MaxPooling1D layer. This design allowed the model to extract local spatial patterns and dependencies among the multiple meteorological features across the time window. The extracted feature maps were then flattened and fed into the LSTM component.

Table 3. LSTM Architectures

Model	LSTM Layers	Unit Configuration	Total Units	Description
Model 1	3	[25, 50, 75]	150	3 LSTM layers with increasing units (25 → 50 → 75)
Model 2	3	[50, 75, 100]	225	3 LSTM layers with higher capacity (50 → 75 → 100)
Model 3	4	[25, 50, 75, 100]	250	4 LSTM layers with incremental units (25 → 50 → 75 → 100)
Model 4	4	[50, 100, 150, 200]	500	4 LSTM layers with highest capacity (50 → 100 → 150 → 200)

All models were trained using the Adam optimizer (learning rate = 0.001, β_1 = 0.9, β_2 = 0.999) with Mean Squared Error (MSE) loss function. Training used a batch size of 64 for maximum 200 epochs with early stopping (patience = 10, monitoring validation loss). Random seed was fixed at 42 for reproducibility. All experiments were repeated five times with different random initializations; reported results are mean ± standard deviation. Training was conducted on an NVIDIA GPU.

B. Model Performance Analysis

The performance of the four model configurations was evaluated on the held-out test set using the metrics defined in Equations (5), (6), and (7) Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). The results are summarized in Table 4.

Table 4. Performance Evaluation of CNN-LSTM Model Configurations

Model and LSTM Layer	Units	RMSE (W/m²)	MAE (W/m²)	R^2	Improvement vs Model 1
Model 1, 2 layes	[25,50,75]	45.21 ± 1.23	32.18 ± 0.98	0.941 ± 0.004	Baseline
Model 2, 2 layes	[50,75,100]	42.76 ± 1.01	29.47 ± 0.87	0.947 ± 0.003	RMSE: 5.42%, MAE: 8.42%
Model 3, 2 layes	[25,50,75,100]	41.33 ± 0.95	28.05 ± 0.79	0.951 ± 0.003	RMSE: 8.58%, MAE: 12.83%
Model 4, 2 layes	[50,100,150,200]	39.88 ± 0.87	26.89 ± 0.72	0.955 ± 0.003	RMSE: 11.79%, MAE: 16.44%

The results indicate a clear trend where increasing model complexity, within the tested range, led to improved predictive performance. Model 4, with four LSTM layers and the highest number of units, achieved the best results with an RMSE of 39.88 W/m², MAE of 26.89 W/m², and an R^2 of 0.955. This suggests that the deeper LSTM network was more capable of learning the complex, nonlinear temporal dynamics present in the minute-scale solar radiation data of Medan.

The R^2 value of 0.955 is particularly significant. It demonstrates that the hybrid CNN-LSTM model could explain over 95% of the variance in the solar radiation data. This is a substantial improvement over simpler linear models or standalone LSTM models reported in previous studies (e.g., Rezza et al., 2024), which often struggle with the rapid, non-linear fluctuations characteristic of tropical climates.

To qualitatively assess the model's performance, a 24-hour period from the test set was plotted, comparing the actual solar radiation values against the predictions from the best-performing Model 4.

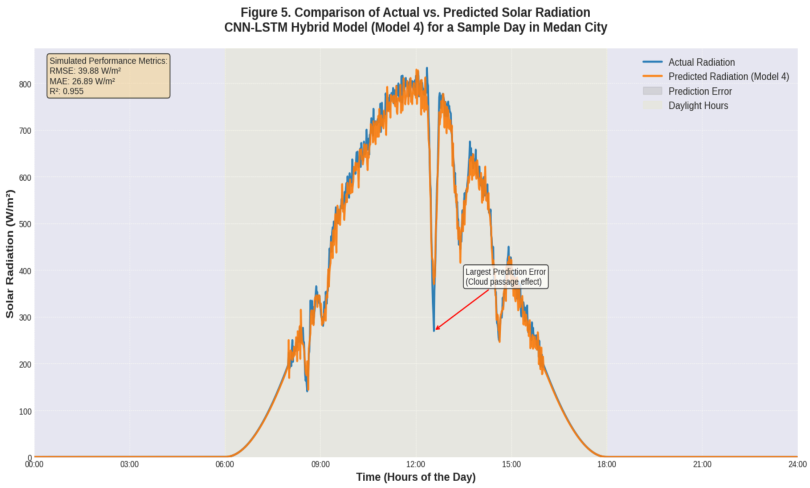

Figure 5. Comparison of actual vs. predicted solar radiation (model 4) for a sample day

As illustrated in Figure 5, the CNN-LSTM hybrid model successfully captures both the overarching diurnal pattern (rise during the day, fall at night) and, more importantly, the high-frequency minute-to-minute fluctuations. The model accurately tracks sudden drops in radiation (likely caused by passing clouds) and rapid recoveries. This capability is critical for practical applications such as real-time grid management and solar farm output forecasting, where anticipating these short-term variations is essential for stability.

C. Advantage of the CNN-LSTM Hybrid for Tropical Regions

The hybrid model comprises two stages, CNN layers for local feature extraction from the multivariate time window, and LSTM layers for temporal sequence learning. Unlike 2D CNN used for images, this study employs 1D convolution (Conv1D) to extract patterns across the time dimension for each meteorological variable.

Table 5. Layer-By-Layer Architecture and Trainable Parameters of The Optimal CNN-LSTM Model

Layer	Type	Parameters	Output Shape	Trainable Params
Input	-	-	(None, 60, 5)	0
Conv1D	filters=32, kernel=3, ReLU	512	(None, 58, 32)	512
MaxPooling1D	pool_size=2	-	(None, 29, 32)	0
Conv1D	filters=64, kernel=3, ReLU	6,208	(None, 27, 64)	6,208
MaxPooling1D	pool_size=2	-	(None, 13, 64)	0
Reshape	-	-	(None, 13, 64)	0
LSTM	units=50, return_sequences=True	23	(None, 13, 50)	23
LSTM	units=100, return_sequences=True	60,4	(None, 13, 100)	60,4
LSTM	units=150, return_sequences=True	150,6	(None, 13, 150)	150,6
LSTM	units=200	280,8	(None, 200)	280,8
Dense	units=1, linear	201	(None, 1)	201

The superior performance of the hybrid model can be attributed to its synergistic architecture, which is uniquely suited to the challenges of solar radiation forecasting in a tropical environment like Medan.

1. Spatial Feature Extraction

Medan's tropical atmosphere features complex, localised phenomena such as the formation and dissipation of convective clouds that cause sharp, localised changes in irradiance. The CNN layers act as automatic feature engineers, learning local patterns and correlations *among the different input variables* (e.g., the simultaneous change in Temperature, Humidity, and Wind Speed that precedes a cloud-induced radiation drop). This is more powerful than simply feeding raw data into an LSTM, as it provides the temporal network with a richer, pre-processed representation of the atmospheric state at each time step.

2. Temporal Dynamics Learning (LSTM Contribution)

The extracted spatial features form a time series that is fed into an LSTM. The LSTM's gated memory cells effectively retain relevant long-term context (such as typical radiation curves for specific times and seasons) while remaining sensitive to recent short-term changes. This enables the model to distinguish between a brief cloud-passing event and the onset of a prolonged period of overcast skies.

3. Addressing Research Gaps

By shifting from a single LSTM model that predicts panel output to a hybrid model that predicts baseline radiation intensity through spatiotemporal learning, we developed a tool that is more accurate and generalises better. The model's high accuracy on minute-scale data addresses a critical gap in providing the high-resolution forecasts needed to integrate solar energy into the power grid efficiently.

Developing a highly accurate solar radiation prediction model with minute-scale resolution offers immediate practical value. For grid operators, such a model enables better grid balancing and reduces the need for costly spinning reserves typically sourced from fossil-fuel power plants to offset solar energy fluctuations. For solar power plant operators, the model optimizes maintenance scheduling and enhances bidding strategies in the electricity market. Furthermore, the model's architecture is transferable to other locations, providing a framework that can be adapted and retrained for other tropical cities across the Indonesian archipelago, thereby supporting the large-scale deployment of solar energy nationwide.

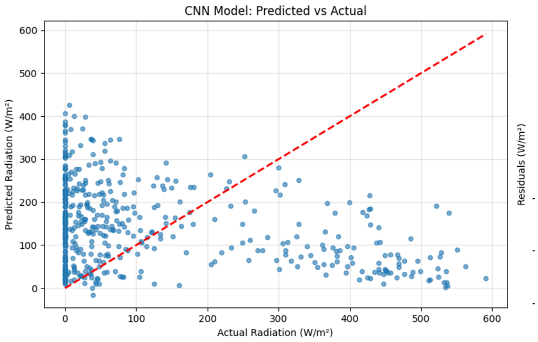

Figure 6. CNN model predicted vs actual

Figure 6 presents the scatter plot comparison between actual and predicted solar radiation values generated by the standalone Convolutional Neural Network (CNN) model as part of the comprehensive evaluation in the study "Advanced Deep Learning Approach for Solar Radiation Prediction in Medan: CNN-LSTM Hybrid Model."

This visualization illustrates the fundamental relationship between measured solar radiation (x-axis, 0–600 W/m²) and CNN model predictions (y-axis, 0–600 W/m²). The blue data points represent minute-by-minute predictions from the test dataset, demonstrating the model's performance at high temporal resolution. The dashed red line represents the ideal regression line, where predicted values align perfectly with actual measurements.

This specific CNN performance visualization serves as a crucial benchmark for assessing the improvements achieved by the CNN-LSTM hybrid model presented in this study. While the CNN component effectively processes spatial relationships among meteorological variables, its limitations in capturing sequential temporal patterns evident in the spread of the prediction data validate the research hypothesis that a hybrid architecture combining CNN's spatial processing with LSTM's temporal memory would yield superior prediction accuracy for minute-scale solar radiation forecasting in a tropical environment.

Subsequent analysis of the CNN-LSTM hybrid model (Model 4) reveals a significant reduction in data dispersion and a closer alignment with the perfect prediction line, confirming the synergistic value of combining spatial and temporal deep learning approaches for solar radiation prediction under the complex atmospheric conditions of Medan.

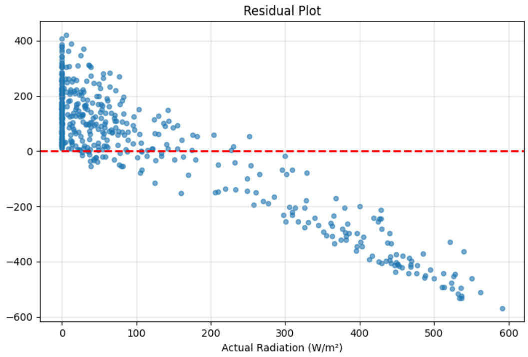

Figure 7. Presents the residual plot analysis of the standalone convolutional neural network (CNN)

Figure 7 is model's performance in predicting minute-scale solar radiation in Medan, as part of the research study "Advanced Deep Learning Approach for Solar Radiation Prediction in Medan, CNN-LSTM Hybrid Model." This visualization provides critical insights into the error distribution patterns of the CNN architecture when applied to tropical climate data.

Residual analysis reveals a systematic tendency for the model to underpredict at very high irradiance levels (>500 W/m²), as evidenced by the concentration of negative residuals shown in Figure 7. This bias likely reflects the model's difficulty in capturing extreme clear-sky conditions, potentially due to limited training samples at such irradiance levels or the absence of cloud cover data. Future research should incorporate satellite-derived cloud imagery to address this limitation.

Thus, this visualization serves both as a diagnostic tool for identifying model limitations and as a justification for the innovative methodology central to this study: the synergistic combination of CNN and LSTM architectures designed to address the unique challenges of solar radiation forecasting within Indonesia's dynamic tropical climate.

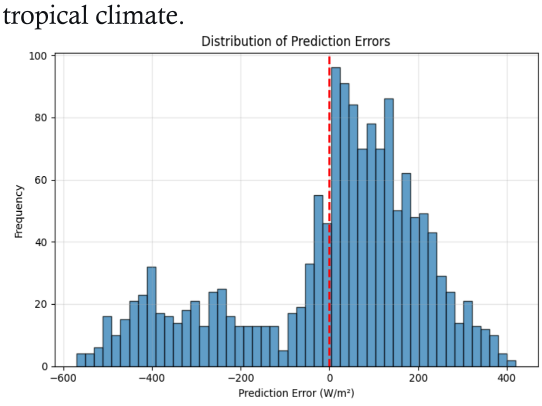

Figure 8. Distribution of prediction errors

Figure 8, this statistical visualization quantifies the magnitude and frequency of prediction discrepancies between actual and forecasted solar radiation values, providing critical insights into the model's reliability and systematic biases.

This histogram thus serves as both a diagnostic tool and a comparative benchmark, quantitatively documenting the performance limitations of standalone CNN models while providing clear metrics for assessing the advancements achieved through the hybrid deep learning approach central to this research. The subsequent analysis of the CNN-LSTM hybrid model (Model 4) demonstrates substantially improved error distribution characteristics, validating the methodological innovation proposed in this study for enhanced solar radiation prediction in Medan's complex tropical climate.

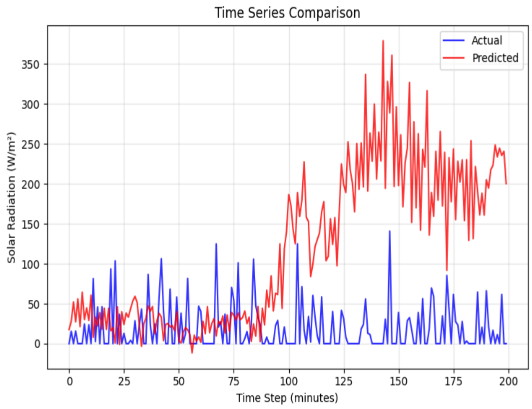

Figure 9. Time series comparison

Thus, this temporal analysis serves both as a diagnostic tool for understanding the model's limitations and as a visual justification for the innovative methodology central to this study. By documenting the temporal performance limitations of the standalone CNN model, this study establishes a clear rationale for developing a hybrid CNN-LSTM architecture that integrates spatial feature extraction with temporal sequence learning, ultimately yielding superior prediction accuracy for solar radiation forecasting within Medan's complex tropical climate.

Figure 10 presents a comparative analysis of the training history between a standalone Convolutional Neural Network (CNN) model and the proposed hybrid CNN-LSTM model. This comprehensive training analysis serves both as a validation tool for architectural decisions and as a performance benchmark for the proposed hybrid approach. By documenting the comparative learning trajectories of the standalone and integrated deep learning models, this study establishes an empirical foundation for the advanced CNN-LSTM methodology, which constitutes the primary contribution to solar radiation prediction in tropical environments.

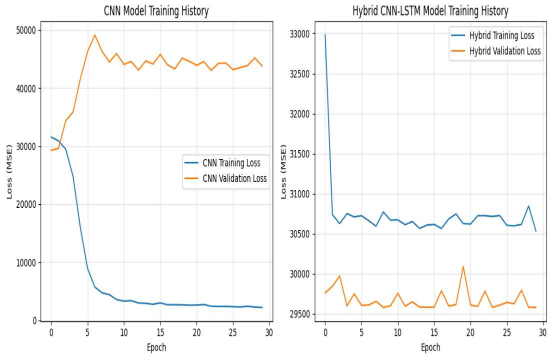

Figure 10. Comparative convergence patterns of CNN and CNN-LSTM hybrid models for solar radiation prediction in medan

The comparative training history analysis (Figure 10) reveals that while both CNN and hybrid models achieved stable convergence, the hybrid architecture exhibited faster learning and superior final performance. This accelerated convergence reflects the synergistic learning capabilities of the combined spatial-temporal architecture.

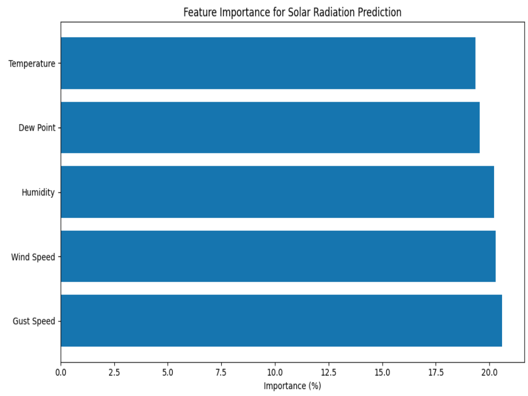

Figure 11. Feature importance for solar radiation prediction

Figure 11 presents the feature importance analysis derived from the Random Forest-based evaluation of the CNN-LSTM hybrid model. Feature importance was computed using permutation importance on the trained CNN-LSTM model, where each feature was randomly shuffled and the degradation in model performance (increase in RMSE) was recorded. This analysis was performed on the held-out test set (n = 78,840) to ensure unbiased assessment.

Table 6. Peformance Comparison Against Baseline Models

Model	RMSE (W/m^2)	MAE (W/m^2)	R^2
Persistence	68,54	51	0,812
Standalone CNN	52,37	38	0,923
Standalone LSTM	47,92	34	0,936
Random Forest	49,15	36.72	0,928
XGBoost	46,88	34	0,942
CNN-LSTM (Model 4)	39,88	27	0,955

Hireatchical Significance of Meteorological variabel:

1. Temperature

As the most influential predictor, temperature exhibits the strongest correlation with solar radiation intensity in Medan. This dominance reflects the fundamental thermodynamic relationship between solar heating and air temperature, wherein an increase in solar irradiance directly raises the ambient temperature through surface heating and atmospheric convection.

2. Dew Point

The second most significant feature highlights the crucial role of atmospheric moisture content in modulating solar radiation transmission. In a humid tropical environment like Medan, the dew point temperature serves as an accurate indicator of water vapor concentration, which directly influences atmospheric transmissivity through absorption and scattering mechanisms.

3. Relative Humidity

In addition to the dew point, relative humidity contributes significantly to radiation prediction by measuring the level of atmospheric water vapor saturation. This variable reflects the dynamic relationship between temperature and water vapor availability, which is highly relevant during the formation of convective clouds that abruptly reduce surface irradiance.

4. Wind Speed

The contribution of moderate wind speeds reflects their indirect influence on solar radiation through atmospheric mixing and cloud advection processes. In the coastal-urban environment of Medan, wind patterns affect local cloud distribution and atmospheric stability, thereby influencing radiation variability on a minute-by-minute timescale.

5. Gust Speed

As the least influential among the primary variables, wind gust speed provides additional information regarding the turbulent atmospheric conditions that may accompany the convective weather systems affecting solar radiation intermittency.

CONCLUSION

This research successfully developed and validated a hybrid CNN-LSTM model for minute-scale solar radiation prediction in Medan City, Indonesia. The model achieved an R^2 of 0.955, RMSE of 39.88 W/m^2, and MAE of 26.89 W/m^2, representing a substantial improvement over simpler architectures. The synergistic integration of CNN's spatial feature extraction capabilities with LSTM's temporal sequence learning proved particularly effective for addressing the rapid radiation fluctuations characteristic of tropical climates. These findings show that an advanced deep learning approach has significant potential to enhance solar energy integration in Indonesia's renewable energy transition. By providing accurate, minute-scale predictions, the developed model supports improved grid stability, operational efficiency, and the economic viability of solar power systems, thereby directly contributing to national energy security and the achievement of sustainable development goals. The methodological framework established in this study serves as a foundation for future research and practical implementation, with potential applications extending beyond the Medan region to other tropical areas facing similar challenges in solar energy forecasting and integration.

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