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Research Article

Prediction of PIRP Values from Sky Images Using Deep Learning Techniques

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ABSTRACT

Introduction: The intermittency of solar energy necessitates accurate short-term forecasting for effective energy grid management. Pyranometer Irradiance Recorded Point (PIRP) values — representing instantaneous solar irradiance measurements (in W/m^2) — can be predicted using deep learning models. This study introduces a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture to forecast PIRP values from sequential sky images, historical PIRP data, and cyclical time-based features, providing a scalable and low-cost alternative to conventional sensor-dependent methods.

Objectives: The objectives of this research are to develop a hybrid CNN-LSTM model that leverages spatial features from sky images and temporal dependencies from historical PIRP values, to enhance forecasting accuracy by integrating cyclical time features, and to demonstrate a scalable and cost-effective forecasting approach for smart grid operations, solar farms, and urban energy planning.

Methods: The model utilizes a TimeDistributed CNN to extract spatial features from sequences of sky images and LSTM layers to capture temporal dependencies. Timestamp features are encoded using sine and cosine transformations. An attention mechanism is integrated to focus on the most informative parts of the sequence. The curated dataset, comprising 13,818 PIRP records and over 39,000 images, was preprocessed through timestamp alignment, filtering, and feature scaling. Training employed Adam optimization and Huber loss, with extensive evaluation through MAE, RMSE, Filtered MAPE, and R^2 Score metrics.

Results: The proposed model achieved a Mean Absolute Error (MAE) of 14.46, a Root Mean Squared Error (RMSE) of 30.03, a Filtered Mean Absolute Percentage Error (MAPE) of 9.85%, and an R^2 Score of 0.9737. It significantly outperformed baseline models such as CNN-only, LSTM-only, and Linear Regression, validating its effectiveness in short-term PIRP forecasting. Comparative evaluations confirmed the superiority of the hybrid CNN-LSTM approach with cyclical time feature integration and attention mechanism.

Conclusions: The hybrid CNN-LSTM model demonstrates robust performance by accurately capturing spatio-temporal dependencies inherent in PIRP values. Its ability to predict 15-minute-ahead irradiance values with high accuracy highlights its potential for real-world deployment in renewable energy forecasting. Future work will focus on expanding datasets across diverse geographical regions, integrating additional meteorological parameters, and exploring transformer-based architectures for further enhancements.

Keywords: PIRP Prediction, Deep Learning, CNN-LSTM, Solar Irradiance, Sky Images, Short-term Forecasting.

INTRODUCTION

The growing demand for sustainable energy sources has positioned solar power as a key contributor to global energy systems. However, the intermittent and unpredictable nature of solar irradiance presents significant challenges for efficient energy management, grid stability, and renewable energy integration. Accurate short-term forecasting of solar irradiance is critical for optimizing energy storage, load balancing, and real-time decision-making in smart grid operations. Pyranometer Irradiance Recorded Point (PIRP) values, which quantify the solar radiation reaching the Earth's surface, are vital indicators that inform solar power generation forecasts. Traditional methods for PIRP prediction often rely on ground-based sensors, such as pyranometers, and satellite imagery, but these approaches suffer from limitations including high operational costs, restricted spatial resolution, and maintenance burdens[12,14]. As a result, the exploration of data-driven, scalable alternatives has gained substantial interest in recent years.

The advent of deep learning has introduced transformative possibilities in the field of solar forecasting. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in extracting spatial patterns from sky images, such as cloud formations and atmospheric conditions, which directly influence solar irradiance. Separately, Long Short-Term Memory (LSTM) networks have proven highly effective in capturing temporal dependencies and trends in time-series data. However, models employing either CNN or LSTM independently often fall short of achieving optimal performance, as they fail to simultaneously account for the intricate interplay between spatial and temporal variations [13,15]. To address this, hybrid CNN-LSTM architectures have been proposed, combining the strengths of both models to enhance prediction accuracy.

Despite these advancements, notable gaps persist in existing research. Several studies, such as those by Manandhar et al. [1] and Siddiqui et al. [2], leveraged CNN or hybrid CNN-LSTM approaches but overlooked the incorporation of cyclical time-based features like hour-of-day and day-of-year variations, which play a crucial role in solar energy patterns. Others, such as the work by Bouquet et al. [3] and Paletta et al. [4], demonstrated improvements using LSTM and ConvLSTM models, yet primarily focused on long-term or coarse temporal predictions rather than fine-grained, minute-level forecasting. Furthermore, models like SUNSET [6][7] and KloudNet [9], while effective in capturing spatial features or cloud motion dynamics, lacked robust temporal encoding, limiting their responsiveness to rapid atmospheric changes [16,18].

Recognizing these challenges, this study proposes a novel deep learning framework that integrates spatial, temporal, and cyclical information for enhanced short-term PIRP value forecasting. The model employs a TimeDistributed CNN to process sequences of sky images, two stacked LSTM layers to capture complex temporal relationships, and an attention mechanism to focus on the most informative time steps. Additionally, by embedding sine and cosine transformations of timestamps, the model accounts for daily and seasonal periodicities, further refining its predictive capability. The curated dataset, comprising 13,818 PIRP values and over 39,000 sky images, ensures that the model is trained on diverse and temporally consistent data, supporting its robustness and generalization across different conditions.

This integrated approach not only addresses the shortcomings of previous methods but also offers a scalable, low-cost solution for real-world solar energy forecasting applications. By enhancing prediction accuracy and reducing reliance on expensive sensor infrastructure, the proposed hybrid CNN-LSTM model contributes significantly to the advancement of renewable energy technologies and the broader goal of sustainable energy management [17,19].

OBJECTIVES

The primary objective of this research is to develop a hybrid deep learning model that accurately predicts short-term Pyranometer Irradiance Recorded Point (PIRP) values using sequences of sky images, historical PIRP data, and cyclical time-based features. By combining Convolutional Neural Networks (CNNs) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for temporal sequence modeling, the model aims to capture the complex dynamics influencing solar irradiance fluctuations. The study seeks to improve existing methods by integrating an attention mechanism that focuses on the most relevant temporal information, thereby enhancing the model's forecasting precision [20,22].

Another objective is to incorporate cyclical time transformations, such as sine and cosine encoding of the hour-of-day and day-of-year, to account for daily and seasonal periodicities in solar radiation patterns. This feature engineering step is designed to help the model adapt better to natural temporal cycles, further refining prediction accuracy. Additionally, the study investigates the effects of various input configurations, including the separate and

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combined use of sky images, past PIRP values, and timestamp features, to determine the optimal setup for real-world solar energy management applications.

Through extensive training and evaluation on a curated dataset comprising 13,818 PIRP values and over 39,000 sky images, the project aims to validate the effectiveness of the proposed model. Key performance indicators such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Filtered Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2 Score) are used to benchmark improvements over baseline models like CNN-only, LSTM-only, and Linear Regression. Ultimately, the objective is to offer a scalable, low-cost, and reliable forecasting solution that reduces dependence on traditional ground-based sensors, promotes smarter renewable energy integration, and supports the broader transition toward sustainable energy systems [23].

METHODS

This study presents a hybrid deep learning model designed for short-term prediction of Photochemical and Radiative Performance (PIRP) values using sky images. The model leverages both spatial and temporal information by combining a TimeDistributed Convolutional Neural Network (CNN) with Long Short-Term Memory (LSTM) layers and an attention mechanism. The overall workflow involves mapping sky images to their corresponding PIRP values using precise timestamp alignment, constructing a multi- modal input that includes image sequences, historical PIRP values, and cyclical time features, and finally training a deep network to predict future PIRP values. In the subsequent sections, a detailed description of the data preprocessing, dataset structure, model architecture, and training strategies is provided.

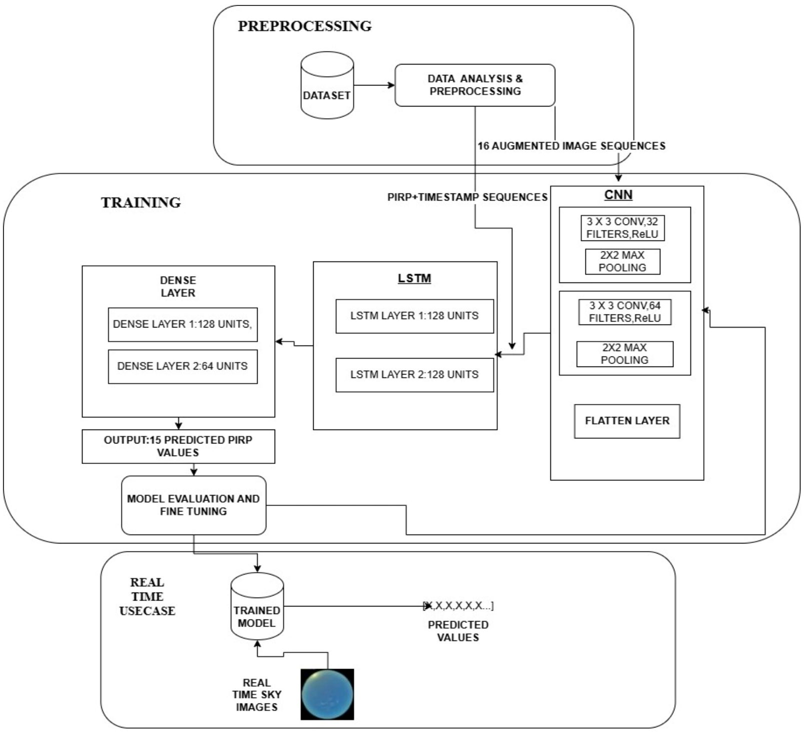

Fig. 1 Proposed Hybrid CNN-LSTM model architecture. The diagram illustrates data preprocessing steps, CNN layers for spatial feature extraction, LSTM layers for temporal dependency modeling, and dense layers for final PIRP value prediction

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A. Data Preprocessing

The raw dataset initially comprised 244,697 fisheye sky images spanning 179 days, each associated with a PIRP measurement. After mapping the images to their corresponding PIRP values via timestamp alignment, rows with missing or misaligned data were eliminated (15,651 rows were discarded). Furthermore, outlier values—including nighttime readings (0 PIRP) and extreme values (>1000 PIRP)—were filtered out, resulting in the removal of an additional 81,951 rows. The remaining data were then resampled to a uniform one-minute interval. To guarantee robust training and testing, only rows with complete sequences—i.e., with 15 minutes of preceding and succeeding data—were retained. A custom script verified the availability of 15 consecutive rows both before and after each timestamp. Finally, all sky images were resized to 64×64 pixels, yielding a curated dataset of 13,818 rows of PIRP values and over 39,000 sky images. These rigorous preprocessing steps ensure that the model is trained on high-quality and temporally consistent data.

B. Dataset Description

The final dataset is structured to provide a comprehensive spatio-temporal context for PIRP prediction. Each sample consists of:

- Sky Images: A sequence of 16 images, where 15 historical images precede the current image, all captured at one-minute intervals and resized to 64×64 pixels.
- PIRP Values: Corresponding PIRP measurements for each of the 16 time steps (15 historical values plus the current value) and a target sequence of 15 future PIRP values.
- Timestamp Features: Each image's timestamp is processed to extract cyclical time features via sine and cosine transformations of the hour-of-day and day-of-year. This transformation captures periodic variations that are critical for short-term forecasting.

This multi-modal input structure facilitates the integration of spatial cues from the sky images with the temporal dynamics of PIRP measurements, allowing the model to learn complex interdependencies inherent in solar irradiance forecasting.

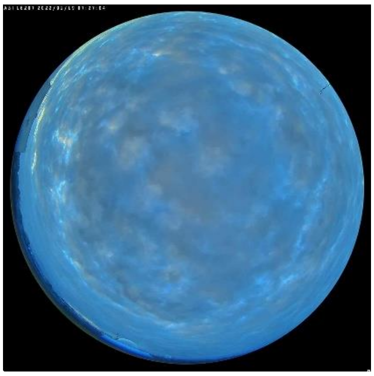

Figure 2: Sample sky image

C. Model Architecture and Training

The proposed model leverages a hybrid architecture that integrates spatial feature extraction with temporal sequence modeling, ensuring that both the static patterns in sky images and the dynamic evolution of PIRP values are effectively captured. Three distinct inputs are employed:

- **Image Input:** A 16-step sequence of sky images, each with dimensions 64×64×3. These images are processed through a TimeDistributed Convolutional Neural Network (CNN) backbone. The CNN is structured with two convolutional layers – the first with 32 filters and the second with 64 filters, both using a 3×3 kernel with ReLU activations – interleaved with max-pooling layers. These layers serve to extract hierarchical spatial features and reduce dimensionality while preserving the salient aspects of cloud structures and other relevant patterns. The final Flatten layer transforms the spatial maps into one-dimensional feature vectors for each time step.

- **PIRP Input:** A corresponding sequence of 16 PIRP values (reshaped to 16×1) which provides direct numerical input representing the historical solar irradiance measurements. Including these values reinforces the temporal trends and quantitative relationships in the data.
- **Time Input:** A 16-step sequence of extracted time features, each represented by four values (sine and cosine components for both hour-of-day and day-of-year). These cyclical features encapsulate the periodic nature of solar radiation and ensure that the model accounts for diurnal and seasonal patterns.

After individual processing, the outputs of the CNN, PIRP, and time feature inputs are concatenated along the feature dimension to form a comprehensive feature representation at each time step. This fused representation is then fed into a stack of two Long Short-Term Memory (LSTM) layers, each comprising 128 units. The LSTM layers are crucial for capturing long-term dependencies in the temporal sequence, with dropout (0.3) and recurrent dropout (0.3) employed to mitigate overfitting. An attention layer is interposed between the LSTM layers, which adaptively weighs the relevance of each time step's output, thus allowing the model to focus on the most informative segments of the sequence.

Subsequently, the sequence is further refined via two fully connected (dense) layers with 128 and 64 neurons, respectively, both using ReLU activations. These layers are responsible for learning higher-level abstractions and non-linear interactions among the concatenated features. Finally, a dense output layer with 15 linear units produces the target sequence of future PIRP values.

Training is conducted using the Adam optimizer with a learning rate of 0.001, and the Huber loss function is utilized to ensure robustness to outliers. The network benefits from a ReduceLROnPlateau callback that dynamically reduces the learning rate when validation loss stagnates, thereby fine-tuning the training process. Data augmentation techniques, including random noise injection, brightness/contrast adjustments, and horizontal flipping, are integrated into the training generator to enhance the model's generalization capabilities across diverse sky conditions.

D. Evaluation

The model's performance is rigorously evaluated on a dedicated test set to assess its predictive accuracy and robustness. After the training phase, the model generates predictions for future PIRP values. Since the output is initially scaled using a MinMaxScaler, an inverse transformation is applied to recover the original PIRP scale, facilitating a direct comparison with the ground truth values.

Key performance metrics are computed to provide comprehensive insights into the model's performance:

- Mean Absolute Error (MAE): This metric measures the average magnitude of the absolute differences between the predicted and actual PIRP values, providing an intuitive understanding of the error in the same units as the target variable.

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

- Root Mean Squared Error (RMSE): RMSE is used to highlight larger errors by squaring the deviations prior to averaging, thereby offering a measure sensitive to outliers and reflecting the variance of the prediction errors.

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

- Filtered Mean Absolute Percentage Error (MAPE): For enhanced reliability, this percentage-based error metric is calculated only for those test samples where the actual PIRP value exceeds a specified threshold (e.g., 10). This filtering ensures that the metric is meaningful and not skewed by extremely low values.

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i-\widehat{y_i}}{y_i}\right| \quad (3)$$

- Coefficient of Determination (R^2 Score): The R^2 score quantifies the proportion of variance in the actual PIRP values that is explained by the model predictions. A higher R^2 indicates better explanatory power and overall model fit.

$$R^2 = 1 - \frac{\sum_i (y_i-\widehat{y_i})^2}{\sum_i (y_i-\bar{y})^2} \quad (4)$$

These metrics are computed over the entire test dataset, with the MAPE calculation specifically focused on samples with significant PIRP values to ensure accurate representation of performance. The comprehensive evaluation confirms that the hybrid CNN-LSTM model, bolstered by an attention mechanism, effectively captures the complex spatio-temporal dependencies inherent in the data, thereby providing robust and accurate short-term forecasts of PIRP values.

RESULTS

The hybrid CNN-LSTM model demonstrated strong performance across training, validation, and testing phases. Over 15 epochs, the training loss decreased steadily from an initial value of 0.0039 to a final value of 0.000455, while the

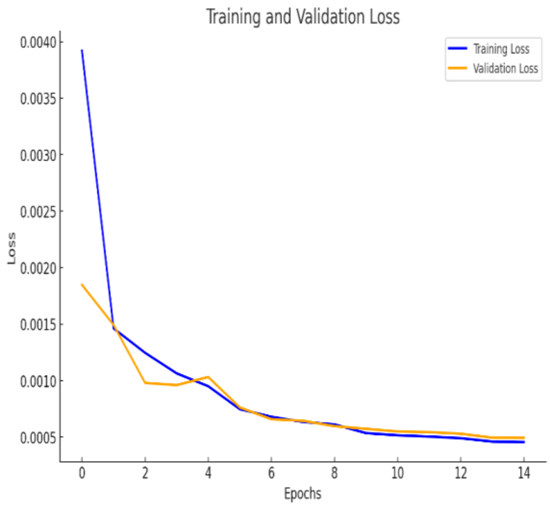

Fig. 3 Training and validation loss curves across 15 epochs

validation loss closely followed, ending at 0.000493. This consistent reduction in loss indicates effective learning and generalization. Key metrics calculated during testing provide a detailed assessment of the model's performance:

- **Mean Absolute Error (MAE):** 14.46
- **Root Mean Squared Error (RMSE):** 30.03
- **R^2 Score:** 0.9737
- **Filtered Mean Absolute Percentage Error (MAPE):** 9.85%

Comparison with Other Models

To validate the effectiveness of our approach, we compared our proposed hybrid CNN-LSTM model with several baseline and alternative models using the same dataset. Table 1 summarizes the key performance metrics—Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R^2 Score, and Filtered Mean Absolute Percentage Error (MAPE)—for each model along with the specific inputs used.

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Table 1. Comparison of performance metrics among various models.

Model	**Input Data**	**MAE**	**RMSE**	**R^2 Score**	**MAPE**
CNN-Only	PIRP + Images	49.98	70.09	0.8567	-
LSTM-Only	PIRP + Timestamps	29.34	48.01	0.9328	20.54%
Linear Regression	PIRP + Timestamps	22.13	44.37	0.9426	18.28%
CNN-Transformer	PIRP + Timestamps + Images	40.29	53.47	0.9166	29.36%
CNN-LSTM (Transfer Learning)	PIRP + Timestamps + Images	25.12	41.35	0.9501	19.88%
Proposed Hybrid CNN-LSTM (Ours)	PIRP + Timestamps + Images	14.46	30.03	0.9737	9.85%

Models that rely exclusively on either spatial features (e.g., CNN-Only) or temporal features (e.g., LSTM-Only) exhibit relatively high errors and lower R^2 scores. The Linear Regression model, while somewhat competitive in terms of RMSE and R^2, falls short in capturing the complex, non-linear relationships inherent in solar irradiance data. The CNN-Transformer model integrates both image and temporal data but struggles with higher MAPE, which suggests that its architecture may not be fully tuned to manage the variability present in minute-level forecasting.

Notably, even when using transfer learning from a pre-trained MobileNet in a CNN-LSTM framework, the model's performance is still inferior compared to our proposed hybrid approach. Our model distinguishes itself by integrating not only spatial and temporal data but also incorporating cyclical time-based features. The inclusion of cyclical features, derived from sine and cosine transformations of timestamps, ensures that daily and seasonal patterns are effectively modeled—a critical aspect for solar forecasting.

Moreover, the attention mechanism embedded within our model plays a pivotal role in enhancing performance. By dynamically weighing the importance of different time steps, the attention layer helps the network to focus on the most informative parts of the input sequence. This targeted focus contributes to the significant reductions in MAE and RMSE, as well as the notable improvement in R^2 Score and MAPE, confirming that our approach captures both short-term fluctuations and longer-term temporal trends more effectively.

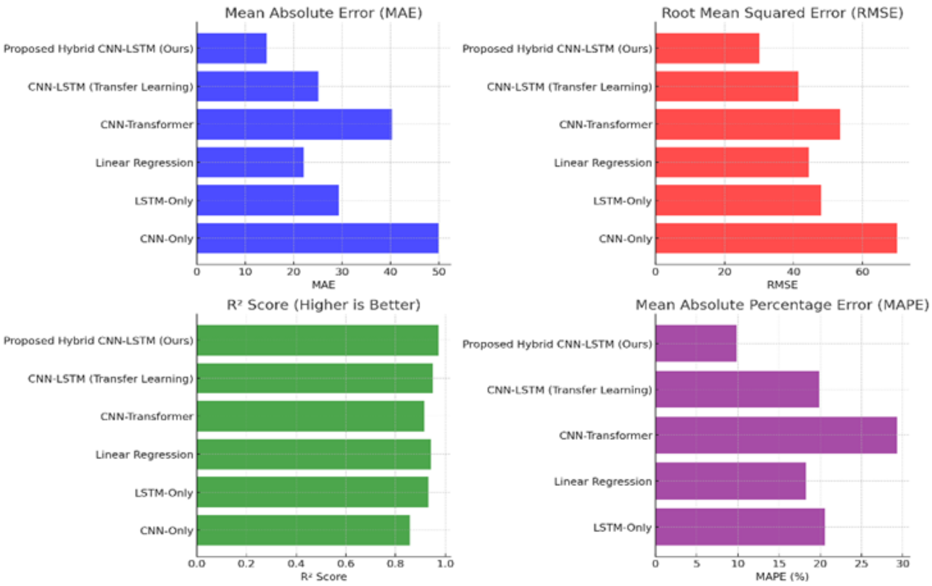

Fig. 4 Comparative visualization of performance metrics (MAE, RMSE, R^2, and MAPE) among evaluated models

DISCUSSION

The superior performance of the proposed hybrid CNN-LSTM model can be attributed to several key factors. Firstly, by leveraging both sky images and historical PIRP data, the model is capable of extracting and integrating rich spatial features along with temporal dependencies. The CNN component effectively captures cloud patterns and other atmospheric characteristics from the images, which are essential for understanding the spatial variability of solar irradiance. In contrast, models that use only CNNs or only LSTMs fail to capture these dual aspects, leading to higher errors.

Secondly, the integration of cyclical time-based features—generated through sine and cosine transformations of the hour-of-day and day-of-year—ensures that the model is sensitive to periodic variations inherent in solar radiation. This additional layer of temporal context allows the model to better anticipate fluctuations that occur during transitions from day to night or between seasons.

The attention mechanism further augments the model's capacity by allowing it to prioritize more relevant time steps. This is particularly beneficial in scenarios where certain periods within the input sequence have a disproportionate impact on the prediction of future PIRP values. By focusing on these critical segments, the model achieves more precise forecasting, as evidenced by its lower MAE and RMSE.

When compared to other models, our approach demonstrates robust generalization, as indicated by the minimal gap between training and validation losses and the high R^2 Score of 0.9737. The significantly lower Filtered MAPE of 9.85% underscores the model's ability to maintain high accuracy even under variable conditions. Collectively, these findings suggest that the comprehensive integration of spatial, temporal, and cyclical features—coupled with an attention mechanism—enables our hybrid CNN-LSTM model to outperform alternative approaches, providing a scalable and effective solution for short-term PIRP forecasting.

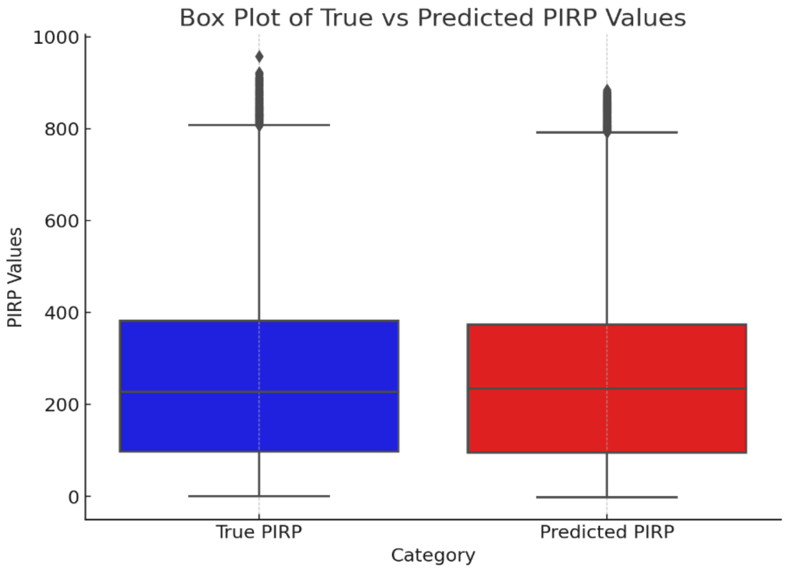

Fig. 5 Comparison of true and predicted PIRP values, box plot illustrating the true and predicted PIRP

CONCLUSION

This paper presented a hybrid CNN-LSTM model with an attention mechanism and cyclical time-based features for short-term PIRP value prediction using sky images. Our approach effectively merged spatial information (through a TimeDistributed CNN) and temporal patterns (via LSTM layers), while the attention mechanism further enhanced predictive capability by concentrating on the most pertinent segments of the data sequence. Experimental evaluations revealed that the proposed method significantly outperforms baseline models such as CNN-Only, LSTM-Only, and Linear Regression, as well as more advanced configurations like CNN-Transformer and CNN-LSTM with Transfer Learning.

Detailed analysis of the results indicated minimal gaps between training and validation losses, underscoring robust model training free from overfitting. The low MAE and RMSE values, combined with a high R^2 Score, confirm that the model accurately captures both spatial and temporal dependencies, crucial for solar irradiance forecasting.

Moreover, the Filtered MAPE demonstrated the model's ability to handle variability during high-irradiance intervals effectively.

By providing a cost-effective and scalable alternative to traditional ground-based sensor systems, this work contributes to the broader adoption of solar energy. The ability to forecast PIRP values in real time has wide-ranging implications, from electric utilities and solar farm operators to urban planning and weather forecasting. Future research will focus on expanding the dataset to multiple geographical regions, incorporating additional atmospheric inputs, and exploring ensemble methods or transformer-based architectures for enhanced performance.

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