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Conference paper

Enhancing Photovoltaic Power Forecasting through Hybrid Deep Learning Models: A CNN-RNN Approach for Grid Stability and Renewable Energy Optimization

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ABSTRACT

This paper addresses the critical need for accurate photovoltaic (PV) power generation predictions to ensure efficient grid integration and management, especially considering the variability and intermittency of solar power. By exploring advanced deep learning techniques, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and a hybrid CNN-RNN model, the study aims to enhance the accuracy and reliability of solar power forecasts. The CNN model achieved an accuracy of 0.84, while the RNN reached 0.94, with the highest accuracy of 0.99 attained by the hybrid CNN-RNN model. These models provide vital tools for mitigating fluctuations in solar power output, improving grid stability, and optimizing energy distribution. The study contributes to the advancement of renewable energy forecasting, helping to ensure a more sustainable and reliable energy future, while also supporting efforts to reduce CO_2 emissions and combat climate change.

1. INTRODUCTION

The integration of photovoltaic (PV) systems into the power grid presents significant technical challenges due to the fluctuating and unpredictable nature of solar energy. These problems lead to grid instabilities, voltage fluctuations and overloading of existing grid infrastructures, which in turn significantly impairs energy distribution and grid security.

Power prediction algorithms offer an advanced technical solution that not only overcomes the technical problems of integrating PV systems into the power grid, but also brings economic and ecological advantages. By using these technologies, the challenges of grid integration of PV systems can be

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effectively overcome, and the reliability and economic efficiency of solar energy production can be significantly improved. By accurately predicting energy production, these algorithms enable more stable and efficient grid control, ultimately leading to a more secure and sustainable energy supply.

Various works have addressed the topic of power prediction in photovoltaic (PV) systems.

(Yesilbudak et al., 2016), (Long et al., 2014) emphasize the importance of data analysis and data-driven empirical modeling, which reflects the real system behavior and serves as input for the prediction algorithms. This is crucial for achieving robust and accurate predictions.

(Abuella & Chowdhury, 2015), (Zeng & Qiao, 2013), (Lee et al., 2018), (Elsaraiti & Merabet, 2022) emphasize the development of diverse models for solar power forecasting, each with unique strengths. (Abuella & Chowdhury, 2015) focuses on multiple linear regression, showing better accuracy under clear skies and for shorter time frames, while Paper (Zeng & Qiao, 2013) introduces an SVM-based model that utilizes meteorological data to significantly outperform autoregressive models. (Lee et al., 2018) leverages convolutional neural networks (CNNs) for more accurate predictions without the need for extensive data preprocessing, outperforming traditional methods. (Elsaraiti & Merabet, 2022) evaluates Random Forest, ANN, and XGBoost, concluding that XGBoost, paired with PCA, delivers the best performance with minimal errors, whereas Random Forest and ANN show a tendency to overfit, particularly ANN when using Feature Importance. These studies highlight the importance of selecting the appropriate model and input data for optimizing solar power forecasting accuracy.

In this paper, we address the need for advanced predictive models in photovoltaic (PV) power generation, emphasizing their role in enhancing grid integration and management. The fluctuating nature of solar power presents unique challenges to maintaining grid stability, necessitating accurate and reliable forecasting methods. We explore the application of deep learning techniques, particularly Recurrent Neural Networks (RNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks, to predict solar power output with high accuracy. This study evaluates these models' using metrics like the R2 score, focusing on their effectiveness in reducing the impact of power production fluctuations on grid operations. Our findings highlight the potential of these advanced models to improve the reliability and efficiency of solar power systems, contributing significantly to the integration of renewable energy sources into the grid.

2. EXPLORATORY DATA ANALYSIS : STATISTICS, CORRELATION AND VISUALIZATION

In order to make accurate predictions about the performance of the photovoltaic system, it is essential to thoroughly analyze all data that can impact its performance. By exploring and analyzing the data, we can gain deeper insights and identify which data is crucial for evaluation. The data analysis process involves checking the input matrix required for calculation and modeling. Only data that positively influences the process should be considered. The data analysis covers six key characteristics of the data set: current in amperes (Ia), voltage in volts (Ua), temperature in °C (TEMP), humidity in % (H), and power in kW (P).

The data analysis encompasses the examination of data distribution, boxplot representations, and correlation, as depicted in Figures 1 to 4.

2.1 Data Distribution

Fig. 1 shows the mean $\overline{X}$ and the standard deviation (σ) for all features, indicating their central tendency and the degree of variability or scatter around the mean.

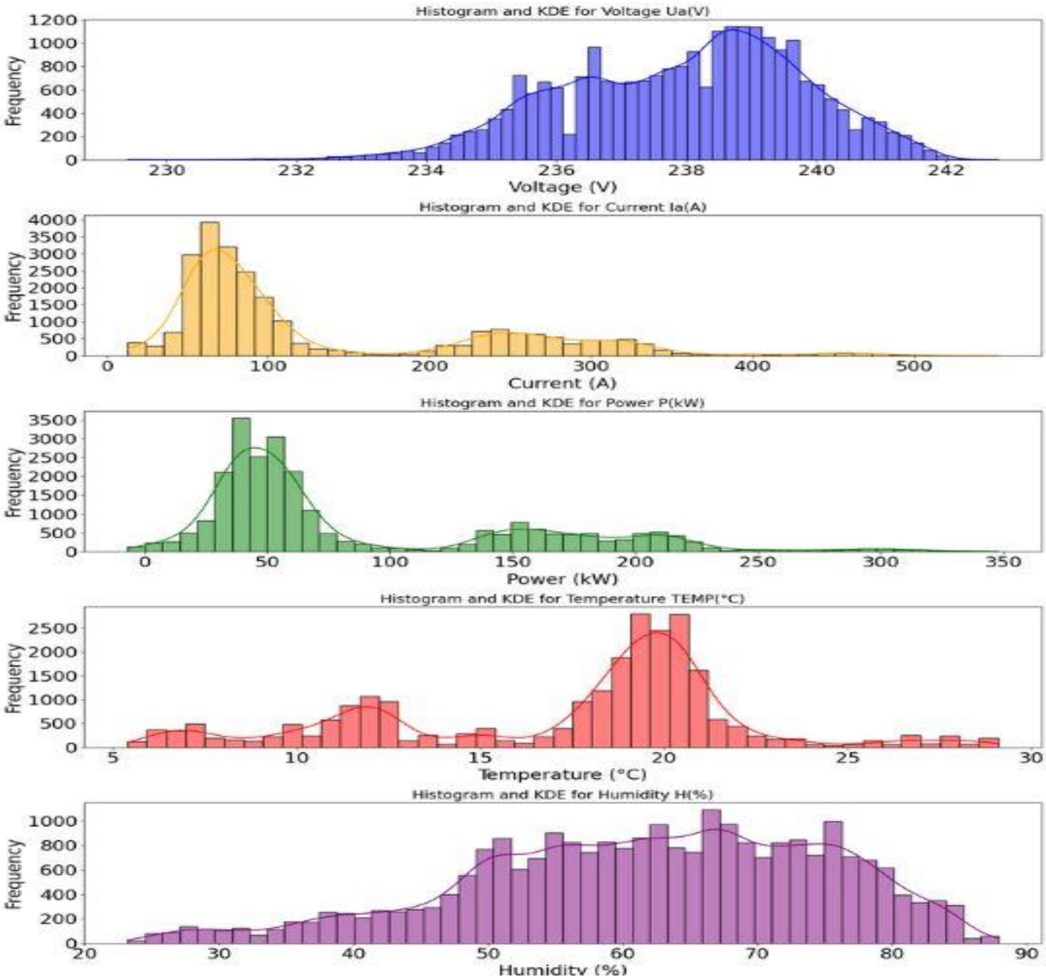


Fig 1. Data Distribution

The mean statistic:

These values of mean $\overline{X}$ and standard deviation σ were calculated as follows:

$$\overline{X} = \frac{\sum_{i=1}^{n} Xi}{n}$$

Where xi represents the individual values in the dataset, and n is the number of values. Standard Deviation:

$$\boldsymbol{\sigma} = \sqrt{\frac{\sum_{i=1}^{n}(\boldsymbol{xi} - \overline{\boldsymbol{x}})^2}{\boldsymbol{n-1}}}$$

Where

Xi represents each individual value in the dataset; $\overline{X}$ is the mean of the sample; n is the number of values in the dataset.

The data distribution and statistics in Fig. 1 reveal fluctuations and asymmetrical data distribution, particularly in current and power, clearly reflects irregular performance and environmental conditions. Specifically, 50% of the power values lie between 39.02 kW and 142.98 kW, indicating a skewed spread that underscores the system's inconsistent performance.

2.2 Distribution and Outlier

The boxplot in Fig. 2 shows the following conclusions: The variables associated with energy production (current and power) have a wider distribution and more outliers, suggesting fluctuating operating conditions. On the other hand, voltage and humidity appear more stable, with fewer outliers. The data indicates well-regulated voltage control. However, the high number of outliers in current and power could suggest a need for optimization in power control or the influence of external factors, such as variable weather conditions. It is also possible that the outliers in power are caused by periods of high solar irradiation, when the photovoltaic system reaches its peak performance.

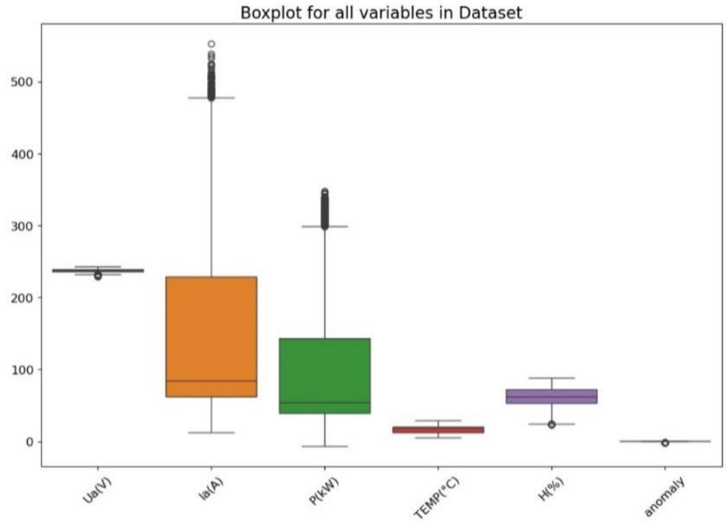


Fig 2. Boxplot

2.3 Pair plot

In Fig. 3, the pairplot indicates significant variation and potential non-linear relationships between the energy variables (current and power). This information is crucial for managing and optimizing a photovoltaic system, particularly in terms of temperature control and efficiency under different environmental conditions. Additionally, outliers or unusual patterns should be further investigated to ensure the reliability and performance of the system.

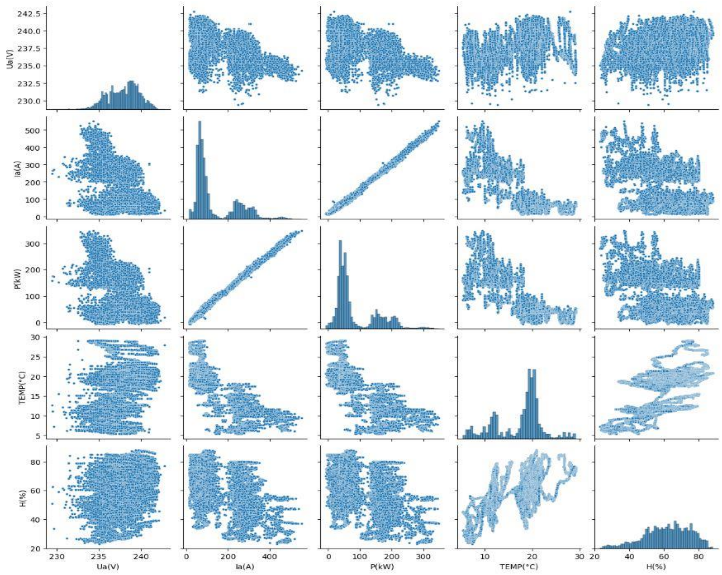


Fig 3. Pairplot presentation

2.4 Data correlation

Analysis of the correlation matrix in Figure 4 shows significant relationships between the variables that are consistent with the expected behavior of a photovoltaic system. Temperature shows a significant inverse relationship with current and power, suggesting potential areas for optimization in thermal management to maintain efficiency. In addition, humidity shows a less pronounced but still significant relationship with other variables, indicating its potential influence on system performance. Understanding these correlations is critical to maximize photovoltaic system operation and energy yield.

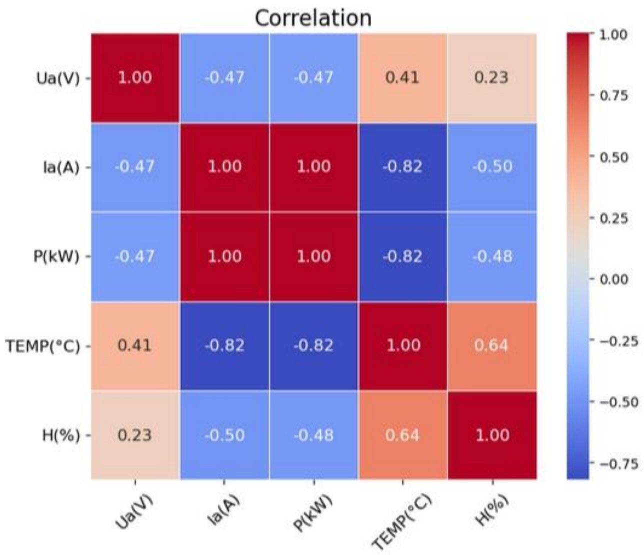


Fig 4. correlation matrix

2.5 Clustering

As shown in Fig. 5, the unsupervised learning cluster analysis has identified three distinct operating conditions of the photovoltaic system, based on a combination of electrical and environmental variables.

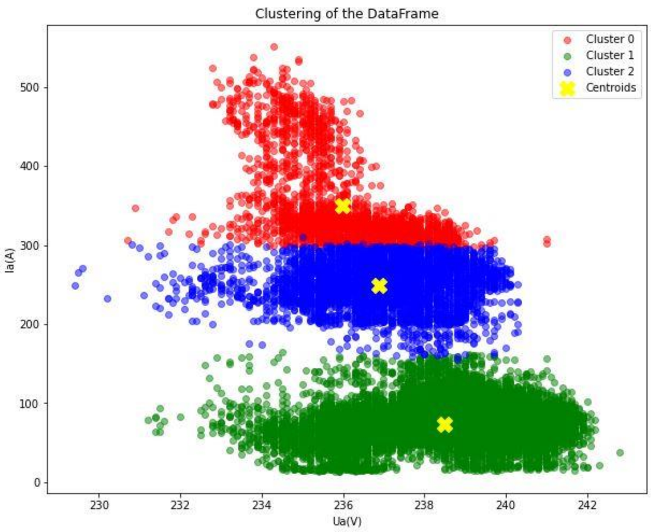


Fig 5. unsupervised learning / Clustering

The clusters are as follows:

- Cluster 0 (High current and power, low temperature and humidity):

This cluster is characterized by a voltage of 235.98 V, high current of 349.34 A, and a high power of 229.59 kW at low temperatures (10.94°C) and low humidity (48.98%). These conditions suggest times of maximum production in cooler weather, which is favorable for efficiency. Despite being the smallest cluster, Cluster 0 exhibits the most intense operating parameters.

- Cluster 1 (Low current and power, high temperature):

This cluster is the largest, with a voltage of 238.49 V, low current (73.67 A), and a lower power of 46.53 kW at higher temperatures (20°C) and higher humidity (65.72%). It indicates frequent periods of inefficient production, likely due to heat impacting the plant's efficiency.

- Cluster 2 (Medium Current and Power, Low Temperature):

This cluster is characterized by a voltage similar to Cluster 0 (236.88 V), with medium current (248.34 A) and medium power (159.48 kW) at cool temperatures (10.99°C) and medium humidity (53.88%). These conditions represent moderate periods of operation with stable performance.

Cluster sizes:

Cluster 1 is the largest with 17,559 data points, Cluster 2 is medium with 4,701 data points, and Cluster 0 is the smallest with 2,508 data points. Conclusion: Cluster 0 demonstrates optimal conditions for maximum production, Cluster 1 presents challenges at high temperatures, and Cluster 2 offers balanced performance under favorable conditions. These results provide valuable insights for maintenance planning and efficiency improvements.

3. MODEL DEVELOPMENT

In addressing the problem of time series forecasting for photovoltaic power prediction, we have explored various state-of-the-art deep learning architectures, including Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and hybrid models combining both, such as CNN-RNN architectures. Bidirectional Long Short-Term Memory (BiLSTM) networks are particularly effective for capturing long-term dependencies in time-series data, as they process inputs in both forward and backward directions, allowing the model to consider both past and future data points. This capability is especially useful for time-series data like solar power generation, where trends are influenced by historical as well as future contexts. CNNs, on the other hand, excel at extracting short-term local patterns and trends through convolutional filters, making them efficient in identifying patterns such as daily cycles. This is crucial for solar power data, which exhibits strong temporal dependencies, including periodic variations throughout the day.

3.1 Data Processing

The process of parsing dates entails the transformation of date and time information from a string format into Python's datetime object. This transformation is of significant importance due to the fact that datetime objects support arithmetic operations and other time-based manipulations, which are indispensable for time-series analysis.

Setting datetime as an index serves a crucial purpose. It facilitates the slicing and indexing of data based on time, a feature that is essential for time-series forecasting. Moreover, it enables resampling (for instance, from minutes to hours), rolling windows, and other time-based transformations.

Neural networks, in general, exhibit superior performance and faster training on data normalized or standardized. Normalization adjusts the data to fit within a specific range of values (0, 1), which is beneficial when different features possess different units and scales. On the other hand, standardization scales data to have zero mean and unit variance, which is advantageous if the data distribution is normal.

In the context of Normalization versus Standardization:

- Normalization, also known as MinMax Scaling, transforms features by scaling each feature to a given range, typically 0 to 1. This is achieved by subtracting the minimum value of each feature and then dividing by the range.
- Standardization, also referred to as Z-score Normalization, removes the mean and scales each feature/variable to unit variance.
- The choice between normalization and standardization depends on the specific requirements:
- Normalization should be employed when a bounded range is needed, and the shape of the data distribution is not assumed.
- Standardization should be used when the data follows a normal distribution and there is a need to handle outliers.

3.2 CNN Model architecture

Convolutional Neural Networks (CNNs) (Bouvrie, 2006) (Gu et al., 2018) are primarily designed for 2 dimensions surface processing tasks, such as segmentation, object detection, and image classification. However, they have also been successfully applied to time-series prediction tasks. (Liu et al., 2019), including solar power forecasting . The idea is to use CNNs to learn spatial or temporal patterns from time-series data by treating the data like a one-dimensional image.

A CNN-based model for solar power prediction can capture local patterns in time-series data, such as periodic trends or abrupt changes in solar power generation due to weather conditions. By applying convolutional filters, CNNs can automatically learn the most relevant features from historical data (Perera et al., 2024), which can improve the prediction performance.

As can be seen from figure 6 The CNN (Convolutional Neural Network) model used for solar power prediction is designed to capture local patterns in time-series data such as daily or seasonal variations in solar irradiance and weather conditions. The key components of this CNN model include:

Convolutional Layer (Conv1D): This layer applies convolutional filters to the input data (number of samples, time steps, number of features) , where " number of samples" allows for a variable batch size, time steps represents the sequence length, and " number of features " refers to the number of features in the dataset per time step. to detect short-term patterns or trends, such as daily cycles in solar power.

1. MaxPooling Layer (MaxPooling1D): This down-samples the input, reducing the complexity of the model while retaining important features. It helps to prevent overfitting by simplifying the learned representations.
2. Dropout Layer: is a regularization method where a portion of neurons is randomly deactivated during training to reduce overfitting and enhance the model's generalization ability..
3. Dense Layer: Fully connected layers that learn higher-level patterns and relationships between the extracted features to make the final prediction.

The CNN model for solar power prediction is computationally efficient and suitable for identifying localized patterns in time-series data, which makes it effective for tasks like predicting short-term solar power output.

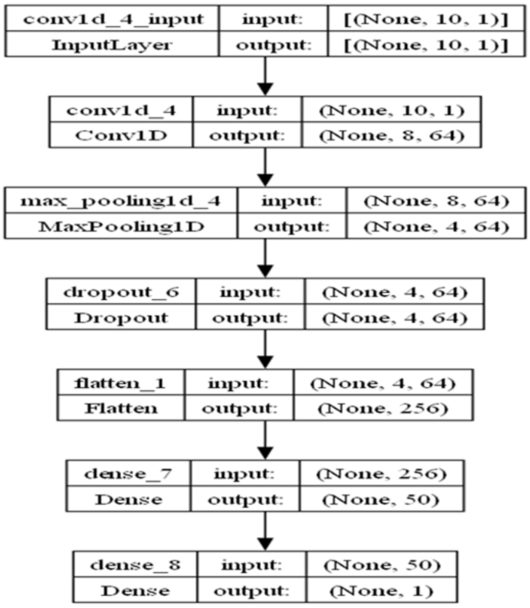


Fig 6. CNN model Architecture

3.3 RNN model Architecture

Bidirectional Long Short-Term Memory (BiLSTM) (Graves & Schmidhuber, 2005) Recurrent Neural Networks (RNNs) (Hopfield, 1982) have proven to be highly effective for solar power prediction due to their ability to capture both past and future dependencies in time-series data. Solar power generation is influenced by a range of factors, including weather conditions, historical trends, and temporal patterns such as daily and seasonal cycles. By using BiLSTMs, you can account for these dependencies more effectively, improving forecasting accuracy.

The model plot in figure 7 offers a visual breakdown of the neural network architecture, highlighting the various layers and their connections. The following provides a detailed explanation of each component in the model:

- Input Layer: This layer is designed to accept data with a specified shape (number of samples, time steps, number of features) respectively The total number of sequences or data points, the length of the input sequence, The number of variables or features available for each time step (e.g., solar irradiance, temperature, etc.).
- First Bidirectional LSTM Layer: Consists of 50 units in each direction, resulting in 100 units due to the bidirectional setup. It processes the input data in both forward and backward directions. Since `return_sequences=True`, the layer outputs a sequence of 100 features for each of the 10 time steps, preserving the temporal sequence.
- Second Bidirectional LSTM Layer: Similar to the first, this layer also contains 50 units in each direction, totaling 100 units. However, it does not return the full sequence (`return_sequences=False`), instead providing only the final time step's output. This output condenses the entire input sequence into a 100-feature representation, capturing information from both directions.
- Dense Layer: A fully connected layer that outputs a single continuous value for each input, making it suitable for regression tasks like predicting solar power output in kilowatts (P(kW)), based on the features processed by the preceding layers.

The data moves through the network layer by layer, undergoing transformations and reductions in complexity until the final prediction is made in the output layer.

In Fig. 6, the structural analysis highlights the role of each layer in managing raw sequential inputs, capturing bidirectional temporal patterns, and producing a predictive output. The use of bidirectional LSTM layers is particularly beneficial for time-series forecasting, as it enables the model to consider both past and future data, improving the accuracy of predictions.

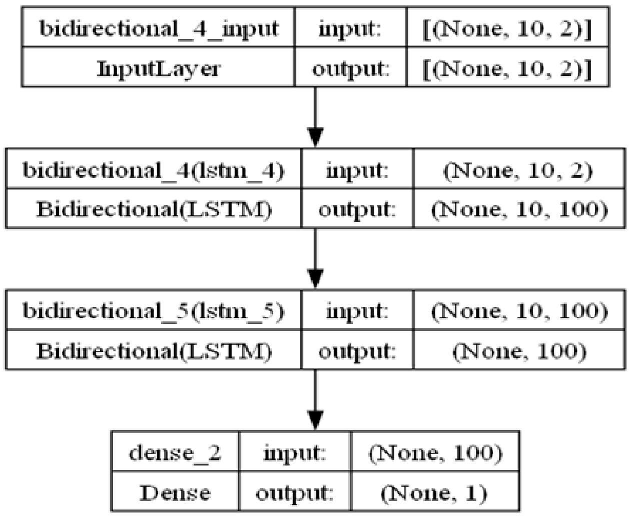


Fig 7. Bilstm model architecture

3.4 CNN-RNN model Architecture

The RNN-CNN model architecture combines Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) (Hoffmann et al., 2017) to leverage the strengths of both approaches for time-series prediction tasks.

- RNN Layer: The RNN, often implemented as an LSTM or GRU, processes the input sequentially, capturing temporal dependencies and long-term patterns in the data. It outputs hidden states that encode the time-series information over time.
- CNN Layer: After the RNN layer, a CNN is applied to extract local patterns from the sequential data. The Conv1D layer applies filters to the time-series data to detect features such as periodic trends or sudden changes.
- Dense Layer: The processed features are then passed through fully connected (Dense) layers that learn complex relationships between the extracted features and the final output.

This hybrid architecture (Lee et al., 2018) combines the RNN's ability to capture sequential dependencies with CNN's efficiency in feature extraction, making it well-suited for tasks like solar power prediction or other time-series forecasting challenges.

4. TRAINING AND EVALUATION

The dataset, represented by arrays X (features) and y (target variable), is divided into training and testing subsets to evaluate the model's performance on unseen data. The division is performed by determining a split index at 80% of the dataset length, allocating 80% of the data for training and the remaining 20% for testing.

4.1 Model Training

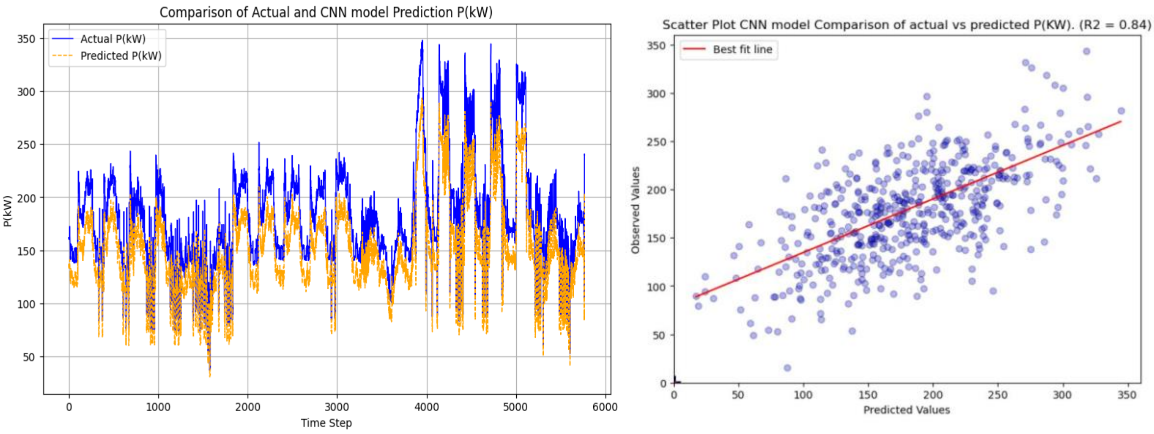
Model training is carried out using thee neural network's CNN, BILSTM and CNN-BILSTM models, applied to the training data. The key parameters for the training process are as follows:

- Epochs: The model undergoes five training cycles, with each epoch representing a full pass through the entire training dataset.
- Batch Size: Data is processed in batches of 32 instances, improving computational efficiency and optimizing gradient updates.
- Validation Data: The model's performance is assessed on the test data during each epoch, providing an ongoing assessment of its ability to generalize beyond the training data.
- Verbose: Set to 1, this option allows detailed logs during training, enabling real-time monitoring of progress and performance.

This approach highlights the importance of both effective training and consistent evaluation on a test dataset. The configuration ensures the model can learn effectively from the training data while the validation metrics provide a reliable measure of its generalization to new data, promoting the development of robust neural network models for predictive tasks.

4.2 Evaluation results

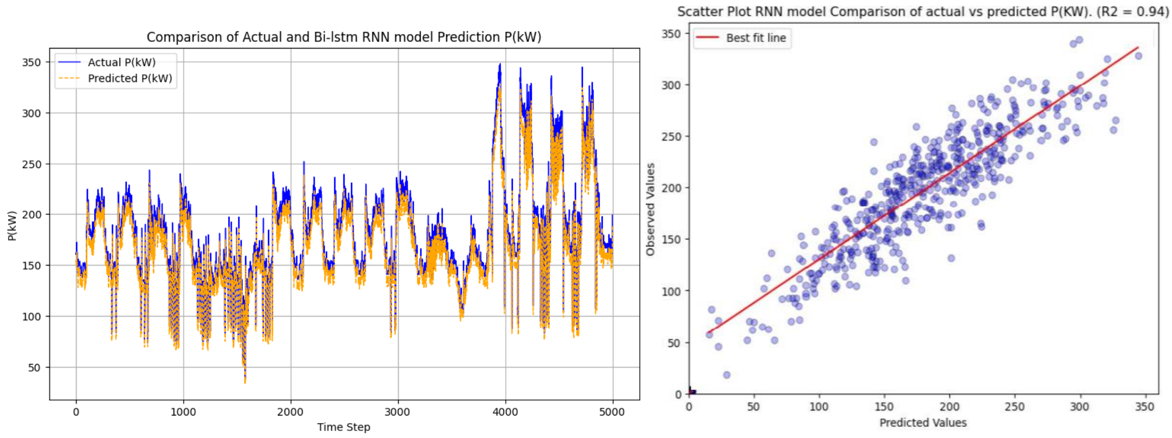
Figures 8, 9, and 10 each consist of two plots representing the three models: CNN, RNN, and the hybrid CNN-RNN, respectively. (a) A time series comparison of actual and predicted power values (P in kW) over time steps, and (b) A scatter plot comparing actual vs predicted values with a best-fit line, demonstrating the accuracy of the models and the correlation between observed and predicted power outputs.



(a) (b)

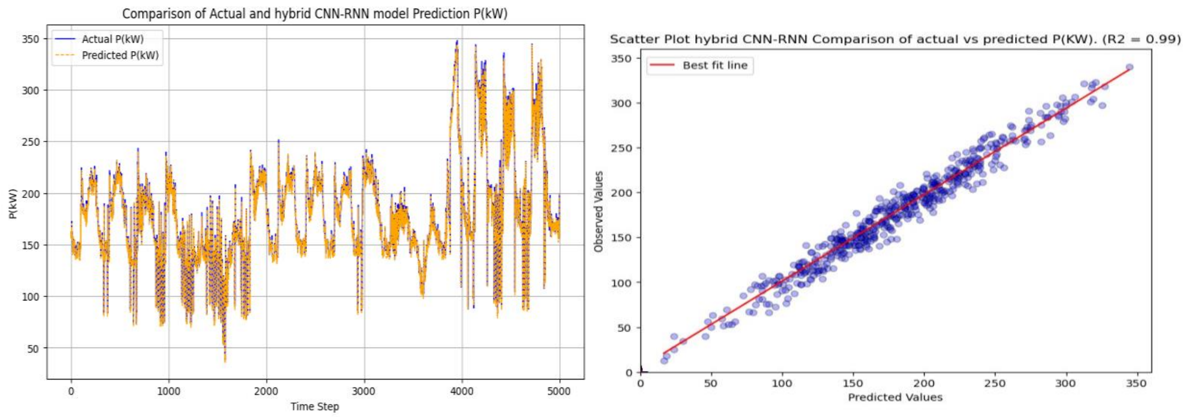
Fig 8. CNN model Comparison and scatter plot of actual vs predicted P(KW).

Both the CNN, Bi-LSTM RNN, and CNN-RNN hybrid models show a volatile pattern with peaks and troughs, suggesting cyclical behaviour in the data that likely reflects daily usage patterns. Across all models, the predicted values generally track the actual values well, implying good overall model performance. However, in all three models, there are notable divergences at different points. For the CNN model, discrepancies appear around time steps 1500, 2500, and 3500, while the Bi-LSTM RNN model shows divergences around time steps 1000, 3000, and 4500. The CNN-RNN hybrid model, while combining the strengths of both architectures, still exhibits errors around time steps 2000, 3500, and 4500. These divergences suggest that each model struggles with certain complex patterns in the data, underestimating or overestimating the actual P(kW). In conclusion, while all models capture the general trends of power output, they show some discrepancies that require further analysis. Understanding whether these errors are systematic or random is essential for refining the models and improving performance. This analysis provides a valuable starting point for evaluating model effectiveness and identifying areas for improvement.



(a) (b)

Fig 9. RNN model Comparison and scatter plot of actual vs predicted P(KW).



(a) (b)

Fig 10. hybrid CNN-RNN Comparison and scatter plot of actual vs predicted P(KW).

The evaluation results for the solar power prediction models show clear differences in performance:

- CNN (0.84): The CNN model, which excels at capturing short-term local patterns in the data, achieved an accuracy of 0.84. While it effectively detects daily or periodic trends, it struggles with long-term dependencies, leading to lower overall accuracy.
- RNN (0.94): The RNN model, with an accuracy of 0.94, performs better because it captures temporal dependencies and long-term patterns in the time-series data, which is critical for solar power prediction. Its ability to understand sequential data over time gives it an edge over CNN.
- CNN-RNN (0.99): The hybrid CNN-RNN model outperforms both individual architectures with an accuracy of 0.99. This combination leverages the local pattern detection of CNN and the long-term dependency management of RNN, resulting in superior performance. The hybrid model

captures both short-term fluctuations and long-term trends, making it ideal for accurate solar power prediction.

The results suggest that the CNN-RNN model is the most suitable architecture for solar power forecasting, offering the highest accuracy by integrating the strengths of both CNN and RNN.

5. CONCLUSION

This study has demonstrated the effectiveness of advanced machine learning and deep learning techniques, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and hybrid CNN-RNN models, in predicting photovoltaic power output. By employing these models, we have significantly improved the accuracy and reliability of solar power forecasts, which are critical for managing the integration of solar energy into power grids. The results show that these sophisticated forecasting tools can mitigate the impacts of the inherent variability and intermittency of solar power, enhancing grid stability and facilitating more efficient energy distribution. Specifically, CNN models effectively capture spatial dependencies, while RNN and Bi-LSTM networks excel in processing temporal sequences. The hybrid CNN-RNN model combines both strengths, delivering strong overall performance. However, as observed, each model faces challenges in fully capturing complex patterns, emphasizing the need for further refinement.

This research not only contributes to the technical field of energy forecasting but also supports the broader goal of advancing renewable energy integration, ensuring a more sustainable and secure energy future. By optimizing these models through ongoing development, we can continue to improve the performance of solar power systems and strengthen their role in global energy generation, helping reduce CO2 emissions and combat climate change. This work underscores the potential of deep learning techniques to drive the adoption of renewable energy and advance efforts to achieve cleaner, more efficient energy systems worldwide.

NOMENCLATURE

EDA	Exploratory Data Analysis	BiLSTM	Bidirectional long short-term memory
NN	Neural network	CNN	Convolutional neural network
DNN	Deep neural network	MAE	Mean Absolute Error
RNN	Recurrent neural network		

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