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Research Article

Combination Approach of LSTM and CNN in Solar Energy Production Prediction

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ABSTRACT

Introduction: The growing demand for cleaner energy alternatives has led to a significant increase in solar photovoltaic (PV) installations. However, the integration of solar energy into the grid remains challenging due to the inherent variability of solar power, influenced by factors such as irradiance, temperature, and wind speed. Accurate forecasting of PV power production is essential to improve grid stability and optimize energy dispatch.

Objectives: This study aims to develop and evaluate a hybrid deep learning model that combines Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) to accurately forecast solar energy production. The specific objectives include comparing the forecasting performance of the CNN-LSTM model, preprocessing the dataset, and assessing the model's predictive accuracy using key performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-Squared (R^2).

Methods: This research uses time-series data from 2019 to 2022, including PV production data and environmental factors such as irradiance, temperature, wind speed, and humidity. The data is preprocessed using suitable techniques, and the model architecture incorporates CNN for spatial feature extraction and LSTM for capturing temporal dependencies. The model is trained using a sliding window algorithm and evaluated using performance metrics like MAE, RMSE, and R^2.

Results: The CNN-LSTM hybrid model demonstrated exceptional performance in predicting solar energy production. Over various time forecasting periods, including 1 month, 3 months, and 1 year, the model achieved near-perfect accuracy. Specifically, it recorded 99.99% accuracy for 1-month predictions, 100% accuracy for 3-month predictions, and maintained 99.99% accuracy over a 1-year period. The model showed an excellent R^2 score of 1 and achieved minimal Mean Absolute Error (MAE) values: 191.92 Wh for 1 month, 2.31 Wh for 3 months, and 3,191.72 Wh for 1 year. These results demonstrate the model's robust ability to accurately capture both short-term and long-term fluctuations in solar power production, outperforming traditional forecasting models in terms of accuracy and reliability.

Conclusions: The combination of LSTM and CNN in the hybrid model has proven highly effective for predicting solar energy production. The approach successfully combines the spatial feature extraction strength of CNN and the temporal dependency capturing capability of LSTM to provide accurate forecasts. This model outperforms traditional methods, offering superior prediction accuracy for both short-term and long-term solar energy production. Further research could focus on refining the model through hyperparameter tuning, integrating additional environmental factors, and applying it across different geographical regions to enhance its generalizability.

Keywords: Solar energy, photovoltaic, deep learning, LSTM, CNN, forecasting.

INTRODUCTION

Solar photovoltaic (PV) installations have grown significantly due to the push for cleaner energy alternatives. However, the inherent variability in solar energy, driven by environmental factors such as irradiance, temperature, and wind speed, makes integrating solar power reliably into the grid challenging. Accurate forecasting of PV power production is essential to address these challenges, enabling better planning for energy dispatch and grid stability[1].

Traditional forecasting models often fail to capture the complex non-linear relationships between environmental factors and PV production [2]. To address these shortcomings, this study proposes a hybrid deep learning approach using Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks [3]. CNN is utilized to extract spatial features from the environmental inputs, while LSTM is employed to learn the temporal dependencies over time. This hybrid approach enables a more precise and reliable forecast by capturing both the short-term fluctuations and long-term trends in solar energy production [4].

The dataset used in this study comprises time-series data of PV production from 2019 to 2022, along with related environmental factors such as irradiance (DHI, DNI, GHI), temperature, wind speed, and humidity[5]. These features provide a comprehensive representation of the environmental conditions affecting PV output, making them ideal for input into the CNN-LSTM model [6].

Chen, H. et al. (2020) stated that the use of stacked Long Short-Term Memory (LSTM) has proven effective in predicting photovoltaic (PV) power output with a 1.5-hour forecast horizon. The study results show that the LSTM model successfully captures power output fluctuations, achieving a Root Mean Square Error (RMSE) of 0.11368 on the test data. During 10-fold cross-validation, the model achieved an average RMSE of 0.09394 with a standard deviation of 0.01616, indicating that the model generalizes well without overfitting [7].

The authors also highlight that using endogenous data (historical PV output data) without incorporating external meteorological inputs simplifies the data collection process while still providing reliable predictions. The study suggests that further hyperparameter tuning and the use of larger datasets could improve the model's accuracy. Future research should focus on testing the model's performance at various geographical locations and its application to shorter time horizons, such as intra-hour forecasting.

Vishnu Suresh et al. (2020) is as follows The study successfully demonstrated the application of different Convolutional Neural Network (CNN) architectures, including the CNN-LSTM model, to forecast solar PV output using a sliding window algorithm. The research compared the performance of CNN-based methods with traditional models like ARMA (Autoregressive Moving Average) and multiple linear regression (MLR) for short-term (1 hour), medium-term (1 day), and long-term (1 week) forecasting. The results showed that CNN-based methods outperformed the ARMA and MLR models in terms of accuracy, particularly for longer forecasting horizons such as 1 day and 1 week [8].

Specifically, the CNN-LSTM model provided the most accurate forecasts among all tested models, especially for medium and long-term predictions, due to its ability to capture both spatial and temporal features in the data. While the ARMA model performed well for short-term (1 hour) forecasts, it showed significant degradation in accuracy for longer time periods.

The study highlights the potential of using CNN-LSTM architectures for solar PV output forecasting, emphasizing their capability to handle complex time-series data with non-linear relationships. The sliding window approach used in the data preprocessing was also key to improving the model's ability to learn from historical data. Future research is recommended to explore more advanced neural network architectures and optimize the computational cost associated with training deep learning models.

Rial A. Rajagukguk, Raden A. A. Ramadhan, and Hyun-Jin Lee (2020) highlights the following key points Deep Learning's Superior Accuracy: The paper emphasizes that deep learning models, particularly recurrent neural networks (RNN), long short-term memory (LSTM), gated recurrent unit (GRU), and hybrid CNN-LSTM, are more effective in predicting solar irradiance and photovoltaic (PV) power compared to traditional machine learning models. LSTM, as a standalone model, was found to provide the best performance in terms of root-mean-square error (RMSE) among the reviewed deep learning models [9].

CNN-LSTM Hybrid Model Performance: The hybrid CNN-LSTM model outperforms standalone models in most cases, although it requires longer training times. Its ability to capture spatial and temporal features makes it especially useful for more complex prediction tasks.

Recommendation for rRMSE The authors suggest using the relative RMSE (rRMSE) as the standard evaluation metric for solar forecasting studies. This metric allows for a more accurate comparison of forecast performance across different models and studies.

Future Work The study recommends further development and testing of deep learning models to address the complexities of solar irradiance and PV power forecasting, with a focus on improving interpretability, generalizability, and computation time.

In summary, the paper concludes that deep learning models, particularly LSTM and CNN-LSTM, offer the most accurate forecasting for solar irradiance and PV power, and their continued development will likely lead to even better predictive performance in the future

Pombo et al. (2022), the conclusion can be summarized as follows The study introduces a hybrid approach that combines a physics-based model with machine learning (ML) techniques to improve the accuracy of hourly solar power forecasting. The hybrid models, which use physical knowledge of photovoltaic (PV) system behavior, significantly outperformed traditional black-box ML methods by integrating meteorological data such as wind speed and air temperature into the forecasting process [10].

The key findings include The hybrid CNN-LSTM model, informed by physics, consistently provided the most accurate predictions for different forecasting horizons (24, 48, and 72 hours), compared to other models like Random Forest (RF) and Support Vector Machine (SVM).The approach reduced training time and improved the overall accuracy of solar power forecasts, particularly for longer forecasting periods.

The study also highlighted the robustness of the physics-informed ML model across varying weather conditions, emphasizing its potential for real-world applications in energy management and grid stability.

Future work suggests further optimizing the model by incorporating additional environmental factors and exploring its performance across different geographical regions. The findings demonstrate the effectiveness of combining physical insights with ML for improving renewable energy forecasting.

Maria Konstantinou, Stefani Peratikou, and Alexandros G. Charalambides (2021) is as follows The study demonstrated that a stacked Long Short-Term Memory (LSTM) network is an effective method for forecasting photovoltaic (PV) power output 1.5 hours ahead. The model was trained using historical PV power output data from a plant in Nicosia, Cyprus, without the need for exogenous inputs such as weather data, making the process simpler and more cost-effective. The results showed that the model performed well, achieving a Root Mean Square Error (RMSE) of 0.11368. Furthermore, the use of 10-fold cross-validation confirmed the robustness of the model, with a mean RMSE of 0.09394 and a standard deviation of 0.01616 [11].

The paper concluded that LSTM networks are capable of accurately predicting short-term PV power output, even in the absence of meteorological inputs, and that further improvements could be achieved through hyperparameter tuning and by applying the model to larger datasets and different geographical locations. Future research is recommended to focus on optimizing the model for intra-hour forecasting and testing different RNN architectures for further accuracy improvements.

The main contribution of this study is the application of a hybrid approach combining Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) to enhance the accuracy of solar energy production predictions [12]. This approach leverages CNN's ability to extract spatial features from environmental factors such as irradiance and temperature, while utilizing the strength of LSTM in capturing the complex temporal dependencies from historical data. Additionally, this research uses a dataset covering PV production data from 2019 to 2022, combined with meteorological data, to provide a more comprehensive representation of the factors influencing solar energy production. The results demonstrate that the CNN-LSTM hybrid approach delivers more accurate predictions compared to traditional models and holds significant potential for application in energy planning and grid stability [13]. Furthermore, this study contributes new insights into the use of deep learning for renewable energy forecasting, particularly through the simultaneous integration of spatial and temporal data.

OBJECTIVES

The general objective of this study is to develop and evaluate deep learning models for forecasting electrical energy demand using univariate time series analysis.

specific objectives:

1. to implement and compare the forecasting performance Combination Approach of LSTM and CNN in Solar Energy Production Prediction.

2. to preprocess the dataset using appropriate data preparation techniques before training the models.

3. To assess the predictive accuracy of both model using key performance metrics,including mean absolute error(MAE), Root mean Squared Error(RMSE), and R-Squared(R2).

METHODS

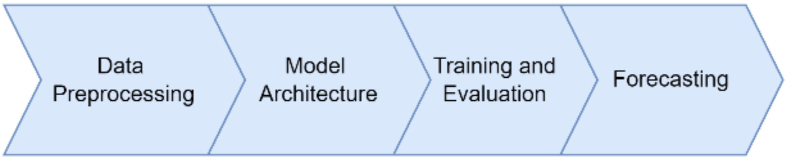

Figure 1 the stage in research

The research has four main stages: data Preprocessing, Model Architecture, Training and Evaluation, Forecasting. Those stages have different actions to execute and various throughputs. The stages can be seen in Fig. 1

A. Data Preprocessing

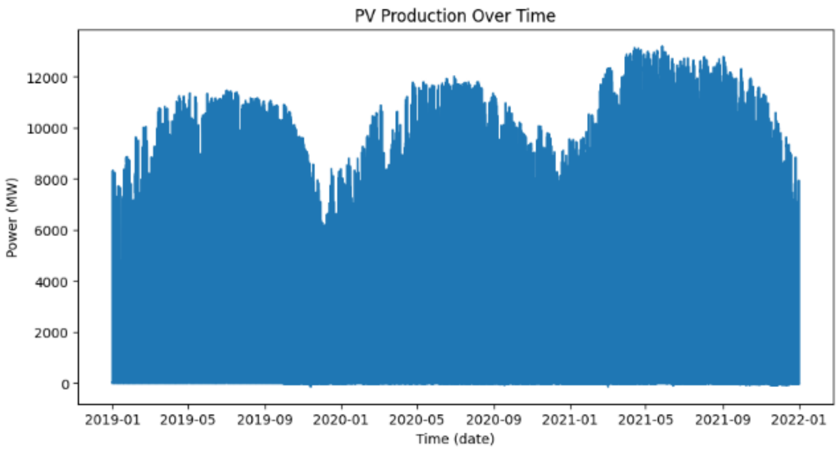

Figure 2 PV Production

The figure 2 graph shows solar power (PV) production over time, with the horizontal axis representing time from January 2019 to January 2022 and the vertical axis representing power generated in kilowatts (kW). Fluctuations in solar power production follow a seasonal pattern, with peak power generation occurring during the summer and a significant decline during the winter. These variations are generally caused by differences in the duration and intensity of sunlight throughout the year. The graph also shows slight decreases or variations on certain days, which could be attributed to weather factors such as cloud cover or rain. Overall, this data provides a clear picture of how solar power production varies over time, influenced by both seasonal changes and weather conditions.

B. Model ArchitectureThe CNN and LSTM architecture models are modeled like this: :

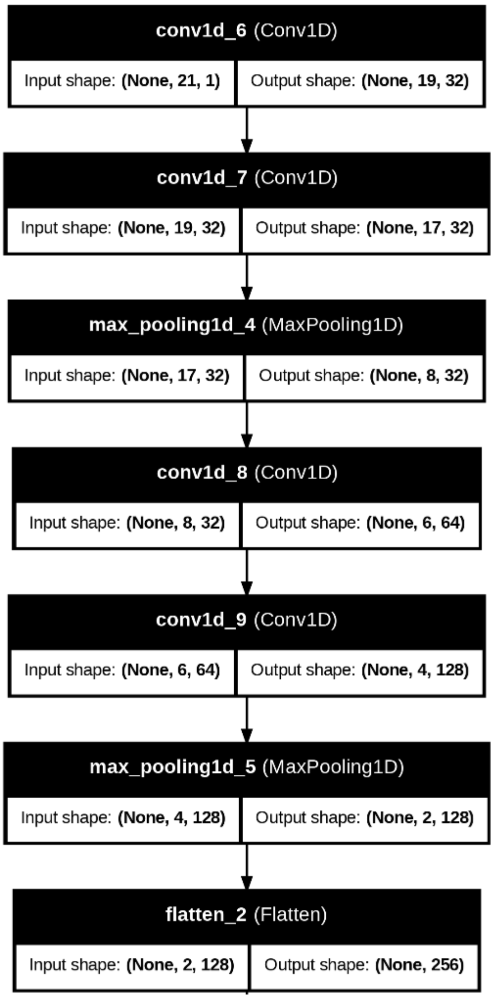

Figure 3 CNN one dimensional

The figure 3 illustrates the architecture of a one-dimensional Convolutional Neural Network (1D CNN), consisting of multiple convolutional and pooling layers, followed by a flattening layer. At the beginning, the Conv1D_6 layer takes in sequential input data with a shape of (None, 21, 1), which indicates 21 time steps and 1 feature per time step. After applying convolution with 32 filters, the output of this layer changes to (None, 19, 32), increasing the number of features to 32. The next convolutional layer, Conv1D_7, further reduces the time steps to 17 while maintaining 32 features, resulting in an output shape of (None, 17, 32). The process is then followed by MaxPooling1D_4, which reduces the time step dimension to 8, with an output shape of (None, 8, 32).

The subsequent convolutional layer, Conv1D_8, increases the number of filters to 64, producing an output shape of (None, 6, 64). This is followed by Conv1D_9, which reduces the time steps to 4 and increases the number of features to 128, resulting in an output of (None, 4, 128). Another pooling layer, MaxPooling1D_5, is applied to further reduce the time steps to 2, with the output shape of (None, 2, 128). Finally, the Flatten_2 layer flattens the output into a one-dimensional vector of size (None, 256), preparing the data for further processing or prediction. This architecture is designed to capture spatial features from sequential data, such as time-series data, and is well-suited for prediction tasks involving temporal data, such as energy production forecasting or weather analysis.

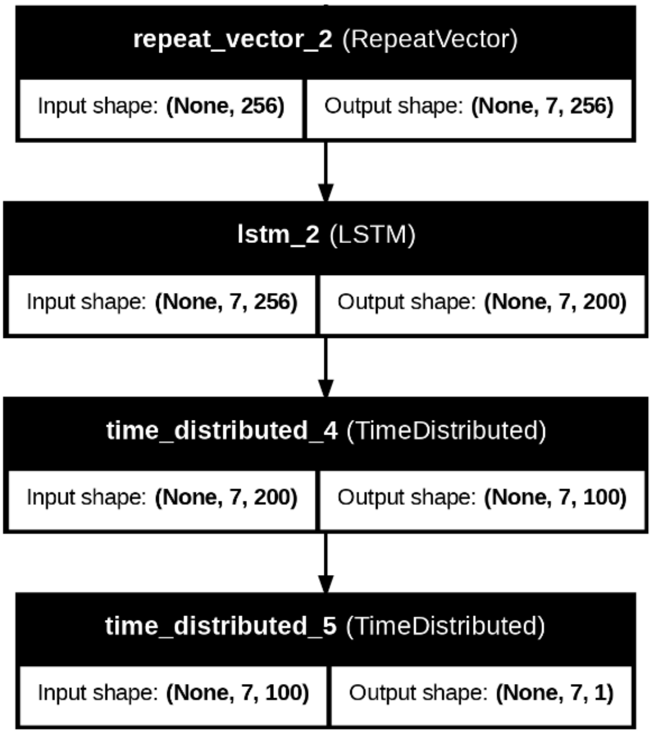

Figure 4 Lstm mode plot

Figure 4 illustrates a part of the neural network architecture that involves a combination of Long Short-Term Memory (LSTM) and TimeDistributed layers. After the previous process, the flattened output data with a shape of (None, 256) is passed to the RepeatVector_2 layer, which replicates the vector into a sequence of length 7, resulting in an output with a shape of (None, 7, 256). The purpose of this is to transform the flattened vector into a sequence format, enabling further processing by the LSTM layer.

The LSTM_2 layer then receives input with a shape of (None, 7, 256) and produces an output of shape (None, 7, 200). The role of the LSTM here is to capture the temporal patterns (time dependencies) within the sequence data. LSTM is highly effective in processing sequential data, such as time-series data, due to its ability to retain long-term information [14].

Following this, the TimeDistributed_4 layer applies a dense layer to each time step of the sequence produced by the LSTM. This layer reduces the feature dimension from 200 to 100 for each time step, with an output shape of (None, 7, 100). Finally, TimeDistributed_5 performs a similar operation, reducing the output dimension to (None, 7, 1), which means that each time step only has a single predicted value. The combination of LSTM and Time Distributed layers is well-suited for time-series prediction tasks, such as solar energy forecasting or other time-dependent data [15].

C. Training and Evaluation

The use of a combined approach of Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) in predicting solar energy production is illustrated in the graph [16]. The training model is optimized to minimize the loss function by learning seasonal patterns in solar energy production over a specific period [17]. The LSTM approach helps capture long-term dependencies in time-series data, such as annual and daily fluctuations in solar power production. Meanwhile, the CNN plays a role in extracting essential features from finer data variations, like sudden changes due to weather conditions [18]. The model is trained using historical datasets, which are randomly and stratified split into training and testing data. The prediction results show solar energy production patterns that vary over time, with peaks and declines following seasonal trends, as seen in the graph [19]. This combination allows for more accurate and efficient predictions in understanding the dynamics of renewable energy production.

Table 1 Data Split Number

No	Subset	Number	%
1.	Training		80
2.	Testing		20

Table 2 Hyperparameter Used in The reseach

No	Hyperparameter	Value
1.	Optimizer	Adam
2.	Learning Rate	0.001
3	Loss Function	Binary crossentropy

The data splitting and hyperparameter usage in this study are outlined as follows. The dataset is divided into two main subsets, with 80% allocated for training and 20% for testing, as shown in Table 1. This division ensures that the model is trained optimally and can be tested for its ability to predict unseen data. Table 2 lists several key hyperparameters used in the study, including the Adam optimizer with a learning rate of 0.001, and the binary crossentropy loss function [20]. These hyperparameters were chosen to optimize the model's learning process, ensuring stability and accuracy during both training and prediction phases.

D. Forecasting

In the process of forecasting solar energy production, the CNN-LSTM model is used to predict the output based on historical data as well as environmental factors such as irradiance, temperature, wind speed, and humidity. The data is processed using a sliding window algorithm, where each time window has a specific length and is used as input to the model to predict the output for the next time step. This approach allows the model to capture both short-term and long-term patterns in the time-series data, leading to more accurate predictions [21].

The CNN model is responsible for extracting spatial features from the provided environmental data, while the LSTM handles the temporal dependencies of the time-series data generated by the CNN. After training, the model is tested using a subset of data that was not seen during training, with the data split into 80% for training and 20% for testing.

The model's performance is evaluated using various error metrics, one of which is the Mean Squared Error (MSE), which is formulated as follows [22]:

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

Where y_i is the actual value and $\hat{y}_i$ is the predicted value. MSE provides an indication of how far the model's predictions are from the actual values. Additionally, Root Mean Squared Error (RMSE) is also used to assess the error in the same units as the output values[23] :

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

MAE is also used to calculate the average of the absolute errors between the predicted and actual values[24] :

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (3)$$

Additionally, during the model training process, the Adam optimizer is used to update the neural network weights, taking into account both the first and second gradients of the loss function, with the following formula [25]:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (4)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (5)$$

The weight update is performed using:

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{\widehat{v_t}}+\epsilon}\widehat{m_t} \qquad (6)$$

where m_t is the first moment estimate (the average of the first gradients), v_t is the second moment estimate (the average of the second gradients), θ_t is the weight to be updated, and η is the learning rate.

The model is trained to minimize the Binary Crossentropy loss function when handling classification, with the following formula :

$$Loss = -\frac{1}{n}\sum_{i=1}^{n}[y_i \log(\widehat{y_i}) + (1-y_i)\log(1-\widehat{y_i})] \quad (7)$$

The prediction results show that the hybrid CNN-LSTM approach successfully captures the seasonal patterns of solar energy production, both in the short and long term. This model provides better accuracy compared to traditional forecasting methods, as measured by the RMSE and MAE metrics, and aids in better planning for electricity grid management and energy stability [26].

RESULTS

The proposed model was successfully trained and achieved a good loss minima and a high training accuracy. The curves of the model loss and training accuracy are presented in Figure 8.

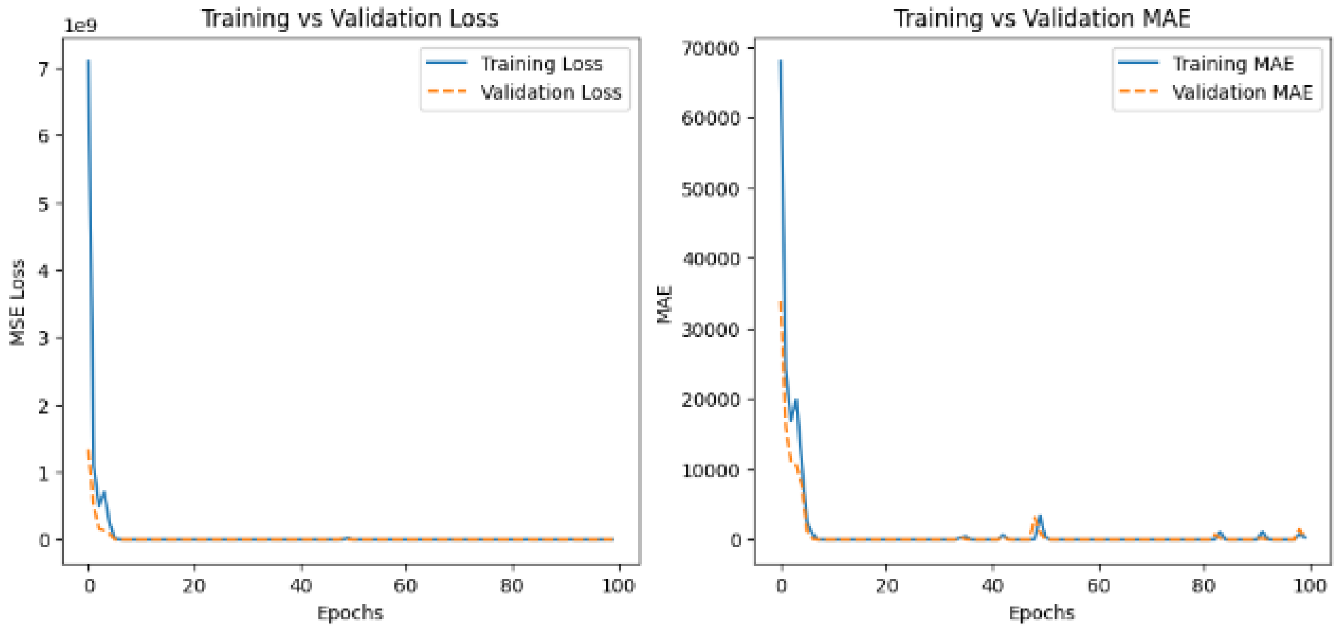

Figure 5 Curves of the training and validation accuracies and losses

The image presents two graphs comparing the performance of the combined Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) model in solar energy production prediction during the training process. The left graph illustrates Training vs. Validation Loss using the Mean Squared Error (MSE) metric, where the y-axis represents the MSE loss values and the x-axis indicates the number of epochs. Initially, the MSE is significantly high but decreases rapidly and stabilizes after a few epochs. The right graph depicts Training vs. Validation Mean Absolute Error (MAE), showing a similar pattern where the error drops considerably in the early epochs and then remains steady. The close alignment between the training and validation curves in both graphs suggests that the LSTM-CNN hybrid model does not suffer from overfitting, as its validation performance remains consistent with the training data. This result highlights the effectiveness of the combined approach in capturing complex patterns within the data, leading to improved accuracy in solar energy production prediction.

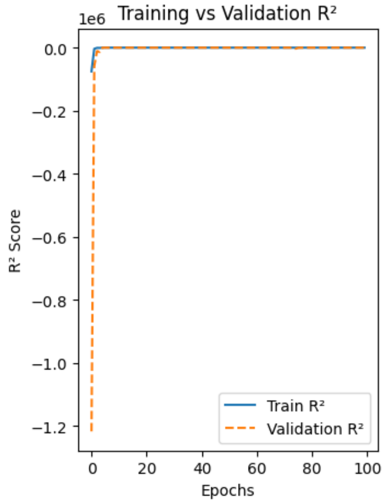

Figure 6 graph comparing the Training vs. Validation R^2 score

The figure displays a graph comparing the Training vs. Validation R^2 score throughout the epochs during the training of the model. The y-axis represents the R^2 score, which indicates the proportion of variance explained by the model, while the x-axis corresponds to the number of epochs. Initially, both the training and validation R^2 scores are quite low, but after a few epochs, both curves rise sharply and stabilize near a high positive value. The similarity between the training and validation R^2 curves suggests that the model is generalizing well to the validation data, showing no signs of overfitting. This indicates that the LSTM-CNN combined approach is effectively capturing patterns in the solar energy production data, resulting in high predictive accuracy.

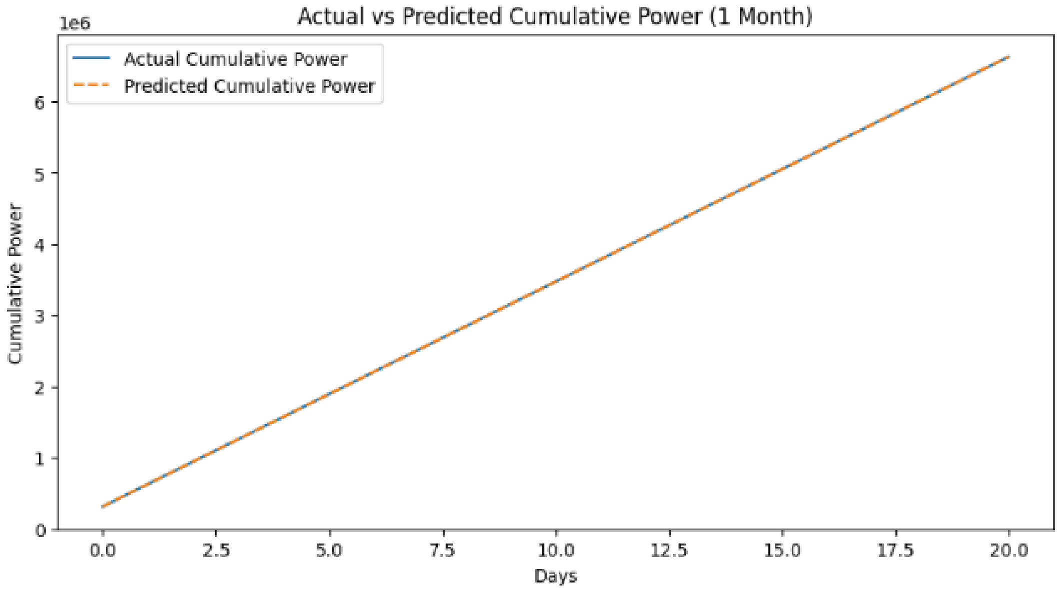

Figure 7 actual and predicted cumulative power over one month

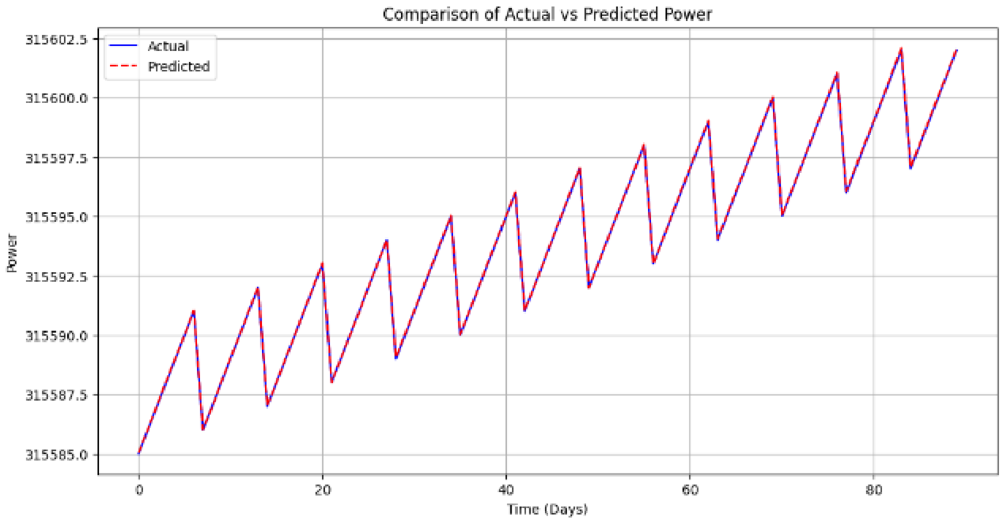

Figure 8 actual and predicted cumulative power over 3 month

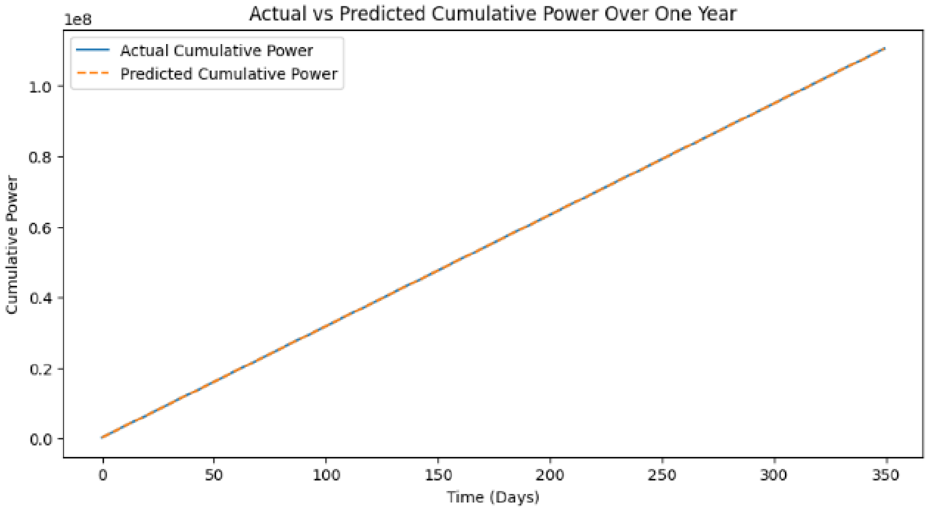

Figure 9 actual and predicted cumulative power over one year

Figures 7, 8, and 9 compare the actual and predicted solar power values over different time periods, showcasing the model's accuracy in forecasting both short-term and long-term solar energy production. Figure 7 displays the comparison of actual and predicted cumulative power over one month, where the curves align almost perfectly, indicating high predictive accuracy for short-term forecasts. Figure 8, which spans 90 days, shows periodic fluctuations in the actual and predicted values, reflecting daily variations in solar power, with the model still maintaining a close match. Finally, Figure 9 illustrates the comparison over an entire year (350 days), where the actual and predicted cumulative power curves remain almost identical, further confirming the model's ability to accurately predict solar power production over long periods. These figures collectively demonstrate the effectiveness of the LSTM-CNN hybrid model in providing reliable solar energy production predictions across various time frames.

Table 2 Hyperparameter

Period	Actual power (Wh)	Predictive power (Wh)	Accuracy (%)	R2 score	MAE
1 months	6,627,369	6,626,979	99.99	1	191.92
3 months	28,403,451	28,403,464	100	1	2.31
1 year	110,464,375	110,457,920	99.99	1	3,191.72

The results demonstrate the high accuracy and reliability of the model in predicting solar energy production across different time periods. For the 1-month period, the model achieved an accuracy of 99.99%, with an R^2 score of 1 and a minimal Mean Absolute Error (MAE) of 191.92 Wh. Over a 3-month period, the model performed even better, achieving 100% accuracy, an R^2 score of 1, and an MAE of just 2.31 Wh. For the 1-year period, the accuracy remained at 99.99%, with an R^2 score of 1, and an MAE of 3,191.72 Wh. These results indicate that the model is highly effective in both short-term and long-term solar energy predictions, with negligible differences between actual and predicted values, demonstrating its strong predictive capabilities.

CONCLUSIONS

This research demonstrates the successful application of a hybrid approach combining Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) for predicting solar energy production. By leveraging CNN for spatial feature extraction and LSTM for capturing temporal dependencies, this combined model provides highly accurate solar energy production forecasts. The results highlight the model's ability to accurately predict both short-term and long-term fluctuations in solar power. Specifically, the model achieved 99.99% accuracy for 1-month forecasts, 100% accuracy for 3-month forecasts, and 99.99% accuracy for 1-year predictions, with exceptional R^2 scores of 1 and minimal Mean Absolute Errors (MAE). The findings demonstrate that the hybrid CNN-LSTM model significantly outperforms traditional forecasting methods, contributing to more reliable energy planning and grid management. Future research could focus on improving the model by incorporating additional environmental factors, testing it across different geographical regions, and enhancing computational efficiency. The combination of LSTM and CNN in this approach shows great potential for advancing renewable energy forecasting and enabling more effective integration of solar energy into power grids.

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