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An Efficient Deep Learning Architecture for Photovoltaic Systems to Forecast the Power Output

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Climate change is compelling more and more countries to adopt renewable energy sources, namely solar power, as a viable alternative to conventional energy sources. Photovoltaic power production is significantly influenced by weather conditions, primarily depending on solar irradiation, and is both highly variable and difficult to anticipate. This unpredictability poses a challenge for power generation. Precise photovoltaic output forecasts significantly enhance solar power plants' functioning. Ensuring the robustness of power plants' functioning is crucial for providing reliable energy to clients. The motivation for this study stems from the current acceptance and advancements in deep learning models, as well as their practical use in the energy industry. The proposed model combines two deep learning architectures: the Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN). A dataset obtained from Rabat, Morocco, is employed as a practical example to demonstrate the efficacy of the proposed topology. Based on error measures such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE), the suggested hybrid framework outperforms typical machine learning and deep learning algorithms regarding prediction accuracy, precision, and consistency.

Keywords: Photovoltaic Systems, Deep Learning, Prediction, Long Short-Term Memory, Convolutional Neural Network.

1. Introduction

The globe is anticipated to transition into a more environmentally friendly period with the widespread growth of Renewable Energy Sources (RES) [1]. These sources are progressively becoming more common in everyday power use. The Earth gets abundant sun emissions regularly, which enables solar power to surpass other resources and facilitates electricity production via the photoelectric impact. Solar energy has significant potential for substituting fossil fuels. The Sun is a nuclear reactor, providing enough electricity for everyone on Earth. Despite its potential, it still needs to be fully used. Solar energy is the predominant renewable energy source on Earth, with additional sources such as hydroelectric, wind, tidal, geothermal energy, and biofuels.

Being a colossal power plant, the Sun operates without needing maintenance or fuel. Furthermore, the waste produced from its operations does not need to undergo any processing and does not present any environmental hazards [2] [40]. The time needs to cultivate energy sources devoid of greenhouse gas emissions to guarantee an equitable economy and preserve the environment. Fossil fuel reserves are diminishing, increasing prices significantly. The economic benefits derived from these assets have had a more substantial impact than the desire to decrease greenhouse gas emissions. The growing use of RES has shown their pure and boundless potential as attractive substitutes for energy generation.

Electricity is crucial in promoting economic growth and technical advancement, which are necessary for fast urbanization and industrialization [3]. With the increasing global energy consumption, there is a corresponding increase in the demand for generating and distributing electricity [4][31]. Government and international organization regulations facilitate the adoption and development of RES [5]. The European Union aims to reduce greenhouse gas emissions by 80% and generate all its power from RES by 2050 [6][33]. On average, the terrestrial surface gets a solar irradiation of 1432 W/m^2 daily. The total worldwide absorption of this solar energy is estimated to be 2.3 * 1201 MW [7]. This energy quantity is enough to meet the energy needs of all countries [36].

Precise forecasts of photovoltaic plants' power output enable a substantial improvement in the reliability of solar power generation and its integration into a nation's energy mix [8][35]. However, the unpredictable nature of solar power generation remains a significant worry that hinders its widespread integration into global power grids [9]. Precise prediction of solar energy generation aids in strengthening the power grid's ability to withstand challenges and optimizing the application of solar energy [38]. The expansion of solar household systems has facilitated the accumulation of substantial quantities of time-series data via smart meters. This guarantees the prompt retrieval of data, the automatic collection of measurements, and precise data generation.

The salient findings of this study report are briefly described as follows:

- A proposed hybrid architecture for forecasting the power output of a solar plant is a combination of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) models. This architecture is used to predict power outcomes throughout various time frames, both in the past and future.
- The information is obtained from a solar facility in Morocco, containing many variables. The data set includes power production tracks, climatic factors, and the plant's power consumption.
- The relationship between the look-back value and the accuracy of the model's predictions is examined, and the appropriate value for each predictive model is provided. This enables us to choose the suitable variables for each prediction model accurately.

2. Literature evaluation

Literary techniques used to forecast photovoltaic (PV) power include inherent constraints. The persistence and statistical approaches cannot handle nonlinear information. The issues of local minima, intricate structure, and overfitting are present in both Artificial Neural Network (ANN) [10] [32] [37] and Adaptive Neuro-Fuzzy Inference System (ANFIS) [11] approaches. The performance of Support Vector Machine (SVM) is influenced by the choice of kernel operation, penalty factor (C), and tube radius (e) [39]. Extreme Learning Machine (ELM) exhibits a problem of arbitrary choosing of input loads and concealed node biases [12]. The method refers to the techniques that have encountered challenges accessing information gathered by local agencies [13]. The satellite information used in remote sensing methods needs a better resolution, while sky pictures have the disadvantage of limited sight from the ground [30].

Deep learning approaches have been utilized to address the constraints of linear, machine learning, and physical prediction frameworks. Deep Learning is a sophisticated kind of machine learning [14][42]. It can extract profound characteristics from PV power production and provide superior predicting outcomes compared to persistent, physical, and mathematical models.

The CNN and Recurrent Neural Network (RNN) [15] are deep learning models that estimate PV power. Lulu et al. suggested a deep learning technique for estimating solar power generation one hour in advance [16]. It has yielded superior prediction outcomes compared to the Multilayer Perceptron (MLP) [17] and SVM techniques. The Particle Swarm Optimization (PSO) method was ultimately employed for load dispatch optimization [18]. The LSTM approach demonstrated superior performance in solar power prediction over the Support Vector Regression (SVR) and feed-forward neural network techniques, as evidenced by its lowest Root Mean Square Error (RMSE) of 0.072 and Mean Bias Error (MBE) of 0.003. An LSTM algorithm demonstrated a lower assessment RMSE value of 4.326 for short-term forecasting of PV power production compared to other deep learning approaches [19][41].

Using an LSTM network, a novel technique is suggested for predicting power production one day in advance [20]. The program relies on information provided by local meteorological agencies. When tested on a half-year database, it has shown a predicting accuracy of 16.52% higher than that of backpropagation neural network, Logical Regression (LR), and perseverance approaches. The suggested technique demonstrates a 38.7% improvement in RMSE compared to previous methods when applied to a one-year testing data set. Abdel-Basset et al. have used the deep learning approach to conduct PV power forecasts on a weekly and daily schedule [21]. The findings showed that the suggested strategy outperformed previous methods based on site adaptation events by 36%. An LSTM-based deep learning model demonstrated an average prediction skill of 51.4% for day-ahead forecasting, surpassing the performance of the persistence system. The LSTM network demonstrates a superior RMSE skill score (19%) compared to the CNN and MLP networks, which achieved 14% and 9% for predicting PV power 1 minute in advance [22][34].

A novel approach was introduced for short-term prediction of PV power, using a hybrid method that combines deep CNN and Variational Mode Decomposition (VMD) techniques [23]. The VMD approach separated the frequency elements from historical time series. An approach combining CNN and Logical Regression (LR) has outperformed previous systems predicting PV power one hour in advance [24]. The hybrid technique described has achieved the lowest RMSE, Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) values of 0.0721, 0.0412, and 14.51, respectively. The suggested hybrid strategy has shown superior accuracy in predicting future outcomes for 2 and 6 hours. A novel approach was devised to anticipate the power output of PV systems on a weekly and seasonal basis [25]. The wavelet transform was employed to convert the original signal into several frequency elements.

The PSO-LSTM model was developed to anticipate power production for multi-region solar systems with a 30-minute lead time [26]. The sensitivity assessment was conducted on several data sets, and the suggested technique demonstrated the lowest RMSE of 18.52, outperforming the standard LSTM and ANN approaches.

However, only data from a single year is taken into account. A hybrid system, which combines Genetic Algorithms (GA) and deep neural networks, was used to predict solar irradiation [27]. The approach demonstrated superior forecasting accuracy across several seasons. The researchers utilized a hybrid approach called GA-LSTM to anticipate the PV power production 4 hours in advance [28]. GA is an antiquated optimization method particularly suitable for discrete situations. The variables of the SVM model were optimized using the Artificial Bee Colony (ABC) method for multi-hour forward forecasting. The ABC technique demonstrated superior accuracy compared to the Cuckoo-Search SVM [29]. Nevertheless, the ABC method is known for its sluggishness and vulnerability to stagnation.

3. Proposed hybrid method using CNN and LSTM for PV power prediction

3.1 CNN

CNN is a kind of deep learning design that has been successfully used in several fields and has shown impressive performance. CNN is a hierarchical feature extraction that can autonomously acquire high-level characteristics from source sequences.

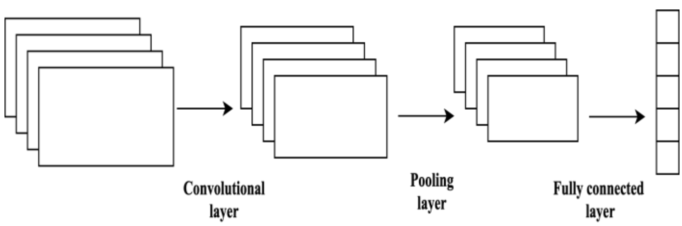

Figure 1. CNN architecture

Figure 1 illustrates the fundamental architecture of a CNN, which comprises several kinds of levels, including convolutional, pooling, and fully connected. The responsibilities of each layer are summarized as follows:

The convolution level is a crucial element of a CNN and consists of many convolution kernels that produce new feature mappings. The convolution process effectively extracts local features, utilizing shared kernel weights throughout all input mappings.

The pooling level is frequently utilized to decrease the in-plane dimensionality of input mappings, thus lowering the number of learnable variables and mitigating the risk of overfitting. The pooling processes might vary in kinds, including max pooling and mean pooling.

The fully connected level is frequently employed for high-level inference. It translates the characteristics processed by the convolution and pooling levels to the output level.

Furthermore, the convolution levels (or pooling level) are enhanced by a non-linear activation operation, such as the hyperbolic tangent variable (tanh) and the Rectified Linear Unit (ReLU).

3.2 LSTM

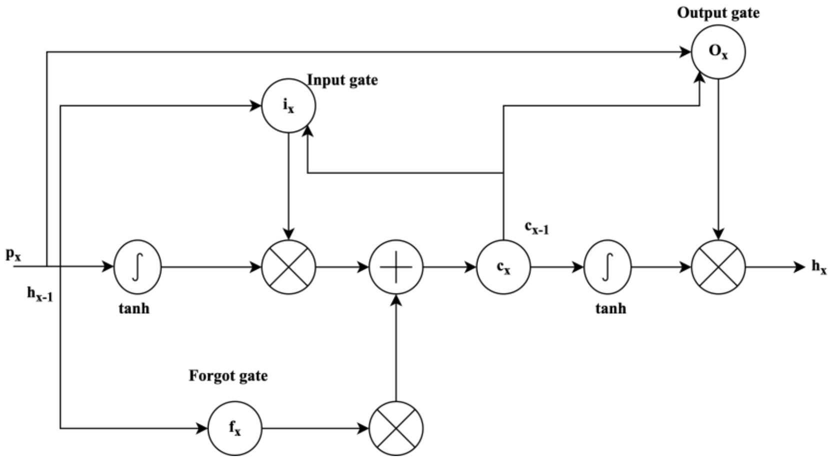

Figure 2. LSTM architecture

LSTM is a sophisticated CNN structure capable of learning dependencies across long distances. Figure 2 depicts the architecture of an LSTM block, including an input gateway (i_x), a forget gateway (f_x), an output gateway (o_x), a memory unit (m_x), and output values (h_x). The block relies on two external resources: the present inputs p_x and the past outputs h_{x-1}. The input gateway controls the inputs to modify the memory unit, while the forget gateway determines which information should be discarded from the block. The output gateway regulates the output depending on the inputs p_x, prior outputs h_{x-1}, and memory unit c_x. The recursive calculations of the LSTM component are depicted in Equations (1) to (5).

$$i_x = \alpha\{W_{p_i}p_x + W_{h_i}h_{x-1} + W_{c_i}C_{x-1} + b_i\} \quad (1)$$

$$f_x = \alpha\{W_{p_f}p_x + W_{h_f}h_{x-1} + W_{c_f}C_{x-1} + b_f\} \quad (2)$$

$$c_x = f_x \odot c_{x-1} + p_x \odot \tanh\{W_{p_c}p_x + W_{h_c}h_{x-1} + W_{c_c}C_{x-1} + b_c\} \quad (3)$$

$$O_x = \alpha\{W_{p_o}p_x + W_{h_o}h_{x-1} + W_{c_o}C_{x-1} + b_o\} \quad (4)$$

$$h_x = o_x \odot \tanh(c_x) \quad (5)$$

The symbol $\odot$ represents the element-wise products. The function $\alpha\{.\}$ is the sigmoid operation, defined as $\alpha(\mathrm{i}) = \frac{1}{1+\exp(-\mathrm{i})}$. The weight matrix W_{p_x} represents the connection strength between the present inputs p_x and the input gateway i_x. The word b_x represents the bias. Likewise, the other weight matrices in the forget gateway, output gate, and memory cell exhibit identical circumstances. Unlike the conventional CNN, the LSTM has a memory cell (c_x) accumulates activity across time, allowing the gradient to propagate over several time steps.

3.3 Hybrid framework design

This research uses a hybrid technique that combines CNN and LSTM to predict PV power accurately. This method allows us to effortlessly and automatically learn the individual input/output correlations. Figure 3 displays the architectural design of the suggested technique.

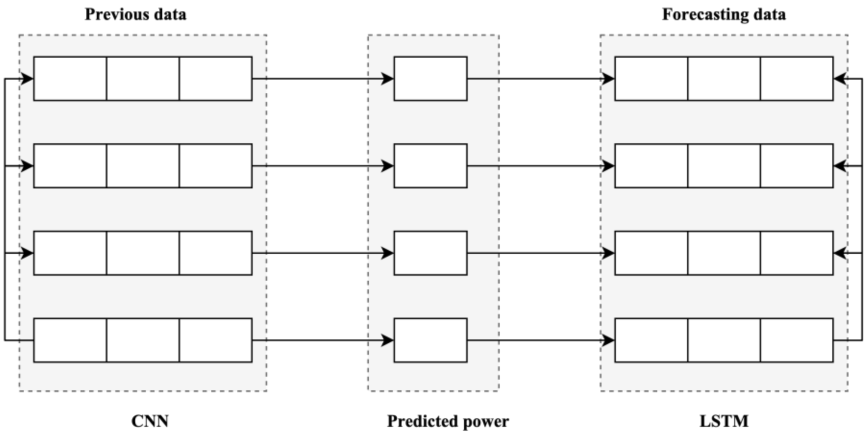

Figure 3. Hybrid model for PV power prediction

This research uses a CNN model to predict the future output power P_l^{n+1} based on the prior output power at time n+1 on consecutive days. This research hypothesizes that the PV power values, namely P_{l-1}^{n+1} and P_{l-2}^{n+1}, provides further insights into the prevailing weather situations, and aids in forecasting P_l^{n+1}. The research extracts a vector containing the prior output power information by examining the resultant power matrix, as shown in Equation (6).

$$P_l = \left[P_{l-1}^{n+1}, P_{l-2}^{n+1}, \cdots, P_{l-k}^{n+1}\right]^T \in R^{L\times N} \quad (6)$$

The variable P_{l-1}^{n+1} represents the power result at the (n+1)th time on the (l-1)th day. The matrix P_l is transformed into an image $R^{L\times N}$ having a certain height H and width W. It is essential to understand that once the input length of the CNN is established, the window size cannot be changed. The LSTM model uses the previous output power P_l^n to estimate the future output power P_{l-1}^{n+1}. LSTM is capable of capturing the temporal dynamics of the most recent data to predict outcomes accurately. The inputs of LSTM are shown in Equation (7).

$$P_m = \left[P_l^n, P_l^{n-1}, \cdots, P_l^{n-F}\right]^T \in R^F \quad (7)$$

P_l^n represents the power production at the nth period on the l-th day. $P_m \in R^F$, where F represents the inputs and the window length of the LSTM.

The prediction outcomes of the suggested approach thoroughly include the CNN and LSTM algorithms. The logical regression is computed by amalgamating the estimations derived from the CNN and LSTM, denoted in Equation (8).

$$p^f = \alpha L_{CNN}^f + \beta L_{LSTM}^f \tag{8}$$

The variable p^f represents the anticipated output power of the suggested approach. L_{CNN}^f and L_{LSTM}^f represent the corresponding prediction outcomes of the CNN and LSTM models. The CNN is allocated a non-negative weighting α, whereas the LSTM is assigned a non-negative weighting β. The weight that is not negative follows the condition $\alpha + \beta = 1$, and it is more advantageous to compute the mean of the predicted outcomes. The CNN variables are tuned together using backpropagation, which reduces the loss value specific to the job. The LSTM variables are improved using backpropagation through time.

3.4 Performance analysis

The models' forecasting performance is assessed by comparing the discrepancy between the anticipated and observed values. The accuracy of estimating PV output power is evaluated using MAE and RMSE, as well as the coefficient of determination (R^2). The assessment requirements are as stated in Equations (9) to (11), and the mean value of the input is shown in Equation (12).

$$MAE = \frac{1}{M}\sum_{i=0}^{M-1}\left|L_N^M - L_N^F\right| \tag{9}$$

$$MRMSE = \sqrt[2]{\frac{1}{M}\sum_{i=0}^{M-1}\left(L_N^M - L_N^F\right)^2} \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=0}^{M-1}\left(L_N^M - L_N^F\right)^2}{\sum_{i=0}^{M-1}\left(L_N^M - L_{mean}^M\right)^2} \tag{11}$$

$$L_{mean}^M = \frac{1}{M}\sum_{i=0}^{M-1} L_N^M \tag{12}$$

Let M be the total number of samples tested. L_N^M and F represent the measured and estimated output power, accordingly. L_{mean}^M represents the mean value of the observed power in the test data set. It is essential to mention that the predicting model exhibits more accuracy when the MAE and RMSE values are less. The predicting model is more effective when the value of R-squared (R^2) is closer to 1.

4. Results and analysis

The selection process included choosing a 15Watt PV system. Information was gathered from January 2023 to May 2024.

Table 1. Dataset analysis

Parameter	Minimum	Maximum	Average	Standard deviation
Consumption (kW)	15.3	109.4	52.3	27.4
Production (kW)	5.9	63.2	28.4	14.2
Temperature	0	37	25	5.2
Wind speed (km/hr)	8	59	19.4	6.3
Humidity (%)	36	92	76.4	9.4
Cloud cover (%)	0	83.4	25.3	21.6
Sun hour (hr)	3.5	15.3	10.8	2.8

Table 1 presents a comprehensive summary of the different elements within the dataset, including the lowest and highest values. On May 12, the PV facility reached its peak electricity output of 60.9 kW in a single day. On January 13, 2024, the power production reached a low of 5.7 kW, along with the corresponding average and standard deviation measurements.

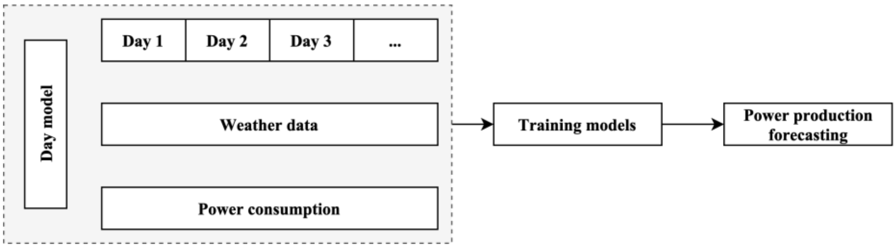

Figure 4. Dataset preparation

Figure 4 illustrates the methodology used for generating projections one day ahead using machine learning and deep learning algorithms. The input characteristics are classified into three distinct types. The first group comprises the power output records over one year and three months. The second grout includes meteorological factors such as wind speed, temperature, and others obtained from an online weather service. The final category encompasses the facility's electricity usage. The input parameters are sent to the established methods to predict the power output for the subsequent day.

The hybrid structure utilizes CNN and LSTM layers to predict power generation by extracting complicated characteristics from various sensor parameters and preserving complex irregular trends. The design of the hybrid framework was modified based on the structure and variable adjustments of the network's constituent layers. The hybrid model comprises a Convolutional Layer, Pooling Layer, LSTM, and Time Distributed layer. Each layer independently regulates the quantity of filtration, the dimension of the kernel, and the strides. The learning speed and accuracy are influenced by modifying these variables, depending on the features of the data used for training. By adjusting the variable, either increasing or decreasing it, we can verify the improvement in efficiency. Gaining a comprehensive understanding of the characteristics of the input records is crucial as it enables the modification of variables and the development of an appropriate model for power generation prediction. The power generation information is a dataset that contains many factors and consists of daily information from seven distinct parameters. The convolution technique emulates specific neurons' reactions to visual inputs.

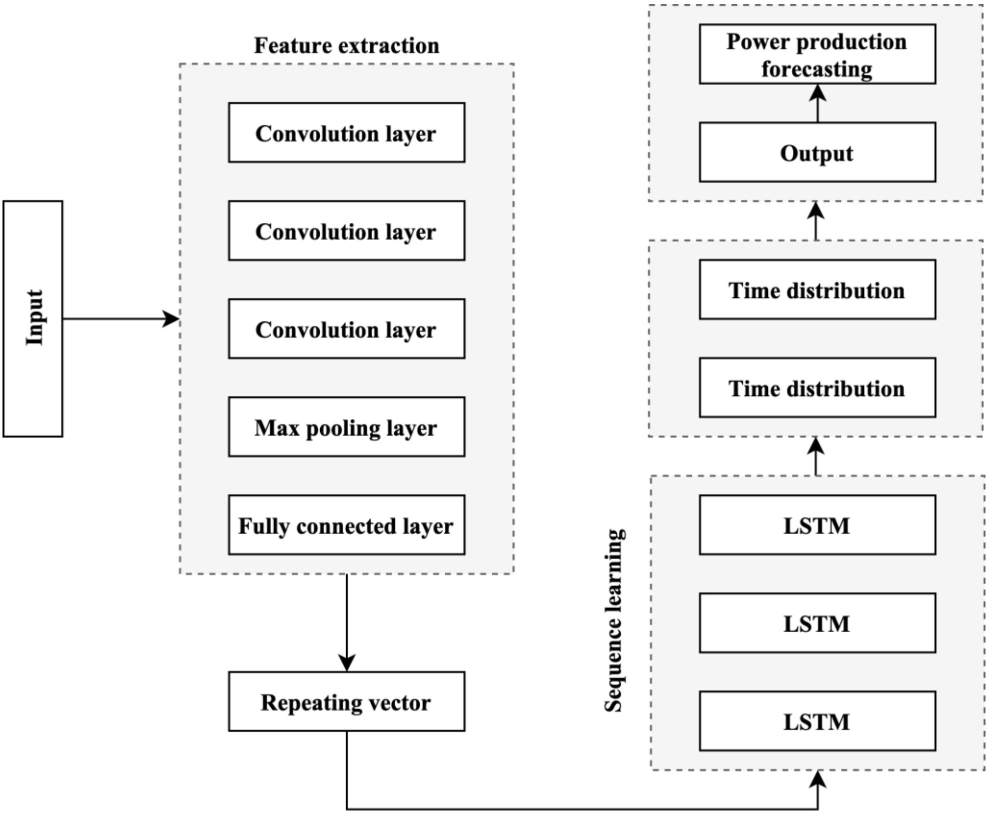

Figure 5. The hybrid model design

Figure 4 depicts the proposed architecture of the hybrid framework. The CNN framework consists of three CNN levels, followed by a max-pooling level. The outcomes are then flattened. The first convolutional level processes the input sequence, which showcases the discovery of feature mappings. The second level duplicates the procedure on the feature mappings produced by the first level. The third layer replicates similar procedures to enhance the prominent characteristics. Each layer of the CNN consists of a certain number of feature maps, namely 16, 32, and 64 for the three corresponding layers. Each layer uses a kernel dimension of three-time steps to process the input sequences. A max-pooling layer simplifies the feature maps by retaining just the top one-quarter of the signals. The fully connected feature mappings are organized into a linear vector following the pooling level. The Repeat Vector layer establishes a connection between the two sub-topologies by iteratively duplicating the internal image of the input sequence, with each duplication corresponding to a time phase in the resultant sequence. The vector series is then sent to the extended short-term memory decoder. The decoder section mentioned has three LSTM layers, with each level having 16, 32, and 64 units, respectively. Unlike the CNN layer, each LSTM layer generates the whole sequence of outputs, not just the final result. Each separate subdivision generates a value for every predicted period. Two levels spread throughout time are used before the final output level to elucidate each time step in the output order.

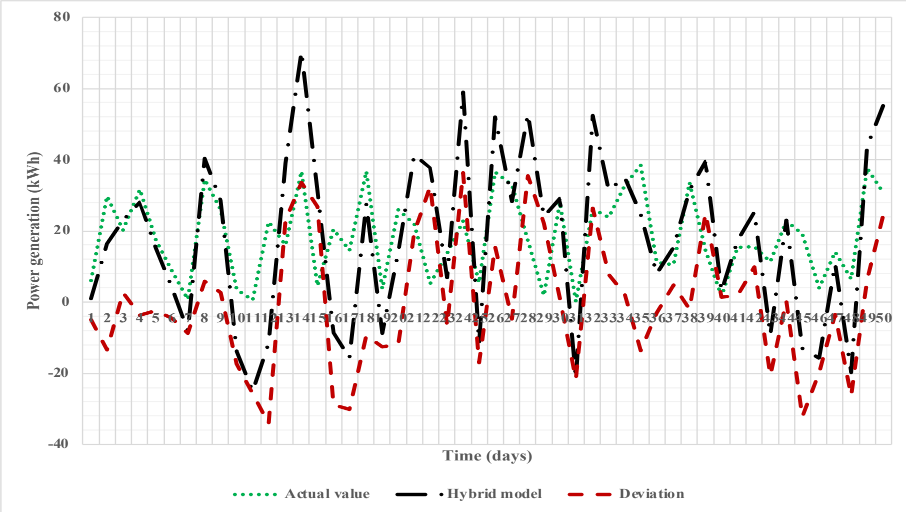

Figure 6. Power production results

The hybrid network's predicted outcomes are shown in Figure (6). The outcomes of the suggested technique are contrasted with those of the linear regression method. The hybrid technique outperforms the classic model in predicting the overall features of energy generation. It effectively predicts local attributes—the linear regression method is better to predict this database's regional and global properties. The proposed hybrid method demonstrates superior performance when dealing with time series data. The integration of CNN and LSTM levels yields precise predictions for the electricity generation of PV systems. Thus, unlike the LR approach, the proposed design effectively represents the unpredictable energy output structure.

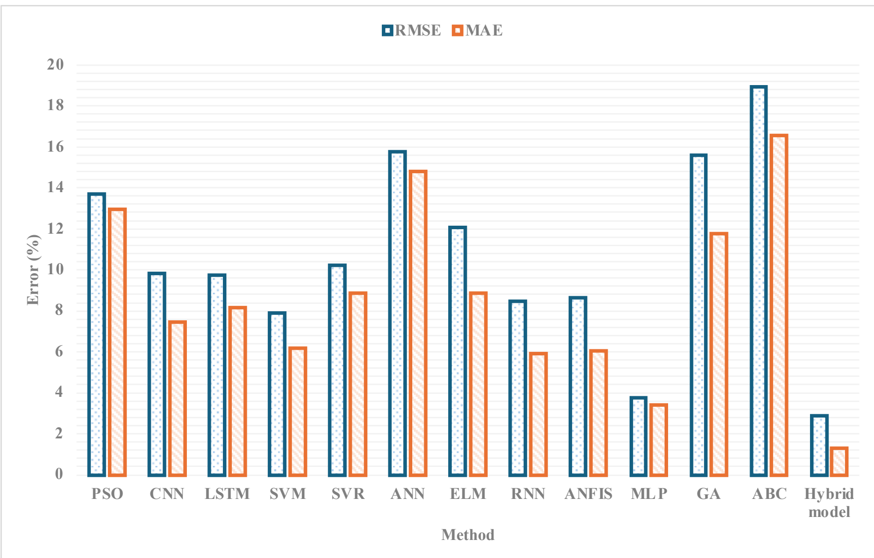

Figure 7. Error analysis of the different methods

Figure (7) compares the efficiency of several machine learning scenarios, as measured by their RMSE and MAE error levels. The graph demonstrates that the four machine learning algorithms had poor performance, with their error values near each other. Unlike other scenarios, the hybrid approach has the highest RMSE and MAE error values of 2.9 and 1.32, indicating that it is the least proficient approach. The implemented design has reduced error values by 50%, significantly improving prediction accuracy.

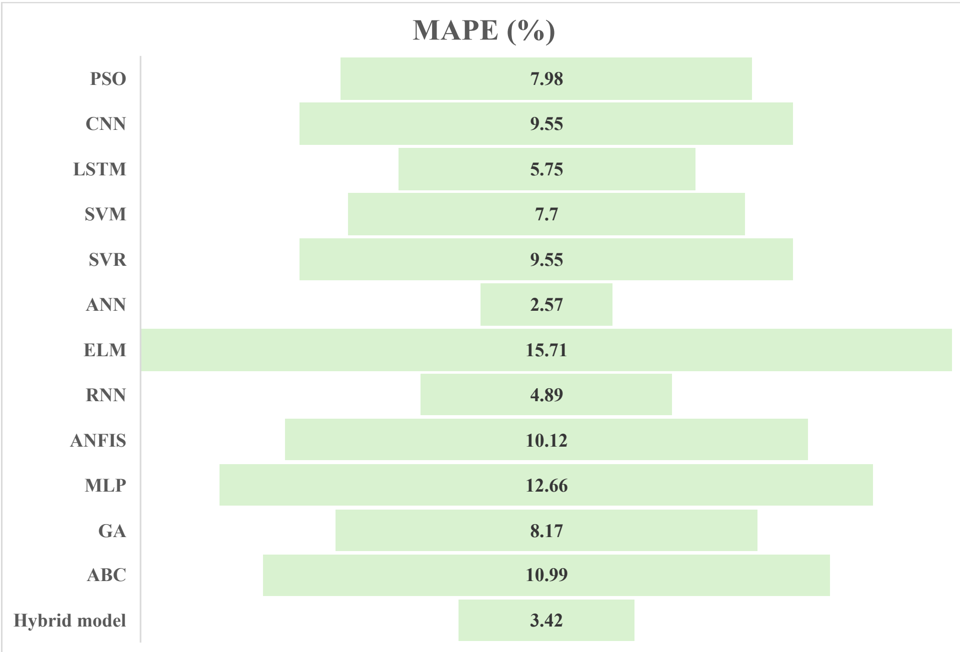

Figure 8. MAPE analysis of the different methods

Figure (8) compares the LSTM and hybrid models regarding their look ahead and look back time windows. When used with any look-forward number, a lookback value 10 produced precise forecasts. The only difference is in the final variant, whereby the use of a 14-day lookback proved to be more efficacious in predicting the next seven days compared to the utilization of a 10-day lookback. This might be due to the anticipated extended duration, necessitating a larger dataset for training the algorithm to provide precise predictions.

5. Conclusion and findings

This research introduces a hybrid model that is both trustworthy and successful in predicting the energy production of PV plants. The model does this by extracting characteristics of meteorological factors that impact power output. To validate the proficiency of the proposed model, several machine learning and deep learning models have been utilized for comparison, including a wide range of case situations. The hybrid framework has shown enhanced accuracy in forecasts by combining the notable capabilities of all models. In addition, it identified the unpredictable patterns of power production that need to be accurately foreseen by traditional machine learning methods. The statistical data demonstrate that the proposed architecture predicts more accurately than the individual models. The hybrid model exhibits a rise in MAPE value of 3.42%, RMSE of 2.9%, and MAPE of 1.32%, respectively, compared to the LSTM system.

In contrast to the CNN model for predicting one day, the MAPE value of the hybrid system has seen a 3.27% rise. The primary reason for this is that the hybrid topology combines the benefits of the CNN (which captures the spatial characteristics of the information) and the LSTM (which handles the temporal aspects of the data). These data indicate hybrid structures are more effective than single models in most circumstances. It is crucial to include more look-back days to provide accurate projections as the expected period increases. The primary reason for this phenomenon is that a longer projected period needs more historical data to generate more accurate predictions. This correlation is evident when examining the 12 and 14-day look-back periods about the three and 7-day forecasts.

Consequently, PV systems are increasingly integrated into electric networks worldwide. The suggested hybrid design is ideal for system operators and energy suppliers to enhance decision-making in power system optimization and management. It enables efficient setup of power system reserves, economic delivery, unit contributions, and demand response. The improved hybrid model has performed remarkably well predicting the next day's PV power. Some enhancements still need to be implemented. The hybrid model indicates wind power generation, energy prices, and load usage forecasts. However, more research will be undertaken to investigate customer behavioral traits and use the gathered data to enhance the electrical power prediction system.

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