Solar Power Forecasting using Deep Learning Hybrid CNN-RNN Technique

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Abstract: *Predicting the power production of large-scale renewable energy facilities, especially solar systems, shapes the future of clean energy. Accurate weather forecasts are crucial for solar power generation. We use the Genetic Algorithm (GA) to tune Convolutional Neural Network (CNN) hyper parametersto solve this problem and improve prediction accuracy. The GA's fitness function is determined by correlating hyper parameters and CNN performance and evaluation metrics. The GA optimizes hyper parameters for better forecasting across evaluation indices. We compare our findings with hybridized CNN-RNN, LSTM, and KNN-SVM forecasting algorithms without tuned hyper parameters to evaluate our strategy. GA-CNN outperforms all other methods. We use GA-CNN to add structural and data variety to our machine learning hybrid model to improve accuracy. We use the four ways and a comparable strategy to anticipate solar power for a given site. We test the method using a Jodhpur real-time series dataset. The validation dataset helps pick parameters, while the training dataset builds the prediction model. Performance measures including MAE, RMSE, MSE, and sMAPE are used to evaluate findings. Finally, using these performance indicators, we compare the results of the various alternative tactics with our proposed strategy. Our technique properly forecasts solar power generation, enabling more efficient and effective renewable energy use*

Keywords*:* Solar Power Forecasting, CNN, RNN, LSTM, SVM, KNN

I. INTRODUCTION

Although solar energy is intermittent, there are various ways in which it may be used to help poor nations eventually overcome their energy problems. As a rapidly developing and fiscally astute nation surrounded by oceans and mountains, India relies in part on long-lasting producers such as air currents, sunlight, heat from the earth's crust, load in the vast natural reservoirs present on 75% of the earth's surface, electricity from plant and animal products, and power using molecular bonds in some chemicals. This region requires reliable sources that can generate approximately four times the amount of energy now used in order to address the technological gap in this fast expanding financial industry.

The number of PV power producing systems using available solar beams is rising continuously. A lot of attention has been placed on forecasting plant output since human demand is constant despite variations in PV plant production. When PV electricity is scarce, we may employ alternative grid-based energy generation methods, which is another justification for forecasting demand. When we have extra power, we may also feed the grid with it. A balanced application of force in both interior and exterior directions will be the outcome of this accurate guessing. [9-11]

Infrastructure for the generation of both renewable and nonrenewable energy is under the control of grid operators. If it is possible to estimate the changing output in any way, dispatching control will be successful in providing stable power to the load. PV output guessing hence becomes a significant general application. The equipment for calculating PV power based on solar rays is made up of a few essential mechanics. It is obvious that ambient light is erratic. To stop sunlight from damaging the panels, an extremely erratic cloud cover is in place. Therefore, a significant work is accomplished if the weather elements can be forecast. [12]. Several machine learning approaches will be employed to forecast accurate power estimations for solar electricity. In every situation, the CNN-RNN consistently outperforms the

SVM, LSTM, and numerous other methods. A few examples of machine learning models are K-nearest neighbor, Convolution Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Support Vector Machine (SVM), and Hybrid of CNN-RNN. The Jodhpur real-time series dataset will be used to validate the proposed method.

II. MACHINE LEARNING TECHNIQUES

A. Convolution Neural Network

The deep learning class of machine learning algorithms is dominated by convolution neural networks (CNNs). The goal of a convolutional neural network (CNN) is to learn a difficult job by applying a series of convolution filters to the input data and then classifying the resulting data. Since the turn of the 21st century, computers equipped with CNN have shown remarkable proficiency in areas like as reading handwritten numbers, locating objects, and recognizing human voice.

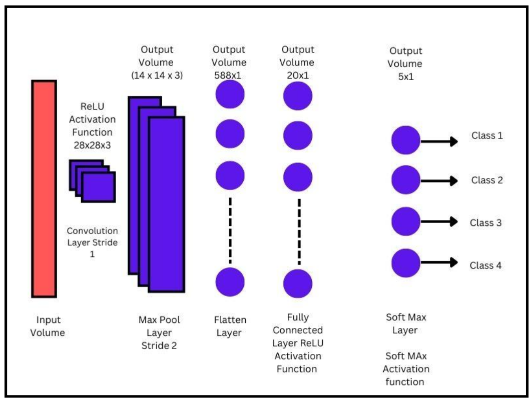

Figure 1 CNN Structure of Layers

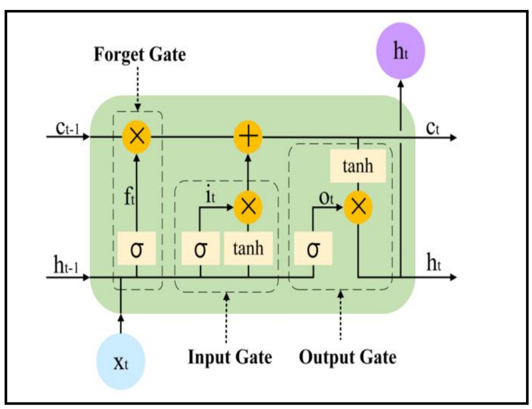

Figure 2 Proposed CNN Structure

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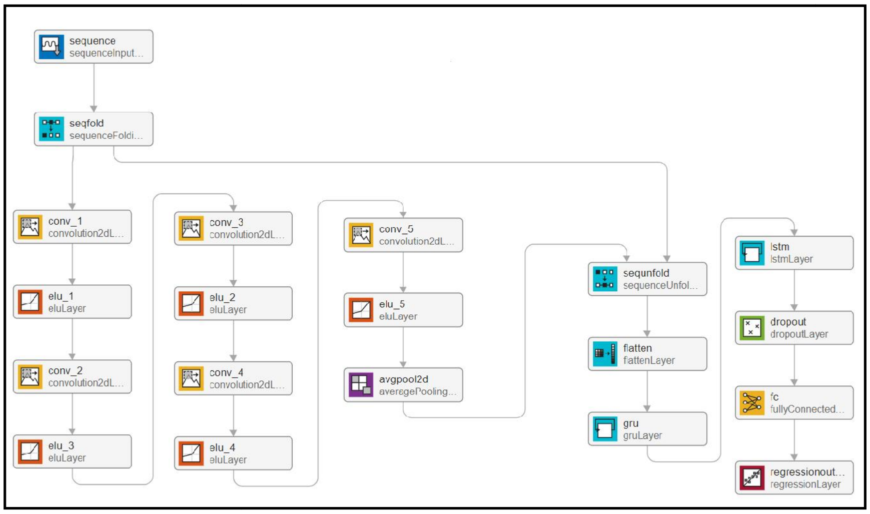

Figure 3 Basic LSTM Structure

B. LONG SHORT TERM MEMORY

Specialized recurrent neural networks (RNNs), or long short-term memory networks (LSTM), were originally presented in [17]. RNN is a neural network (NN) that uses recurrent connections between neurons to learn from both the information it has already learned and new information to come up with a better answer. However, due to the gradient disappearing and explosion issues, it is challenging to get valuable information when two RNN cells are placed far apart from one another. The solution is provided by memory cells, a special kind of neuron. The solution is provided by memory cells, a subtype of special neurons. These special neurons enable the LSTM to store pertinent information over any duration. By altering the forget gate f(t), input gate i(t), and output gate o(t), three separate regulating gates, LSTM cells may also learn what information needs to be read, stored, and wiped from the memory.
Figure 4.7 Gated LSTM Structure of a Neuron with Weights.

C. HYPER PARAMETER

In this study we have considered two hyper parameter of our proposed CNN model for the optimization:
Dropout Rate : Dropout is a regularization technique used in the context of Convolutional Neural Networks (CNNs) to avoid over fitting and enhance the model's generalization performance. The likelihood of deactivating a neuron in a layer of a neural network during training is referred to as the dropout rate. At each update step of the training process, dropout randomly sets a portion of the input units or neurons to zero. This indicates that the units' output is momentarily disregarded or "dropped out." Dropout does this by preventing the neural network from being overly dependent on particular neurons or characteristics, hence requiring the network to acquire more reliable and generalised representations. The likelihood of each neuron in a layer being dropped out is determined by the dropout rate, a hyperparameter. The normal range is 0 to 1, with 0 denoting no dropout (all neurons stay active) and 1 denoting total dropout (all neurons are silenced). The dropout rate typically ranges between 0.5 and 1, although it might change based on the particular issue and network design. Dropout is often disabled during inference or testing, while creating predictions based on fresh, unforeseen input, and the entire network is used without losing any neurons. To get more accurate and predictable forecasts, this is done. Dropout regularisation may be used with CNNs to lessen overfitting, increase the network's capacity to generalise to new data, and improve the model's overall effectiveness.
Batch Size: The amount of training examples or samples that are sent through the network in one forward and backward pass is referred to as the batch size. It reflects the total number of data points that the training algorithm handled during each iteration or update step. The complete training dataset is split up into batches throughout the training process, and the weights of the network are updated for each batch based on the computed gradients. The CNN's training dynamics

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and computing performance may be impacted by the batch size selection. The batch size in CNN (Convolutional Neural Network) refers to the number of samples processed in a single forward/backward pass of the network. It is a hyperparameter that can be adjusted when training a CNN. The batch size has an impact on both memory usage and training dynamics.

III. GENETIC ALGORITHM

A Genetic Algorithm (GA) is a powerful search and optimization technique that draws inspiration from the principles of natural selection and genetics. By mimicking the process of evolution, it has the ability to solve complex optimization problems efficiently. At the core of the Genetic Algorithm is a population of potential solutions. Each individual in the population represents a candidate solution to the problem at hand. Through a process of evolution over generations, the algorithm employs genetic operators to generate new individuals with improved fitness. High-dimensional, non-convex optimisation issues are ideally suited for genetic algorithms (GA), a population-based search technique. The quality of any given solution may be directly evaluated by defining a fitness function. Furthermore, since there are no gradients involved in the optimisation process, it is not necessary to be able to derive the fitness function. Genetic Algorithm (GA) is a computational optimization technique inspired by the process of natural selection and evolution. It is a heuristic search algorithm that mimics the principles of genetics and natural selection to find optimal or near-optimal solutions to complex problems. Genetic algorithms are particularly useful for solving optimization problems where the search space is large, complex, or continuous. They explore the search space by iteratively evolving a population of potential solutions, allowing them to find near-optimal solutions even in the presence of constraints, nonlinearities, and multiple objectives. GAs have been successfully applied to a wide range of real-world problems, including engineering design, scheduling, routing, feature selection, and parameter optimization in machine learning algorithms. They offer a robust and efficient approach to search for solutions in complex and uncertain problem domains.

TABLE I GENETIC ALGORITHM PARAMETERS

Parameter	Type / Value
Population size	50
Initialization	Random
Selection Mechanism	Tournament
Crossover Function	Crossover Heuritic
Mutation Operator	Gaussian
Termination Criteria	
Pareto Set Fraction	0.35
Parallel Evaluation of Function	Yes
Creation	NonLinear
Population Data Type	Double Vector

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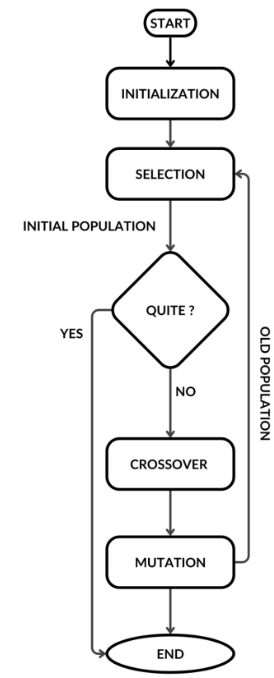

Figure 4: GA working flowchart

It is important to note that hyperparameter optimization is an iterative and time-consuming process. It requires careful experimentation, evaluation, and fine-tuning to find the best hyperparameter values for a specific deep learning task. Additionally, domain knowledge and understanding of the problem at hand are crucial for effective hyper parameter optimization.

IV. METHODOLOGY

An use of AI in this area is machine learning (ML). Artificial neural networks (ANN), long short-term memories (LSTM), random forests (RF), K-NN, SVR, and other well-liked ML forecasting models are frequently employed in solar power applications. The most fundamental machine learning architecture is an ANN [11]. Similar to the neurons in the real brain, a group of linked artificial neurons forms the foundation of an ANN, and each connection can send messages to neighboring neurons. Input, hidden, and output layers make up the fundamental ANN structure, also referred to as a multi-layer perceptron neural network. Neurons inside the input layer relay information to neurons in the hidden layer via activation mechanisms.

CORRELATION AND REGRESSION ANALYSIS

The Regression analysis was performed to explore the relationship between the evaluation indices of CNN and its two selected hyper parameters . The findings of this analysis are presented in Table 5.1 and Table 5.2, which display the results for sMAPE and nRMSE respectively.

Regression Analysis: Smape Versus Dropout Rate, Batch Size:

Upon examining the results, it is evident that the obtained P values are significantly low, typically expected to be below 0.5. Specifically, for the sMAPE evaluation index, the DropOut Rate and Batch size exhibit P values of 0.006 and 0.268, respectively. These values indicate a statistically significant relationship between the evaluated hyper parameters and the sMAPE index.

Based on the analysis, an equation representing the regression relationship is derived and depicted as eq. 5.1. This equation serves as a mathematical representation of the identified relationship between the hyper parameters and the

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evaluation indices. It encapsulates the insights gained from the analysis, providing a quantitative understanding of how the hyper parameters impact the performance of the CNN model.

TABLE II CORELLATION ANALYSIS FOR sMAPE VERSUS HYPER PARAMETERS

Term	Coef	SE Coef
Constant	0.29525	0.00149
DropOut Rate	-0.00835	0.00185
Batch Size	-0.000018	0.000015

The regression analysis conducted in this study offers valuable insights into the relationship between the hyper parameters and evaluation indices of CNN. It provides a foundation for understanding the impact of these hyper parameters on the model's performance and allows for informed decision-making in optimizing the CNN architecture for improved results.

sMAPE = 0.29525 -0.00835 DropOut Rate - 0.000018 Batch Size (1)

Regression Analysis: nRMSE versus DropOut Rate, Batch Size :

The analysis further culminated in the derivation of a regression equation that accurately represents the relationship between nRMSE and the aforementioned hyper parameters . This equation, denoted as eq. 5.6, serves as a mathematical model capturing the dependencies uncovered through the analysis. By employing this equation, it becomes possible to quantitatively assess the impact of the hyper parameters on the nRMSE performance metric.

The comprehensive analysis conducted in this study sheds light on the relationship between the hyper parameters ,DropOut Rate, and Batch Size, and the nRMSE evaluation index. The findings underscore the importance of these hyper parameters in influencing the model's performance. Armed with this knowledge, researchers and practitioners can make informed decisions regarding hyperparameter optimization to enhance the model's accuracy and effectiveness

nRMSE = 0.1633 - 0.0401 DropOut Rate - 0.000231 Batch Size (2)

TABLE III CORRELATION ANALYSIS OF RMSE V/S HYPER PARAMETERS

Term	Coef	SE Coef	T-Value
Constant	0.1633	0.0238	6.85
DropOut Rate	-0.0401	0.0297	-1.35
Batch Size	- 0.000231	0.000233	-0.99

HYPER PARAMETERS OPTMIZATION

The GA assesses the fitness of solutions after a randomly initialised start. Then, a subset of solutions is picked, with better solutions more likely to be picked. In an effort to increase their effectiveness, these solutions are reconfigured. In order to further explore the parameter space, some of the new solutions are then randomly modified. The newly "created" solutions are then assessed for fitness, and the process is continued until a suitable solution is identified, the quality of the solutions stops improving, or a certain time or computational work threshold is reached. The procedure is visualised in Figure 1. We run the GA three times using the same input data because it has certain stochastic components. In order to generate statistically meaningful data, the training procedure should preferably be performed numerous times for each configuration of the hyper parameters because the random weight initialization of a CNN also introduces stochastic aspects. However, because it would significantly lengthen the optimization process, this is not realistic. Figure 5.9 illustrates the GA's general procedure. Some CNNs are chosen to act as "parents" once each CNN's suitability has been assessed. The "children" of these parents are recombined to form the current generation, which also includes the top three CNNs from the previous generation. The variation of hyperparameter values can also rise as a result of particular hyper parameters mutating. A total of 30 generations are completed for each optimisation cycle.

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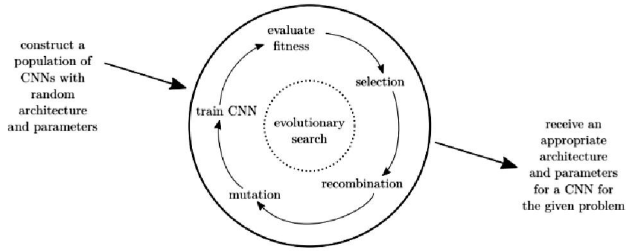

Figure 5: GA-CNN Cycle

EVALUATORS AND ESTIMATORS:

Several indicators are selected and employed as estimators in the research and analysis to evaluate methodologies and the accuracy of predictions provided.Some have been employed here, such as mean absolute error, mean square error, and root mean square error, which are briefly explained below.

Normalized Mean Absolute Error

The Normalized Mean Absolute Error (NMAE) is an error quantity defined in equation 5.1 that examines the forecast's average absolute error.

$$NMAE_k = \frac{1}{N}\sum_{t=1}^{N} | \in_{t+k} | \qquad (5.1)$$

Another word for Mean Absolute Error is Mean Absolute Deviation (MAD). This value represents the overall mistake that happened as a consequence of forecasting and should be as little as possible. This error varies with scale and is impacted by data processing and measurement scale.

Normalized Mean Squared Error

The Normalized Mean Squared Error (NMSE) is an error quantity calculated by averaging the squared errors using the Normalized Sum of Squared Error (NSSE):

$$NMSE_k = \frac{1}{N}\sum_{t=1}^{N} | \in_{t+k}^2 | \qquad (5.2)$$

In this error, positive and negative faults do not cancel one other out, and large individual errors are punished more harshly.

Normalized Root Mean Square Error

It is a form of error that squares the NMSE is the Normalized Root Mean Squared Error (NRMSE). Equation 4.3 defines it.

$$NRMSE_k = \left(\frac{1}{N}\sum_{t=1}^{N} | \in_{t+k}^2 |\right)^{1/2} \qquad (5.3)$$

Symmetric Mean Absolute Percentage Error (sMAPE)

SMAPE is a metric for measuring precision that uses percentage (or relative) errors. There is no lower bound or upper constraint on SMAPE like there is with the mean absolute percentage error. The outcome of the preceding calculation is, in fact, between 0 and 200. A percentage inaccuracy between zero and one hundred is considerably simpler to understand. That's why the following formula is so common (i.e. no factor 0.5 in denominator) in actual practice:

$$sMAPE = \frac{1}{N}\sum_{n=1}^{t} \frac{|Y_{Pred,n} - Y_{Test,n}|}{(Y_{Pred,n} + Y_{Test},n)/2} \qquad (5.4)$$

Where, $Y_{(Pred,n)}$ and $Y_{(Test,n)}$ are the predicted actual values of the testing dataset.

The above mentioned evaluators have been used for identifying the performance of the proposed and other implemented machine learning and deep learning techniques for the PV power generation forecasting.

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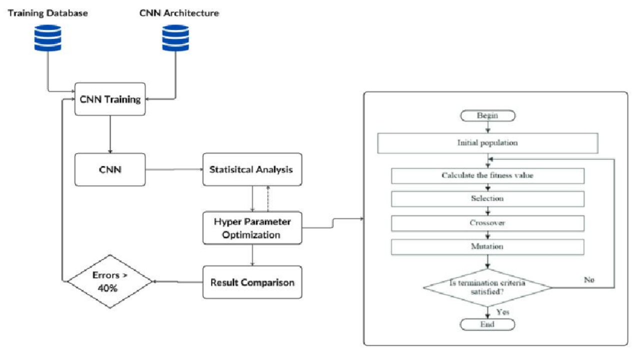

Figure 6: Flowchart of GA-CNN Methodology

V. RESULTS AND DISCUSSION

In this work we have acquired the data from the Meteonorm 8 for the Jodhpur Location where the solar power forecasting needs to be implemented for enhancing the renewable power penetration in the power demand. We have imported the four types of datasets from the mentioned sources, Daily Global Radiation (DGR), Daily Average Temperature (DAT), Daily Average Diffusion and Global Radiation (DAD & DAGR), Daily Total Power Energy Generation (DTEG). Each of the Dataset consists of 8761 data points from 1st January, 2020 to 31st December, 2020. Figure toFigure shows the HAT, DGSR of the given data set.

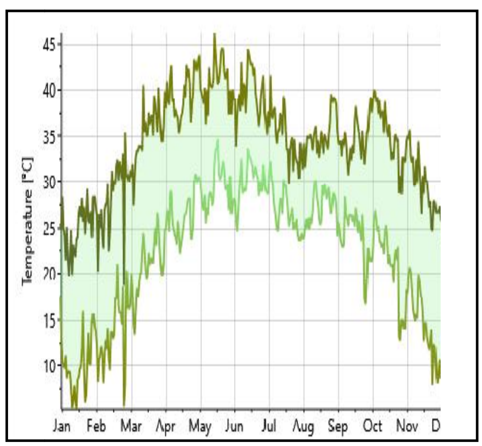

Figure describes the plot for the maximum and minimum daily temperature range fort eh described location. The Figure 3.4 describes the Daily Average Diffusion and Global Radiation in kWh/m2. This plot has been generated from the dataset generated for the given location. Figure gives us the graphical representation of daily sunshine hours for the entire year. Figure describes the Daily Average Temperature in the box plot for the entire year. From January to December.

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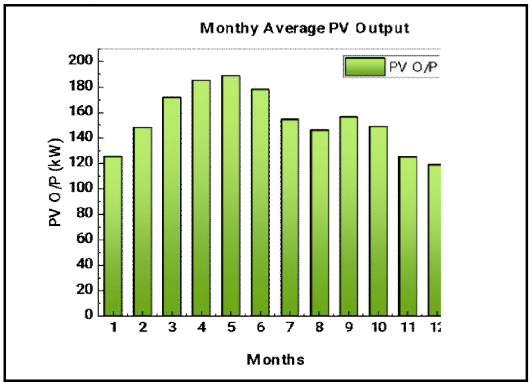

Figure 7 Figure Monthly Average Radiation in kWh/m^2

Our research work heavily relies on evaluating the predictive performance using key evaluation parameters such as RMSE, MAE, MSE, and sMAPE. These parameters serve as reliable indicators for assessing the accuracy and effectiveness of the implemented methods and predictions.

To conduct our analysis, we employed the GA-CNN, HCRNN, LSTM, and KNN-SVM techniques, leveraging the available dataset. By utilizing these approaches, we aimed to extract meaningful insights and uncover patterns within the data.

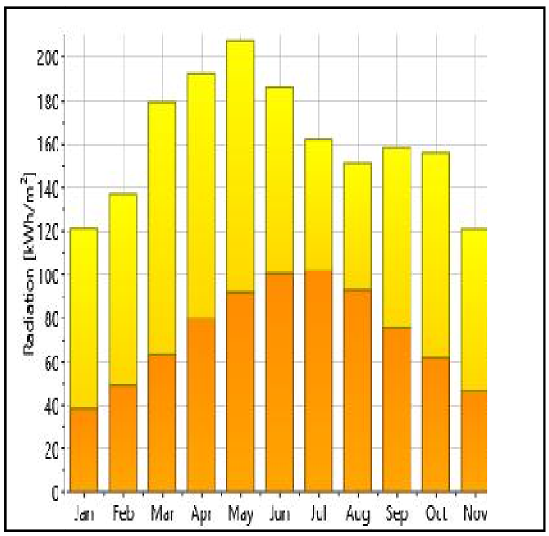

Figure 8 Figure Monthly Average Radiation in kWh/m^2

The outcome of the GA-CNN (Genetic Algorithm - Convolutional Neural Network) can exhibit variability depending on the specific application and problem under consideration. In this study, the GA-CNN, CNN-RNN, LSTM, and KNN-SVM techniques were implemented using the provided dataset. To visually illustrate the performance, Figure 4.1 showcases the comparison between the forecasted and observed sequences based on the sMAPE metric for the GA-CNN proposed technique. Similarly, Figures 6.2 to 6.8 present corresponding plots for the CNN-RNN, LSTM, and KNN-SVM methods, respectively.The plotted results clearly demonstrate that the GA-CNN approach yields the lowest symmetric mean absolute percentage error of 0.2925, outperforming the other implemented algorithms. Specifically, the CNN-RNN technique achieves an sMAPE of 0.2949, LSTM obtains 0.38806, and KNN-SVM achieves 0.3302. These findings emphasize the superior forecasting capabilities of the GA-CNN technique in comparison to the other methods investigated in this study. Furthermore, it was observed that the implementation of lower batch sizes and higher dropout rates in the previous techniques resulted in an increased number of iterations per epoch, consequently extending the execution time for forecasting. However, with the adoption of the proposed GA-CNN technique, the number of iterations has significantly reduced from 19,000 to 1,200, leading to improved results within a shorter time frame. This optimization allows for faster and more efficient forecasting, enhancing the overall performance of the model.

Overall, the results demonstrate the effectiveness of the GA-CNN approach, showcasing its superiority in terms of accuracy and computational efficiency compared to the other investigated techniques.

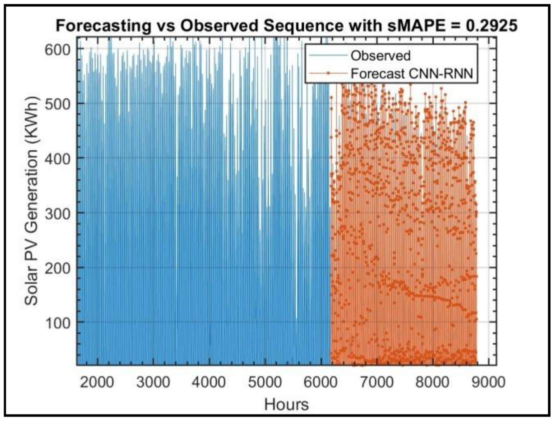

Figure 7 Forecasting and Observed Sequence for proposed method (GA-CNN)

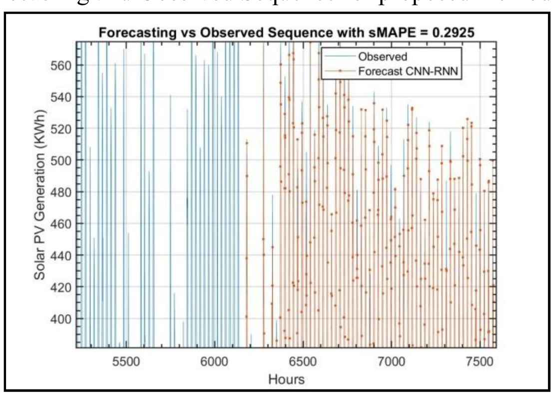

Figure 8 Zoomed figure for forecasting sequence for proposed technique

Method Applied	NMSE	NMRSE	NMAE	SMAPE	RSQUARE
LSTM	425.2452	1.434	1.0293	0.3881	11474
KNN-SVM	52.4675	0.5037	0.2713	0.3302	403.3046
CNN-RNN	4.0944	0.1407	0.0791	0.2949	56.594
GA-CNN	2.0589	0.126	0.0257	0.2925	45.487

TABLE IV COMPARATIVE RESULTS ALL IMPLEMENTED TECHNIQUE

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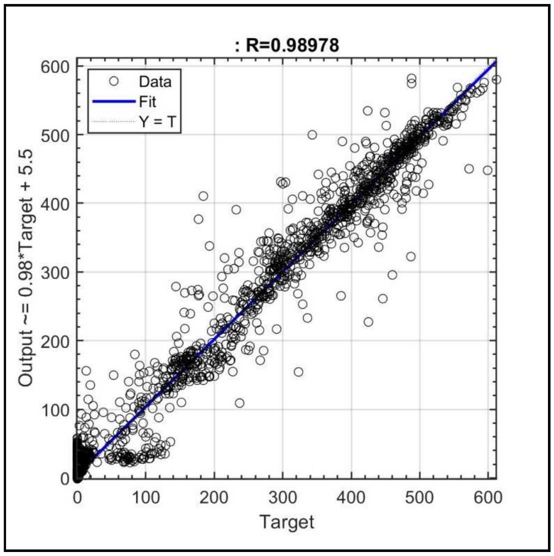

Figure 9 Regression Plot for the GA-CNN technique

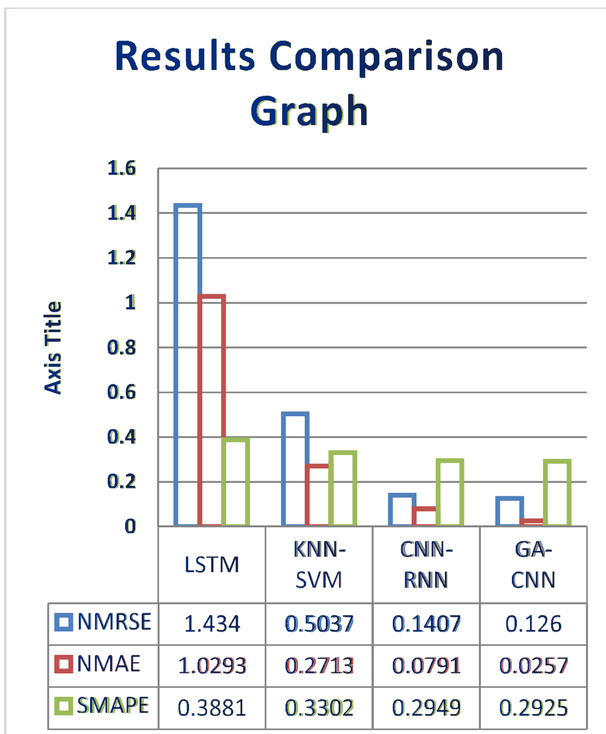

Figure 10 Comparative results and analysis

VI. CONCLUSION

In this study, we have conducted an extensive evaluation of our proposed technique for solar power forecasting. The results have unequivocally demonstrated that the GA-CNN method outperforms alternative approaches across a range of evaluation indices. The optimization of hyperparameters, specifically the dropout rate and batch size, has played a significant role in enhancing the performance of the GA-CNN model.

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By optimizing these hyperparameters, we have not only achieved superior results but also managed to reduce the overall iterative time. The maximum number of iterations, which is heavily influenced by the chosen batch size, has been effectively reduced. This finding aligns with the existing literature, which has consistently emphasized the importance of hyperparameter optimization in machine learning tasks.

Optimizing hyperparameters is a critical step in improving the performance and generalization capabilities of machine learning models. In this regard, Genetic Algorithm (GA) has emerged as a valuable tool for automating the search process and systematically identifying optimal hyperparameter configurations.

The successful implementation and validation of our GA-CNN technique, coupled with the reduction in iterative time and improved performance, underscore the significance of hyperparameter optimization in achieving accurate and efficient solar power forecasting. Our findings contribute to bridging the existing gap in the literature and provide further evidence of the need for systematic hyperparameter optimization methods such as GA.

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