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Global solar energy estimation using improved greedy based genetic algorithm with deep convolutional neural network

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ABSTRACT

Demand for solar energy increases and it is required to manage the supply of energy effectively. Accurate detection on patterns of energy consumed assist in taking appropriate decisions on generating energy. Even though many traditional techniques have predicted the consumption rate, still improvement is needed in prediction accuracy. The pre-processing is performed initially for handling missing values. The feature selection is accomplished using improved greedy based genetic algorithm (GGA) to extract best features to enhance the performance of the model. Output from feature-selection is passed as input to the classification phase using proposed deep convolutional neural network (CNN) in which future solar energy patterns are classified and predicted timely basis power consumption and it optimize the model by minimize the error. The prediction accuracy is estimated through evaluation metrics such as mean square error (MSE), mean absolute percentage error (MAPE) and root mean square error (RMSE) 0.423, 0.652, and 0.215, respectively. The outcomes achieved in terms of accuracy at 99.75, precision at 99.28, sensitivity, and recall at 100 revealed the efficiency of the proposed classification model. As a result, the proposed future prediction of solar energy was considered efficient since it achieved reduced error values than other prediction algorithms. It assists in maintaining stability in solar-energy based systems.

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1. INTRODUCTION

Managing adequate generation of solar energy based on demand patterns makes smoother flow of electricity during peak requests for solar energy. It is accomplished through efficient prediction of energy flow in peak operating hours in the energy-based systems. In this manner, the suggested research [1] has focused on forecasting of electrical energy consumption generated by the renewable energy sources based on hourly basis. Prediction has been exploited through machine learning (ML) algorithm which has optimally allocated the operational hours of water pumps with the intention of reducing the predicted peak. Regular monitoring and control on devices have reduced the weekly and daily deviations on electrical consumption greater than 15%. Rate of load transferred, total energy produced through renewable sources, and accuracy in every day has determined the potential outcome of the prediction model. Similarly, recommended research [2] have used an open-dataset for measuring of energy usage, production of solar energy along with building of air-leakage data from commercial buildings. Solar energy collected information from 6 years of time have been measured as 1 hour through micro-inverters based on monthly and daily predictions. It has utilized the specific dataset for prediction and estimation of operational outcomes. Mismatches occurred between the drained water heat-recovery devices and rate of consumption has been considered an important factor which have been resolved through considered probabilistic method [3] of estimating the monthly basis consumption strategy. It has observed from 113-residences for the prediction of consumption patterns. It has performed assessment of the system in order to determine the uncontrolled supply, especially from solar energy.

Earlier predictions on energy usage through analyzing the solar radiation and demand patterns assist in managing renewable energy effectively [4], [5]. To this purpose, the suggested study [6] has utilized long short-term memory (LSTM) based neural network (NN) which has been enhanced through attention and decomposition of input data. Selective concentration to the input patterns has been given for the analysis of the energy consumed daily. Renewable energy sources like fuel cells, solar -panels for effective storing of energy and ground-sourced heater pumps have been used in extensive applications for preventing greenhouse gas emissions and providing sustainability [7], [8]. Investigations on suggested research [9] have analyzed the impacts of renewable energy on the constructional building along with the flow of electricity in order to satisfy the total amount of demand in energy. The optimal source of energy required for every block has been estimated through linear programming. Energy loads have determined variation in the flow during the day time and the maximum level of heater demands occur in winter morning has also been analyzed. Though, several data-driven methods have been utilized for building energy prediction models, enhancement in robustness, generalization and accuracy has been found to be challenging, and in the suggested research [10] support vector-based regression technique has been used in which the higher non-linearity has been approximated by the linearity with the multiple distortions in the high dimensional data mapped with the vector. Larger office building [11] with hourly cooling on summer has been recorded for analysis. The nonlinear and volatile nature of power demand and supply has occurred due to fluctuating weather conditions such as temperature and solar radiation. In considered analysis [12], optimal extreme learning machine (ELM) has been employed for forecasting the volatile and non-linear solar-energy prediction with variable weather conditions. Performance on the ELM approach has been explored through relevant attributes such as hidden layers, biases, and weights. teaching and learning-based optimization (TLBO) have been used for handling the computational complexities. Integration of ELM with TLBO has forecasted the solar-energy generation based on hourly, daily, and monthly. The performance of the model has been assessed by evaluating error metrics such as MSE, MAE, and MAPE [13].

Although traditional studies have delivered many methods and techniques in prediction analysis of energy consumption to provide the energy source based on the demand, the minimum error rate in the prediction using classification still requires improvement for accurate prediction of solar energy consumption patterns [4], [14]. Moreover, the consumed energy prediction alone has not assisted in minimizing the overloading condition but is also required for maintaining adequate energy sources to supply for the demand based on hourly, daily, and weekly predictions.

To overcome the above-mentioned issues, ML and deep learning (DL) based algorithm is used. The feature selection uses an improved greedy-based genetic algorithm (GGA) to choose the best dataset features for analysis. DL-based deep convolutional neural network (CNN) for prediction algorithm is used for classification process and solar energy patterns prediction with effective pre-processing of input data is used in present research for enhancing the accuracy. The main intention of the proposed research is to enhance the prediction efficiency of energy consumption based on solar energy sources. The utilization of advanced algorithms such as the improved GGA for feature selection and deep CNN for classification indicates a step towards more accurate and efficient energy management systems and addresses the challenges of conventional studies in gaining efficient future prediction of solar energy consumed. Depending on the analysis made from different approaches, the motivation of the present research is being framed as follows:

- To perform prediction of the solar energy consumption with the input data collected from the global solar energy dataset observed from New Delhi and Kolkata and perform pre-processing with categorical encoding.
- To execute feature selection using an improved greedy-based genetic algorithm (GGA) for selecting the best features required for the future prediction of solar energy consumption patterns and also for minimizing the complexity by reducing dimensions.
- To accomplish the classification task with a deep convolutional neural network (CNN) algorithm to classify the accurate electric power consumed in a timely basis with minimized error.
- To perform predictions on hourly, daily, and monthly time duration and evaluate the loss obtained in the prediction process with the performance metrics like accuracy, root mean square error (RMSE), mean absolute error (MAE), and mean square error (MSE) to determine the efficacy of the model.

2. LITERATURE REVIEW

The succeeding section discusses on several existing methodologies used in the process of predicting future energy patterns with the collected energy information since accurate forecast on solar-energy is required for maintaining reliable operation on energy-systems. For this purpose, suggested research [15] has utilized hybrid technique of sequential one-step ahead-models which accumulated 144 hour supply. Different inputs have been covered over 6 days of forecasting area in which every horizon has been trained for every one hour. It has utilized XGBoost and CatBoost methods for boosting the accuracy in prediction. Outcomes have highlighted the models with previous month, current month of solar energy predictions to forecast energy consumption patterns of 1-month ahead. Renewable energy load has been forecasted with the mixture of various load patterns such as institutional, commercial, energy systems, and residential areas for reliable supply of energy. The operational behavior of the solar energy has been administered in considered research [16]. Using daylight as the fundamental source in residents has served to administer the daily needs of lights and seasonal variations to accompany the occupants about the rate of consumption.

Climate based daylight modelling (CBDM) in recommended research [17] have performed evaluations on the hourly basis to assess the extent of daylight requirement. In order to improve the performance of systems, forecasting the future demand has been found to be a significant task. For predicting, considered research [18] have utilized deep neural networks for prediction of one day ahead of global-horizontal irradiation. It has performed predictions with the daily recorded data and has analyzed on parameters affecting accuracy. Forecasting performance has been assessed with error metrics which have exhibited efficacy of the prediction model. Aggregation on demand and supply forecast has helped in controlling the generation of solar energy and assisted in effective storage. It has been found to be mandatory for avoiding both oversized and under-sized of energy systems. The result in [19] has carried out five year of energy consumption data and processed with MATLAB for calculation of demand for satisfying future energy needs. Every day capacity has been realized and has predicted that demand for solar energy has increased in five years of time. Demand growth has been estimated over the period of time and the productive power has been coupled with demand on 3 hours for morning power supply and two hours of mid-day and 4 hours of evening supply. Solar-energy prediction has been considered as significant for development of solar power plants through its capability in meeting the demands of the user. Considered research [20] has presented a methodology in predicting solar-energy based on ML and DL techniques. It has evaluated on short term and real time predictions but it has ensured optimized-prediction on energy. Through analysis on dataset for timely consumption, Pearson-correlation has been deployed for identification of relevancy in rate of consumption at particular peak demand levels.

Production of power from solar radiation has been predicted with the integration of ML technique with the regression based methodology of forecasting 1 hour ahead of solar power [21]. Even though annual and seasonal forecasting has been performed with different ML algorithms, the regression on daily basis has classified the original dataset into training and testing of subset for enhancing the prediction accuracy. In order to reduce carbon-emissions and demand level energy supervision, the ability of predictions in different patterns of load has been identified which also significant. It has analyzed solar-energy utilizing areas for figuring out the alterations in the energy demand and impacting factors for changing energy utilities. It also has estimated energy requirement in medium- and long-term utilities. Energy based systems have required the forecasting information of power consumption in different patterns and moreover, the accurate prediction of monthly usage assist in the prediction of medium to long term demand and contributes considerably in the process of dispatch and energy management in solar energy systems. Consequently, larger datasets have been required for the determination of accurate prediction by the methodology and has been affected in traditional approaches with the scarce data. Due to insufficiency in data, complications in forecasting have increased. By analyzing all drawbacks in existing studies, proposed research is being designed to provide effective prediction accuracy.

The review conducted on traditional research have utilized several artificial intelligence-based prediction methods for prediction of energy consumption with information collected on daily, hourly and monthly. The common limitations with respect to validation on prediction have been analyzed from the traditional literatures and are given as follows:

- Multi-step CNN based solar energy prediction mechanism has extracted consumption of energy data but needs to be enriched with larger datasets which can provide effective outcomes in the demand based prediction analysis [21], [22].
- The prediction has been performed with various fluctuations in utilities for everyday classification with ML methods on forecasting 1 hour ahead of global solar radiation can enhance the prediction accuracy with efficient methods [19], [23].

3. PROPOSED METHODOLOGY

The proposed energy management approach categorizes the consumption of energy on every month through patterns of demand and supply based on features associated with solar energy sources capable of achieving greater prediction efficiency. Existing researchers have predicted the consumption of energy but are inadequate with factors of accuracy and loss in prediction based on the perspective of energy constraints. To this purpose, proposed research is motivated to provide techniques involving data pre-processing of global solar energy dataset, feature selection using improved combination of genetic algorithm (GA) and the greedy-sequential process and classification using deep CNN algorithm for solving energy consumption and distribution efficiency, which extends battery lifetime. However, providing solutions in energy management alone cannot afford the complete level of efficiency of the model. Hence, the present research intends to focus on adopting future energy prediction mechanism for stable supply of solar energy to systems that highlights the forward-thinking nature of the research. Figure 1 provides a clear framework of the proposed methodology, showcasing a structured approach to predictive energy management. The overall architectural diagram of the proposed prediction model is illustrated in Figure 1.

As depicted in Figure 1, the proposed prediction methodology represents the mechanism which is divided into three stages of implementation such as pre-processing, feature selection, and classification. First, input solar energy features are taken from the global solar energy dataset the initial phase of processing input features with checking of missing values and label encoding to minimize the model's complexity and to prevent the biased model development. With the processed data, selecting features is accomplished using improved GGA to reduce computation complexity in the accurate prediction of solar energy. Such selected features are consequently passed on into the third phase of classification, in which the deep CNN algorithm is used in classifying the consumption pattern in different months. The advantage of extracting features is that it enhances the classification accuracy and estimates the minimum loss acquired through the prediction model. For elucidating the efficiency of the present prediction method, validation is being accomplished with various evaluation metrics such as MSE, accuracy, MAE, and RMSE internally, and classification efficiency is being compared with other algorithms for determining the effectiveness of the present research. Prediction outcomes were analyzed at hourly, daily, and monthly intervals to evaluate the efficacy of the system.

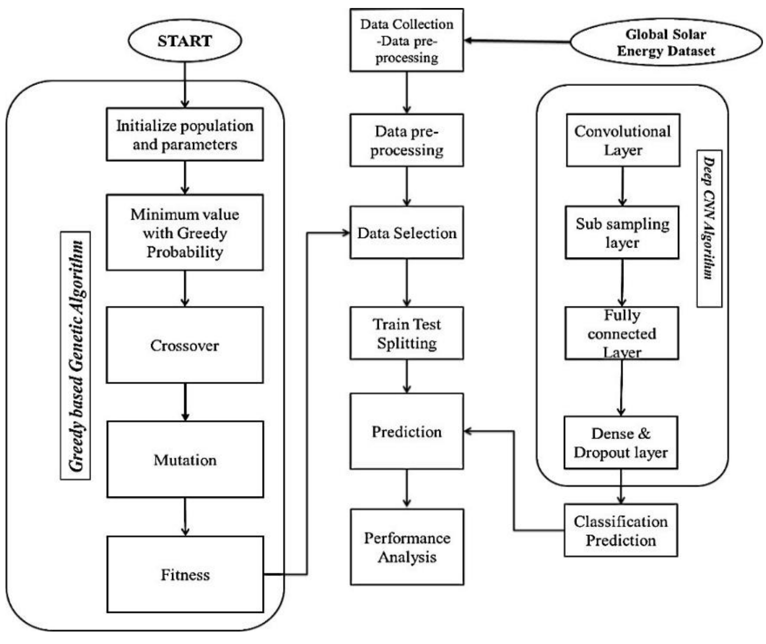

Figure 1. Overall architectural diagram of the proposed model

3.1. Feature selection by improved GGA

The proposed work utilizes improved greedy genetic algorithm (GGA) algorithm was used for feature selection to identify the most relevant temporal and complex features for analysis and selecting the best features by integrating genetic algorithm (GA) with the greedy-based strategy. The procedure of predicting out best feature choices at each stage is the importance of the greedy approach. Such best energy features from every data sequence are being grouped for predicting the energy demand fluctuations to distinguish normal and peak flow patterns. The combination of GA and the greedy-sequential process is being utilized to solve the difficulties with the maximum and extreme search space exploration. The greedy approach is induced as the operator into the genetic algorithm in accelerating the searching capabilities and enhances chromosome fitness appropriately. Crossover operation performed between the individual results in the exploitation between two given parents. Gene in the chromosome is being modified by organizing the diverse nature of individuals among the population. The working nature of improved GGA is presented in Algorithm 1.

Algorithm 1. Improved greedy based genetic algorithm
Begin
  Generate the initial population POP_{ii} (0);
  Estimate POP_{ii} (0);
  Repeat
    Select parents;
    Generate new chromosomes using crossover;
    Applied mutation on the new chromosomes;
    Applied greedy sequential function;
    Estimate POP_{ii} (t_i);
  Until (Terminating condition is reached);
End;

As illustrated in Algorithm 1, the operational process starts with the population generation by random distribution for increasing diversity. Accordingly, the population is encompassed with multiple solutions representing the chromosomes of individuals. Each chromosome has a finite variable group simulating genes. Distribution of solutions around search space aggregates diversity and improves the prediction of promising segments. The selection of the fittest individuals leads to the genes contributing to the creation of the next generation. Until the algorithm reaches the point of criterion, it improves the population with three significant operators. Consequently, the best solution from the finally retrieved population counts returns the best global optimal path for the problem. Controlling attributes in the method are being changed depending on the detecting performance. Along with that, crossover operation is also significant for attaining efficient outcomes. For identification, chromatic numbers are being assigned. Improved GGA begins with the initial population of $POP_{ii}(0)$ with a feasible group of energy attributes. The objective function is represented as OF_i through which the population group is obtained through the effective selection of features that predict the degradation in supply of solar energy through changes predicted from the influencing weather data. The function of the initial population is formulated by generating various chromosomes with different parameters in a random manner.

The selection method is used in which two significant individuals are selected randomly from the group population and picks out the needed features as the parent. With the assistance of acrossover operator, two various parents with two-children remain to be generated with the genetic element of parents. Through the GA method, three-point operators are effectively used in selecting optimal features. Uniformity in mutation assists in introducing and preserving diversity in genetic population and it is being applied with smaller-probability. Along with that, GA utilizes the greedy process in which verification of constraints on the problem for each child node is not needed for all genes. A distinguished attribute acquired from a neighbor indicates that it has been affected in certain cases. However, it must be among the utilized attributes in chromosomes, and modification is being performed if no such occurrences are identified. The hybridization of greedy with GA selects the best energy consumption parameters required for predicting the flow of energy. Outcome obtained are passed on to the classification process to predict the average demand and supply patterns of energy.

3.2. Classification by deep CNN

DCNN falls under deep neural networks (DNN), used mainly for identifying patterns in input energy data. The classification process is undertaken using deep CNN technique by utilizing a three-dimensional neural pattern analysis. In order to maintain stability in power supply to solar energy-based systems, disruptions in supply due to sudden peak flow are required to be predicted and accomplished with the deep CNN algorithm. Through fluctuations in energy supply or due to other factors, performance is affected and leads to an unstable condition. The proposed algorithm effectively identifies the patterns based on features selected from improved GGA. It is accomplished through figuring out the impacting factors that affect fluctuations in solar energy. The pseudocode for deep CNN is provided as Pseudocode 1.

Pseudocode 1. Deep convolutional neural network
Input: Number on KDD CUP 999 Data Source in IoT
1: Attack Manipulation Function (Kdd Cup 99 Data Source)
2: Confusion Matrix⇐ Kdd Cup 99 Data Source

3: Extract Features from Confusion Matrix
4: State Training Data Set (0,1) & Testing Dataset (0,1)
5: Set Sequential Deep Learning Model
6: If Kdd Cup 99 Data Set =1 Then
7: Collect 0s and 1s Information Classification
8: AM ⇐ Sequential Deep Learning Model
9: End If
10: Training Data Set, AM_i ← Data Set
11: If Training Data Set =1, Then
12: Attack Manipulations (AM_i)⇐ Testing Data Set
13: If AM_i = 1, Then
14: Re-Train the Deep Learning Model
15: Else
16: Set Data Verification and Validation Phase
17: End If
18: End If
19: Sources of Classification Data ⇐ AM_i
20: End If End

From Pseudocode 1, the functionality of the algorithm is indicated with steps in which initially it takes the input data source from the atmosphere containing weather factors that produce solar energy. The variable AM_i is the sequential DL model for training and testing. The training method is operated by adjusting the internal parameters so that the model is correlated to the output with respect to the input. It reduces the training error to its maximum when new input data regarding energy flow are fed into the system. An over-fitting complication is considerably reduced by updating the algorithm by assigning minimized weights. Complex associations within the global-solar energy features impacting continuous supply are being mapped in order to achieve optimality in learning new feature data entering the system and aid in the extraction of beneficial data. Validation and verification of the classification technique yield minimal error and predict important features disrupting the functionality of systems and classifies the future prediction of energy. Predictions are being observed from solar energy sources. Solar radiation are certain parameters that fluctuate the supply of energy to systems, which must be predicted and based on demand and supply is to be maintained for effective energy systems. The algorithm for deep CNN is projected in Algorithm 2.

Algorithm 2. Deep-convolutional neural network
1. Input Dataset (N samples)
2. $\in \leftarrow 10^{-8}, \gamma_{vi} \leftarrow 0.9999, \gamma_{mi} \leftarrow 0.9$
3. $\alpha_{oi} = 0.01$
4. $\rho = \theta r_{i_{sw1}}\{1,2,\infty\}m$
5. $\theta_o \leftarrow N(0, \sqrt{2/N_i}$
6. $t_i, m_i, v_i \leftarrow 0$
7. $t_i = t_i + 1$
8. $g_{it} \leftarrow \nabla_\theta L_i(\theta_{ti_{-1}} - \alpha_{ti}\gamma_{mi}, m_{ti} - 1$ or Sw2 {0,1}
9. $m_{it} \leftarrow \gamma_{mi} m_t - 1 + (1 - \gamma_{mi})g_{it}$
10. $v_{it} \leftarrow \gamma_{v_i} v_t - 1 + \left(1 - \gamma_{v_i}\right)g_{it}$
11. $\theta_t = \theta_{t1} - \nabla_{ti}$

From Algorithm 2, it is clear that classification with deep CNN is involved with numerous layers in the NN and follows a feed-forward based operation. Back-propagation adjusts the learning parameters, such as biases and weights of the network, in order to minimize the cost value. It performs effective classification by analyzing complex and larger data by passing it on to multiple neuron layers. Feature maps or filters in the convolutional layer classify the energy-patterns by adaptively learning spatial features from lower to higher level features. From the algorithm, the variable $\in$ refers to the learning rate and α_{oi} specifies the momentum parameter. The damping ratio is determined by ρ and the process of updating the performance criteria by variable θ_o. Predictions at different time intervals are represented with m_{it}, and γ_{mi} refers to the stability constant. The speed of movement in parameter space is represented by variable v_{it}. Classification based on significant parameters in solar energy predicts the normal operating characteristics and differentiates the energy patterns observed from the dataset.

4. RESULTS AND DISCUSSION

The results obtained using the proposed deep CNN model is evaluated to determine the accuracy and performance efficiency rate of the model. Further, the efficiency of the proposed framework is estimated using metrics such as MSE, accuracy, MAE and RMSE by doing so the effectiveness of the proposed model can be identified.

4.1. Performance analysis

The performance of the proposed system is validated with loss metrics such as MSE, MAE, and RMSE through which benefits of the proposed feature selection and classification algorithm can be determined. Simulation in MATLAB and outcomes achieved from the present prediction model are depicted in Figure 2. From Table 1, it is clear that accuracy achieved through the model is found to be 99.75 and sensitivity of 100. These results indicate the robustness of the proposed model in the prediction of energy consumption. The comparison of the error values obtained from present algorithm with the traditional algorithm is tabulated in Table 2.

From Table 2, it is clearly indicated that error values calculated from ANN, FL, and GRNN is comparatively higher than the proposed model. It is due to the modified GGA and deep CNN, the percentage of error measured in the proposed work is relatively lower (2.023) than the existing methodologies (GRNN – 3.79). The utilization of advanced algorithms such as the improved GGA for feature selection and Deep CNN for classification indicates a step toward more accurate and efficient energy management systems. The graphical representation of the comparison is represented in Figure 2.

Figure 2 shows that error calculation performed with existing and proposed indicates that ANN has the comparatively higher error and the proposed algorithm exhibits its efficiency in terms of MAPE through lower loss values in the prediction process. In addition, another comparison of existing models in terms of R and RMSE is being performed and tabulated in Table 2. From Table 3, it is clear that the proposed mechanism (21% RMSE) achieves lower error values compared to existing empirical (326.8%) and ANN (113.6%) algorithms. The graphical depiction of the comparison is presented in Figure 3.

Table 1. Performance analysis of deep CNN algorithm using MATLAB

Performance metrics	Obtained values
Accuracy	99.75
Sensitivity	100
precision	99.2806
Recall	100

Table 2. Comparative analysis of proposed work with existing algorithm [24]

Model	Error percentage
GRNN error	3.79
FL error	3.99
ANN error	4.95
Proposed	2.023

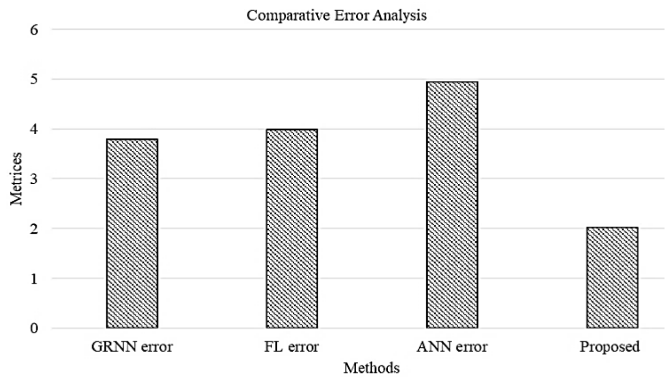

Figure 2. Comparative assessment [24]

Figure 3 shows that the proposed algorithm determines the efficiency through reduced error than empirical and ANN model in predicting the energy consumption pattern. Comparison of measurements in terms of RMSE and R determines the competence of the proposed algorithm. The comparison of the existing methods proposed with respect to various error metrics is recorded in given Table 3.

From Table 4, inference from the comparison specifies that proposed research (RMSE 0.215) is efficient in predicting future energy consumption with reduced loss obtained when compared with different existing models such as LSTM (0.9), CNN (0.98), and multistep CNN stacked LSTM (0.36). The graphical representation of the comparative analysis is projected in Figure 4. From Figure 4, a comparative analysis of various existing methods like LSTM, CNN, and Multistep CNN-based stacked LSTM, it can be noted that the proposed algorithm improved GGA with deep CNN exhibits greater prediction efficiency with minimal loss than other conventional algorithms. In the error measured by each method, proposed model proved to be least erroneous. Thus, it confirms the efficacy and reliability of the proposed model.

Table 3. Performance comparison [25]

Model	R	RMSE (%)
Empirical model	0.9304	326.8
ANN model	0.9744	113.6
Proposed	0.986	21.5

Table 4. Comparing performance efficiency of existing with proposed methodology [22]

Methods	RMSE	MAE	R^2	MSE	MAPE
LSTM	0.9	0.4	0.9	0.82	9.2
CNN	0.98	0.78	0.87	0.99	14.48
Multistep CNN stacked LSTM	0.36	0.18	0.98	0.13	3.11
Proposed	0.215	0.652	0.986	0.0423	2.11

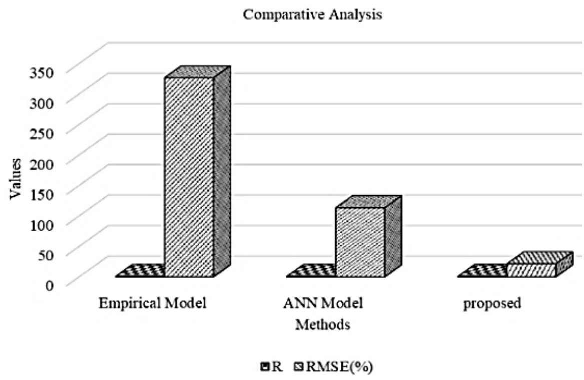

Figure 3. Comparative graphical analysis [25]

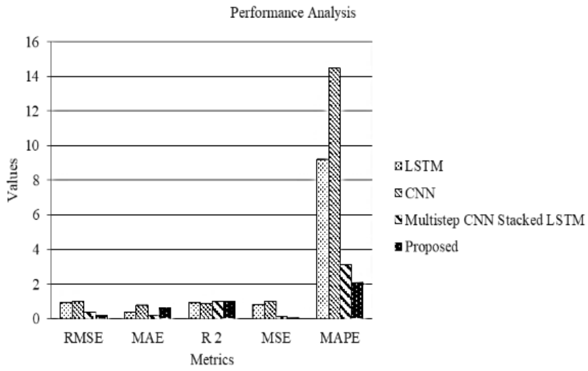

Figure 4. Comparative performance assessment [22]

5. CONCLUSION

The proposed prediction algorithm employed improved GGA for selecting features and performed the classification process by deployment of deep-CNN. Experimentation with MATLAB as a primary tool for analyzing outcomes in predicting the hourly, daily and monthly future solar energy patterns using the proposed algorithm have shown minimum prediction loss. The performance has been evaluated through metrics such as MSE, MAE, and RMSE with values as 0.423, 0.652, and 0.215, respectively. The achieved accuracy of 99.75 shows the efficacy and precision of 99.28 suggests the better reliability of the proposed model when compared to existing models such as CNN (RMSE 0.98, MAE 0.78, MSE 0.99) and LSTM (RMSE 0.9, MAE 0.4, MSE 0.82). Sensitivity and recall at 100 obtained by performance analysis using MATLAB shows improved efficiency of the proposed classification model. The prediction loss acquired was also compared with other traditional algorithms which also confirm the robustness of the proposed model, making it a potential tool system for achieving enhanced prediction accuracy, efficiency, and sustainability in energy management practices. By integrated techniques and cutting-edge algorithms, the research paves the way for advancements in the field of energy management and holds promise for addressing critical issues related to distribution and energy consumption. As a result, the proposed future prediction of solar energy was considered efficient since it achieved reduced error values than other prediction algorithms. It assists in maintaining stability in solar energy-based systems. As future work, the present research was focus on predicting, additional weather parameters which hinders solar energy generation and supply to maintain a stable operational condition and investigating the scalability of the proposed methodology to real-world energy systems with larger datasets can provide understandings into its practical applicability. Additionally, conducting comparative studies with other state-of-the-art algorithms can help validate the effectiveness.

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