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Prediction of Electricity Consumption in Residential Area using Random Forest and CNN with Bi-LSTM

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Abstract: According to an intelligent power management model, the complex and significant task is electric energy consumption forecasting. The electricity utilization has major impacts on energy management, energy distribution costs and environment. While it comes to power usage prediction, the long-standing model contains inherent restrictions like scalability and accuracy. This paper presents a novel artificial technique to predict the electricity consumption in residential area. The panda's package selects the input data based on electricity residential dataset. The Gabor filter is used to pre-process the input data to handle the missing data, executing label encoding and removing unnecessary columns. The Greedy stepwise with correlation feature selection to select the relevant features. In residential area, the electricity prediction is performed using a Random Forest (RF) model and Hybrid CNN–Bi-LSTM Attenuation. The Python software implements the simulations results with respect to various measures namely RMSE, MAE, MSE, confusion matrix, ROC, recall, precision and accuracy. Due to the experimental results, the proposed method reveals better results than previous methods in case of electricity prediction.

Keywords: *Electricity prediction, Gabor filter, hybrid CNN–Bi-LSTM attenuation and Random Forest.*

1. Introduction

Growing prosperity is driving the requirement for electrical energy [1], when there is a dire requirement for greater power; power generators become less efficient and release harmful emissions. The negative effects of these facilities can be lessened with the right power generation system. Furthermore, demand forecasting, or the forecasting of power usage, is becoming increasingly important with the advent of intelligent networks and alternative power providers. The potential evolution of the power usage [2] of a single residence, a power system, a region, or perhaps an entire nation is known as an estimate of load. The projection is executed during a duration known as the anticipated perspective, in several segments. The brief duration load estimation [3] with advance durations of a brief period or a week is typically required for developing and distributing energy organizing, component distribution, and judgments regarding capacity inconsistency.

Since inefficient constructions are the main source of worldwide demand for energy and emissions of carbon dioxide, creating environmentally friendly and cost-effective constructions is now essential to protect the surroundings. Constructions [4] use a large amount of power, which contributes to serious ecological problems including airborne pollutants, heat contamination, and warming temperatures, a few of which have a detrimental effect on human

survival. The last few decades have seen a substantial rise in the use of electricity in construction as a result of rapid industrialization and increasing numbers of people. In terms of political, financial, and ecological growth, energy [5] is crucial for the country. It significantly affects humanity, learning, sanitation and healthcare, farming, manufacturing, and the standard of people's lives. Time-ahead electricity planning tools are necessary for many sectors related to electricity.

An essential component of the power strategy sector is power capacity projections. Businesses can make selections about electrical infrastructure, demand-side administration, commodity preservation, distribution scheduling, security precautions, and budgetary preparation thanks to electrical power services. For smart electricity networks [6] to function in decades to come, anticipation is especially important. Due to the centralization of the production of electricity in huge nuclear facilities, the present system of supplying power is unsustainable. Under these conditions, power must be transferred to residents throughout vast expanses, requiring substantial finances for network growth and upkeep as well as a significant amount of expertise degradation. One of the most important energy sources [7] is electricity, which is now considered an essential need for humanity.

Forecasting electrical consumption is crucial for electricity network executives, economic administrators, network administrators, and service shareholders. Unlike other

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renewable assets, consumers can fluctuate significantly throughout different periods. Electricity is a consistent, dependable source that keeps the machinery operating effectively and continually. Once the distribution connections are operational, moving power is simple. It requires little to no upkeep and last for several decades. Electric shortages [8] are the main cause of explosions in locations with power lines. Contamination is produced by electrical generating plants. Pollution of the environment and water from electrical power stations affects the condition of ecosystems. This paper presented a novel Random Forest and hybrid CNN with Bi-LSTM to predict electricity consumption in residential area.

Rest of the paper is arranged as; Section 2 summarizes the existing studies followed by the proposed work is described in Section 3. Section 4 discusses the investigational output and the work is concluded in Section 5.

2. Literature survey:

Banik et al. [9] have described machine learning algorithms to forecast the total amount of electric power used. The simulation has looked at many variables, including moisture, climate, air volume, and stress, which can have a significant influence on the amount of power consumed. These variables have proven to be helpful and prospective criteria in the present estimation of the total usage of electricity. Furthermore, it demonstrated how analysing statistics depending on the period of day might greatly increase reliability. These frameworks require many excessive variables, most of which are impossible to obtain.

Olu-Ajayi et al. [10] have presented Machine Learning (ML) method is acknowledged as the method most suitable for achieving the goals set in a forecasting challenge. As a result, it is currently many investigations to examine the amount of electricity operational buildings use. There aren't numerous investigations looking at whether techniques are appropriate for predicting energy use in structures during the initial phases of development to prevent the erection of additional resource-inefficient structures. To create a simulation that allows architects to provide important complex architectural components and predict typical yearly electricity use while the project is still in the planning phase. Because of the lack of accurate data, these devices are thus regarded as inadequate.

Alden et al. [11] have developed deep learning (DL) techniques and the actual association of climate usage. Instead of using climate projections, it makes use of unique encoder-decoder artificial intelligence patterns. These systems are created depending on information provided by upcoming climate reports. This makes it possible to estimate the general demand of an apartment complex and separate the demand which is usually the most demanding element in a house. Hence, it lacks the need for an independent circuit for surveillance.

Baba et al. [12] have implemented artificial neural networks (ANNs) determined architecture with the capacity to modify the way it operates in response to past variations supplied by a particular set containing the energy used. To highlight the possibilities for automated methods, a supplementary intuition investigation that uses a method to recommend an ideal interruption plan for the power stations delivering the upper-mentioned geographical area will be summarized. This will allow for the completion of repair projects that may occasionally be required or the resting of specific components the estimated usage for a specific time frame exceeds the entire developed electricity. Thus, it does not offer an indicator to assess it.

Khan et al. [13] have determined an ensemble machine learning model to forecast overall capacity usage based on the best choice of characteristics. It focuses on contrasting the suggested approach with other capacity prediction techniques. To be eligible for an effective simulation, it also emphasizes the best environmental characteristics, such as the weather, the speed of the wind, precipitation, moisture, and duration latencies. It can efficiently plan and arrange supplies to deliver top-notch client care. Therefore, it gets harder to create a reliable framework for electricity estimation.

Rocha et al. [14] have evaluated Artificial Intelligence techniques to address the strategy of electrical usage in intelligent houses. The method was used to identify the satisfaction of user levels, which were confirmed by computational calculations using actual information from an automated house. A 51.4% savings in costs demonstrated the effectiveness of the suggested computer vision conjunction when comparing smart residences to those without shared power and storage banks. Nevertheless, it does not attempt to optimize user convenience.

Abera et al. [15] suggested a machine learning algorithm to meet the predicted greatest need and device efficiency intensity. To project the usage of power appliances across different houses, indicate usage figures are computed using overall usage for every device. Only the average regular usage for all the combined residences is calculated for the greatest request utilization of the clients. The suggested method estimation of consumer electricity use yields results with 99.6% reliability. However, the variables from multiple groups are not considered.

Abdulrahman et al. [16] highlighted have been used in projections of potential power consumption, indicating the demand for a better option. To correct the imbalance between market forces, new forecasting approaches utilizing automated methodologies must be created to estimate construction energy usage proactively.

Electricity production and transmission between consumers can be made better with the use of an effective capacity projection. Hence, the limitation of this probabilistic method is its incapacity to analyze complicated usage patterns.

3. Proposed Methodology:

Figure 1 explains the proposed workflow model, which incorporates pre-processing, feature selection and prediction of electricity in residential area. The detailed procedures of proposed work is illustrated in the following section.

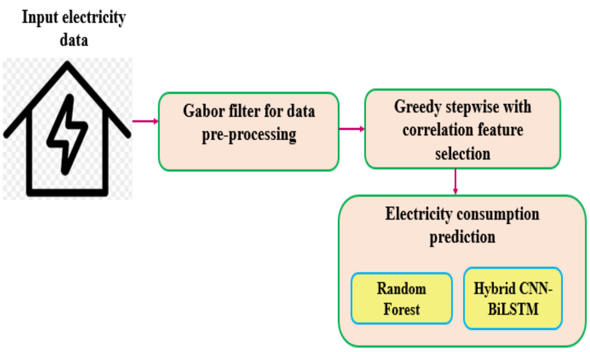


Fig. 1. Proposed workflow model

3.1 Pre-processing

The input dataset is taken from dataset repository and it is format as ".csv" or". xlxs" or".txt". Selects the inputs data and it needed pre-processing for further process. This study used Gabor filter to pre-process the data. At frequency domain, the Gabor transformation function in the location ability is need to resolved because of multifaceted data differentiation. The normalization, time domain synchronization, filling missing values, and removing outliners are major included in electricity data pre-processing to enhance the data quality. The below expression explains the formula of Gabor filter for data pre-processing.

$$G(y,z;\alpha,\beta,\chi,\delta,\gamma) = exp\left(-\frac{y^2+\gamma^2 z^2}{2\delta^2}\right) exp\left(j\left(2\pi\frac{y}{\alpha}+\chi\right)\right) \qquad (1)$$

Where, $\alpha, \beta, \chi, \delta$ and γ are data wavelength, orientation, offset, standard deviation and spatial aspect ratio. From the raw datasets, removes the less probabilities and normal data range outliers out. Gabor filter synchronizes all the data depending upon the sampling system faults [17]. Gabor filter performing label coding, handling missing data, removing unwanted attribute values and drop not requires columns. During feature selection, Gabor filter provides better and pre-processed data thereby enhancing the prediction results.

3.2 Feature Selection

According to the specified class, the data entering is separated to eliminate the unwanted data using Greedy stepwise with correlation (GSC) feature selection model. Based on the pre-processed data, the suitable criteria equip with higher accurate feature selection. Mathematically, evaluates the automatic evaluation model to obtain the performance results accuracy. According to stepwise search algorithm, perform the feature evaluation. Selects the correlation model with number of minimum features and maximum success is achieved. From pre-processed electricity data, selects few classes related to set features and the most efficient model is correlation oriented selecting features [18]. The classification highly correlated with the feature subsets measured using correlation-based model. While selecting optimal feature subsets, additionally utilizing greedy search with correlation-based feature selector that roles a major part in future selection. Figure 2 shows the feature selection model based on GSC.

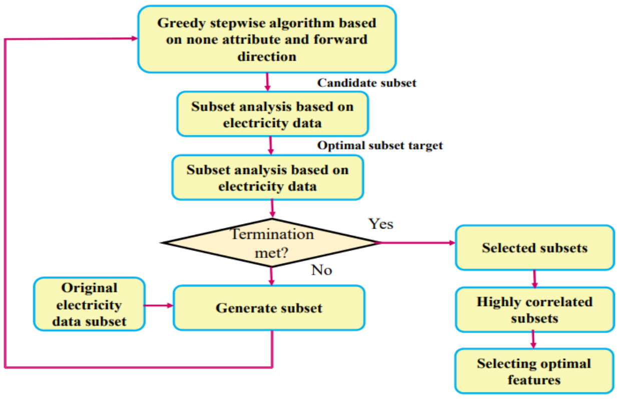


Fig. 2. GSC feature selection model

3.3 Residential Area Electricity Prediction

For decision making, the training and testing sets are divided from the pre-processed data. Among the total data, 80% for data training belongs to evaluation and 20% of testing data to predict electricity consumption in residential area. The time frame generally covers the hours to days. During regression, two different algorithms namely Random Forest and hybrid CNN-BiLSTM to predict the consumption of electricity in residential area.

3.3.1 Random Forest

RF is tree structure classifier with hierarchical order. The electricity consumption data has dimensionality and includes irrelevant features and relevant features. The relevant features are needed for the classifier model and used predetermined probability for the selection of most needed data features from the data [19]. Breiman subdivided the datasets into subset and to design the multiple decision trees with the mapping of random sample features. The architecture of proposed RF is demonstrated in figure 3.

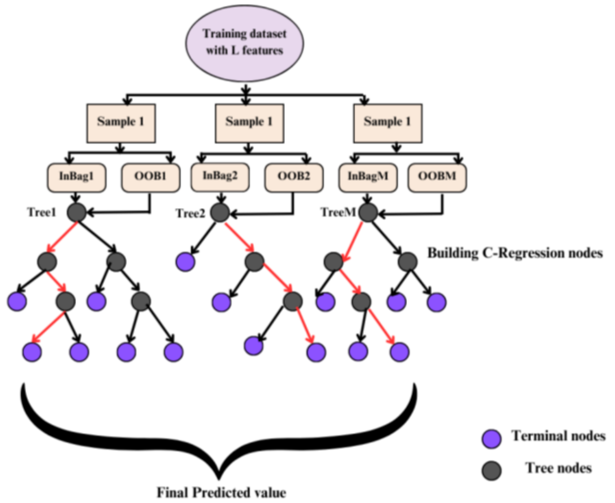


Fig. 3. RF architecture for the prediction of electricity consumption

The RF includes many trainings documents DT and features of NF and can be formulated as,

Step 1: Initialize the predetermined probability sample as $D_T 1, D_T 2, \ldots\ldots, D_T L$.

Step 2: The decision tree model is designed for each $D_T L$document. The sampling of training documents takes place randomly utilizing the subspace of M-dimensionality from the features that are available. The data split at leaf node is better than others and continues till it attains the saturation criterion.

The unpruned trees of number L is merged as $H_1(Y_1), H_2(Y_2), \ldots.$ and set it as ensemble value for the maximized probability classification. The Pseudocode of the RF classifier is displayed in the Algorithm 1.

Algorithm 1: Pseudocode for RF for the prediction of electricity consumption

Begin

Initialize the parameters

Set the features set as L

Select m number of features from L

Where m<<L

Estimate the node m from the m number of features with the association of best split point

Take that node as daughter node with the association of best split point

If stopping criteria attain

Construct the forest using the above step as m number of trees

Else

Repeat the steps

End

Return

stop

3.3.2 Hybrid CNN-Bi-LSTM

In residential area, the hybrid CNN and Bi-LSTM is utilized to predict the consumption of electricity. In the initial module, two CNN layers extracts the input variables as the selected features and fed it to the secondary modules of two Bi-LSTM layers. The two fully connected layers of last modules predicts the consumption of electricity in residential area. Various evaluation measures to compare the results [20]. Figure 4 shows the prediction of electricity consumption using hybrid CNN-Bi-LSTM architecture.

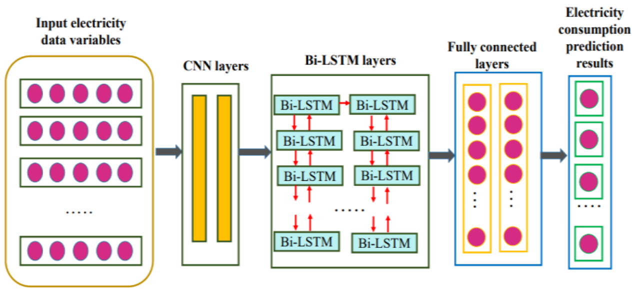


Fig. 4. Hybrid CNN-Bi-LSTM architecture for the prediction of electricity consumption

The filter with onput data of convolution operator applies the feature mapF_n. The next block in the line receives new feature sets. The feature set F provdies the new feature map.

$$gl_j^{Fm} = tan\,h\left(W^{Fm} y_{j:j+F-1} + a\right) \quad (2)$$

Where, $\{y_{1:F}, y_{2:F+1}, \ldots., y_{n:F+1}\}$ defines the input data recievbed from the feature set. Below formula computes the output of max poling layer [21].

$$y_j' = CNN(y_j) \quad (3)$$

The CNN energy consumption related to the input vector isy_j. The Bi-LSTM obtains the CNN network output asy_j'. Below expressions illustrates the formula for understanding Bi-LSTM [22].

$$j_t = \mu(w_j[y_t, z_{t-1}]) \quad (4)$$

$$O_t = \mu(w_O[y_t, z_{t-1}]) \quad (5)$$

$$f_t = tanh\left(w_f([y_t, z_{t-1}])\right) \quad (6)$$

$$z_t = O \times \Theta\, tanh(d_t) \quad (7)$$

The modulation gate input, forget and output gates are j, f and O. The fully connected layers based sigmoid functions arew_j, $w_O$and w_f. The element wise opertaor isΘ.The LSTM efficiency is reduced due to one directional information [23]. In the sequence, the backwarda nd forward directions are combined. The outputs are fused with the integration of LSTM.

$$z(t) = z_f(t) \oplus z_B(m - t + 1) \quad (8)$$

The forward and backward LSTM outputs are z_f and z_B. The energy consumption values are egnertaed with the two fully connected layer obtains the Bi-LSTM outputs.

4. Experimental analysis and investigation

Experimental study is the predominant phase to validate the robustness of the proposed work in predicting the energy consumption and so we have made the study and explained the details in this section. It includes the dataset details, performance metrics used for the analysis and comparative study in a detail.

4.1 Experimental setup

For the demonstration of the study, we have implemented the work in Python (V3.5) in Spyder with TensorFlow backend. For the optimization purpose we have taken the Adam optimizer. The system with the specification of Intel Core i5-6600 processor with the memory of 64 GB and operating system of Ubuntu 16.4 LTS. The optimal selections of hyper parameters are made by conducting various experiments. We have carried 50 epochs with the batch size of 1000 and validation split of 0.2.

4.2 Dataset Description

For the analysis we have taken the RESIDE-AC dataset [24] which is framed in well-structured and can be used easily and available in a .CSV format. the dataset was collected in may 2021 from 8 single AC usage home and 3 with multiple AC usage home. The dataset was collected for 19 summer days and time values are stored in IST with Garud and Envilog captured and can be converted to the UTC by subtracting 5:30 hrs from the time values. For each home the garud records are 27361 and Envilog records of 5472.

4.3 Performance Estimation

For the estimation we have taken the error parameters such as ROC, Mean square error (MSE), Root Mean square error (RMSE), Mean absolute error (MAE), Mean absolute percentage error (MAPE) and overall efficiency. The ROC curve results are plotted in Figure 5. The accuracy is increased to above 90% along with false and true positive rates. The confusion matrix results depicted in Figure 6.

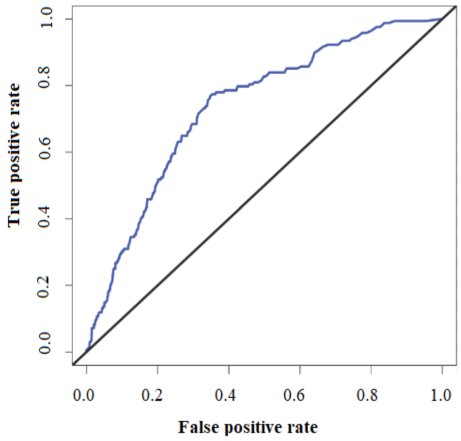


Fig. 5. Roc Curve results

True label \ Predicted label		
	27361	0
	0	5472

Fig. 6. Confusion matrix results

For the comparison we have taken the existing technique such as ML [10], DL [11], and ANN [12] and the proposed RF and hybrid CNN-BiLSTM. Figure 7 demonstrates the MSE based performance estimation of proposed RF and hybrid CNN-BiLSTM incorporated with the existing techniques such as ML, DL, and ANN. The mean square error of proposed hybrid CNN-BiLSTM is lower than the other techniques and in this we have evaluated the experimental study for 50 epochs with batch size of 1000. The MSE of the proposed hybrid CNN-BiLSTM at 50th epoch is 0.2 and RF achieved 0.221 value at 50th epoch. Meanwhile, the rest of the techniques such as ML, DL, and ANN achieved MSE at 50th epoch as 0.43, 0.5, and 0.387 as shown in figure.

The performance estimation based on the RMSE is demonstrated in figure 8. The RMSE of the proposed hybrid CNN-BiLSTM is lower and RF is more or less equal to hybrid CNN-BiLSTM. As mentioned above we have taken 50 epochs and for 50 th epoch, the RMSE of CNN-BiLSTM achieved 0.211 and RF achieved 0.236. The other techniques such as ML, DL, and ANN achieved RMSE at 50 th epoch as 0.476, 0.423, and 0.445 apart. This shows the electricity consumption prediction error is lower for the proposed CNN-BiLSTM.

The MAE based performance estimation is visualized in figure 9. For the estimation 50 epochs are conducted with the batch size of 1000. The MAE of the proposed works RF and CNN-BiLSTM are lower than the other techniques. The RF at 50th epoch provides only lesser MAE value of 0.356 and hybrid CNN-BiLSTM provides lower than this of about

0.276. The other techniques such as ML, DL, and ANN have higher MAE of 0.526, 0.437, and 0.428 apart.

The MAPE based performance estimation is graphically represented in figure 10. The MAPE is measured in percentage and is carried out for 50 epochs. At 50th epoch, the proposed CNN-BiLSTM technique has lesser MAPE of 39.99%, and RF has 57.56%. The rest of the technique have higher MAPE values of 85.4%, 62.34%, and 79.45% respectively. The prediction output of the hybrid CNN-BiLSTM is higher for predicting the electricity consumption in the residential area.

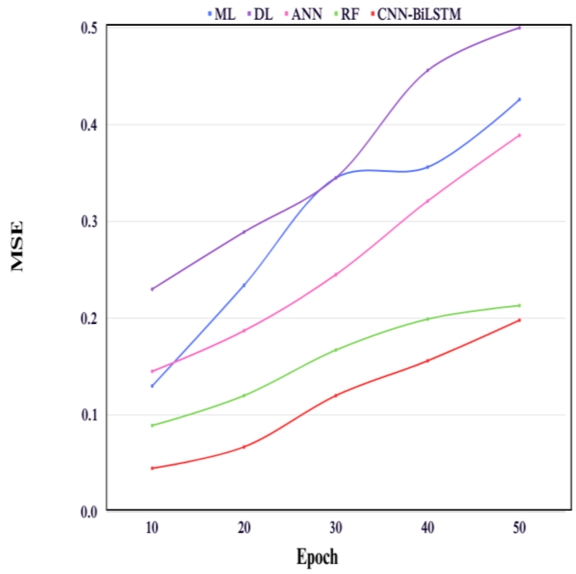


Fig. 7. MSE Performance Based Estimation

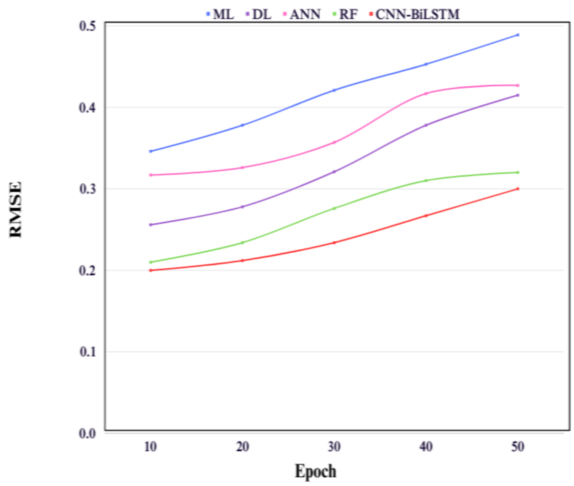


Fig. 8. RMSE Performance Based Estimation

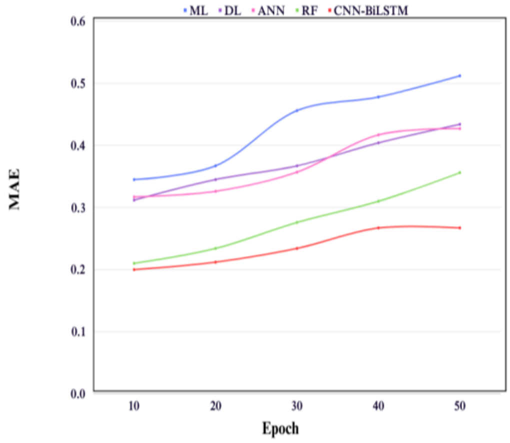


Fig. 9. MAE based Performance Estimation

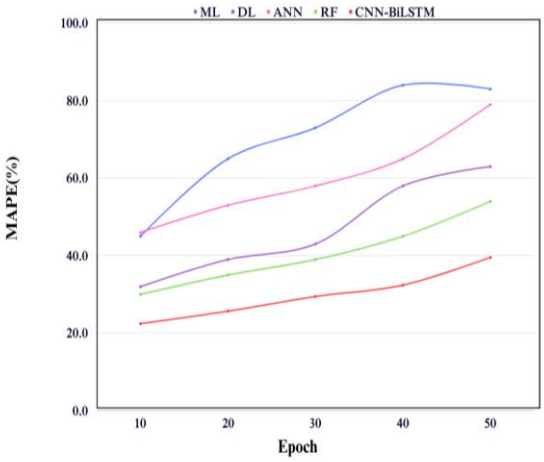


Fig. 10. MAPE based Performance Estimation

The analysis based on the daily basis using the various statistical parameters such as MAE, MAPE, RMSE, MSE, Training time, and Predicting time is displayed in table 1. The proposed CNN-BiLSTM has better performance for the daily basis electricity consumption analysis as shown in table 1. The training time of the hybrid CNN-BiLSTM is higher since we have utilized both hybrid CNN and BiLSTM, however, the predicting time is lesser than all the techniques used for the comparative study.

Table 1. Analysis based on the daily basis

Methods	***MAE***	***MAPE***	***RMSE***	***MSE***	***Training time(s)***	***Predicting time(s)***
ML	0.412	63.24	0.578	0.356	36.21	4.48
DL	0.467	56.39	0.534	0.318	89.87	3.95
ANN	0.356	48.87	0.4867	0.259	78.49	3.45
RF	0.231	25.59	0.318	0.136	45.47	2.11
CNN-BiLSTM	0.1834	17.34	0.2	0.054	62.58	0.58

The analysis of performance for the electricity consumption prediction in the residential area over the week is listed in table 2. The proposed techniques hybrid CNN-BiLSTM and RF are compared along with the existing techniques such as ML, DL, and ANN. The CNN-BiLSTM has better robustness when compared to all the other techniques for the weekly based electricity consumption prediction in both types of residence. Hence this work recommended the CNN-BiLSTM for the prediction over the RF as per the outcomes obtained.

Table 2. Analysis based on the weekly basis

Methods	***MAE***	***MAPE***	***RMSE***	***MSE***	***Training time(s)***	***Predicting time(s)***
ML	0.434	66.74	0.612	0.374	37.45	4.59
DL	0.358	59.27	0.567	0.359	90.45	3.95
ANN	0.420	51.26	0.588	0.278	82.54	4.62
RF	0.278	26.57	0.356	0.158	46.02	2.78
CNN-BiLSTM	0.157	18.67	0.215	0.065	60.67	0.65

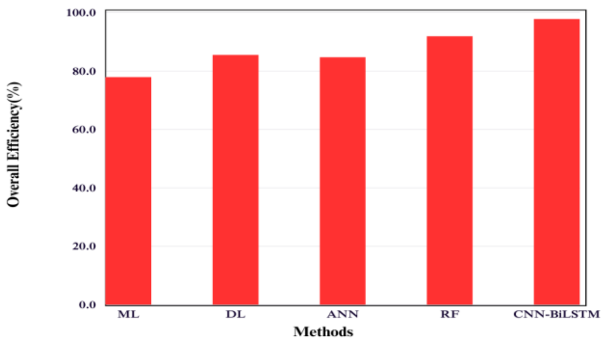


Fig .11. Performance estimation based on overall efficiency

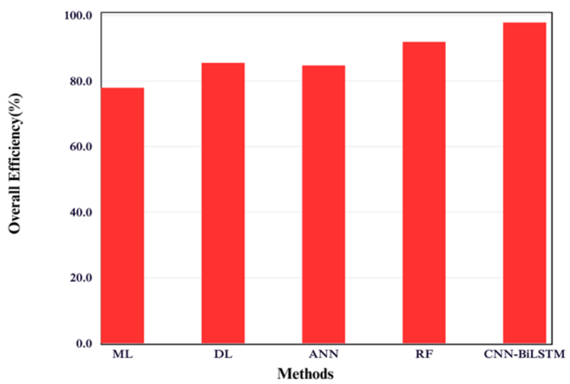
The overall efficiency of the works are conducted to predict the robustness of the works that are taken and for that we have compared the proposed CNN-BiLSTM and RF with other techniques such as ML, DL, and ANN. The hybrid CNN-BiLSTM provides better efficiency than the all other techniques of about 97.23% and RF provides efficiency of 92.35% and rest of the work achieved lower efficiency as graphically presented in figure 11.

Conclusion:

Based on the residential areas, this work proposed a novel random forest and hybrid CNN-Bi-LSTM model for the prediction of electricity consumption. The panda program picks input data from the RESIDE-AC dataset. The Python script implements the simulation findings in terms of different metrics, including RMSE, MAE, MSE, confusion matrix, ROC, recall, precision, and accuracy. The MSE of the proposed CNN-BiLSTM in the 50th epoch is 0.2, whereas the RF reached a value of 0.221. CNN-BiLSTM's RMSE for the 50th epoch was 0.211, whereas RF's was 0.236. The RF at the 50th epoch has a lower MAE value of 0.356, whereas CNN-BiLSTM has a lower value of around 0.276. The training time of the CNN-BiLSTM is longer since we employed both CNN and BiLSTM, but the prediction time is less than any of the approaches used in the comparative research. Overall efficiency belongs to RF is 92.35% and hybrid CNN-BiLSTM is 97.23% than previous ML, DL, and ANN.

Conflicts of interest

The authors declare no conflicts of interest.



References

[1] Dinh, H.T., Yun, J., Kim, D.M., Lee, K.H. and Kim, D., 2020. A home energy management system with renewable energy and energy storage utilizing main grid and electricity selling. IEEE access, 8, pp.49436-49450.

[2] Yan, H., Chen, Y. and Yang, S.H., 2020. UAV-enabled wireless power transfer with base station charging and UAV power consumption. IEEE Transactions on Vehicular Technology, 69(11), pp.12883-12896.

[3] Ge, X., Xu, F., Wang, Y., Li, H., Wang, F., Hu, J., Li, K., Lu, X. and Chen, B., 2022. Spatio-temporal two-dimensions data-based customer baseline load estimation approach using LASSO regression. IEEE Transactions on Industry Applications, 58(3), pp.3112-3122.

[4] Turner, C.J., Oyekan, J., Stergioulas, L. and Griffin, D., 2020. Utilizing industry 4.0 on the construction site: Challenges and opportunities. IEEE Transactions on Industrial Informatics, 17(2), pp.746-756.

[5] Oshnoei, A., Kheradmandi, M. and Muyeen, S.M., 2020. Robust control scheme for distributed battery energy storage systems in load frequency control. IEEE Transactions on Power Systems, 35(6), pp.4781-4791.

[6] Joseph, A. and Balachandra, P., 2020. Smart grid to energy internet: A systematic review of transitioning electricity systems. IEEE Access, 8, pp.215787-215805.

[7] Alam, M.S., Al-Ismail, F.S., Salem, A. and Abido, M.A., 2020. High-level penetration of renewable energy sources into grid utility: Challenges and solutions. IEEE Access, 8, pp.190277-190299.

[8] Bai, Y., Li, J., He, H., Dos Santos, R.C. and Yang, Q., 2020. Optimal design of a hybrid energy storage system in a plug-in hybrid electric vehicle for battery lifetime improvement. IEEE Access, 8, pp.142148-142158.

[9] Banik, R., Das, P., Ray, S. and Biswas, A., 2021. Prediction of electrical energy consumption based on machine learning technique. Electrical Engineering, 103, pp.909-920.

[10] Olu-Ajayi, R., Alaka, H., Sulaimon, I., Sunmola, F. and Ajayi, S., 2022. Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques. Journal of Building Engineering, 45, p.103406.

[11] Alden, R.E., Gong, H., Jones, E.S., Ababei, C. and Ionel, D.M., 2021. Artificial intelligence method for the forecast and separation of total and hvac loads with application to energy management of smart and nze homes. IEEE Access, 9, pp.160497-160509.

[12] Baba, A., 2021. Advanced AI-based techniques to predict daily energy consumption: A case study. Expert Systems with Applications, 184, p.115508.

[13] Khan, P.W. and Byun, Y.C., 2020. Genetic algorithm based optimized feature engineering and hybrid machine learning for effective energy consumption prediction. Ieee Access, 8, pp.196274-196286.

[14] Rocha, H.R., Honorato, I.H., Fiorotti, R., Celeste, W.C., Silvestre, L.J. and Silva, J.A., 2021. An Artificial Intelligence based scheduling algorithm for demand-side energy management in Smart Homes. Applied Energy, 282, p.116145.

[15] Abera, F.Z. and Khedkar, V., 2020. Machine learning approach electric appliance consumption and peak demand forecasting of residential customers using smart meter data. Wireless Personal Communications, 111, pp.65-82.

[16] Abdulrahman, M.L., Ibrahim, K.M., Gital, A.Y., Zambuk, F.U., Ja’afaru, B., Yakubu, Z.I. and Ibrahim, A., 2021. A Review on Deep Learning with Focus on Deep Recurrent Neural Network for Electricity Forecasting in Residential Building. Procedia Computer Science, 193, pp.141-154.

[17] Flores, V.H. and Rivera, M., 2020. Robust two-step phase estimation using the Simplified Lissajous Ellipse Fitting method with Gabor Filters Bank preprocessing. Optics Communications, 461, p.125286.

[18] Pourhashemi, S.M. and Mashalizadeh, A.M., 2013. A novel feature selection method using CFS with Greedy-Stepwise search algorithm in e-mail spam filtering. Semantic Scholar: Seattle, WA, USA, 15.

[19] Huang, N., Lu, G. and Xu, D., 2016. A permutation importance-based feature selection method for short-term electricity load forecasting using random forest. Energies, 9(10), p.767.

[20] Le, T., Vo, M.T., Vo, B., Hwang, E., Rho, S. and Baik, S.W., 2019. Improving electric energy consumption prediction using CNN and Bi-LSTM. Applied Sciences, 9(20), p.4237.

[21] Li, K., Hu, C., Liu, G. and Xue, W., 2015. Building's electricity consumption prediction using optimized artificial neural networks and principal component analysis. Energy and Buildings, 108, pp.106-113.

[22] Mohsenian-Rad, A.H. and Leon-Garcia, A., 2010. Optimal residential load control with price prediction in real-time electricity pricing environments. IEEE transactions on Smart Grid, 1(2), pp.120-133.