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CNN-BiGRU-SA for Residential Electricity Consumption Forecasting

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Abstract: Accurate forecasting of residential electricity consumption is essential for efficient energy management and smart grid operations. This paper proposes an enhanced deep learning model based on a Convolutional Neural Network integrated with Bidirectional Gated Recurrent Units and a Self-Attention mechanism (CNN-BiGRU-SA) to improve prediction accuracy and computational efficiency. The model utilizes the UCI Electricity Consumption dataset, where data preprocessing and normalization are performed, followed by feature selection using the Maximal Information Coefficient (MIC) to retain the most relevant attributes. The CNN component extracts temporal features, while the BiGRU captures bidirectional dependencies with reduced complexity compared to BiLSTM, and the self-attention mechanism emphasizes important features for improved learning. Experimental results demonstrate that the proposed CNN-BiGRU-SA model outperforms traditional machine learning models and the CNN-BiLSTM-SA approach, achieving a high R^2 score of 0.9782 along with lower RMSE and MAE values. These results confirm that the proposed extension provides an efficient, accurate, and scalable solution for residential electricity consumption forecasting in modern energy systems.

Index terms - *Residential Electricity Consumption, Load Forecasting, Convolutional Neural Network, Bidirectional GRU, Self-Attention Mechanism, Maximal Information Coefficient, Deep Learning*

1. INTRODUCTION

Accurate forecasting of residential electricity consumption is essential for ensuring efficient energy management, grid stability, and demand-side optimization in modern power systems. However, electricity consumption patterns are highly dynamic and influenced by multiple factors such as user behavior, weather conditions, and appliance usage. Traditional forecasting approaches often struggle to capture these complexities, leading to unreliable predictions. In particular, recent studies have highlighted issues such as the persistence forecast effect, where models tend to rely heavily on recent observations, resulting in delayed and overconfident predictions [1].

To overcome these limitations, various machine learning and hybrid approaches have been proposed for electricity consumption forecasting. Hybrid models combining random forest and artificial neural networks have demonstrated improved performance by capturing nonlinear relationships in energy data [2]. Similarly, time-series models such as SARIMA have been widely used for demand forecasting; however, their effectiveness is limited when dealing with highly nonlinear and non-stationary residential consumption patterns [3]. Supervised machine learning techniques applied to smart meter datasets have further shown that data-driven models can better capture variations in electricity usage and peak demand [4]. Moreover, comparative studies indicate that machine learning methods consistently outperform traditional statistical approaches in terms of accuracy and bias when applied to complex energy forecasting problems [5].

Motivated by these findings, this paper proposes an enhanced deep learning framework for residential electricity consumption forecasting using a combination of Convolutional Neural Networks (CNN), Bidirectional Gated Recurrent Units (BiGRU), and a Self-Attention (SA) mechanism. The proposed CNN-BiGRU-SA model effectively captures both local temporal features and long-term dependencies while reducing computational complexity compared to BiLSTM-based architectures. Additionally, the Maximal Information Coefficient (MIC) is employed for feature selection to improve model efficiency and accuracy. Experimental results demonstrate that the proposed extension achieves superior performance compared to traditional machine learning models and existing deep learning approaches, making it a robust solution for real-world energy forecasting applications.

2. LITERATURE SURVEY

2.1 Avoiding Overconfidence in Predictions of Residential Energy Demand through Identification of the Persistence Forecast Effect:

For many contemporary power system solutions and smart applications that support network operation, grid stability, and demand-side management—the majority of which rely on reliable and accurate forecasts—forecasting home electricity consumption is crucial. The techniques generating these forecasts use statistical regularity in past data to extrapolate future load. Predictions then regress toward the most recent consumption value employed in the input set if such regularity is absent. Predictions therefore lag one step behind the real load data, which might have an impact on how reliable they are and how well applications work. This behavior is not detected by current assessment techniques, which might lead to overconfidence in prediction outcomes. In this study, we: I) define and systematically analyze this behavior, which we refer to as the Persistence Forecast Effect, and show its effects; II) suggest a novel technique, called 1-Step-Shifting, to identify its existence; and III) analyze and determine the connection between the effect and data irregularity. To further illustrate the Persistence Forecast Effect, its ramifications, and its connection to statistical regularity in historical data, we present a case study that applies cutting-edge forecasting algorithms to a real-world dataset of power consumption data from 69 homes.

2.2 Hybrid Machine Learning Model for Electricity Consumption Prediction Using Random Forest and Artificial Neural Networks:

In order to make better management decisions and business strategies, power usage prediction is crucial. In order to anticipate power usage in Thailand, this study provides a hybrid machine learning model that combines a backpropagation neural network (BPNN) with dimensionality reduction and feature selection techniques. An actual dataset containing relevant predictor variables from open sources is used to create and test the prediction models. These models are trained, assessed, and validated using open geospatial data collected from a real service as well as geographic, meteorological, industrial, and household data. To identify the important predictor variables, machine learning techniques including principal component analysis (PCA), stepwise regression (SWR), and random forest (RF) are employed. The BPNN is used to build the prediction models utilizing all available variables as a baseline for comparison and variables chosen using dimensionality reduction and feature selection techniques. The most relevant determinants of energy usage are chosen in addition to developing a prediction model. The hybrid model of RF with BPNN regularly performs better than the other models, according to the comparison. In order to plan and manage the energy demand, the suggested hybrid machine learning model from this study can forecast power usage.

2.3 Forecasting Electricity Demand In Ghana With The Sarima Model:

Demand forecasting is a difficult topic of interest for many businesses whose primary goal is to enhance their steadily expanding consumer requests and demand and aid in boosting their income generating. In the power sector, the tale is the same. Power or electrical producers find it challenging to store large amounts of the energy they produce, which makes it difficult to accurately estimate the amount of electrical energy needed to balance supply and demand as well as minimize or eliminate increasing transmission losses. This study investigates possible time series models for forecasting or predicting energy consumption in Ghana's Western Regions. In order to help with study design and determine the amount of power customers in the area require, secondary data was formally obtained from the ECG regional headquarters. Time series data analysis toolpak program was used for this. The models developed are feasible for future consumption projections and other investments in alternative power source projects to fulfill these future demands, according to the results. The flexibility of the developed models can be highly helpful and supplemental to developing effective and efficient energy strategies, given the region's rising patterns of energy consumption.

2.4 Prediction of domestic power peak demand and consumption using supervised machine learning with smart meter dataset:

Electricity consumption forecast is essential for efficient energy management. Since power consumption varies by appliance, improved power and peak demand forecasting is vital for power generation and distribution system planning and development. This prediction study helps service providers and the government understand client lifestyles. Prediction and forecasting models are difficult to use and don't fulfill standards. Electric vehicles will boost worldwide power demand by 3% next year, according to the prediction. Many machine learning algorithms classify and make decisions. However, existing approaches have poor forecast accuracy, resulting in wasteful power generating decisions. This research offers a random forest supervised learning model to predict power consumption and peak demand. For improved analysis and predictions, the random forest classifier is fed the vast smart meter dataset gathered during different seasons. This method excels in accuracy, stability, and generalization. This research also compares previous models' performance. Performance research demonstrates that this model outperforms the others with 95.67% accuracy and improved precision and recall.

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2.5 Chapter 4 - Forecasting week-ahead hourly electricity prices in Belgium with statistical and machine learning methods:

Predicting power prices is difficult since weather, electricity use, and seasonal factors affect the series. Energy firms need reliable estimates for operational management and short- to mid-term planning. Statistical and machine learning (ML) forecasting methods have been developed in the literature throughout the years. In energy market forecasting, research have proven ambiguous on whether method is better. Extrapolation tasks require independent statistical and ML assessments of explanatory variable value-added. This chapter summarizes both techniques. The Belgian electricity market is used to compare the forecasting ability of neural networks and random forest against statistical approaches. ML approaches provide more accurate and biased projections, according to our findings. External factors enhance statistical and ML techniques, but the latter group improves more. We also demonstrate the benefits of integrating projections within and across households. We conclude by discussing each approach's drawbacks and suggesting additional study.

3. METHODOLOGY

i) Proposed Work:

The proposed work focuses on developing an efficient and accurate deep learning model for residential electricity consumption forecasting using a hybrid CNN-BiGRU-SA architecture. The model integrates Convolutional Neural Networks (CNN) for extracting meaningful temporal features from electricity usage data, Bidirectional Gated Recurrent Units (BiGRU) for capturing sequential dependencies in both forward and backward directions with reduced computational complexity, and a Self-Attention (SA) mechanism to emphasize the most significant features influencing prediction outcomes. To further enhance model performance, the Maximal Information Coefficient (MIC) is employed for feature selection, ensuring that only the most relevant attributes are considered during training. The proposed system is evaluated using the UCI Electricity Consumption dataset and compared with traditional models such as Linear Regression and Support Vector Machines, as well as the CNN-BiLSTM-SA model. Experimental results demonstrate that the CNN-BiGRU-SA model achieves superior accuracy, faster convergence, and lower error rates, making it a reliable and scalable solution for residential electricity consumption forecasting.

ii) System Architecture:

The system architecture is designed as a structured deep learning pipeline for residential electricity consumption forecasting, beginning with data acquisition from the UCI dataset followed by preprocessing steps such as data cleaning, normalization, and sequence generation. Feature selection is performed using the Maximal Information Coefficient (MIC) to retain the most relevant attributes and improve model efficiency. The processed data is then fed into the core CNN-BiGRU-SA model, where Convolutional Neural Networks (CNN) extract temporal features, Bidirectional Gated Recurrent Units (BiGRU) capture bidirectional sequential dependencies with reduced computational complexity, and the Self-Attention mechanism highlights the most significant features influencing predictions. Finally, the model outputs consumption forecasts, which are evaluated using metrics such as R^2, RMSE, and MAE, ensuring accurate, efficient, and scalable electricity consumption prediction.

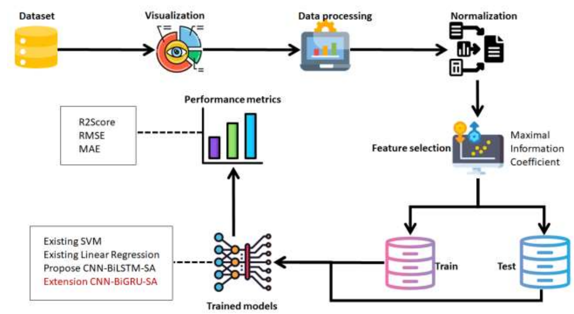

Fig.1. Proposed Architecture

iii) MODULES:

1. Data Loading Module

This module is responsible for importing the residential electricity consumption dataset from the UCI repository and preparing it for further processing.

2. Data Visualization Module

This module generates graphical representations of electricity consumption data to understand patterns, trends, and variations in usage.

3. Data Processing Module

In this module, raw data is cleaned, missing values are handled, and the data is transformed into a structured format suitable for model training.

4. Normalization Module

This module scales all input features to a uniform range, ensuring equal contribution of features and improving model convergence and accuracy.

5. Feature Selection Module (MIC)

This module applies the Maximal Information Coefficient (MIC) algorithm to select the most relevant features, reducing redundancy and improving model efficiency.

6. Data Splitting Module

This module divides the dataset into training and testing sets to ensure proper model training and evaluation on unseen data.

7. Model Generation Module

This module builds and trains multiple models including SVM, Linear Regression, CNN-BiLSTM-SA, and the extended CNN-BiGRU-SA model.

8. Performance Evaluation Module

This module evaluates model performance using metrics such as R^2 score, RMSE, and MAE to compare accuracy and error rates.

9. Electricity Consumption Prediction Module

This module generates final electricity consumption predictions using the trained CNN-BiGRU-SA model.

iv) ALGORITHMS:

1. Support Vector Machine (SVM)

SVM is used as a baseline machine learning algorithm to evaluate forecasting performance against advanced deep learning models. It constructs an optimal hyperplane that separates data points in a high-dimensional space to perform prediction.

In this work, SVM provides a reference for comparison by demonstrating how traditional models handle electricity consumption data. However, due to its limited ability to capture temporal dependencies and nonlinear patterns in time-series data, it results in comparatively lower accuracy.

2. Linear Regression

Linear Regression is a fundamental statistical method used to model the relationship between input features and electricity consumption by fitting a linear equation to the observed data.

Although it is simple, interpretable, and computationally efficient, Linear Regression cannot effectively handle complex and nonlinear relationships present in electricity consumption data. As a result, it produces higher prediction errors compared to advanced models.

3. Proposed CNN-BiLSTM-SA

The proposed CNN-BiLSTM-SA model combines Convolutional Neural Networks (CNN), Bidirectional Long Short-Term Memory (BiLSTM), and a Self-Attention mechanism to improve forecasting accuracy. CNN extracts temporal features, while BiLSTM captures long-term dependencies in both forward and backward directions.

The Self-Attention mechanism further enhances the model by assigning importance to relevant features, allowing it to focus on critical patterns in electricity consumption data. This integration significantly improves prediction performance compared to traditional machine learning methods.

4. Extended CNN-BiGRU-SA

The extended CNN-BiGRU-SA model improves upon the proposed model by replacing BiLSTM with Bidirectional Gated Recurrent Units (BiGRU). This modification reduces computational complexity while maintaining the ability to capture sequential dependencies.

BiGRU has fewer parameters than BiLSTM, resulting in faster training and improved efficiency. Combined with CNN for feature extraction and Self-Attention for feature weighting, this model achieves the highest accuracy with lower RMSE and MAE, making it the most effective approach for residential electricity consumption forecasting.

4. EXPERIMENTAL RESULTS

The experimental evaluation of the proposed system was conducted using the UCI residential electricity consumption dataset to assess the performance of different forecasting models. Initially, traditional machine learning algorithms such as Support Vector Machines and Linear Regression were implemented as baseline models. The results indicate that these models achieved lower prediction accuracy, with R^2 scores of 0.6248 and 0.4587 respectively, along with higher RMSE and MAE values, demonstrating their inability to effectively capture nonlinear and temporal patterns in electricity consumption data. In contrast, the proposed CNN-BiLSTM-SA model showed a significant improvement, achieving an R^2 score of 0.9712, which highlights its capability to model complex consumption behavior.

Further enhancement was achieved through the extended CNN-BiGRU-SA model, which outperformed all other models in terms of accuracy and efficiency. The model achieved the highest R^2 score of 0.9782 along with the lowest RMSE (0.0162) and MAE (0.0091), indicating superior predictive performance and reduced error rates. The improvement is attributed to the use of BiGRU, which reduces computational complexity while maintaining strong temporal learning capability, and the Self-Attention mechanism, which emphasizes important features. These results confirm that the CNN-BiGRU-SA model provides a more accurate, efficient, and scalable solution for residential electricity consumption forecasting compared to both traditional and existing deep learning approaches.

Accuracy: A test's accuracy is determined by its capacity to distinguish between healthy and ill cases. To gauge the accuracy of the test, find the percentage of examined instances that had true positives and true negatives. According to the computations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

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Precision: Precision is the number of affirmative cases or the classification's accuracy rate. The following formula is applied to assess accuracy:
Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$Precision = \frac{TP}{(TP + FP)}$$

Recall: A model's ability to recognise every instance of a pertinent machine learning class is measured by its recall. The ratio of accurately predicted positive observations to the total number of positives indicates how well a model can identify class instances.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: Mean Average Precision is one ranking quality metric (MAP). It considers the number of relevant recommendations and their position on the list. MAP at K is calculated as the arithmetic mean of the Average Precision (AP) at K for each user or query.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

F1-Score: An accurate machine learning model is indicated by a high F1 score. combining precision and recall to increase model correctness. The accuracy statistic quantifies the frequency with which a model correctly predicts a dataset.

$$F1 = 2 \cdot \frac{(Recall \cdot Precision)}{(Recall + Precision)}$$

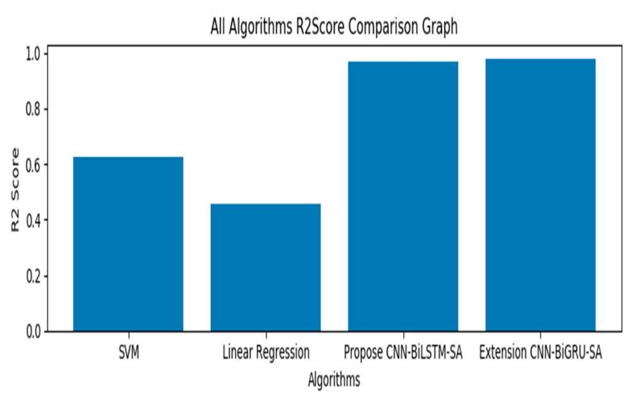

Fig2 comparative analysis of the R^2 score

The R2 ratings of several forecasting algorithms for estimating residential electricity use are compared in this figure. Because of their lower R2 values, traditional models like Support Vector Machines and Linear Regression are less able to capture complex consumption patterns. In contrast, the CNN-BiLSTM-SA model has a higher R2 score and significantly improves prediction accuracy. With the highest R2 value, the extended CNN-BiGRU-SA model performs better than any other method in terms of predicting and explanatory power. This comparison demonstrates the accuracy with which deep learning architectures—particularly CNN-BiGRU-SA—simulate residential premises.

Algorithm	R^2 Score	RMSE	MAE
Existing SVM	0.6248	0.0673	0.055
Existing Linear Regression	0.4587	0.0809	0.0557
Proposed CNN-BiLSTM-SA	0.9712	0.0187	0.0102
Extended CNN-BiGRU-SA	**0.9782**	**0.0162**	**0.0091**

Table 1.Performance Comparison of Forecasting Model

The R2 score, RMSE, and MAE metrics are used in this table to examine how well different forecasting algorithms estimate home electricity usage. Higher error rates result from the lower R2 values, higher RMSE and MAE, and poorer predictive power of traditional models like Linear Regression and Support Vector Machines. The accuracy is greatly increased by the CNN-BiLSTM-SA model, which yields reduced error levels and a high R2 score. With the highest R2 score and the lowest RMSE and MAE, the enlarged CNN-BiGRU-SA model outperforms the others in household power consumption forecasting, exhibiting improved precision, effectiveness, and longevity.

5. CONCLUSION

This paper presented an advanced deep learning approach for residential electricity consumption forecasting using a hybrid CNN-BiGRU-SA architecture. The proposed system effectively integrates Convolutional Neural Networks for feature extraction, Bidirectional Gated Recurrent Units for capturing temporal dependencies with reduced complexity, and a Self-Attention mechanism for highlighting important features. Additionally, the use of the Maximal Information Coefficient for feature selection improves data quality and enhances model performance. The results demonstrate that deep learning-based approaches significantly outperform traditional machine learning models such as Support Vector Machines and Linear Regression in handling complex and nonlinear electricity consumption patterns.

The experimental analysis confirms that the extended CNN-BiGRU-SA model achieves superior performance with the highest R^2 score of 0.9782 and the lowest RMSE and MAE values among all evaluated models. The replacement of BiLSTM with BiGRU reduces computational cost while maintaining high prediction accuracy, making the model more efficient and scalable. Therefore, the proposed approach provides a reliable and effective solution for residential electricity consumption forecasting, with potential applications in smart grid systems, energy management, and demand-side planning.

6. FUTURE SCOPE

Future work can focus on enhancing the proposed CNN-BiGRU-SA model by incorporating advanced deep learning techniques such as transformer-based architectures and ensemble learning to further improve forecasting accuracy. The integration of external factors such as weather conditions, occupancy behavior, and real-time sensor data can provide more comprehensive insights into electricity consumption patterns. Additionally, the model can be extended for real-time deployment in smart grid environments to support dynamic load management and energy optimization. Exploring transfer learning and adaptive models may also help in improving performance across different regions and datasets, making the system more robust and scalable for practical applications.

REFERENCES

[1] H.B.Akyol, C.Preist, and D.Schien,''Avoiding over confidence inpredictions of residential energy demand through identification of the persistence forecast effect,'' IEEE Trans. Smart Grid, vol. 14, no. 1, pp. 228–238, Jan. 2023.

[2] W. Kesornsit and Y. Sirisathitkul, ''Hybrid machine learning model for electricity consumption prediction using random forest and artificial neu ral networks,'' Appl. Comput. Intell. Soft Comput., vol. 2022, pp. 1–11, Apr. 2022.

[3] P. Y. A. Andoh, C. K. K. Sekyere, L. D. Mensah, and D. E. K. Dzebre, ''Forecasting electricity demand in Ghana with the sarima model,'' J. Appl. Eng. Technol. Sci., vol. 3, no. 1, pp. 1–9, Dec. 2021.

[4] R. Geetha, K. Ramyadevi, and M. Balasubramanian, ''Prediction of domestic power peak demand and consumption using supervised machine learning with smart meterdataset,'' Multimedia Tools Appl., vol. 80, no. 13, pp. 19675–19693, May 2021.

[5] E. Spiliotis, H. Doukas, V. Assimakopoulos, and F. Petropoulos, ''Fore casting week-ahead hourlyelectricity prices in Belgium with statistical and machine learning methods,'' in Mathematical Modelling of Contemporary Electricity Markets. New York, NY, USA: Academic, 2021, pp. 59–74.

[6] C. Xiuhua and M. Xiren, ''Periodical fluctuant prediction model in dig ital household power consumption,'' Low Voltage Apparatus, no. 22, pp. 23–25, Jan. 2007. 71564

[7] X.Li, C.P.Bowers, and T.Schnier, ''Classification of energy consumption in buildings with outlier detection,'' IEEE Trans. Ind. Electron., vol. 57, no. 11, pp. 3639–3644, Nov. 2010.

[8] E. Jahani, K. Cetin, and I. H. Cho, ''City-scale single family residential building energy consumption prediction using genetic algorithm-based numerical moment matching technique,'' Building Environ., vol. 172, Apr. 2020, Art. no. 106667.

[9] M.Zolfaghari and B.Sahabi, ''A hybrid approach to model and forecast the electricity consumption by Neuro Wavelet and ARIMAX-GARCH mod els,'' Energy Efficiency, vol. 12, no. 8, pp. 2099–2122, Dec. 2019.

[10] N. Arghira, L. Hawarah, S. Ploix, and M. Jacomino, ''Prediction of appli ances energy use in smart homes,'' Energy, vol. 48, no. 1, pp. 128–134, Dec. 2012.

[11] K. P. Amber, R. Ahmad, M. W. Aslam, A. Kousar, M. Usman, and M. S. Khan, ''Intelligent techniques for forecasting

electricity consump tion of buildings,'' Energy, vol. 157, pp. 886–893, Aug. 2018.
[12] L. C. P. Velasco, D. Lou, G. Paolo, and M. Bryan, ''A hybrid model of autoregressive integrated moving average and artificial neural network for load forecasting,'' Int. J. Adv. Comput. Sci. Appl., vol. 10, no. 11, pp. 14–16, 2019.
[13] I. F. Syah, M. P. Abdullah, H. Syadli, M. Y. Hassan, and F. Hussin, ''Data selection test method for better prediction of building electricity consumption,'' Jurnal Teknologi, vol. 78, nos. 5–7, pp. 67–72, May 2016.
[14] S. Farzana, M. Liu, A. Baldwin, and M. U. Hossain, ''Multi-model pre diction and simulation of residential building energy in urban areas of Chongqing, South West China,'' Energy Buildings, vol. 81, pp. 161–169, Oct. 2014.
[15] W. Alkhatib, A. Alhamoud, D. Böhnstedt, and R. Steinmetz, ''Hybrid model for large scale forecasting of power consumption,'' in Advances in Computational Intelligence. Cham, Switzerland: Springer, 2017, pp. 661–672.
[16] H. Saxena, O. Aponte, and K. T. McConky, ''A hybrid machine learning model for forecasting a billing period's peak electric load days,'' Int. J. Forecasting, vol. 35, no. 4, pp. 1288–1303, Oct. 2019.
[17] M. K. Kim, Y.-S. Kim, and J. Srebric, ''Predictions of electricity con sumption in a campus building using occupant rates and weather elements with sensitivity analysis: Artificial neural network vs. linear regression,'' Sustain. Cities Soc., vol. 62, Nov. 2020, Art. no. 102385.
[18] S.-X. Yang and Y. Wang, ''Applying support vector machine method to forecast electricity consumption,'' in Proc. Int. Conf. Comput. Intell. Secur., Nov. 2006, pp. 929–932.
[19] G.K.F.T so and K.K.W.Yau, ''Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks,'' Energy, vol. 32, no. 9, pp. 1761–1768, Sep. 2007.
[20] C. Wang, T. Bäck, H. H. Hoos, M. Baratchi, S. Limmer, and M. Olhofer, ''Automated machine learning for short-term electric load forecasting,'' in Proc. IEEE Symp. Ser. Comput. Intell. (SSCI), Dec. 2019, pp. 314–321.
[21] S. Rahman, M. G. R. Alam, and M. M. Rahman, ''Deep learning based ensemble method for household energy demand forecasting of smart home,'' in Proc. 22nd Int. Conf. Comput. Inf. Technol. (ICCIT), Dec. 2019, pp. 1–6.
[22] K.Yan, X.Wang, Y.Du, N.Jin, H.Huang, and H.Zhou, ''Multi-stepshort term power consumption forecasting with a hybrid deep learning strategy,'' Energies, vol. 11, no. 11, p. 3089, Nov. 2018.
[23] K.Aurangzeb, ''Short term power load forecasting using machine learning models for energy management in a smart community,'' in Proc. Int. Conf. Comput. Inf. Sci. (ICCIS), Apr. 2019, pp. 1–6.
[24] Z.Guo, K.Zhou, X.Zhang, and S.Yang, ''A deep learning model for short term power load and probability density forecasting,'' Energy, vol. 160, pp. 1186–1200, Oct. 2018.
[25] M.Alhussein, K.Aurangzeb, and S.I.Haider, ''Hybrid CNN-LSTM model for short-term individual household load forecasting,'' IEEE Access, vol. 8, pp. 180544–180557, 2020.
[26] X.Xiongand Y.Wei, ''Theanalysis and predication of energy use in smart homes based on machine learning,'' in Proc. Int. Conf. Comput. Data Sci. (CDS), Aug. 2020, pp. 381–386.
[27] G. Dlamini and S. Megha, ''Predicting household power consumption: Using gradient boosting and deep quantile regression model,'' J. Phys., Conf. Ser., vol. 1694, Dec. 2020, Art. no. 012031.
[28] J. Hyeon, H. Y. Lee, B. Ko, and H. J. Choi, ''Deep learning-based house hold

electric energy consumption forecasting,'' J. Eng., vol. 2020, no. 13, pp. 639–642, 2020.

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