RESEARCH PAPER

Efficient Smart Home Energy Consumption Management Using IoT and Hybrid Deep Learning Models

Prakash Kumar Pathak *[1]**Rahul kumar Mohanty** [2]
[1]Professor, Computer Science and Engineering,Gandhi Engineering College (GEC Autonomous), Bhubaneswar, Odisha, 752054, India Prakashpathak2015@gmail.com
[2]Research Schelor M.Tech (Data Science) 4th SEMGandhi Engineering College (GEC Autonomous), Bhubaneswar, Odisha, IndiaBhubaneswar, Odisha, 752054, India
rahulkmohanty333@gmail.com

Background: The rapid growth of the Internet of Things (IoT) has accelerated the development of sophisticated smart home solutions for efficient energy management. However, precisely estimating household energy consumption is still difficult due to the dynamic, nonlinear nature of appliance usage patterns. This study describes an IoT-enabled smart home energy consumption prediction system that uses machine learning and deep learning to increase energy efficiency and reduce excessive power use.
Objective: In this paper, we aim to develop an efficient IoT-enabled smart home. This study analyzes smart home energy data using machine learning and deep learning approaches to increase prediction accuracy and reduce energy waste. Various classical, ensemble, and deep learning models are implemented and compared to determine the most effective technique for intelligent and sustainable energy management in smart homes.
Material/methods: In this paper, we have used the 14-classifier to predict an efficient smart home using machine learning and deep learning. We utilized the Appliances Energy Prediction dataset to achieve the task. Out of the 14 classifiers, some are traditional, such as ET, RF, LR, XGBoost, LightGBM, KNN, GB, SVR, DT, and AdaBoost, and deep learning models like Hybrid LSTM-GRU, LSTM Network, Proposed Ensemble, and Optimized Extra Trees.
Result: Our experimental observation revealed that the proposed Hybrid LSTM-GRU mode performs well, with an MAE of 5.21, an RMSE of 6.43, and an R^2 score of 0.9435, compared to the other models. The suggested framework improves the forecast of smart home energy consumption while also supporting intelligent, sustainable, and energy-efficient IoT-based smart home management systems.

Keywords: IoT, ML, DL, Hybrid LSTM-GRU, Energy Consumption Prediction, Smart Energy Management, Deep Learning.

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1. Introduction

The swift advancement of Internet of Things (IoT) technology has transformed conventional residences into intelligent smart home ecosystems capable of automated surveillance, communication, and energy management. Smart homes utilise interconnected sensors, intelligent meters, and advanced devices to monitor appliance activity and enhance energy efficiency in real time. Due to increasing global energy demand and environmental issues, efficient energy consumption management has become a significant research focus in smart grid and sustainable computing applications. Recent advancements in machine learning and deep learning have significantly improved the efficacy of smart home energy forecasting. Conventional machine learning models, including Linear Regression, Decision Trees, Random Forests, and Gradient Boosting, have been extensively employed for residential energy prediction; yet, these techniques frequently inadequately represent intricate temporal connections and nonlinear consumption patterns. To mitigate these limitations, deep learning architectures like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have been prevalent for time-series energy forecasting owing to their proficiency in learning sequential patterns [1]. There have been numerous recent studies that have demonstrated the effectiveness of hybrid deep learning methods in the prediction of smart energy. Ou et al. [1] introduced ConvLSTM and CNN-LSTM hybrid models for smart home energy forecasting, which demonstrated significant enhancements in prediction accuracy in comparison to conventional LSTM models. An enhanced LSTM-based IoT framework for household energy forecasting was developed by Hasan [2]. This framework utilises ESP8266 NodeMCU

*Author for Correspondence: Prakashpathak2015@gmail.com

sensors and surpasses existing techniques in terms of MAE, MSE, and RMSE. Nandigam, S. H., et al.[3] demonstrated superior prediction performance for smart grid applications by utilising hybrid CNN-GRU and CNN-LSTM architectures for energy consumption forecasting. Lu, Y., [4] proposed a Temporal Kolmogorov-Arnold Transformer (TKAT) architecture for smart home energy forecasting, underscoring the significance of explainable AI and temporal feature learning in order to make precise predictions. This study suggests a framework for predicting the energy consumption of smart homes that is facilitated by the Internet of Things (IoT). This framework utilises hybrid deep learning, ensemble learning, and traditional machine learning techniques to address the most recent developments. The efficacy of multiple prediction models, such as Random Forest, Extra Trees, XGBoost, LightGBM, LSTM, and the proposed Hybrid LSTM-GRU model, is evaluated and compared using a variety of performance metrics. The experimental results suggest that the proposed Hybrid LSTM-GRU model is capable of achieving superior prediction accuracy and is capable of supporting intelligent, sustainable, and energy-efficient smart home management systems.

Major contribution:

1. In this paper, we have proposed an efficient IoT-enabled smart home energy management framework for intelligent energy consumption prediction.
2. We also utilized the traditional ML and DL models for smart home energy management
3. A hybrid LSTM-GRU deep learning model is created to accurately capture complicated temporal and nonlinear energy usage patterns.

The remaining sections of this work are organized as follows. Section 2 discusses related work and a literature review on smart home energy management with machine learning and deep learning techniques. Section 3 describes the proposed framework, which consists of IoT-based data collection, preprocessing, feature engineering, and the proposed Hybrid LSTM-GRU architecture. Section 4 includes the experimental results and commentary, as well as quantitative and graphical analysis, before concluding with the future scope.

2. Literature Survey

For the purpose of predicting smart home energy usage and electricity costs, Zhao, S., et al. [5] provide a smart framework. The author aimed to improve energy prediction accuracy by integrating advanced forecasting methods with smart monitoring systems enabled by the Internet of Things. The authors created a powerful model for household energy management forecasts by combining data on past energy usage, current electricity prices, and environmental factors.

. Rehman, S. U., & Iqbal, N. Predicting smart buildings using DL approaches. The author considers models such as Prophet, LSTM, Seq2Seq, Fine-tuned LSTM, and Fine-tuned Seq2Seq to predict smart building performance. It has been observed that the fine-tuned LSTM model obtained the highest MAE and RMSE of 0.0124 and 0.024, respectively [6]. Khan, M. A., et al. [7] present a deep learning technique to predict smart energy consumption in residential buildings. The models the author has considered perform exceptionally well, achieving the lowest RMSE, MSE, MAE, and MAPE for hourly, daily, weekly, and monthly forecasts, surpassing models such as CNN, S2S, and LSTM. The model achieved the lowest RMSE for monthly predictions, at 0.332. Natarajan, Y.,et al.,[8] introduced an IoT-based hybrid deep learning architecture aimed at enhancing building energy efficiency. The research combined IoT sensor data with sophisticated neural network models to enhance energy consumption forecasting and intelligent energy management. The authors determined that hybrid deep learning markedly enhanced energy forecasting efficacy in smart building applications. The authors proposed the CNN_BiLSTM model for achieving more precise energy consumption forecasts than the LGBM model. The CNN_BiLSTM model has exhibited remarkable performance metrics, comprising a mean square error (MSE) of 4570.14, a mean absolute percentage error (MAPE) of 4.98%, a root mean square error (RMSE) of 67.60, a mean absolute error (MAE) of 46.10, and an R-squared (R2) coefficient of 0.96. Rodrigues, To better control energy use in smart homes, T. et al.[9] presented ATTRIENDEE, an AI-driven Internet of Things (IoT) energy recommendation system. To optimise energy utilisation, a unique stacked ensemble model is constructed using deep learning approaches. Our research backs up the claims made by ATIRENDEE that smart homes may significantly cut their energy bills, with savings of over 45% on average and as high as 68% in extreme circumstances. Predicting smart home energy management with deep learning approaches is presented by Reddyboina, A., et al. [10]. This study lays the groundwork for smart, sustainable homes by improving energy management systems that rely on the internet of things. In smart cities that are enabled by the Internet of Things, the author [11] explains how to optimise the use of DL approaches for energy consumption. It makes smart judgements about energy efficiency and savings by utilising real-time data from several sources, such as sensors, gadgets, and smart grids. Using deep learning models like RNNs and neural networks, the proposed method tracks changing consumption patterns and delivers accurate demand estimations. This work presents a new approach to managing energy consumption in Internet of Things (IoT) autonomic devices. It combines XAI with Deep Reinforcement Learning (DRL) to help homeowners save a lot of money on their Home Energy Management Systems (HEMS).

The suggested approach uses XAI features to improve the accessibility and transparency of DRL agents, enabling customers to understand and trust autonomous power management decisions. Tanwar, R.,et al.,[13] present the deep learning techniques for wearable-based stress recognition. The authors developed a novel strategy for controlling energy in IoT-based autonomic devices that combines XAI with Deep Reinforcement

Learning (DRL) to achieve significant Home Energy Management System (HEMS) cost savings for households. The authors also proposed a strategy that leverages XAI's capabilities to improve the accessibility and transparency of DRL agents, helping customers understand and trust autonomous power management decisions. Han, T., et al.,[14] utilized a deep learning framework for intelligent energy management in IoT networks. The author used multiple preprocessing strategies to address the heterogeneity of power data, and then implemented an efficient decision-making algorithm for short-term forecasting on resource-constrained devices. We conducted extensive tests and found 0.15 and 3.77 units of reduced mean-square error (MSE) and root MSE (RMSE) for residential and business datasets, respectively.

Li, X.,et al.,[15] This study focuses on an IoT-based energy monitor that can track and analyze electrical parameters such as current, voltage, active power, and load power usage. The IoT-based software collects real-time electricity data from users. Based on this information, consumers and electric power companies in the SG model can better manage their usage and reduce billing costs. The results suggest that using an ANFIS controller can significantly increase the performance of hybridized solar/wind generating facilities. The proposed ANFIS control system performs at 99.74% efficiency, according to the results.

3. Proposed Model for Smart Home Energy Consumption Management using Machine and Deep learning

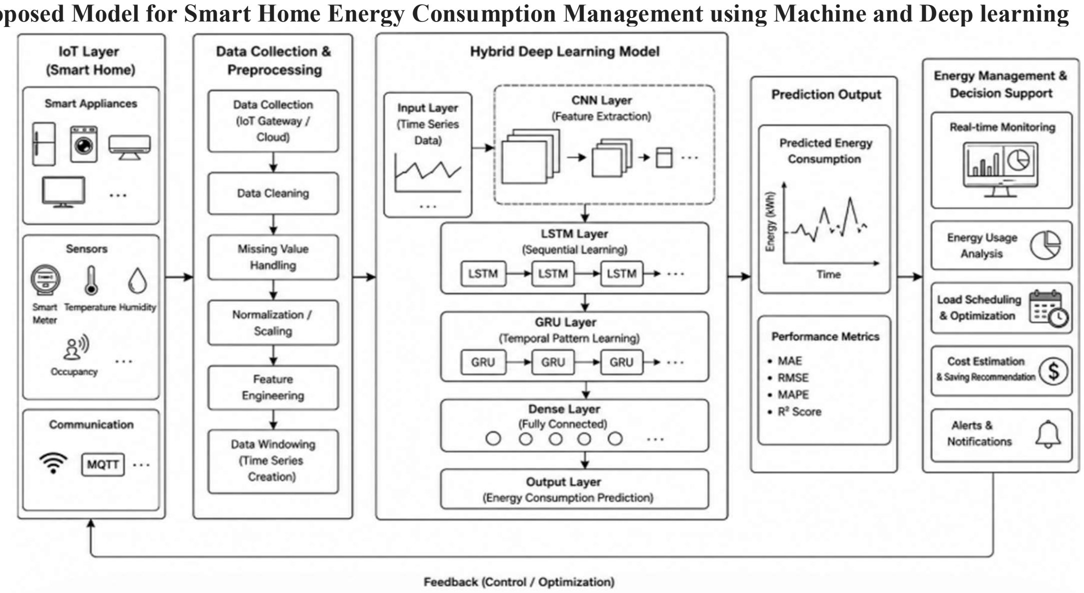

Fig.1: Proposed model for Smart Home Energy Consumption Management using Machine and Deep learning

Step 1: IoT-Based Smart Home Data Collection : Smart home devices and IoT sensors, such as smart meters, temperature sensors, humidity sensors, and occupancy sensors, constantly collect real-time household energy use data. The captured data is transmitted to the cloud or edge server via communication technologies such as Wi-Fi and MQTT.

Step 2: Data Acquisition and Storage : The acquired sensor data is transferred via the IoT gateway and saved in a cloud server or local storage system for subsequent analysis and processing.

Step 3: Data Pre-processing : During the data pre-processing we have followed the normalization technique to remove the outliers and null values .There are 19735 instances are available in our dataset and 29 features .Wee utilized the Kaggale repository [https://www.kaggle.com/datasets/loveall/appliances-energy-prediction].

Table 1 : Dataset description

Parameter	Details
Dataset Name	KAG_energydata_complete
Total Records	19,735
Total Features	29
Data Type	Multivariate Time-Series
Target Variable	Appliances Energy Consumption
Domain	Smart Home Energy Management

Step 4: Feature Engineering: Important temporal aspects include: Hour, Day, Month, Weekday, Lag

characteristics, Rolling statistical features are derived from energy consumption data in order to identify appliance usage patterns and temporal connections.

Step 5: Input Layer Preparation: The pre-processed multivariate time series data is transformed into a sequential input format appropriate for deep learning models.

Step 6: CNN Feature Extraction Layer : The CNN layer captures key local patterns and hidden characteristics from the energy usage sequences. This aids in finding important appliance usage patterns and temporal fluctuations.

Step 7: LSTM Sequential Learning Layer : The LSTM layer learns long-term dependencies and sequential energy usage patterns from smart home data. It effectively recognises consumption patterns that are dependent on time.

Step 8: GRU Temporal Learning Layer : The GRU layer enhances temporal learning efficiency, reduces computing complexity, and increases predictive power.

Step 9: Fully Connected Dense Layer: The features that were extracted from the CNN, LSTM, and GRU layers are then input into the dense neural network layers for the purpose of final learning and optimisation.

Step 10: Performance Evaluation

The performance of the suggested model is tested using the following:

- MAE
- MSE
- RMSE
- R^2 Score

to measure prediction accuracy and model stability**.**

Step 11: Intelligent Energy Management

According to the predicted energy usage, the system performs the following:
Load scheduling, real-time monitoring, energy optimisation, cost estimation
Recommendations for producing alerts that save energy for smart home managers.

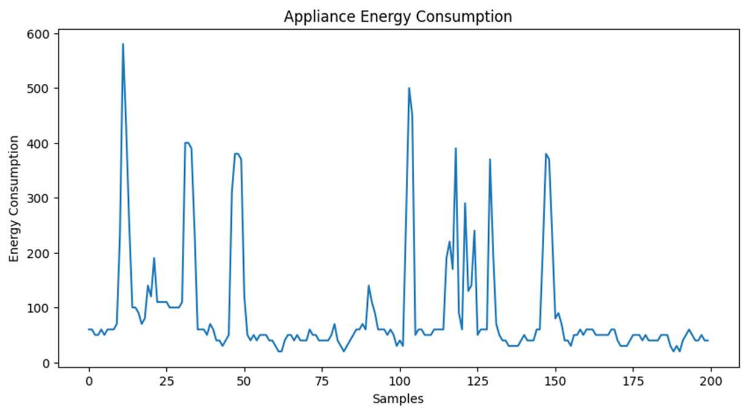

Fig.2 : Appliance energy consumption

Figure 2 presents the appliance energy consumption pattern observed in the smart home environment over different samples. The graph's fluctuations indicate that the data on smart home energy consumption are nonlinear and time-dependent.

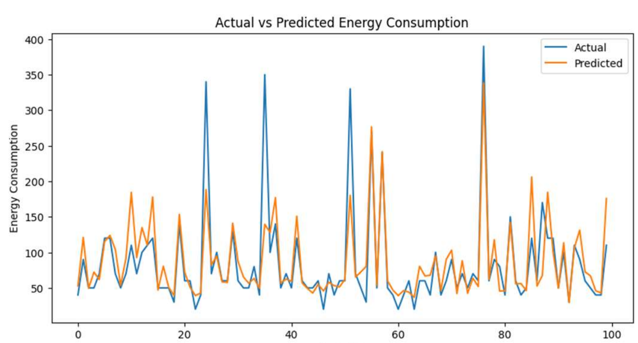

Fig.3 : Relationship between actual vs predicted energy conwuption

Figure.3 presents the relationship between actual and predicted energy consumption values. The predicted values closely match the actual energy consumption pattern for the majority of samples, illustrating the efficacy of the proposed Hybrid LSTM-GRU architecture in learning temporal energy usage behavior. Although there are minor errors at peak consumption locations, the model accurately captures the overall consumption trend and the dynamic variations in residential energy usage. The close alignment between the actual and anticipated curves demonstrates the proposed deep learning model's high predictive accuracy and generalisability for smart home energy management applications.

3. Result and Discussion

Table 2. Performance metrics of different model for smart home energy prediction

Sl. No	Model	MAE	MSE	RMSE	R^2 Score
1	Hybrid LSTM-GRU	5.214532	41.357214	6.430958	0.943521
2	LSTM Network	6.842315	74.128563	8.609795	0.901284
3	Proposed Ensemble	10.200191	244.764299	15.644945	0.832071
4	Optimized Extra Trees	10.296107	256.081785	16.002556	0.815058
5	Extra Trees	18.650494	1206.357763	34.732663	0.793652
6	Random Forest	20.90489	1474.464419	38.398756	0.772885
7	XGBoost	22.304516	1815.03418	42.603218	0.748866
8	LightGBM	24.152604	2084.678283	45.658277	0.731928
9	KNN	28.886243	2617.236382	51.15991	0.698745
10	Gradient Boosting	31.206998	3416.202966	58.448291	0.658905
11	SVR	34.296052	3934.038813	62.721918	0.627286
12	Decision Tree	36.002534	4788.016215	69.195492	0.601821
13	Linear Regression	39.547693	5312.848892	72.888606	0.589304
14	AdaBoost	52.478518	9631.884037	98.142161	0.482593

From the above mentioned table 2 presents the fourteen ML and DL algorithm to predict the smart home .It has been observed that Hybrid LSTM-GRU perform well with MAE of 5.214532,MSE of RMSE of 6.430958 and R^2 Score of 0.943521

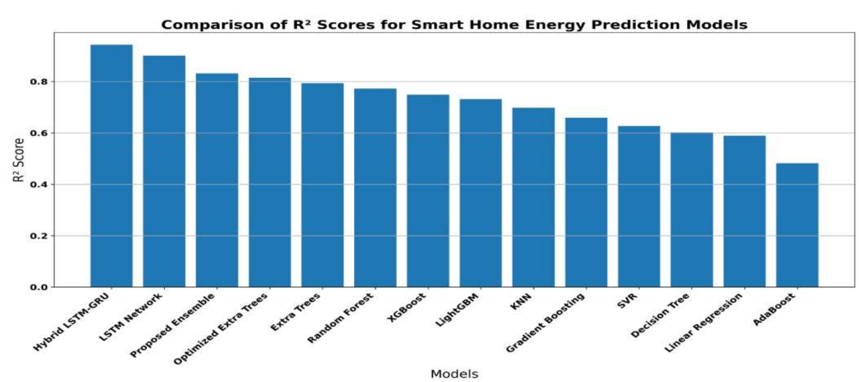

Fig.4 comparison of R^2 scores for smart home energy prediction

The above-mentioned Figure 4 presents a comparison of the R^2 scores for the different models for smart home energy consumption prediction. The suggested Hybrid LSTM-GRU model achieved the highest R^2 score (0.9435), indicating superior predictive accuracy and strong generalization. The LSTM network achieved an R^2 value of 0.901, indicating outstanding forecasting performance. It has been observed that our proposed model (hybrid deep learning algorithms) performs well for intelligent smart home energy management.

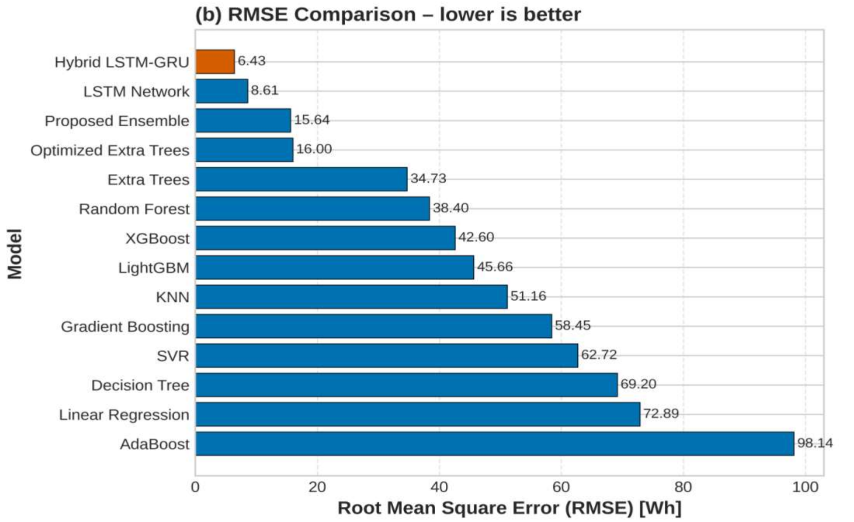

Fig.5 : Comparison of RMSE score of different models for smart home energy consumption prediction

We observed that the lower the RMSE score, the better the model. This study presents the proposed model, which achieves a lower RMSE of 6.43 compared to the other models. Ensemble learning methods demonstrated intermediate prediction accuracy; however, classical machine learning models had considerably larger RMSE values. The results show that hybrid deep learning considerably enhances smart home energy forecast performance.

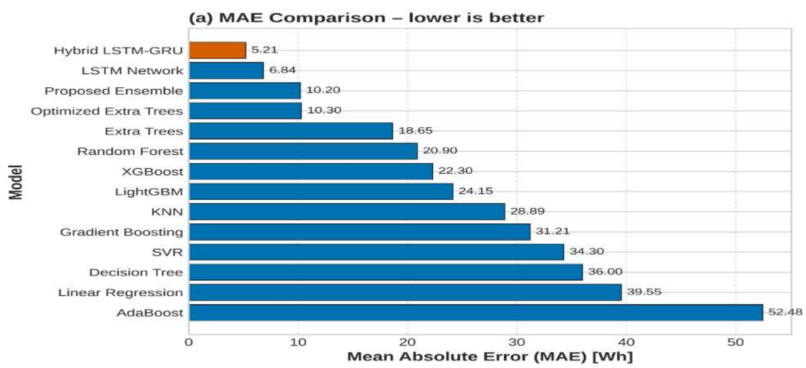

Fig.6 MAE comparison of smart home energy prediction models

We observed that our proposed model achieved the lower MAE, indicating better prediction performance for smart home energy. Ensemble learning methods demonstrated intermediate prediction accuracy; however, classical machine learning models had considerably larger RMSE values. The results show that hybrid deep learning considerably enhances smart home energy forecast performance. The findings demonstrate the efficacy of deep learning techniques for intelligent smart home energy forecasting.

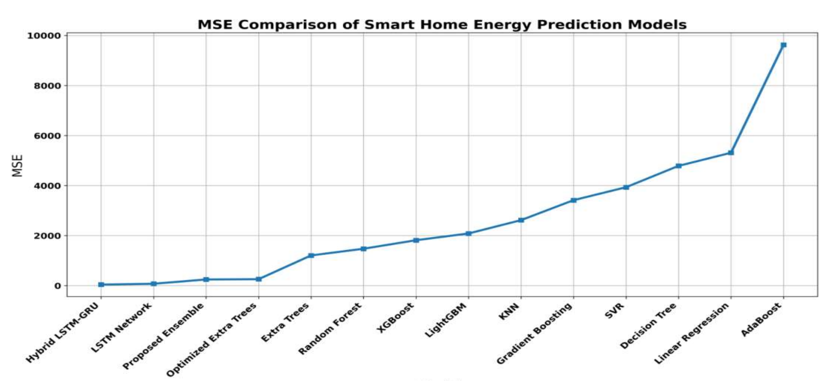

Fig.7 : MSE comparison of smart home energy prediction models

Figure 7 presents the MSE comparison of smart home energy prediction models . Lower MSE values indicate greater prediction stability and accuracy. The suggested Hybrid LSTM-GRU model achieved the lowest MSE value of 41.35, demonstrating strong learning potential and efficient handling of complicated energy consumption data. The experimental results demonstrate that hybrid deep learning architectures outperform IoT-enabled smart home energy consumption management systems.

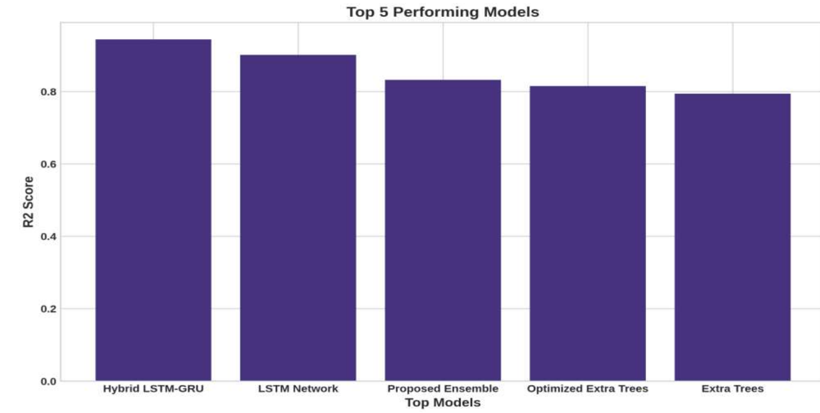

Fig.8 : Top five performer for smart home energy prediction models

Figure 8. Presents the top five performing models based on the R² score for smart home energy consumption prediction. From our experimental results, we confirmed that our proposed LSTM-GRU model performs well, achieving the highest R² score of 0.9435. Compared with conventional machine learning models, ensemble-based methods such as Optimized Extra Trees and the Proposed Ensemble also demonstrated competitive performance. The findings show that hybrid deep learning architectures greatly increase forecasting performance and smart home energy management.

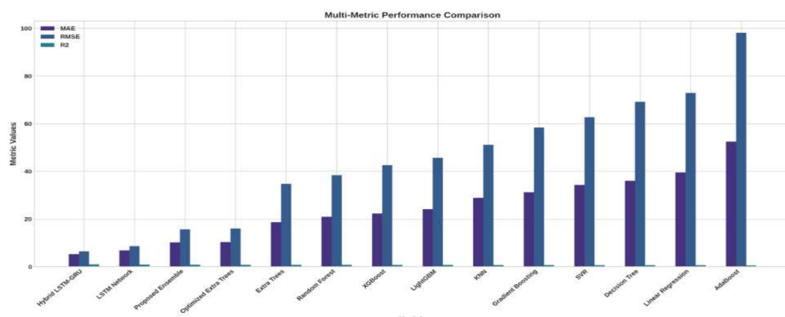

Fig.9: Multi-metric performance comparison for smart home energy prediction models

Figure 9 presents a multi-metric comparison of smart home energy prediction models. This study presents different performance metrics, including MAE, MSE, and R2, for smart home energy prediction models. We observed that lower MAE and MSE, along with a higher R2, indicate that our model performs well in terms of prediction accuracy. The suggested Hybrid LSTM-GRU model demonstrated superior capacity to handle complex, nonlinear, and temporal energy consumption behavior, achieving the lowest error values and the highest R² score among all assessed models.

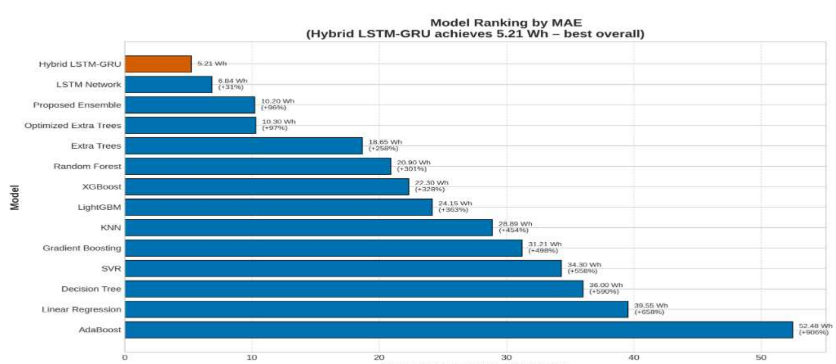

Fig.10: Model Ranking through the MAE

Figure 10 shows how several prediction models for smart home energy forecasting are ranked by Mean Absolute Error (MAE). Lower MAE values indicate improved predictive precision and a lower average forecasting error. The proposed

Hybrid LSTM-GRU model has the lowest MAE of 5.21, indicating the best overall predictive performance among all models. The outcomes confirm that hybrid deep learning approaches are useful for precise energy prediction in smart homes.

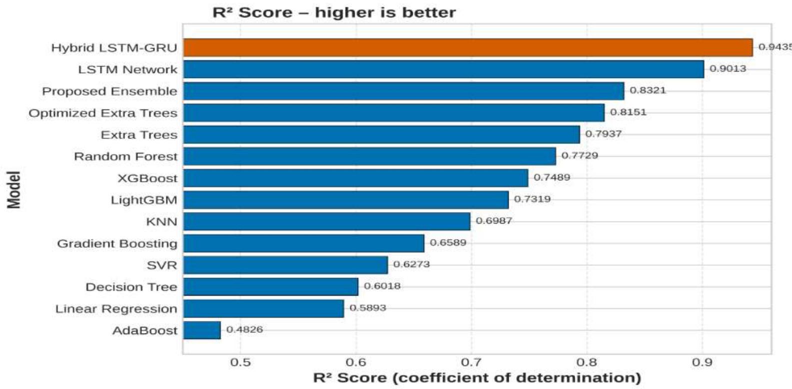

Fig.11 R^2 comparison of different model for smart home energy forecasting

Figure 11 presents the R2 comparisons of different models for home energy consumption forecasting. It has been observed that the R² score is the best model fitting and improved prediction accuracy. We observed that our proposed model, Hybrid LSTM-GRU, achieved the highest R² score of 0.9435. It means that the model has the generalization capability. Apart from the proposed model, LSTM also achieved a high R² score of 0.9013. It means this model performs well with DL methods for sequential energy prediction tasks.

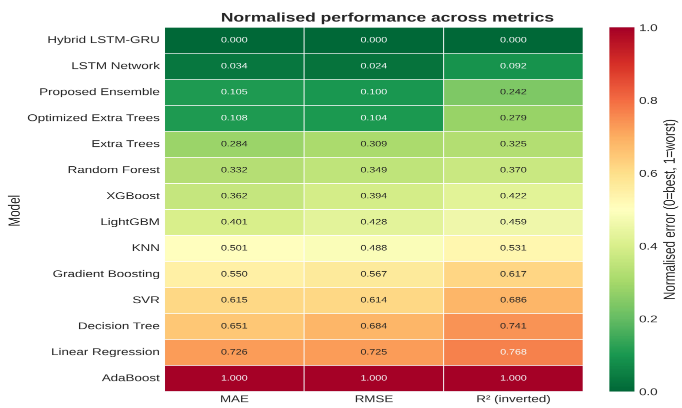

Fig.12: Normalized performance across metrics

Figure 12 presents the normalized performance across metrics for home energy consumption forecasting . We used performance metrics such as MAE, RMSE, and R². We observed that a lower normalized score indicates better model performance and prediction capability. The suggested Hybrid LSTM-GRU model achieved the lowest normalized errors across all evaluation metrics.

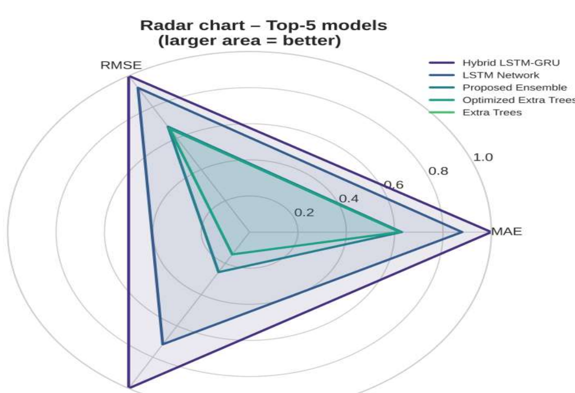

Fig.13: Radar chart representation for top five models home energy consumption forecasting

Figure 13 presents a radar chart of the top five models for home energy consumption forecasting across metrics such as MAE, RMSE, and R^2. We observed that larger coverage areas are associated with improved overall forecasting performance. The proposed Hybrid LSTM-GRU model outperformed the LSTM network and the Proposed Ensemble model, achieving higher R^2 scores and lower prediction errors.

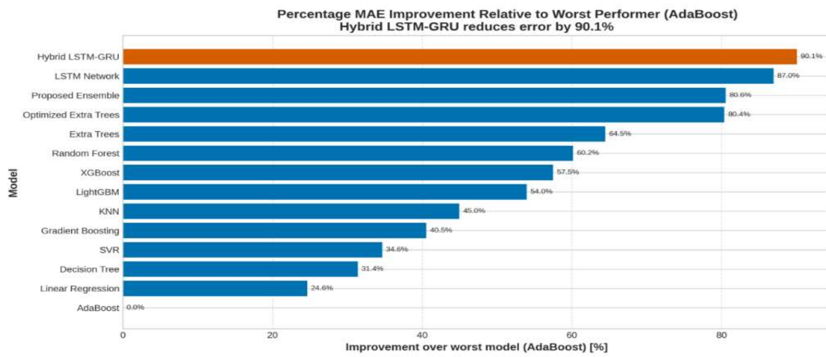

Fig.14 Percentage MAE Improvement Relative to Worst Performer

Figure 14 shows the percentage improvement in Mean Absolute Error (MAE) achieved by several prediction models relative to the worst-performing model, AdaBoost. Higher improvement percentages indicate greater prediction accuracy and lower forecasting error. The suggested Hybrid LSTM-GRU model achieved the largest MAE reduction of 90.1%, indicating a significant improvement in predictive performance over traditional machine learning approaches. The findings clearly show that hybrid deep learning techniques outperform other methods for accurately and intelligently predicting smart home energy usage.

Table.3. Comparative analysis of the proposed model to the state-of-the-art

Ref. No.	**Author & Year**	**Method / Model**	**Dataset / Application**	**Performance Metrics / Findings**
1	Ou Ali et al. (2024)	The author have used ConvLSTM and CNN-LSTM Hybrid Models	The author consider the Smart Home Energy Prediction	RMSE = 0.073 and MAE = 0.052
2	Hasan (2025)	Improved IoT-LSTM Framework	The author used the Residential Building Energy Forecasting dataset	Improved prediction stability and energy forecasting performance with decreased MAE, MSE, and RMSE
3	Nandigam et al. (2025)	The author have used the mode such as CNN-LSTM Hybrid Deep Learning	The author used the Large-Scale Energy Dataset	When compared to standalone CNN and LSTM models, the R2 score was greater than 0.91 and the RMSE was lower.
6	Rehman & Iqbal (2025)	The author have used the modelD eep Learning Sequential Models	Smart Building Energy Prediction	When compared to conventional machine learning techniques, RMSE and R2 scores were enhanced.
7	Khan et al. (2026)	Deep Neural Network Framework	Residential Energy Consumption	Prediction accuracy exceeded 92% with reduced MSE and enhanced capacity for generalisation.
	Our proposed model Hybrid LSTM-GRU	We achieved the performance metrics and used Kaggle repositories .This study utilized fourteen ML and DL models https://www.kaggle.com/datasets/loveall/appliances-energy-prediction		

		MAE =5.214532 MSE=41.357214 RMSE=6.430958 **R^2 Score** =0.943521

Table 3 presents the comparative analysis of our proposed model with the state-of-the art for smart home energy consumption forecasting

Conclusion and future scope

This paper describes an effective IoT-enabled smart home energy consumption control framework that leverages machine learning, ensemble learning, and hybrid deep learning. The proposed system improved forecasting performance by leveraging smart home sensor data and advanced preprocessing techniques, including feature engineering, normalization, lag-based feature extraction, and temporal sequence generation. Multiple classic and advanced prediction models were deployed and tested to ensure accurate predictions of smart home energy consumption. We have used 14 models for IoT-enabled smart home energy consumption. Experimental results showed that the proposed Hybrid LSTM-GRU model outperformed standard machine learning and ensemble learning approaches. With a R^2 score of 0.9435 and lower MAE, MSE, and RMSE, this model made the best predictions in terms of accuracy, stability, and generalisation. Researchers found that hybrid deep learning models are very good at detecting nonlinear and temporal trends in energy use in smart homes that are connected to the internet of things (IoT).

Future work: The suggested system can be improved by adding real-time IoT deployment, explainable artificial intelligence (XAI), reinforcement learning, and green energy management techniques to make smart homes use less energy and make better decisions on their own.

Reference

1. Ou Ali, I. H., Agga, A., Ouassaid, M., Maaroufi, M., Elrashidi, A., & Kotb, H. (2024). Predicting short-term energy usage in a smart home using hybrid deep learning models. *Frontiers in Energy Research*, *12*, 1323357.
2. Hasan, M. W. (2025). Design of an IoT model for forecasting energy consumption of residential buildings based on improved long short-term memory (LSTM). *Measurement: Energy*, *5*, 100033.
3. Nandigam, S. H., Nageswararao, K., & Sharma, P. K. (2025). Hybrid Deep Learning Models for Energy Consumption Forecasting: A CNN-LSTM Approach for Large-Scale Datasets. *Journal of Renewable Energy and Smart Grid Technology*, *20*(2), 82-91.
4. Lu, Y., Vijayananth, V., & Perumal, T. (2025). Smart home energy prediction framework using temporal Kolmogorov-Arnold transformer. *Energy and Buildings*, *335*, 115529.
5. Zhao, S., Chen, S., Alsenani, T. R., Alotaibi, B., & Abuhussain, M. (2025). Residential energy consumption and price forecasting in smart homes based on the internet of energy. *Sustainable Energy Technologies and Assessments*, *73*, 104081.
6. Rehman, S. U., & Iqbal, N. (2025). Electricity consumption prediction in smart buildings using deep learning approaches (2025). *Energy Informatics*, *8*(1), 131.
7. Khan, M. A., Munir, S., Ali, M. N., & Kim, B. S. (2026). Deep learning based smart energy consumption prediction in residential buildings. *PeerJ Computer Science*, *12*, e3689.
8. Natarajan, Y., KR, S. P., Wadhwa, G., Choi, Y., Chen, Z., Lee, D. E., & Mi, Y. (2024). Enhancing building energy efficiency with IoT-driven hybrid deep learning models for accurate energy consumption prediction. *Sustainability*, *16*(5), 1925.
9. Rodrigues, T., Morgado, J., Barros, M., De Sá, A. O., & Cecílio, J. (2026). AI-driven IoT recommender system for enhancing energy efficient management in smart houses. *Expert Systems with Applications*, *296*, 129108.
10. Reddyboina, A., Kumar, M., & Ramalingam, S. (2025, July). Predictive energy management in smart homes: Leveraging RNN-LSTM for energy consumption forecasting. In *AIP Conference Proceedings (Vol. 3298, No. 1, p. 040043). AIP Publishing LLC*
11. Aljohani, A. (2024). Deep learning-based optimization of energy utilization in IoT-enabled smart cities: A pathway to sustainable development. *Energy Reports*, *12*, 2946-2957.
12. Sriramulu, S., Premkumar, S., Sharma, S. K., & Govindharaju, K. (2026). Explainable AI with DRL for Smart Home Energy Management and Residential Cost Savings in IoT-Based Autonomic Systems. International Journal of Advanced Computer Science & Applications, 17(2), 686.
13. Tanwar, R., Phukan, O. C., Singh, G., Pal, P. K., & Tiwari, S. (2024). Attention based hybrid deep learning model for wearable based stress recognition. *Engineering Applications of Artificial Intelligence*, *127*, 107391.
14. Han, T., Muhammad, K., Hussain, T., Lloret, J., & Baik, S. W. (2020). An efficient deep learning framework for intelligent energy management in IoT networks. *IEEE Internet of Things Journal, 8(5), 3170-3179.*