Journal of IoT and Cybersecurity Systems

Artificial Intelligence-Based Building Electricity Consumption Prediction Using Light Gradient Boosting Machine for Time Series Regression

Ida Bagus Putu Arkananta, Fiqih Nuraffi Rachmansyah, Ghania Rabbanni Hidayat, Nabila Nur Halisa, and Gigih Angun Farmala

Abstract. The problem of this research is Increasing electricity consumption in buildings has become a significant challenge in energy management and electricity load planning due to dynamic usage patterns influenced by operational schedules, environmental conditions, and temporal factors. The research gap identified is that machine learning techniques have been widely applied for electricity forecasting, but studies that integrate temporal, environmental, and historical consumption features within a unified prediction framework are still relatively limited. This study proposes an Artificial Intelligence-based building electricity consumption prediction framework using Light Gradient Boosting Machine (LightGBM) and time series regression techniques. The proposed approach integrates data preprocessing, feature engineering, environmental variables, temporal information, building identifiers, and historical electricity consumption records to improve forecasting accuracy. The dataset was processed chronologically and divided into training and validation sets without shuffling to preserve temporal dependencies. Model performance was evaluated using Root Mean Squared Error (RMSE). Experimental results demonstrate that the proposed model achieved an average RMSE of 143.36 and successfully captured the overall trend of electricity consumption across different buildings. The findings indicate that the integration of temporal, environmental, and historical consumption features contributes to effective forecasting performance and supports data-driven energy management applications. Future research may focus on incorporating occupancy information, real-time sensor measurements, and advanced deep learning approaches to further improve forecasting accuracy.

Keywords: Building Electricity Consumption Prediction, LightGBM, Time Series Regression, Machine Learning, Energy Management, Load Forecasting.

Author(s):

Ida Bagus Putu Arkananta
Department of Electrical Engineering, President University, Jl. Ki Hajar Dewantara, Kota Jababeka, Cikarang Utara, Bekasi 17550, Indonesia
E-mail: ida.arkananta@student.president.ac.id

Fiqih Nuraffi Rachmansyah
Department of Electrical Engineering, President University, Jl. Ki Hajar Dewantara, Kota Jababeka, Cikarang Utara, Bekasi 17550, Indonesia
E-mail: fiqih.rachmansyah@student.president.ac.id

Ghania Rabbanni Hidayat
Department of Electrical Engineering, President University, Jl. Ki Hajar Dewantara, Kota Jababeka, Cikarang Utara, Bekasi 17550, Indonesia
E-mail: ghania.hidayat@student.president.ac.id

Nabila Nur Halisa
Department of Electrical Engineering, President University, Jl. Ki Hajar Dewantara, Kota Jababeka, Cikarang Utara, Bekasi 17550, Indonesia
E-mail: nabila.halisa@student.president.ac.id

Gigih Angun Farmala
Department of Electrical Engineering, President University, Jl. Ki Hajar Dewantara, Kota Jababeka, Cikarang Utara, Bekasi 17550, Indonesia
E-mail: gigih.farmala@student.president.ac.id

Corresponding Author: Ida Bagus Putu Arkananta (ida.arkananta@student.president.ac.id)

How to Cite This Article: Arkananta, I. B. P., Rachmansyah, F. N., Hidayat, G. R., Halisa, N. N., & Farmala, G. A. (2026). Artificial Intelligence-Based Building Electricity Consumption Prediction Using Light Gradient Boosting Machine for Time Series Regression. Journal of IoT and Cybersecurity Systems, 1(1), 15–30. https://doi.org/10.58291/jicss.v1i1.3

Received : 28 May, 2026; Revision: 10 June, 2026; Accepted: 7 July, 2026; Publication: 9 July, 2026.

1. Introduction

Electricity consumption in buildings has become one of the major concerns in modern energy management systems due to the continuous growth of commercial, educational, and industrial activities. Buildings contribute a substantial portion of overall electricity demand, making efficient energy utilization and load management increasingly important. The growing complexity of electricity usage patterns, influenced by operational schedules, occupancy levels, and environmental conditions, presents significant challenges for building managers and energy planners (Čegovnik et al., 2023; Gassar, 2024; Yazici et al., 2022).

Accurate forecasting of electricity consumption plays an important role in supporting energy efficiency, reducing operational costs, and improving decision-making processes. Without reliable prediction systems, energy management often relies on manual estimation or historical averages that may not adequately reflect future demand conditions. Such limitations can result in inefficient resource allocation, increased operational expenses, and difficulties in maintaining optimal energy consumption levels (Cordeiro-Costas et al., 2023; Pallonetto et al., 2022).

Recent advances in artificial intelligence and machine learning have provided new opportunities for improving electricity consumption forecasting. Various machine learning techniques have been successfully applied to identify complex relationships between historical consumption data and influencing factors, enabling more accurate forecasting compared with traditional statistical approaches (Adebayo Olusegun Aderibigbe et al., 2023; Akhtar et al., 2023). Among these approaches, Light Gradient Boosting Machine (LightGBM) has attracted considerable attention due to its computational efficiency, scalability, and strong predictive performance in regression tasks involving large datasets and multiple input variables.
.
Although machine learning techniques have been widely applied to electricity load forecasting, further research is needed to evaluate the combined influence of temporal information, environmental variables, building characteristics, and historical consumption patterns within a unified framework. Therefore, this study proposes an AI-based building electricity consumption prediction system using LightGBM time series regression, integrating data preprocessing, feature engineering, model training, and performance evaluation using Root Mean Squared Error (RMSE) to develop and assess a predictive model that supports accurate electricity consumption forecasting and data-driven energy management decisions (Baul et al., 2024; Suhartomo et al., 2025; Tae et al., 2023).

The remainder of this paper is organized as follows. Section 2 presents the literature review related to electricity consumption forecasting and machine learning approaches. Section 3 describes the research methodology and model development process. Section 4 presents the experimental results, while Section 5 discusses the findings and limitations of the study. Finally, Section 6 concludes the paper and provides recommendations for future work.

2. Literature Review

2.1. Building Electricity Consumption Forecasting

Electricity consumption forecasting has become an essential component of modern energy management systems. Accurate forecasting enables building operators to optimize energy utilization, reduce operational costs, improve load planning, and support sustainable energy management practices. Electricity demand in buildings is influenced by various factors, including occupancy levels, operational schedules, weather conditions, building characteristics, and seasonal variations. As a result, forecasting electricity consumption remains a challenging task due to the dynamic and nonlinear nature of energy usage patterns (Rodrigues et al., 2023; Silalahi et al., 2021; Simanjuntak, Heryanto, et al., 2024).

Building electricity forecasting is generally categorized into short-term, medium-term, and long-term forecasting. Short-term forecasting focuses on predicting electricity demand over the next few hours or days and is widely used for operational planning and energy management. Medium-term and long-term forecasting are commonly applied to infrastructure planning, energy policy development, and investment analysis. Among these categories, short-term load forecasting has received considerable attention because of its direct impact on daily building operations and electricity cost optimization (Akhtar et al., 2023; Silalahi et al., 2024; Simanjuntak, Haidi, et al., 2024).

Several studies have demonstrated that accurate forecasting models can significantly improve energy efficiency by enabling proactive decision-making and better resource allocation. Consequently, developing reliable electricity consumption forecasting systems remains an important research area within intelligent energy management and smart building applications (Pallonetto et al., 2022).

2.2. Machine Learning-Based Load Forecasting

Machine learning techniques have been widely adopted for electricity consumption forecasting because of their ability to learn complex relationships from historical data without requiring strict statistical assumptions. Unlike conventional forecasting approaches, machine learning algorithms can model nonlinear patterns and interactions among multiple influencing variables, resulting in improved forecasting performance in many practical applications (Adebayo Olusegun Aderibigbe et al., 2023; Zini & Carcasci, 2023).

Various machine learning methods have been applied in load forecasting studies, including Artificial Neural Networks (ANN), Random Forest, Support Vector Regression (SVR), XGBoost, and Long Short-Term Memory (LSTM) networks. Deep learning approaches such as LSTM have shown strong performance in capturing temporal dependencies within electricity consumption data. However, these methods often require substantial computational resources and large training datasets, which may limit their practicality in certain applications (Al-Jamimi et al., 2023; Bashir et al., 2022; Ullah et al., 2024).

Recent studies have also highlighted the effectiveness of ensemble learning methods for short-term load forecasting. Ensemble algorithms combine multiple decision trees to improve prediction accuracy and reduce overfitting. As a result, machine learning has become one of the dominant approaches for building energy forecasting and intelligent energy management systems (Ibrahim et al., 2022).

2.3. LightGBM for Time Series Regression

Light Gradient Boosting Machine (LightGBM) is an ensemble learning algorithm based on Gradient Boosting Decision Trees (GBDT) that is designed to achieve high predictive performance while maintaining computational efficiency. LightGBM employs histogram-based learning and leaf-wise tree growth strategies, allowing it to process large datasets efficiently and reduce training time compared with conventional boosting algorithms (Sitompul et al., 2025; Yao et al., 2022).

In electricity load forecasting applications, LightGBM has demonstrated promising results due to its capability to model nonlinear relationships among environmental, temporal, and historical consumption variables. The algorithm can effectively handle large feature spaces while maintaining strong generalization performance. Previous studies reported that LightGBM-based forecasting models achieved competitive prediction accuracy compared with other machine learning and deep learning approaches for short-term load forecasting tasks (Dudek, 2022; Koukaras et al., 2024).

In addition to prediction accuracy, LightGBM offers advantages in interpretability and scalability, making it suitable for practical deployment in building energy management systems. These characteristics make LightGBM an attractive choice for developing intelligent electricity consumption prediction models.

2.4. Research Gap and Proposed Study

Previous studies have demonstrated the effectiveness of machine learning techniques for electricity load forecasting. However, many existing studies focus on specific forecasting methods or limited feature categories without comprehensively examining the combined effects of temporal information, environmental conditions, building characteristics, and historical consumption patterns within a unified framework. In addition, despite the increasing popularity of LightGBM in forecasting applications, studies investigating its use for building electricity consumption prediction with extensive feature engineering remain relatively limited (Hu et al., 2022; Sitompul et al., 2026).

Therefore, this study proposes a LightGBM-based time series regression framework for building electricity consumption prediction. The model integrates environmental variables, temporal features, building identifiers, and historical electricity consumption data to improve forecasting accuracy. Furthermore, the effects of lagged variables, rolling statistics, temporal attributes, and environmental factors are evaluated using Root Mean Squared Error (RMSE) to assess the effectiveness of the proposed approach for building energy management applications (Raviprabhakaran et al., 2024).

3. Research Methods

This study proposes a machine learning-based framework for predicting building electricity consumption using the Light Gradient Boosting Machine (LightGBM) algorithm. Figure 1 illustrates the overall research workflow of the proposed system, including data collection, preprocessing, feature engineering, model training, prediction, and performance evaluation stages. The implementation process of the proposed forecasting system is presented in Figure 2. The flowchart describes the programming workflow, starting from dataset preprocessing, feature generation, model training, prediction generation, and model evaluation.

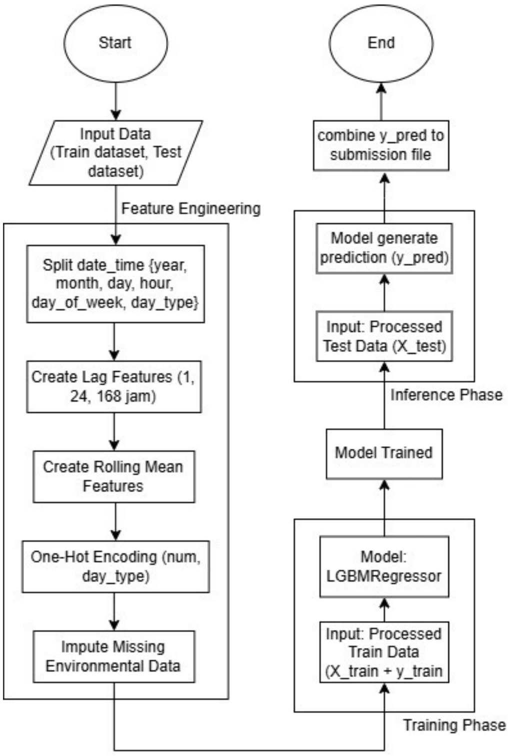

Figure 1. Flowchart Work Process.

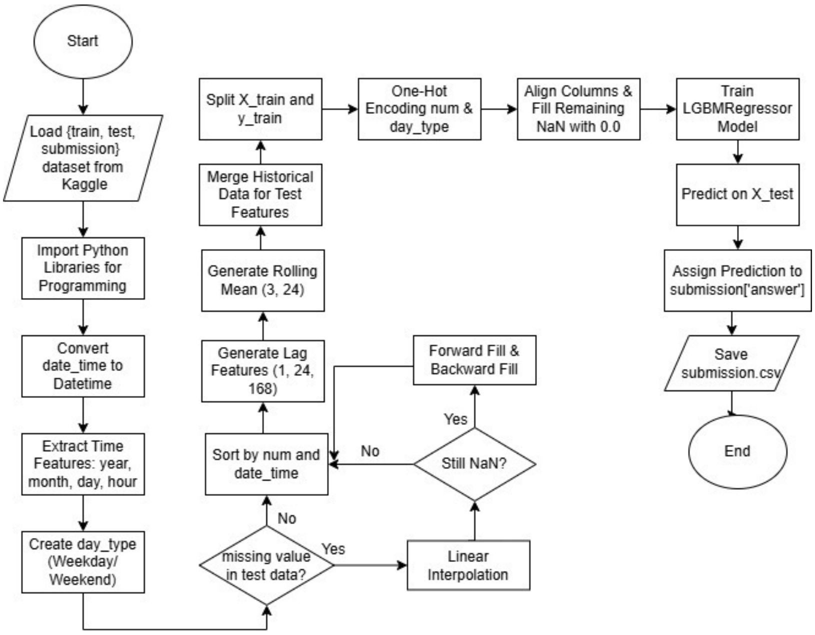

Figure 2. Flowchart Programming

These workflow stages demonstrate how the proposed LightGBM-based forecasting framework processes historical electricity consumption data and generates prediction results for building energy management applications.

3.1. Dataset Description

The dataset used in this study consists of historical building electricity consumption records combined with environmental and temporal information. The target variable is electricity consumption, while the input variables include weather-related features, temporal attributes, building identifiers, and historical electricity usage values. These variables were selected because electricity consumption is influenced by both external environmental conditions and recurring temporal patterns (Zhang & Jánošík, 2024).

To improve prediction performance, multiple categories of features are incorporated into the forecasting framework, including environmental features, temporal information, building-specific characteristics, and historical electricity consumption records. The combination of these features enables the model to capture both short-term fluctuations and long-term consumption trends.

3.2. Environmental Features

Environmental conditions significantly influence electricity consumption patterns, particularly through their impact on heating, ventilation, and air conditioning (HVAC) systems. Therefore, several weather-related variables are incorporated into the forecasting model, including temperature (°C), precipitation (mm), wind speed (m/s), humidity (%), sunshine duration (hours), and solar radiation (MJ/m^2). These features allow the model to identify relationships between environmental changes and electricity demand.

Weather information is preprocessed by handling missing values, correcting inconsistent measurements, and aligning timestamps with electricity consumption records. This process ensures that environmental variables are synchronized with energy usage data and suitable for model training. The integration of environmental information enhances forecasting robustness, particularly during unusual weather conditions that may affect electricity demand.

3.3. Temporal Features

Electricity consumption exhibits recurring daily, weekly, and seasonal patterns. To capture these characteristics, temporal variables are extracted from timestamp information, including year, month, day, hour, day of week, day of year, and day type (weekday or weekend). These features provide contextual information that enables the model to distinguish between normal consumption cycles and irregular events.

Temporal features are essential for identifying behavioral patterns associated with building operations. For example, electricity consumption is typically higher during working hours and lower during nighttime periods. By incorporating temporal information, the forecasting model can better recognize these recurring trends and improve prediction accuracy.

3.4. Historical Electricity Consumption Features

Historical electricity consumption data serves as the primary source of predictive information. To capture temporal dependencies, lag-based features are generated from previous consumption records. These include lag-1 power, lag-24 power, and lag-168 power, representing consumption values from the previous hour, previous day, and previous week, respectively.

In addition, rolling mean statistics are calculated to capture broader consumption trends and reduce the influence of short-term fluctuations. The combination of lagged observations and rolling statistics enables the model to learn both immediate consumption behavior and medium-term usage patterns, thereby improving forecasting performance.

3.5. Data Preprocessing and Feature Engineering

Prior to model development, all input variables undergo preprocessing to improve data quality and consistency. Missing values are handled through imputation techniques, timestamps are converted into datetime format, and records are sorted chronologically to preserve the temporal structure of the dataset.

Feature engineering is then performed to transform raw observations into informative predictors. Temporal variables, lag features, and rolling statistics are generated and combined with environmental attributes to create a comprehensive feature set. These engineered features enable the model to capture complex relationships among electricity consumption drivers and improve generalization performance.

3.6. LightGBM Regression Model

The forecasting model employed in this study is Light Gradient Boosting Machine (LightGBM), an ensemble learning algorithm based on Gradient Boosting Decision Trees (GBDT). LightGBM constructs multiple decision trees sequentially, where each subsequent tree attempts to minimize the prediction error produced by previous trees. To provide a clear representation of the proposed forecasting procedure, the overall prediction framework is summarized in Algorithm 1.

Algorithm 1 Electricity Consumption Prediction using LightGBM

```
1:  Import historical electricity consumption dataset
2:  Preprocess data:
3:          Handle missing values
4:          Convert time to datetime format
5:          Sort data chronologically
6:  Generate features:
7:          Extract temporal features (hour, day, day of week)
8:          Create lag features (lag-1, lag-24, lag-168)
```

Split dataset into training and validation sets (no shuffling)
Train LightGBM regression model using training data
Predict electricity consumption on validation data
Evaluate model performance using RMSE
Visualize actual vs predicted values
return Predicted electricity consumption and RMSE

The algorithm is selected because of its computational efficiency, scalability, and ability to model nonlinear relationships among input variables. By combining environmental information, temporal characteristics, building identifiers, and historical consumption features, the model learns complex consumption patterns and generates future electricity demand predictions.

3.7. Model Training and Prediction

The prepared dataset is divided into training and validation subsets without random shuffling in order to preserve chronological order. The training data are used to construct the LightGBM regression model, while the validation data are employed to evaluate forecasting performance.

After training, the model performs prediction on unseen observations by utilizing the latest available features. The prediction output represents the estimated electricity consumption for a specific building and time period.

3.8. Performance Evaluation

Model performance is evaluated using Root Mean Squared Error (RMSE), which measures the average magnitude of prediction errors between actual and predicted electricity consumption values. Equation (1.1) describes the mathematical formulation of RMSE used in this study.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

Where: n r presents the total number of observations, y_i denotes the actual electricity consumption value, and $\hat{y}_i$ represents the predicted value. Lower RMSE values indicate better forecasting performance. In addition to numerical evaluation, prediction results are visualized through comparison plots between actual and predicted electricity consumption values to facilitate interpretation of model behavior.

4. Results

4.1. Model Performance Evaluation

The performance of the proposed LightGBM model was evaluated using Root Mean Squared Error (RMSE) as the primary performance metric. RMSE was selected because it measures the average magnitude of prediction errors and provides a quantitative assessment of forecasting accuracy. Lower RMSE values indicate that the predicted electricity consumption values are closer to the actual observations. Figure 3 presents the RMSE values obtained for each building included in the dataset. The results demonstrate that forecasting performance varies across buildings due to differences in electricity consumption characteristics and operational patterns. Some buildings achieved lower RMSE values, indicating higher prediction accuracy, while others exhibited relatively larger prediction errors.

"The overall model performance is summarized in Figure 4, showing an average RMSE of 143.36 across all evaluated buildings. This result indicates that the proposed LightGBM model is capable of generating reasonably accurate electricity consumption forecasts using historical consumption records, environmental variables, and temporal features. After training, the model predicts electricity consumption for unseen observations by utilizing the latest available features, producing estimated consumption values for specific buildings and time periods.

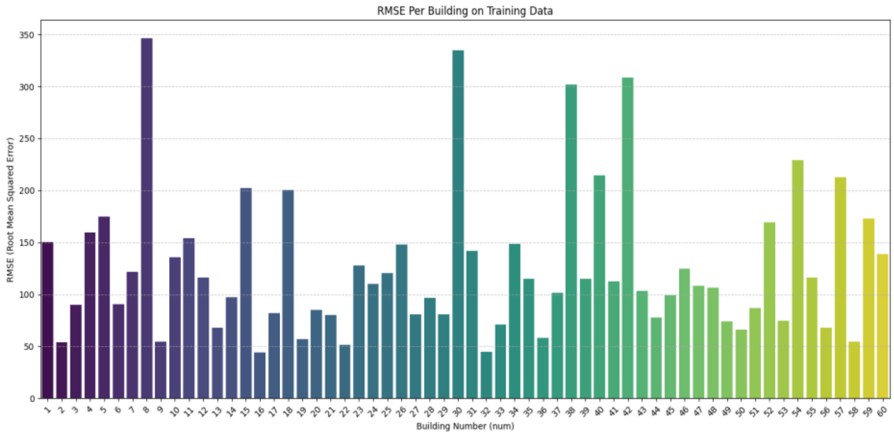

Figure 3. RMSE Per Building

```
--- Overall Model Accuracy on Training Data ---
Overall Root Mean Squared Error (RMSE): 143.36
```

Figure 4. Overall RMSE

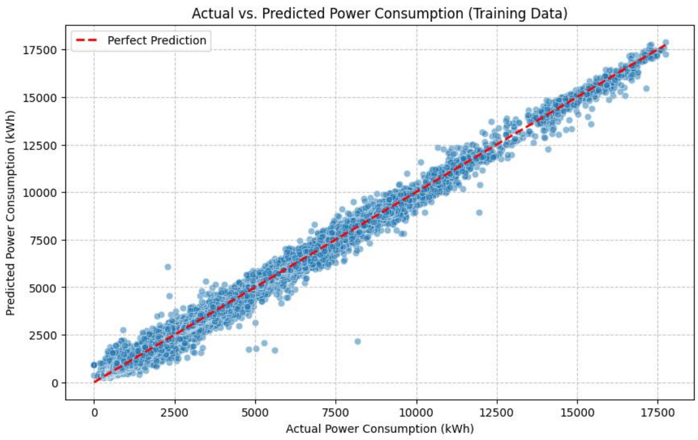

Figure 5. Actual vs Predicted Electricity Consumption

4.2. Prediction Results

To further evaluate forecasting performance, a visual comparison between actual and predicted electricity consumption values was conducted. Figure 5 illustrates the relationship between actual observations and model predictions over the evaluation period. The prediction results show that the proposed model is capable of following the general trend of electricity consumption. Predicted values generally align with actual consumption patterns throughout the observation period. However, several deviations can be observed at specific time intervals where consumption changes rapidly. Despite these deviations, the forecasting model successfully captures the overall consumption dynamics and demonstrates consistent prediction behavior across different operating conditions. The results indicate that the generated feature set and LightGBM regression model effectively represent the underlying structure of electricity consumption data.

4.3. Summary of Results

The evaluation results indicate that the proposed forecasting framework successfully generated electricity consumption predictions using historical consumption data, environmental variables, and temporal information. The model achieved an average RMSE value of 143.36 and was able to reproduce the general consumption trend observed in the dataset.

Furthermore, the visualization results demonstrate that the predicted values follow the actual electricity consumption pattern with acceptable accuracy. These findings suggest that the proposed LightGBM-based time series regression framework provides a practical approach for short-term building electricity consumption forecasting and establishes a foundation for further analysis presented in the next section.

5. Discussion and Limitations

The results demonstrate that the proposed LightGBM-based time series regression model is capable of predicting building electricity consumption with satisfactory accuracy. The obtained average RMSE value of 143.36 indicates that the model successfully captures the general consumption behavior observed within the dataset. The prediction plots further confirm that the generated forecasts follow the overall trend of actual electricity consumption, suggesting that the selected features provide meaningful information for the forecasting process.

One important factor contributing to the model performance is the inclusion of temporal features. Variables such as hour, day of week, and historical consumption patterns allow the model to recognize recurring electricity usage behavior associated with building operations. Electricity demand typically follows predictable daily and weekly cycles, where consumption increases during active operational periods and decreases during off-peak hours. The incorporation of lag features and rolling statistics enables the model to capture these temporal dependencies effectively.

Environmental variables also contribute to forecasting performance by providing contextual information regarding weather conditions that influence electricity demand. Features such as temperature, humidity, solar radiation, precipitation, and wind speed help the model account for variations caused by heating, cooling, and other weather-dependent building operations. The integration of these variables improves the model's ability to adapt to changing environmental conditions and enhances forecasting reliability.

Although the proposed model demonstrates good predictive capability, several prediction errors remain visible in certain periods. These deviations are particularly noticeable during sudden increases or decreases in electricity consumption. Such fluctuations may be influenced by external factors that are not represented within the dataset, including unexpected occupancy changes, special operational events, equipment failures, or irregular building activities. As a result, the model may encounter difficulties when forecasting highly irregular consumption behavior.

Table 1. Comparison of Previous Studies and Proposed Method

Study	Method	Input Features	Performance & Results
Arkananta et al. (2026)	LightGBM Time Series Regression	Temporal, environmental, lag features, rolling statistics, building ID	Average RMSE: 143.36
(Koukaras et al., 2024)	LightGBM, XGBoost, RF, SVR	Historical, temporal, building-related features	LightGBM achieved competitive forecasting accuracy
(Yao et al., 2022)	Hybrid LightGBM-XGBoost	Temporal, weather, historical consumption	Hybrid model outperformed individual models
(Zhang & Jánošík, 2024)	CatBoost-XGBoost Hybrid	Historical, temporal, weather features	Hybrid boosting improved prediction accuracy
(Pallonetto et al., 2022)	RF, ANN, SVR	Historical, calendar, weather, occupancy	Forecasting accuracy varied across models
(Dudek, 2022)	Random Forest	Temporal, historical, weather features	Competitive RMSE performance
(Ullah et al., 2024)	CNN-LSTM Hybrid	Temporal and sequential historical features	Improved sequential forecasting accuracy
(Bashir et al., 2022)	Prophet-LSTM Hybrid	Temporal, historical, seasonal patterns	Hybrid model outperformed standalone LSTM

Table 1 presents a comparison between the proposed method and several previous studies related to electricity load forecasting using machine learning approaches. The comparison highlights differences in forecasting methods, input features, and performance outcomes reported in the literature. The findings of this study are consistent with previous research indicating that machine learning approaches can provide effective solutions for short-term load forecasting problems. Similar studies have reported that ensemble learning techniques, including LightGBM and related gradient boosting algorithms, achieve strong forecasting performance due to their ability to model nonlinear relationships and interactions among multiple variables. The results obtained in this study further support the applicability of machine learning methods for intelligent energy management and electricity demand prediction.

Several limitations should be acknowledged. First, the model relies primarily on historical consumption records, environmental variables, and temporal information, while other potentially relevant factors such as occupancy levels, equipment schedules, and building operational characteristics were not included. Second, the evaluation was conducted using a single dataset, which may limit the generalizability of the findings to different building types and geographic locations. Third, hyperparameter optimization was not extensively explored, and additional tuning strategies may further improve prediction accuracy. Future research may investigate the integration of additional features, advanced optimization techniques, and alternative forecasting models such as XGBoost, CatBoost, LSTM, or Transformer-based architectures to enhance forecasting performance and robustness.

6. Conclusions and Future Directions

This study proposed a building electricity consumption forecasting framework based on Light Gradient Boosting Machine (LightGBM) and time series regression techniques. The developed model integrates environmental variables, temporal information, building identifiers, and historical electricity consumption data to generate future electricity demand predictions. Through data preprocessing, feature engineering, model training, and evaluation processes, the proposed framework successfully produced electricity consumption forecasts with an average RMSE value of 143.36, demonstrating satisfactory predictive performance for building energy management applications. The results indicate that temporal features, environmental variables, and historical consumption patterns collectively contribute to forecasting accuracy. The model was able to capture the overall trend of electricity consumption and generate predictions that closely followed actual observations. These findings suggest that LightGBM is a suitable approach for short-term building electricity consumption forecasting and can support data-driven decision-making for energy planning, load management, and energy efficiency improvement.

Future research may focus on incorporating additional variables such as occupancy information, equipment operating schedules, and real-time sensor measurements to improve prediction accuracy. Further investigation may also compare the performance of LightGBM with other machine learning and deep learning approaches, including XGBoost, CatBoost, Long Short-Term Memory (LSTM), and Transformer-based forecasting models. In addition, advanced hyperparameter optimization techniques and evaluation on larger multi-building datasets may further enhance model robustness and generalizability for real-world deployment.

Author Contributions: Conceptualization: G.R.H. and F.N.R.; Methodology: F.N.R. and I.B.P.A.; Software: F.N.R.; Validation: N.N.H.; Formal Analysis: N.N.H. and I.B.P.A.; Investigation: I.B.P.A.; Data Curation: I.B.P.A.; Visualization: N.N.H. and G.A.F.; Writing—Original Draft Preparation: I.B.P.A., F.N.R., and G.R.H.; Writing—Review and Editing: All authors; Project Administration: G.R.H.; Supervision: Course Lecturer; Funding Acquisition: Not applicable. All authors have read and approved the final version of the manuscript.

Statement on Data Availability: The dataset used in this study is publicly available from the original data repository. The data can be accessed through the corresponding public source provided by the dataset owner.

Acknowledgements: The authors would like to express their sincere gratitude to the Department of Electrical Engineering, Universitas Presiden, for providing academic support throughout this project. The authors also acknowledge the guidance and valuable feedback provided by the lecturer of the Probability and System Analysis course, Ir. Lukman Medriavin Silalahi, A. Md., ST., MT., IPM., ASEAN-Eng., APEC-Eng, during the writing of this manuscript. Furthermore, appreciation is extended to all team members whose collaboration and contributions made the completion of this project possible.

AI Declaration

During the preparation of this manuscript, the authors used AI-assisted technologies to improve language quality and readability. All intellectual content, analysis, and conclusions remain the sole responsibility of the authors.

References

Adebayo Olusegun Aderibigbe, Emmanuel Chigozie Ani, Peter Efosa Ohenhen, Nzubechukwu Chukwudum Ohalete, & Donald Obinna Daraojimba. (2023). Enhancing Energy Efficiency with AI: A Review of Machine Learning Models in Electricity Demand Forecasting. *Engineering Science & Technology Journal*, *4*(6), 341–356. https://doi.org/10.51594/estj.v4i6.636

Akhtar, S., Shahzad, S., Zaheer, A., Ullah, H. S., Kilic, H., Gono, R., Jasiński, M., & Leonowicz, Z. (2023). Short-Term Load Forecasting Models: A Review of Challenges, Progress, and the Road Ahead. In *Energies* (Vol. 16, Issue 10, p. 4060). https://doi.org/10.3390/en16104060

Al-Jamimi, H. A., BinMakhashen, G. M., Worku, M. Y., & Hassan, M. A. (2023). Advancements in Household Load Forecasting: Deep Learning Model with Hyperparameter Optimization. In *Electronics* (Vol. 12, Issue 24, p. 4909). https://doi.org/10.3390/electronics12244909

Bashir, T., Haoyong, C., Tahir, M. F., & Liqiang, Z. (2022). Short term electricity load forecasting using hybrid prophet-LSTM model optimized by BPNN. *Energy Reports*, *8*, 1678–1686. https://doi.org/https://doi.org/10.1016/j.egyr.2021.12.067

Baul, A., Sarker, G. C., Sikder, P., Mozumder, U., & Abdelgawad, A. (2024). Data-Driven Short-Term Load Forecasting for Multiple Locations: An Integrated Approach. In *Big Data and Cognitive Computing* (Vol. 8, Issue 2, p. 12). https://doi.org/10.3390/bdcc8020012

Čegovnik, T., Dobrovoljc, A., Povh, J., Rogar, M., & Tomšič, P. (2023). Electricity consumption prediction using artificial intelligence. *Central European Journal of Operations Research*, *31*(3), 833–851. https://doi.org/10.1007/s10100-023-00844-6

Cordeiro-Costas, M., Villanueva, D., Eguía-Oller, P., Martínez-Comesaña, M., & Ramos, S.

(2023). Load Forecasting with Machine Learning and Deep Learning Methods. In *Applied Sciences* (Vol. 13, Issue 13, p. 7933). https://doi.org/10.3390/app13137933

Dudek, G. (2022). A Comprehensive Study of Random Forest for Short-Term Load Forecasting. In *Energies* (Vol. 15, Issue 20, p. 7547). https://doi.org/10.3390/en15207547

Gassar, A. A. (2024). Short-Term Energy Forecasting to Improve the Estimation of Demand Response Baselines in Residential Neighborhoods: Deep Learning vs. Machine Learning. In *Buildings* (Vol. 14, Issue 7, p. 2242). https://doi.org/10.3390/buildings14072242

Hu, Y., Li, J., Hong, M., Ren, J., & Man, Y. (2022). Industrial artificial intelligence based energy management system: Integrated framework for electricity load forecasting and fault prediction. *Energy*, *244*, 123195. https://doi.org/https://doi.org/10.1016/j.energy.2022.123195

Ibrahim, B., Rabelo, L., Gutierrez-Franco, E., & Clavijo-Buritica, N. (2022). Machine Learning for Short-Term Load Forecasting in Smart Grids. In *Energies* (Vol. 15, Issue 21, p. 8079). https://doi.org/10.3390/en15218079

Koukaras, P., Mustapha, A., Mystakidis, A., & Tjortjis, C. (2024). Optimizing Building Short-Term Load Forecasting: A Comparative Analysis of Machine Learning Models. In *Energies* (Vol. 17, Issue 6, p. 1450). https://doi.org/10.3390/en17061450

Pallonetto, F., Jin, C., & Mangina, E. (2022). Forecast electricity demand in commercial building with machine learning models to enable demand response programs. *Energy and AI*, *7*, 100121. https://doi.org/https://doi.org/10.1016/j.egyai.2021.100121

Raviprabhakaran, V., Pranay, P., Nendralla, B., & Pranay, L. S. (2024). Household Power Consumption Analysis using Machine Learning. *2024 IEEE 4th International Conference on Sustainable Energy and Future Electric Transportation (SEFET)*, 1–6. https://doi.org/10.1109/SEFET61574.2024.10718254

Rodrigues, F., Cardeira, C., Calado, J. M. F., & Melicio, R. (2023). Short-Term Load Forecasting of Electricity Demand for the Residential Sector Based on Modelling Techniques: A Systematic Review. In *Energies* (Vol. 16, Issue 10, p. 4098). https://doi.org/10.3390/en16104098

Silalahi, L. M., Budiyanto, S., Silaban, F. A., Simanjuntak, I. U. V., Rochendi, A. D., & Osman, G. (2021). Optimizing The Performance Of The Power Station Generator Space Lighting System Performance Based On Internet Of Things Using ESP32. *2021 3rd International Conference on Research and Academic Community Services (ICRACOS)*, 219–224. https://doi.org/10.1109/ICRACOS53680.2021.9702010

Silalahi, L. M., Rafi Indrawan, M., Budiyanto, S., Hanafi, D., Hamid, A., & Ronaldo, D. (2024). Smart Home Control System Design using Internet of Things Based Energy Harvesting Technology. *2024 IEEE 6th Symposium on Computers & Informatics (ISCI)*, 43–48. https://doi.org/10.1109/ISCI62787.2024.10667797

Simanjuntak, I. U. V., Haidi, J., Putra, R. F. A., & Silalahi, L. M. (2024). Comparison of MPPT optimization methods for P&O and PSO solar panels to overcome partial shading.

International Journal of Electronics and Telecommunications, *70*(4), 1023–1029. https://doi.org/10.24425/ijet.2024.152090

Simanjuntak, I. U. V., Heryanto, H., Dani, A. W., Salamah, K. S., Silalahi, L. M., & Marsuki, M. (2024). Analysis Of Solar Power Public Street Lighting Optimization With Pvsyst Software In A Residential Complex Area. *International Journal of Electronics and Telecommunications*, *70*(3), 743–749.

Sitompul, E., Firdaus, F., Trisanto, A., & Turnip, A. (2025). Estimation of Soil NPK Content Using LightGBM Method for Precision Agriculture. *2025 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS)*, 1–6. https://doi.org/10.1109/AIMS66189.2025.11229766

Sitompul, E., Ramadhan, M. R. S., & Bukhori, I. (2026). Integrated Intelligent System for Automatic Classification and Counting in a Miniature Packaging Conveyor Using Machine Learning and Deep Learning. *Journal of Intelligent & Fuzzy Systems: Applications in Engineering and Technology*, *50*(1), 34–51. https://doi.org/10.1177/18758967251352077

Suhartomo, A., Juliansyah, W., Turnip, A., & Rohadi, N. (2025). Classification of Heart Rate Variability for Early Detection of Heart Disease Using KNN. *2025 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS)*, 1–5. https://doi.org/10.1109/AIMS66189.2025.11229633

Tae, K. S., Suhartomo, A., & Vincent. (2023). Internet of Things for Real-Time Multi Room Monitoring System. *2023 1st IEEE International Conference on Smart Technology (ICE-SMARTec)*, 13–18. https://doi.org/10.1109/ICE-SMARTECH59237.2023.10461945

Ullah, K., Ahsan, M., Hasanat, S. M., Haris, M., Yousaf, H., Raza, S. F., Tandon, R., Abid, S., & Ullah, Z. (2024). Short-Term Load Forecasting: A Comprehensive Review and Simulation Study With CNN-LSTM Hybrids Approach. *IEEE Access*, *12*, 111858–111881. https://doi.org/10.1109/ACCESS.2024.3440631

Yao, X., Fu, X., & Zong, C. (2022). Short-Term Load Forecasting Method Based on Feature Preference Strategy and LightGBM-XGboost. *IEEE Access*, *10*, 75257–75268. https://doi.org/10.1109/ACCESS.2022.3192011

Yazici, I., Beyca, O. F., & Delen, D. (2022). Deep-learning-based short-term electricity load forecasting: A real case application. *Engineering Applications of Artificial Intelligence*, *109*, 104645. https://doi.org/https://doi.org/10.1016/j.engappai.2021.104645

Zhang, L., & Jánošík, D. (2024). Enhanced short-term load forecasting with hybrid machine learning models: CatBoost and XGBoost approaches. *Expert Systems with Applications*, *241*, 122686. https://doi.org/https://doi.org/10.1016/j.eswa.2023.122686

Zini, M., & Carcasci, C. (2023). Machine learning-based monitoring method for the electricity consumption of a healthcare facility in Italy. *Energy*, *262*, 125576. https://doi.org/https://doi.org/10.1016/j.energy.2022.125576