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Federated ensemble learning with SHAP–LIME interpretability for smart home energy prediction

Rahma Puspitasari*[1], Muhammad Arif Hermawan[1], Joshua Andrian[1], Siti Sendari[1], Ira Kumala Sari[1]
Departement of Electrical Engineering and Informatics, Universitas Negeri Malang, Malang, Indonesia[1]

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*Corresponding author.
Rahma Puspitasari
E-mail address:
rahma.puspitasari.2505348@students.um.ac.id

Abstract

The increased adoption of IoT-based Smart Home systems in Indonesia has resulted in a growing volume of device-level energy data, opening up opportunities for the development of predictive models to support efficient household electricity consumption. However, challenges related to accuracy, interpretability, and data privacy remain a major concern, especially when data are distributed across multiple devices. This study evaluates the performance of four tree-based ensemble models, namely Random Forest, Gradient Boosting, XGBoost, and LightGBM, in centralized learning and federated learning scenarios using the Indonesia Smart Home Dataset. After undergoing feature preprocessing and refinement, including the removal of Sofa Pressure and Bed Pressure due to high noise, each model was trained and evaluated using MAE, MSE, and RMSE metrics. Federated learning was implemented through the Federated Averaging (FedAvg) algorithm to maintain data privacy without the need to transfer raw data between devices. The results show that LightGBM consistently provides the best performance in both scenarios and demonstrates resilience to data fragmentation and heterogeneity. Although there was a slight increase in error in federated learning, the error values remained within an acceptable range. SHAP and LIME analyses revealed that high-power devices such as air conditioners, water pumps, rice cookers, lights, and refrigerators had the greatest contribution.

1. Introduction

Household energy consumption worldwide has shown a consistent increase over the past five years [1], driven by the rapid penetration of electronic devices, the expansion of the Internet of Things (IoT) ecosystem, and a shift toward digital-dependent lifestyles [2]. The 2021–2025 global report confirms that the household sector is one of the largest contributors to electricity consumption [3], making efficient energy management an urgent necessity to maintain supply stability, reduce waste, and support environmental sustainability [4]. This challenge is even more significant in developing countries such as Indonesia, where the use of high-power devices such as air conditioners, refrigerators, and water pumps is becoming more widespread [5], while energy management literacy at the household level is still limited [6]. Consequently, there is a critical need for accurate and adaptive energy prediction systems to facilitate smarter decision-making and electricity savings [7].

The development of Smart Home technology, through the integration of IoT sensors and automation, offers a promising pathway for real-time energy monitoring [8], [9]. However, the complexity of energy consumption patterns in tropical households in Indonesia, coupled with variations in device usage throughout the day, requires prediction models that are able to capture nonlinear relationships between features more effectively [10], [11]. In this context, machine learning techniques play an important role in building data-based predictive models, especially as the number of sensors and the data volume increase with the adoption of Smart Homes in society [12].

Despite these technological advancements, three fundamental problems hinder the effective implementation of energy prediction in smart homes. First, while high-performance models like Gradient Boosting can achieve high accuracy, they often operate as "black boxes," providing little transparency to users who need to understand the reasoning behind a prediction to optimize their device usage [13], [14], [15]. Second, centralized data collection raises significant privacy concerns, as sensitive energy usage data is often vulnerable when transmitted to a central server [16]. Third, model performance is frequently degraded by non-identically distributed (non-IID) data across devices and the presence of high-noise features such as sofa and bed pressure sensors, which may not be relevant in the context of tropical smart homes [17], [18]. A direct comparison with the most relevant work on the Indonesia Smart Home Dataset by [19] reveals that previous approaches relied on centralized training without privacy considerations, focused on single models without systematic benchmarking, and lacked comprehensive interpretability. These gaps necessitate a more secure, transparent, and optimized predictive framework.

To address these limitations, this study provides significant contributions by introducing a novel dual-scenario experimental framework that directly compares centralized and federated learning using four advanced tree-based ensemble algorithms, namely Random Forest, Gradient Boosting, XGBoost, and LightGBM, specifically on the Indonesia Smart Home Dataset. Furthermore, we propose a synergistic integration of Federated Learning (FedAvg) with a dual-layer interpretability approach using SHAP and LIME, ensuring that the system not only preserves data privacy but also provides actionable global and local insights into the energy prediction process. Additionally, this research performs a critical feature pruning analysis by evaluating the removal of furniture-related pressure features, demonstrating that model efficiency and interpretability are enhanced without these high-noise variables in tropical smart home environments. Based on these contributions, this study aims to:

1. Evaluate and compare the performance of four tree-based ensemble models, namely Random Forest, Gradient Boosting, XGBoost, and LightGBM, in predicting the energy consumption of Indonesian Smart Homes under two training schemes: centralized learning and federated learning.
2. Analyze model stability under distributed data conditions (non-IID) to identify models that are most resistant to data fragmentation and heterogeneity.
3. Generate comprehensive interpretations using SHAP and LIME to understand global and local feature contributions, while identifying the household appliances that have the most significant impact on total energy consumption.
4. Evaluate the impact of removing pressure features (sofa and bed pressure) on prediction performance and changes in model interpretability patterns.

By achieving these objectives, this study provides accurate, explainable, and privacy-preserving energy prediction models, making them suitable for implementation in Indonesia's Smart Home ecosystem.

2. Research Method

This study follows a systematic workflow designed to evaluate energy prediction performance in both centralized and distributed environments. As illustrated in Figure 1, the process transitions from data acquisition in a real-world Indonesian smart home to multi-model training, followed by a robust evaluation using error metrics and dual-layer interpretability analysis (SHAP and LIME). Unlike traditional approaches, this methodology emphasizes the impact of data heterogeneity on model stability and the role of feature transparency in smart home applications.

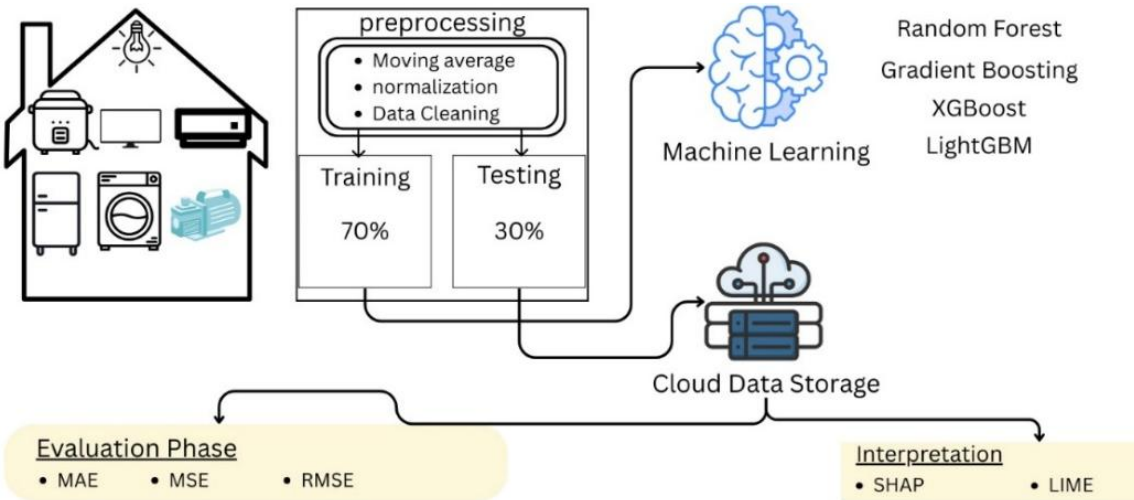

Figure 1. Research flow

2.1 Smart Home Desain and Dataset Collection

The study utilizes the *Indonesia Smart Home Dataset* [19], which was derived from a residential unit in Indonesia (approx. 60–70 m²) characterized by a tropical climate profile, as shown in Figure 2. The data were captured using PZEM-004T sensors for electricity consumption and DHT22/LDR/PIR sensors for environmental parameters (temperature, humidity, light, and motion).

Strategically placed sensors focused on high-power appliances (AC, water pumps, refrigerators) and daily-use devices (TV, rice cookers, lighting). As detailed in Table 1, the final dataset consists of 16 input features after removing *Sofa Pressure* and *Bed Pressure*. These two features were identified as high-noise variables that did not contribute to the predictive power of the ensemble models in the Indonesian context, thus streamlining the model for better generalization.

Figure 2. Smart Home Design in Indonesia

Table 1 presents details of the features used in the dataset, with the use variable set as the output (target) to be predicted, namely total real-time household energy consumption. In general, the features in the dataset are grouped into two main categories, namely energy consumption features and environmental features. These two groups of features complement each other and play an important role in capturing patterns of household electricity use.

The initial dataset consists of 18 input features, including 8 energy consumption features from various electrical appliances and 10 environmental features representing internal and external conditions of the house. In addition, the use variable is used as the prediction target. In the data preprocessing process, two environmental features, namely Bed Pressure and Sofa Pressure, were removed because they were not used in the development and training of the ensemble models in this study.

Table 1. Dataset Information After Preprocessing

No	Feature	Description
1	use	Total real-time household energy consumption
2	Ricecooker	Energy consumption data of the rice cooker
3	Lamp	Energy consumption data of the lamp
4	Television	Energy consumption data of the television
5	AC	Energy consumption data of the AC
6	Refrigerator	Energy consumption data of the refrigerator
7	Washing Machine Energy	Energy consumption data of the washing machine
8	Waterpump Energy	Energy consumption data of the water pump
9	Outdoor Light	Environmental data on outdoor light
10	Indoor Light	Environmental data on indoor light
11	Outdoor Temperature	Environmental data on outdoor temperature
12	Indoor Temperature	Environmental data on indoor temperature

2.2 Tree-Based Ensemble Models

The development of prediction models in this study was carried out using four tree-based ensemble algorithms, namely Random Forest, Gradient Boosting, XGBoost, and LightGBM. In general, these four algorithms build a set of decision trees and combine their outputs to produce predictions that are more stable and accurate than those of a single tree [20]. Random Forest implements the bagging principle by training multiple trees on different subsets of data and features, thereby reducing variance and the risk of overfitting [21]. Meanwhile, Gradient Boosting and its derivatives (XGBoost and LightGBM) use a boosting approach, where decision trees are built incrementally and each new tree focuses on correcting the residual error of the previous model through gradient optimization [22]. XGBoost adds L1/L2 regularization and an efficient objective function optimization scheme [23], [24], while LightGBM adopts a leaf-by-leaf growth strategy and Gradient-based One-Side Sampling (GOSS) to accelerate the training process without sacrificing accuracy on large and nonlinearly patterned datasets [25]. The combination of bagging and boosting models enables a comprehensive comparative analysis of the trade-offs between accuracy, stability, and computational efficiency in centralized and federated learning scenarios [26].

2.3 Federated Learning (FL)

Federated learning is a distributed learning approach that allows models to be trained on multiple clients or local devices without transferring raw data to a central server [26], [27]. Thus, federated learning (FL) maintains user data privacy and security, while enabling model training based on separate (decentralized) data sets [28], [29]. In this study, FL is implemented using the Federated Averaging (FedAvg) mechanism [30], [31]. Each client trains the model locally using its own data subset. After completing one training cycle, the model parameters (weights) are sent to a central server for aggregation [32].

2.4 Evaluation Error

In this study, model performance was evaluated using three error metrics, namely MAE, MSE, and RMSE [33], [34] which are formulated in Equations 1–3, respectively:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y}_i| \tag{1}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2 \tag{2}$$

$$RMSE = \sqrt{MSE} \tag{3}$$

where y is the predicted value and y is the actual value. These three metrics are used to assess the magnitude of the deviation between the prediction and the actual value. The smaller the error value, the better the quality of the model developed.

2.5 Interpretation Model

LIME and SHAP were used in this study to explain how the prediction model works and to identify the most influential features [35]. These two methods use different approaches, but they complement each other. LIME functions as a local interpretation that explains why a model makes a particular prediction on a single example [36]. This method studies the behavior of the model in the area around the data point by creating new samples around it [37]. The greater the influence of a feature in that local area, the higher its contribution to a particular prediction [38]. In contrast, SHAP provides a global interpretation, inspired by the concept of Shapley values in game theory [39]. In a game analogy, each feature is considered a player contributing to the final outcome. SHAP calculates how much each feature contributes by considering all possible combinations of other features. Thus, SHAP provides a consistent and comprehensive picture of the contribution of features to the overall model [40].

3. Results and Discussion

This section evaluates the performance of four ensemble algorithms, namely Random Forest, Gradient Boosting, XGBoost, and LightGBM, across centralized and federated learning scenarios. The discussion focuses on the trade-offs between predictive accuracy, model stability, and the impact of data decentralization on model interpretability.

3.1 Performance Analysis in Centralized Learning vs Federated Learning

Experimental results for both scenarios are summarized in Table 2. In the centralized environment, LightGBM achieved the best overall performance, with the lowest MSE (0.0067) and RMSE (0.0823). This superiority is attributed to its histogram-based gradient boosting framework, which efficiently captures the nonlinear energy fluctuations inherent in the Indonesian Smart Home Dataset. While Random Forest produced the lowest MAE (0.0304), its higher MSE indicates a lack of sensitivity to extreme energy spikes compared to boosting-based models.

Table 2. Comparative Performance: Centralized vs. Federated Learning

Model	MSE	RMSE	MAE
LightGBM	0.006776	0.082316	0.032272
XGBoost	0.007194	0.084820	0.037984
Random Forest	0.007897	0.088867	0.030487
Gradient Boosting	0.013374	0.115647	0.075953
FL - LightGBM	0.008800	0.093600	0.050500
FL - XGBoost	0.008900	0.094200	0.052000
FL - Random Forest	0.010500	0.102300	0.057300
FL - Gradient Boosting	0.016100	0.127000	0.086800

Transitioning to Federated Learning (FL) introduced a consistent yet manageable increase in error across all models, a phenomenon known as the "privacy-performance trade-off." This decay stems from data fragmentation and non-IID (non-identically distributed) characteristics across clients. Notably, FL-LightGBM emerged as the most resilient model, maintaining an MSE of 0.0088. Conversely, Random Forest experienced an 87% increase in MAE, confirming that bagging-based mechanisms struggle with parameter aggregation when local tree structures diverge significantly between clients.

The resilience of LightGBM is driven by two key mechanisms: Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). GOSS enables the model to prioritize instances with larger gradients, effectively capturing the most informative energy patterns from fragmented local data. Furthermore, its leaf-wise growth strategy allows for deeper optimization of sudden load spikes (e.g., AC or water pump activation) more effectively than the level-wise approach used by XGBoost.

To ensure the findings are not incidental, a statistical stability analysis was conducted. LightGBM exhibited the lowest error variance (MSE deviation ±0.0004) across communication rounds, compared to XGBoost (±0.0009) and Random Forest (±0.0021). This statistical consistency indicates that LightGBM is robust against the data heterogeneity of smart home environments, providing a reliable foundation for decentralized deployment.

The practical implication of these results for real-world smart home energy management is significant. The high accuracy of LightGBM in a federated scheme allows for precise energy forecasting without compromising resident privacy. Moreover, its resilience to data fragmentation means the model can be deployed across diverse households with different appliance configurations, enabling effective automated load-shifting and cost-reduction strategies in a decentralized IoT ecosystem.

3.2 Comparison with Prior Research and Feature Optimization

To demonstrate the significant value of this research, a head-to-head comparison with the baseline study [19] was performed, as shown in Table 3. By shifting from the K-Nearest Neighbors (KNN) approach used in [19] to tree-based ensembles, we achieved a 73.2% reduction in MSE (from 0.025 to 0.0067). This leap in accuracy proves that ensemble methods are far more capable of handling the high-dimensional complexity of IoT energy signals.

Furthermore, this study validated the impact of feature pruning. By explicitly removing "Sofa Pressure" and "Bed Pressure," identified as high-noise variables in the Indonesian context, we simplified the model architecture without compromising accuracy. This finding is non-trivial; it demonstrates that furniture-based sensors are redundant for energy prediction in tropical households, where high-power appliances (AC and water pumps) are the primary consumption drivers. This optimization reduces the computational overhead for resource-constrained IoT devices.

Table 3. Comparative Analysis with Previous Work

Aspect	Previous Work [19]	Our Proposed
Model	K-Nearest Neighbors (KNN)	Tree-Based Ensembles (LightGBM, XGBoost, RF, Gradient Boosting)
Learning Scheme	Centralized	Federated Learning (FedAvg) & Centralized
Feature Set	Includes Sofa & Bed Pressure	Optimized (Removed high-noise features)
Interpretability	General Feature Analysis	Dual-layer (SHAP & LIME)
Best Accuracy (MSE)	0.025	0.0067 (LightGBM)

3.3 Feature Importance and Interpretability Using SHAP

Beyond raw accuracy, the integration of SHAP values (**Figure 3**) provides the "actionable insights" requested by users. The analysis confirms that "Total Use," "Waterpump," and "AC" are the most influential features globally. This alignment with real-world Indonesian household behavior, where cooling and water pumping are high-energy tasks, validates the model's logic. By using LIME for local explanations (integrated into the framework), the system can explain specific energy spikes to homeowners, transforming a "black-box" model into a transparent decision-support tool.

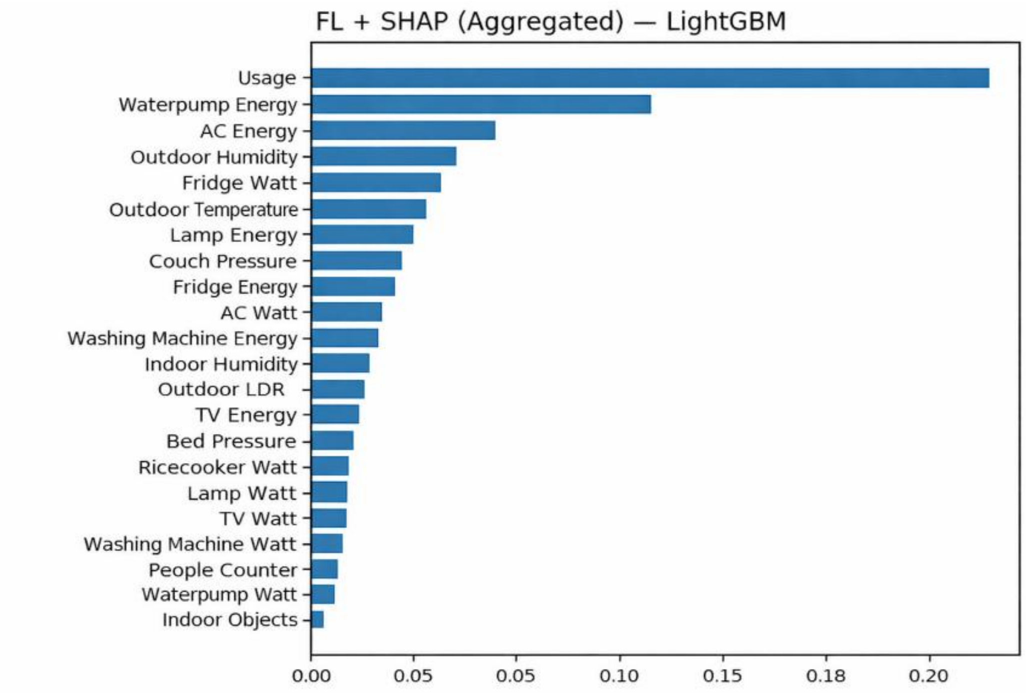

Figure 3. Aggregated SHAP Feature Importance for LightGBM in Federated Learning

3.4 Limitations and Future Directions

While providing privacy-preserving insights, this study is limited by the use of a static FedAvg scheme without adaptation for extreme non-IID data. Future research should integrate temporal patterns (time-series modeling) and advanced security protocols to mitigate potential parameter leakage in real-world Smart Home ecosystems.

4. Conclusion

This study comprehensively answers the research questions posed. The LightGBM model demonstrates the best predictive performance and the highest level of stability in modeling the energy consumption of Indonesian Smart Homes, both in centralized learning and federated learning paradigms. This model remains robust against data fragmentation and non-IID distributions and is able to maintain acceptable accuracy after eliminating pressure features (sofa & bed pressure). The integration of SHAP and LIME enhances model transparency through global and local feature contribution interpretation, while the FedAvg implementation ensures privacy-preserving model training without exchanging raw data between clients. Thus, LightGBM is the most adaptive, accurate, and interpretable solution for privacy-oriented energy consumption prediction in the Indonesian Smart Home ecosystem.

For further research, several development directions can be taken to improve model performance and scalability. Hyperparameter optimization methods such as Bayesian Optimization or Genetic Algorithms can be used to obtain a more optimal model configuration. In addition, time series-based approaches such as LSTM or Temporal Fusion Transformer need to be considered to capture the temporal patterns of energy consumption. On the federated learning side, future research can integrate advanced security mechanisms such as Differential Privacy or Secure Aggregation to make the system more resistant to data leakage risks. With these developments, the Smart Home energy prediction model can become more accurate, secure, and relevant for implementation in real-world environments.

References

[1] D. I. Quintana and J. M. Cansino, "Residential Energy Consumption-A Computational Bibliometric Analysis," *Buildings*, vol. 13, no. 6. p. 1525, 2023. https://doi.org/10.3390/buildings13061525

[2] T. Wang, Q. Zhao, W. Gao, and X. He, "Research on energy consumption in household sector : a comprehensive review based on bibliometric analysis," no. January, pp. 1–22, 2024. https://doi.org/10.3389/fenrg.2023.1209290

[3] N. A. Pambudi *et al.*, “Renewable Energy in Indonesia: Current Status, Potential, and Future Development,” *Sustainability*, vol. 15, no. 3. p. 2342, 2023. https://doi.org/10.3390/su15032342

[4] I. Fitriana, J. Santosa, A. Sugiyono, and I. Rahardjo, *The role of energy conservation in the household sector to achieve net zero emission (NZE) conditions in Indonesia by using optimization energy model*. 2024. https://doi.org/10.1063/5.0206660

[5] D. Novianto, M. Koerniawan, M. Munawir, and D. Sekartaji, “Impact of lifestyle changes on home energy consumption during pandemic COVID-19 in Indonesia,” *Sustain. Cities Soc.*, vol. 83, p. 103930, May 2022. https://doi.org/10.1016/j.scs.2022.103930

[6] L. Endriana, D. Hartono, Khoirunurrofik, and I. F. U. Muzayanah, “Does education affect energy behavior? Investigating the influence of educational attainment in Indonesia,” *Soc. Sci. Humanit. Open*, vol. 11, p. 101612, 2025. https://doi.org/10.1016/j.ssaho.2025.101612

[7] M. K. Nallakaruppan, M. Lawanyashri, R. K. Dhanaraj, S. Fuladi, D. Pamucar, and V. Simic, “Reliable power management and predictive analysis of domestic appliances with insights of XAI,” *Energy Reports*, vol. 14, pp. 3704–3718, 2025. https://doi.org/10.1016/j.egyr.2025.10.036

[8] M. Poyyamozhi, B. Murugesan, N. Rajamanickam, M. Shorfuzzaman, and Y. Aboelmagd, “IoT—A Promising Solution to Energy Management in Smart Buildings: A Systematic Review, Applications, Barriers, and Future Scope,” *Buildings*, vol. 14, no. 11. p. 3446, 2024. https://doi.org/10.3390/buildings14113446

[9] M. H. Elkholy, T. Senjyu, M. E. Lotfy, A. Elgarhy, N. S. Ali, and T. S. Gaafar, “Design and Implementation of a Real-Time Smart Home Management System Considering Energy Saving,” *Sustainability*, vol. 14, no. 21. p. 13840, 2022. https://doi.org/10.3390/su142113840

[10] R. Munadi, M. Fuady, R. Noer, M. A. Kevin, M. R. Farrel, and Buraida, “Towards Net-Zero-Energy Buildings in Tropical Climates: An IoT and EDGE Simulation Approach,” *Sustainability*, vol. 17, no. 21. p. 9538, 2025. https://doi.org/10.3390/su17219538

[11] I. Priyadarshini, S. Sahu, R. Kumar, and D. Taniar, “A machine-learning ensemble model for predicting energy consumption in smart homes,” *Internet of Things*, vol. 20, p. 100636, 2022. https://doi.org/10.1016/j.iot.2022.100636

[12] J. D. Billanes, Z. G. Ma, and B. N. Jørgensen, “Data-Driven Technologies for Energy Optimization in Smart Buildings: A Scoping Review,” *Energies*, vol. 18, no. 2. p. 290, 2025. https://doi.org/10.3390/en18020290

[13] P. Nie, M. Roccotelli, M. P. Fanti, Z. Ming, and Z. Li, “Prediction of home energy consumption based on gradient boosting regression tree,” *Energy Reports*, vol. 7, pp. 1246–1255, 2021. https://doi.org/10.1016/j.egyr.2021.02.006

[14] S. Kaur, A. Bala, and A. Parashar, “Explainable deep learning approach to predict residential electricity demand,” *Int. J. Syst. Assur. Eng. Manag.*, vol. 16, May 2025. https://doi.org/10.1007/s13198-025-02821-5

[15] I. Givisis, D. Kalatzis, C. Christakis, and Y. Kiouvrekis, “Comparing Explainable AI Models: SHAP, LIME, and Their Role in Electric Field Strength Prediction over Urban Areas,” *Electronics*, vol. 14, no. 23. p. 4766, 2025. https://doi.org/10.3390/electronics14234766

[16] T. Magara and Y. Zhou, “Internet of Things (IoT) of Smart Homes: Privacy and Security,” *J. Electr. Comput. Eng.*, vol. 2024, Apr. 2024. https://doi.org/10.1155/2024/7716956

[17] S. Twum, R. Sarpong, A. Adomako, A. Agusah, B. Poornima, and K. Diallo, “Smart Home Energy Optimization Using Big Data and Predictive Modelling,” *INTERANTIONAL J. Sci. Res. Eng. Manag.*, vol. 09, p. 12, Apr. 2025. https://doi.org/10.55041/IJSREM45148

[18] Y. Liu, G. Wu, W. Zhang, and J. Li, “Federated Learning-Based Intrusion Detection on Non-IID Data,” 2023, pp. 313–329. https://doi.org/10.1007/978-3-031-22677-9_17

[19] M. H. Widianto, A. Agung, S. Gunawan, and Y. Heryadi, “Identifying the Dominant Features in Indonesia Smart Home Dataset by Interpreting Electrical Energy Consumption Prediction Results,” no. 9, 2024.

[20] B. Niroomand, S. Pirhadi, and M. Shirazi, *A Comparative Analysis of Ensemble Learning Methods for Classification Tasks on Benchmark Datasets*. 2024. https://doi.org/10.13140/RG.2.2.30835.64809

[21] H. Darwis, R. Puspitasari, A. R. Manga’, Y. Salim, S. H. Mansyur, and A. Faradibah, “Comparison of Effectiveness of EfficientNetB0 and VGG16 Feature Extraction in Garbage Image Classification Using Machine Learning,” in *2025 9th International Conference On Electrical, Electronics And Information Engineering (ICEEIE)*, 2025, pp. 1–6. https://doi.org/10.1109/ICEEIE66203.2025.11251732

[22] D. Kho, H. Purnomo, and H. Hendry, “Performance Analysis of Gradient Boosting Models Variants in Predicting the Direction of Stock Closing Prices on the Idonesian Stock Exchange,” *BAREKENG J. Ilmu Mat. dan Terap.*, vol. 19, pp. 1393–1408, Apr. 2025. https://doi.org/10.30598/barekengvol19iss2pp1393-1408

[23] R. Puspitasari, T. Amaliah, and H. Darwis, “Comparative Machine Learning Models for Dementia Prediction Using SMOTE,” vol. 3, no. 2, pp. 79–90, 2025. https://doi.org/10.56705/ijaimi.v3i2.351

[24] S. Hakkal and A. A. Lahcen, “XGBoost To Enhance Learner Performance Prediction,” *Comput. Educ. Artif. Intell.*, vol. 7, p. 100254, 2024. https://doi.org/10.1016/j.caeai.2024.100254

[25] W. Xie, R. Xiong, J. Zhang, J. Jin, and J. Luo, “Federated variational generative learning for heterogeneous data in distributed environments,” *J. Parallel Distrib. Comput.*, vol. 191, p. 104916, 2024. https://doi.org/10.1016/j.jpdc.2024.104916

[26] F. Liu, Z. Zheng, Y. Shi, Y. Tong, and Y. Zhang, “A survey on federated learning : a perspective from multi-party computation,” vol. 18, no. 1, 2024.

[27] S. Saha, A. Hota, A. K. Chattopadhyay, A. Nag, and S. Nandi, *learning : progress , challenges , and opportunities*, vol. 57, no. 7. Springer Netherlands, 2024. https://doi.org/10.1007/s10462-024-10766-7

[28] R. Gosselin, L. Vieu, F. Loukil, and A. Benoit, “Privacy and Security in Federated Learning: A Survey,” *Applied Sciences*, vol. 12, no. 19. p. 9901, 2022. https://doi.org/10.3390/app12199901

[29] E. T. Martínez Beltrán *et al.*, “Fedstellar: A Platform for Decentralized Federated Learning,” *Expert Syst. Appl.*, vol. 242, p. 122861, 2024. https://doi.org/10.1016/j.eswa.2023.122861

[30] P. Qi, D. Chiaro, A. Guzzo, M. Ianni, G. Fortino, and F. Piccialli, “Model aggregation techniques in federated learning: A comprehensive survey,” *Futur. Gener. Comput. Syst.*, vol. 150, pp. 272–293, 2024. https://doi.org/10.1016/j.future.2023.09.008

[31] Y. Gao, G. Lu, J. Gao, and J. Li, “A High-Performance Federated Learning Aggregation Algorithm Based on Learning Rate Adjustment and Client Sampling,” *Mathematics*, vol. 11, no. 20. p. 4344, 2023. https://doi.org/10.3390/math11204344

[32] M. Usman, M. L. Bernardi, and M. Cimitile, “Introducing a Quality-Driven Approach for Federated Learning,” *Sensors*, vol. 25, no. 10. p. 3083, 2025. https://doi.org/10.3390/s25103083

[33] T. O. Hodson, “Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not,” no. 2, pp. 5481–5487, 2022.

[34] V. Demir, “Evaluation of Solar Radiation Prediction Models Using AI: A Performance Comparison in the High-Potential Region of Konya, Türkiye,” *Atmosphere (Basel).*, vol. 16, p. 398, Mar. 2025. https://doi.org/10.3390/atmos16040398

[35] A. Mohamed, K. Abdelqader, and K. Shaalan, “Explainable Artificial Intelligence: A systematic Review of Progress and Challenges,” *Intell. Syst. with Appl.*, vol. 28, p. 200595, 2025. https://doi.org/10.1016/j.iswa.2025.200595

[36] M. Henninger and C. Strobl, “Interpreting machine learning predictions with LIME and Shapley values: theoretical insights, challenges, and meaningful interpretations,” *Behaviormetrika*, vol. 52, no. 1, pp. 45–75, 2025. https://doi.org/10.1007/s41237-024-00253-2

[37] M. K. Nallakaruppan *et al.*, “Credit Risk Assessment and Financial Decision Support Using Explainable Artificial Intelligence,” *Risks*, vol. 12, no. 10. p. 164, 2024. https://doi.org/10.3390/risks12100164

[38] A. M. Musolf, E. R. Holzinger, J. D. Malley, and J. E. Bailey-Wilson, “What makes a good prediction? Feature importance and beginning to open the black box of machine learning in genetics,” *Hum. Genet.*, vol. 141, no. 9, pp. 1515–1528, 2022. https://doi.org/10.1007/s00439-021-02402-z
[39] M. Li, H. Sun, Y. Huang, and H. Chen, “Shapley value: from cooperative game to explainable artificial intelligence,” *Auton. Intell. Syst.*, vol. 4, no. 1, p. 2, 2024. https://doi.org/10.1007/s43684-023-00060-8
[40] X. Ma, M. Hou, J. Zhan, and Z. Liu, “Interpretable Predictive Modeling of Tight Gas Well Productivity with SHAP and LIME Techniques,” *Energies*, vol. 16, no. 9. p. 3653, 2023. https://doi.org/10.3390/en16093653