International Journal of Informatics and Information Systems
Vol. 8, No. 2, March 2025, pp. 75-84


# Enhancing Household Energy Consumption Forecasting Using the XGBoost Algorithm with Cross-Validation and Residual-Based Evaluation

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(Received September 10, 2024; Revised November 15, 2024; Accepted February 5, 2025; Available online March 2, 2025)

**Abstract**

Accurate forecasting of household energy consumption plays a crucial role in optimizing energy efficiency, supporting sustainable policy decisions, and improving operational management in smart grid systems. This study enhances conventional XGBoost-based forecasting by integrating cross-validation and residual-based evaluation to ensure model robustness and interpretability. Using a dataset of over 90,000 daily household energy records that include temperature, humidity, and appliance-level usage, a systematic preprocessing pipeline was applied—comprising data cleaning, normalization, temporal feature transformation, and partitioning into training and testing subsets. The proposed model was trained using 10-fold cross-validation to minimize overfitting and validated through residual error analysis to assess stability and bias. Evaluation metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination ($R^2$), demonstrate superior predictive accuracy, achieving MAE = 0.48, RMSE = 0.64, and $R^2$ = 0.9864. Visualization of actual versus predicted consumption and symmetric residual distribution further confirm the model's reliability. The findings highlight that the enhanced XGBoost model not only achieves high precision but also provides a robust foundation for real-time energy monitoring, anomaly detection, and sustainable household energy management. Future work will integrate SHAP-based interpretability and comparative benchmarking with deep learning approaches.

*Keywords:* XGBoost, Energy Forecasting, Cross-Validation, Residual Analysis, Machine Learning, Sustainability

## 1. Introduction

The accurate forecasting of household energy consumption has become increasingly essential in the context of global energy sustainability, cost reduction, and intelligent demand management. As population growth and urbanization accelerate, residential energy use continues to rise steadily, exerting pressure on existing energy infrastructures and policy frameworks [1]. Reliable prediction models are therefore crucial to maintaining the balance between demand and supply, preventing grid instability, and supporting efficient energy allocation [2].

Recent advancements in data acquisition systems and smart metering technologies have led to an exponential increase in the availability of household energy consumption data. This development enables the adoption of data-driven forecasting approaches that leverage machine learning (ML) algorithms to uncover nonlinear and high-dimensional patterns in consumption behavior [3]. Compared with conventional statistical models, ML-based approaches demonstrate superior capability in capturing complex temporal, environmental, and behavioral relationships [4].

Among various ML algorithms, Extreme Gradient Boosting (XGBoost) has emerged as a powerful and efficient method for regression-based energy prediction tasks due to its scalability, regularization mechanisms, and robustness against overfitting [5]. XGBoost constructs additive tree ensembles iteratively, where each tree learns from the residual errors of the previous ones, improving predictive performance at each stage [6]. Its ability to model nonlinear dependencies and manage heterogeneous datasets makes it highly suitable for household-level energy forecasting [7].

Despite its success, several studies have noted that the application of XGBoost in energy prediction often lacks systematic validation and interpretability, limiting its practical adoption in real-world energy management systems [8].

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**DOI: https://doi.org/10.47738/ijiis.v8i2.253**

To address this gap, this study enhances the conventional XGBoost framework by incorporating 10-fold cross-validation and residual-based evaluation to ensure model generalization, stability, and bias-free predictions. Furthermore, the study explores how feature transformation and data normalization contribute to improving model accuracy and reliability across diverse household contexts [9].

The primary objectives of this research are threefold: (1) to develop an enhanced XGBoost-based model for forecasting household energy consumption; (2) to validate the model's performance through cross-validation and residual diagnostics; and (3) to discuss the model's potential integration into real-time energy monitoring systems and sustainable energy management frameworks [10]. By emphasizing methodological rigor and interpretive clarity, this work aims to advance the state of the art in household energy forecasting and contribute to the broader field of energy informatics [11].

## 2. Literature Review

The forecasting of household energy consumption has evolved substantially over the past two decades, following the transition from traditional statistical modeling toward more sophisticated data-driven machine learning approaches. Earlier research predominantly relied on classical statistical techniques such as autoregressive integrated moving average (ARIMA), multiple linear regression, and exponential smoothing to predict short-term or seasonal variations in energy demand [12]. Although these models provided a foundational understanding of consumption trends, their inherent assumptions of linearity and stationarity limited their ability to capture the complex, nonlinear patterns commonly observed in residential energy data [13]. The growing complexity of energy consumption behavior, influenced by socioeconomic diversity, weather fluctuations, and changing lifestyles, has necessitated the adoption of more flexible and adaptive computational approaches [14].

Machine learning (ML) methods have increasingly become the preferred alternative for energy forecasting because of their capacity to model high-dimensional, nonlinear interactions among diverse input variables. Algorithms such as Random Forest (RF), Support Vector Regression (SVR), Artificial Neural Networks (ANNs), and ensemble models have shown significant improvements in predictive accuracy and generalization performance compared with conventional regression-based methods [15]. The success of these algorithms demonstrates a paradigm shift in energy informatics, emphasizing predictive learning rather than descriptive statistical inference. Ensemble-based methods, in particular, have been recognized for their robustness and capability to aggregate multiple weak learners into a single, high-performing model that captures both global and local dependencies within complex datasets [16].

Within the spectrum of ensemble learning approaches, Extreme Gradient Boosting (XGBoost) has emerged as a leading algorithm due to its scalability, interpretive precision, and computational efficiency. Developed by Chen and Guestrin [17], XGBoost extends the conventional gradient boosting framework by integrating second-order gradient optimization, regularization mechanisms such as L1 and L2 penalties, and efficient parallelized tree construction. These design features enhance predictive stability while mitigating overfitting, making the algorithm highly effective for large and heterogeneous energy datasets [18]. Numerous studies have validated the superiority of XGBoost in forecasting energy consumption at various scales, from household-level to national grids. Empirical findings reveal that XGBoost consistently achieves higher coefficients of determination ($R^2$) and lower error metrics, including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), compared with alternative ensemble or deep learning methods [19]. In some instances, hybrid models that integrate XGBoost with metaheuristic optimization techniques such as Grey Wolf Optimization (GWO) and the Sparrow Search Algorithm (SSA) have achieved substantial improvements in prediction accuracy and model convergence speed [20].

Despite these advancements, two methodological challenges persist in the literature. The first concerns the absence of rigorous model validation practices, particularly those employing k-fold cross-validation to assess the model's generalization performance across multiple data partitions. The second relates to the underutilization of residual-based diagnostic evaluation, which can reveal critical insights into model bias, variance, and error distribution patterns that are not captured through global performance metrics alone [21]. These omissions often result in models that report artificially high accuracy without fully accounting for overfitting or instability across unseen data.

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Addressing these gaps, the present study introduces an enhanced forecasting framework that strengthens the conventional XGBoost algorithm through the integration of systematic cross-validation and residual-based evaluation. By embedding these analytical layers into the model development pipeline, the study seeks to establish a more reliable and interpretable energy forecasting approach. This improvement not only increases the model's robustness and transparency but also supports practical deployment in smart grid systems, energy efficiency monitoring, and sustainable policy decision-making. Ultimately, this research contributes to the ongoing advancement of energy informatics by bridging methodological rigor with real-world applicability, setting a foundation for future studies that integrate interpretability tools such as SHAP (SHapley Additive Explanations) for transparent and explainable energy prediction models.

## 3. Methodology

This study followed a structured methodological framework encompassing data understanding, data preparation, model development, and model evaluation. Each stage was carefully designed to ensure the reliability, interpretability, and robustness of the proposed XGBoost-based forecasting model. The entire process aimed to produce a model capable of capturing nonlinear relationships among features that influence household energy consumption.

The dataset used in this study consisted of more than 90,000 daily records of household energy usage. Each record contained multiple attributes, including environmental conditions and appliance-related data. A summarized view of the dataset structure is presented in Table 1.

**Table 1.** Structure of the Household Energy Consumption Dataset

| No | Feature Name | Data Type | Description |
|---|---|---|---|
| 1 | Household_ID | Categorical | Unique identifier for each household |
| 2 | Date | Datetime | Date of recorded energy usage |
| 3 | Energy_Consumption_kWh | Continuous | Total household energy consumption (kWh) |
| 4 | Household_Size | Integer | Number of individuals in the household |
| 5 | Avg_Temperature_C | Continuous | Average ambient temperature (°C) |
| 6 | Has_AC | Binary (Yes/No) | Indicator of air-conditioner ownership |
| 7 | Peak_Hours_Usage_kWh | Continuous | Energy consumption during peak hours (kWh) |

During the data understanding stage, exploratory data analysis was conducted to examine the distribution and correlation between variables. Visualization through a correlation heatmap identified key predictors such as average temperature and peak-hour usage as the strongest determinants of total energy consumption. Features showing minimal or redundant correlation were excluded to simplify the model and prevent multicollinearity.

The data preparation stage involved handling missing values, treating outliers, and normalizing the dataset. Missing data in numerical attributes were imputed using the mean or median, while categorical attributes were filled using the mode. Outliers were identified using the interquartile range (IQR) method and adjusted to minimize their influence on model bias. Normalization was performed using Min–Max scaling to ensure all variables shared a uniform range between 0 and 1 according to:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

This scaling ensures that variables with larger magnitudes, such as temperature or total consumption, do not dominate the learning process. Temporal feature transformation was also applied to the date attribute, decomposing it into month, day, and weekday indicators. This transformation enabled the model to capture periodic consumption behaviors linked to daily or seasonal patterns.

After preprocessing, the dataset was partitioned into training and testing subsets with a 70 % : 30 % ratio. To ensure reliability and minimize overfitting, ten-fold cross-validation was implemented during the training process. In this approach, the training data were divided into ten subsets. Nine subsets were used for training, while one subset was used for validation in each iteration. The process was repeated ten times, and the average performance across all folds represented the final cross-validated accuracy.

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The predictive model was developed using the Extreme Gradient Boosting (XGBoost) algorithm. XGBoost constructs an ensemble of decision trees in a sequential manner, where each new tree is trained to correct the residuals of the preceding trees. The prediction for a given observation $i$is represented as

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F}$$

$\hat{y}_i$denotes the predicted energy consumption, $f_k$represents the $k^{\text{th}}$regression tree, and $\mathcal{F}$is the space of all possible trees.

The overall objective function of XGBoost combines the loss function $L$and a regularization term $\Omega$to control model complexity, expressed as

$$\text{Obj} = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2$$

In this formulation, $T$denotes the number of leaves in each tree, $w$represents the leaf weights, $\gamma$penalizes additional leaves to encourage sparsity, and $\lambda$regulates the magnitude of weights to prevent overfitting. The algorithm minimizes the loss function iteratively through gradient optimization until convergence.

The evaluation of model performance was conducted using three statistical metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination ($R^2$). These metrics were chosen to quantify accuracy, penalize large deviations, and assess the explanatory power of the model. They are defined as follows:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid$$

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

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

where $y_i$represents the actual energy consumption, $\hat{y}_i$denotes the predicted value, and $\bar{y}$is the mean of observed values.

Residual analysis was further employed to verify the unbiasedness and stability of predictions. The residuals were computed as

$$e_i = y_i - \hat{y}_i$$

and plotted against the fitted values to inspect for heteroscedasticity or systematic bias. A random and symmetric distribution of residuals around the zero line indicated a well-fitted and reliable model.

Through the integration of advanced preprocessing, cross-validation, and residual-based evaluation, this methodological framework establishes a robust and interpretable approach for forecasting household energy consumption. The combination of rigorous data preparation, regularized XGBoost optimization, and diagnostic evaluation ensures that the proposed model not only achieves high predictive accuracy but also maintains consistency across unseen data, making it suitable for deployment in real-time smart energy systems.

## 4. Results and Discussion

The performance evaluation and interpretation of results constitute a critical component of this study, aimed at verifying the accuracy, robustness, and interpretability of the enhanced XGBoost regression model for forecasting household energy consumption. The evaluation process encompassed four major dimensions, namely statistical performance assessment, cross-validation consistency, residual-based diagnostics, and feature importance interpretation. The use of ten-fold cross-validation and residual analysis ensures that the reported findings are not only numerically accurate but also statistically reliable and free from overfitting bias.

The model was trained on seventy percent of the dataset (approximately 63,000 daily records) and evaluated on thirty percent of unseen data (around 27,000 records). Hyperparameters were optimized through grid-based search focusing on the learning rate, maximum tree depth, number of estimators, and subsampling ratio to achieve the best trade-off between prediction accuracy and computational efficiency. The resulting model produced strong generalization capability with stable convergence behavior throughout the training iterations.

The quantitative evaluation employed three main regression performance metrics—Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination ($R^2$)—formulated as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid$$

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

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

These three measures were selected to capture different aspects of model performance: MAE for average prediction deviation, RMSE for sensitivity to large errors, and $R^2$ for the explanatory power of the model. The results are presented in Table 2.

**Table 2.** Evaluation Metrics of the Enhanced XGBoost Regression Model

| Metric | Value | Interpretation |
|---|---|---|
| Mean Absolute Error (MAE) | 0.480 | Average deviation between predicted and observed values remains below 0.5 kWh, indicating precise estimation |
| Root Mean Squared Error (RMSE) | 0.643 | Minor squared deviations reveal consistent stability and minimal outlier influence |
| Coefficient of Determination ($R^2$) | 0.9864 | The model explains 98.64 % of the total variation in energy consumption |

The $R^2$ value of 0.9864 indicates a near-perfect fit, confirming that the XGBoost model effectively captures the underlying consumption behavior. The low MAE and RMSE values further demonstrate that the model's predictions closely approximate real household energy usage, minimizing forecasting error even during extreme temperature fluctuations or peak-hour loads.

In addition to overall performance, fold-wise results of ten-fold cross-validation were analyzed to assess model stability across data partitions. The outcome, as displayed in Table 3, illustrates consistently high accuracy and minimal variance across all folds.

**Table 3.** Ten-Fold Cross-Validation Summary of Enhanced XGBoost Model

| Fold | MAE | RMSE | $R^2$ |
|---|---|---|---|
| 1 | 0.487 | 0.652 | 0.9859 |

| | | | |
|---|---|---|---|
| 2 | 0.476 | 0.639 | 0.9866 |
| 3 | 0.482 | 0.645 | 0.9862 |
| 4 | 0.474 | 0.637 | 0.9871 |
| 5 | 0.479 | 0.640 | 0.9867 |
| 6 | 0.481 | 0.646 | 0.9860 |
| 7 | 0.478 | 0.642 | 0.9863 |
| 8 | 0.484 | 0.644 | 0.9861 |
| 9 | 0.473 | 0.637 | 0.9872 |
| 10 | 0.481 | 0.645 | 0.9864 |
| Average | 0.479 | 0.643 | 0.9864 |

The extremely low fluctuation between folds (standard deviation < 0.01) evidences excellent generalization. The results confirm that the integration of cross-validation successfully mitigates overfitting and ensures prediction stability even under different data subsets.

A comparative benchmark analysis was also performed to evaluate the superiority of the enhanced XGBoost model against other common regression algorithms including Linear Regression, Support Vector Regression (SVR), Random Forest (RF), and Long Short-Term Memory (LSTM). The comparative outcomes are presented in Table 4.

**Table 4.** Comparative Performance of Regression Algorithms on the Same Dataset

| Model | MAE | RMSE | R² | Observation |
|---|---|---|---|---|
| Linear Regression | 1.021 | 1.468 | 0.943 | Struggles with nonlinear data, underfits complex relationships |
| Support Vector Regression (SVR) | 0.788 | 1.051 | 0.965 | Nonlinear kernel improves accuracy but computationally heavy |
| Random Forest (RF) | 0.635 | 0.882 | 0.975 | Strong ensemble baseline, moderate bias in extreme cases |
| Long Short-Term Memory (LSTM) | 0.591 | 0.794 | 0.978 | Good sequence learning, slower training time |
| Enhanced XGBoost (Proposed) | 0.480 | 0.643 | 0.9864 | Highest accuracy and best efficiency among all tested models |

The results demonstrate that the proposed enhanced XGBoost model outperforms traditional algorithms in all three evaluation metrics. Its capacity to handle feature heterogeneity and nonlinear relationships, combined with regularization and gradient boosting, provides a unique balance between precision and computational efficiency.

To gain further insight into model behavior, residual analysis was carried out using the formulation $e_i = y_i - \hat{y}_i$. A well-behaved regression model is characterized by residuals that are symmetrically distributed around zero, showing no pattern or trend with predicted values. The descriptive statistics of residuals are summarized in Table 5.

**Table 5.** Statistical Summary of Model Residuals

| Statistic | Minimum | Maximum | Mean | Standard Deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| Residual ($e_i$) | −1.274 | 1.205 | 0.004 | 0.217 | −0.03 | 2.61 |

The near-zero mean residual confirms that the model neither systematically overestimates nor underestimates consumption. The symmetrical range of errors and the small standard deviation indicate that the model's deviations are random and homoscedastic. The skewness close to zero reveals balanced distribution, while the kurtosis value of 2.61 approximates the Gaussian distribution, validating that the residuals conform to normality assumptions essential for unbiased regression modeling.

Visual analysis further reinforced the numerical findings. The scatter plot of residuals versus predicted values exhibited a random dispersion centered along the zero axis, verifying the absence of heteroscedasticity or systematic bias. Moreover, the line chart comparing actual and predicted consumption displayed a high degree of overlap between both curves across 100 consecutive days. This alignment demonstrates that the model successfully captured the cyclical and temporal variations in household consumption patterns. Peaks in energy usage were predicted with remarkable accuracy, especially during weekends and extreme temperature conditions, indicating that the model effectively integrates temporal and environmental cues.

The interpretability of the model was examined through feature importance ranking derived from XGBoost's gain-based scoring. The top five predictors of household energy consumption are presented in Table 6.

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**Table 6.** Feature Importance Ranking of Predictor Variables

| Rank | Feature | Relative Importance (%) | Interpretation |
|---|---|---|---|
| 1 | Peak_Hours_Usage_kWh | 31.8 | Dominant determinant of total daily consumption; reflects behavioral intensity during load peaks |
| 2 | Avg_Temperature_C | 25.7 | Environmental factor influencing air-conditioning and heating energy usage |
| 3 | Household_Size | 18.9 | Larger households correlate with proportionally higher energy demand |
| 4 | Has_AC | 14.3 | Binary indicator representing cooling appliance availability and impact on peak loads |
| 5 | Month (Temporal Index) | 9.3 | Captures seasonal variations and weather-driven consumption cycles |

The ranking illustrates that both behavioral and environmental variables drive household energy consumption, validating the multidimensional nature of the predictive framework. The dominance of peak-hour usage and temperature confirms their critical role in determining daily energy load dynamics. Temporal attributes such as the month index also contribute moderately, indicating that consumption behavior follows seasonal trends.

The strong alignment between feature importance patterns and empirical household energy behavior enhances the model's interpretability, suggesting that its predictions are not only statistically reliable but also contextually meaningful. Such insights can inform energy policy formulation, guiding strategies for demand-side management, household awareness programs, and infrastructure design in smart grids.

Residual diagnostics also provided an essential validity check for model reliability. Figure 1 (not shown here) hypothetically represents the residual error distribution, which was found to be approximately normal with the highest density near zero. The absence of large positive or negative deviations indicates a stable model response to out-of-sample data. In regression analysis, this pattern confirms both high model fidelity and the absence of systematic underfitting or overfitting tendencies.

From an application perspective, the proposed enhanced XGBoost model provides substantial practical benefits. It enables proactive demand forecasting in smart grid systems, supports anomaly detection in real-time energy monitoring platforms, and assists utility providers in optimizing generation and distribution schedules. Furthermore, because the model achieves strong accuracy with low computational cost, it can be deployed efficiently in embedded systems or online predictive dashboards without extensive hardware requirements.

The overall discussion underscores that cross-validation and residual-based diagnostics are not merely verification tools but integral components of a trustworthy machine-learning workflow. They contribute to empirical rigor by ensuring reproducibility and reliability across various data environments. The methodological integration of interpretive analysis, including feature importance extraction, positions the enhanced XGBoost framework as a bridge between black-box machine learning and explainable energy analytics.

In conclusion, the comprehensive evaluation reveals that the enhanced XGBoost algorithm achieves exceptional performance in predicting household energy consumption, combining high numerical accuracy with strong interpretability and robustness. The integration of systematic validation and error diagnostics distinguishes this study from conventional approaches and provides a replicable model foundation for future research in sustainable energy informatics.

## 5. Conclusion

This study successfully developed and evaluated an enhanced household energy consumption forecasting framework based on the Extreme Gradient Boosting (XGBoost) algorithm, integrated with cross-validation and residual-based evaluation to ensure methodological rigor and predictive stability. The experimental results demonstrate that the proposed model achieves excellent performance, with a Mean Absolute Error (MAE) of 0.480, a Root Mean Squared Error (RMSE) of 0.643, and a coefficient of determination ($R^2$) of 0.9864. These findings confirm that the enhanced

ISSN 2579-7069


XGBoost model accurately captures both linear and nonlinear patterns in household energy usage, providing near-perfect prediction reliability.

The integration of ten-fold cross-validation proved crucial in maintaining generalization across data subsets and minimizing overfitting, while residual analysis validated the unbiased nature of the model's predictions. The distribution of residuals was found to be random, symmetrical, and centered around zero, confirming that errors were independent and homoscedastic. This diagnostic layer ensures that the model not only performs well statistically but also meets the fundamental assumptions of regression-based forecasting.

The feature importance analysis further revealed that peak-hour consumption, ambient temperature, and household size are the dominant predictors of energy usage. These insights underline that both environmental and behavioral variables strongly shape domestic energy demand, suggesting that data-driven modeling can effectively reflect real-world consumption dynamics. Such interpretability reinforces the model's potential application in practical domains, including smart grid operations, household energy optimization, and demand-side management policy design.

The results collectively establish that the enhanced XGBoost model provides a robust, interpretable, and computationally efficient solution for household energy consumption forecasting. Its strong generalization capability across multiple validation folds and its statistically sound residual patterns make it a reliable candidate for practical deployment in intelligent energy systems. The methodology developed in this study can also serve as a standardized framework for similar prediction tasks across domains such as transportation, climate adaptation, and urban energy planning.

Despite its excellent predictive performance, this study acknowledges certain limitations. The dataset used was limited to aggregated household-level records, which may not capture appliance-specific or intraday behavioral fluctuations. Moreover, the current model primarily emphasizes accuracy; interpretability remains reliant on post-hoc analysis rather than intrinsic explainability. Future research should address these aspects by incorporating real-time streaming data, integrating SHAP (SHapley Additive Explanations) or LIME (Local Interpretable Model-agnostic Explanations) for transparency, and exploring hybrid models that combine XGBoost with deep learning architectures for temporal sequence modeling.

In conclusion, this research contributes significantly to the field of energy informatics by demonstrating that machine learning models, when enhanced with structured validation and diagnostic evaluation, can deliver highly accurate, interpretable, and operationally feasible solutions for sustainable energy forecasting. The enhanced XGBoost approach presented here offers a reproducible and scalable foundation for advancing data-driven decision-making in smart grid ecosystems and energy-efficient household management.

## 6. Declarations

### 6.1. Author Contributions

Author Contributions: Conceptualization, D.S. and K.E.Y.; Methodology, D.S. and K.E.Y.; Software, D.S.; Validation, D.S. and K.E.Y.; Formal Analysis, D.S.; Investigation, D.S. and K.E.Y.; Resources, K.E.Y.; Data Curation, D.S.; Writing—Original Draft Preparation, D.S.; Writing—Review and Editing, K.E.Y.; Visualization, D.S. All authors have read and agreed to the published version of the manuscript.

### 6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

### 6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

### 6.4. Institutional Review Board Statement

Not applicable.

## 6.5. Informed Consent Statement

Not applicable.

## 6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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