

Green Machine Learning for Smart Grid Stability Prediction: Performance and Energy-Efficient Evaluation

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ABSTRACT

The increasing complexity of modern smart grids necessitates intelligent and sustainable predictive models that ensure system stability while minimizing computational energy consumption. This study explores the concept of Green Machine Learning (GML), which integrates high predictive accuracy with energy-efficient computation to promote sustainability in smart grid systems. Unlike conventional benchmarking studies, we propose a sustainability-oriented evaluation framework based on a dual-metric approach (GreenScore and GreenScore*), enabling the joint assessment of predictive accuracy and computational efficiency. This framework serves as a decision-support tool for selecting models under energy and operational constraints. The results demonstrate that MLP has reached the highest level predictive performance (F1 = 0.9736, AUC = 0.9957), while LightGBM offered the best compromise between accuracy and computational efficiency (F1 = 0.9685, AUC = 0.9941). Although Logistic Regression exhibited minimal energy consumption (execution time = 0.03 s), its accuracy was relatively low (0.8027). According to GreenScore and GreenScore*, LightGBM (GreenScore = 0.66, GreenScore* = 0.2646) and Extra Trees (GreenScore = 1.24, GreenScore* = 0.9449) demonstrate superior energy sustainability, while MLP (GreenScore* = 0.0161) and CatBoost (GreenScore* = 0.2171) reflect lower efficiency. Logistic Regression, despite very low computational cost, has a high GreenScore* (533.8422) due to its extremely low execution time but poor predictive performance. Overall, the study confirms that Green Machine Learning enables a multi-objective optimization between predictive performance and energy efficiency, advancing the development of sustainable smart grid management systems.

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1. INTRODUCTION

Ensuring the stability of intelligent power grids has become a central challenge in contemporary energy systems, as the increasing integration of renewable energy sources introduces significant variability and complexity into grid operation [1]. Maintaining stable and reliable grid performance requires not only precise prediction mechanisms but also computationally efficient approaches that align with sustainability goals [2]. Factors affecting grid stability include fluctuating generation from renewables, dynamic demand

patterns, system topology, and real-time control parameters, all of which interact in complex and nonlinear ways [3]. For instance, voltage instability and frequency oscillations often occur under sudden changes in renewable generation or load demand, challenging the resilience of traditional prediction and control systems [4]. The use of artificial intelligence AI in predictive control is growing and the energy cost of computation has become an important aspect of sustainability [5]. In recent years, the evaluation of Machine Learning models has evolved from a purely accuracy-driven paradigm toward a multi-objective optimization framework, where predictive performance, computational efficiency and environmental impact must be jointly considered. This shift is particularly critical in smart grid systems, where large-scale data processing and real-time decision-making impose strict energy and latency constraints.

Relying solely on accuracy may lead to the selection of computationally expensive models that are not suitable for sustainable or real-time deployment. Therefore, this study adopts a Green Machine Learning (GML) perspective, emphasizing the importance of balancing predictive reliability with computational and energy efficiency. This paradigm enables a more realistic and operational evaluation of Machine Learning models in energy-critical environments. Therefore, it is necessary to strike a balance between predictive power and energy efficiency in order to develop environmentally sustainable smart grids [6]. To overcome these challenges, this research addresses the ability of environmentally friendly ML models to predict the stability of smart grids. Specifically, we evaluate and compare the predictive performance and energy efficiency of six machine learning algorithms (Random Forest, Logistic Regression, Extra-trees, LightGBM, CatBoost, and MLP) using a large-scale dataset comprising 60,000 grid samples. The analysis incorporates both performance-focused metrics (precision, Recall, F1, AUC, MCC and Kappa) and energy-oriented indicators (execution time and GreenScore) to assess the overall sustainability of each model. By quantifying both predictive quality and environmental impact, this study contributes to progressing energy-efficient AI in smart grid applications. The objectives of this work can be summarized as follows:

- Enhance the predictability of the stability of smart grids by applying advanced, energy-efficient ML algorithms that are able to model the nonlinear and dynamic behaviors of grids.
- To conduct a comparative evaluation of multiple ML models in terms of both predictive performance and computational sustainability.
- To identify the models that achieve the best trade-off between accuracy and energy consumption using composite indicators such as GreenScore.
- Spotlight the power of green AI technology in improving the reliability and resilience of smart grids.
- To provide insights into how environmentally efficient Machine Learning models can support the digital and ecological transition of modern power systems.
- To enable the design of a sustainable smart grid infrastructure through data-driven, energy-efficient, and high-performance predictive modeling.

Unlike traditional benchmarking studies that focus primarily on accuracy comparison, this work proposes a multi-objective evaluation framework that integrates predictive performance, computational efficiency, and sustainability considerations. The contribution lies not in introducing new algorithms, but in redefining how Machine Learning models are assessed in energy-critical environments such as smart grids. The remaining sections of this research are organized as shown below: Section two discusses related works in the field of energy-efficient machine learning and predictive stability of smart grids. Section three explains the proposed methodology and how to apply the model. Section four presents and discusses the results of the experiments, while the fifth section provides an in-depth analysis and interpretation of the results obtained. Finally, the sixth section concludes the study and highlights possible avenues for future research aimed at promoting sustainable and smart energy systems.

2. RELATED WORKS

2.1. Energy Administration and Intelligent Control in Smart Grids

Recent advancements in smart grid research have increasingly focused on integrating Machine Learning techniques with energy-efficient strategies to enhance grid stability and sustainability. Battula et al. [7] emphasized the importance of intelligent optimization in reducing energy losses and maintaining microgrid stability through adaptive energy management systems. Soliman et al. [8] proposed a robust decentralized control method to ensure voltage stability in islanded microgrids under dynamic renewable conditions, providing a foundation for resilient grid operation. In parallel, Swain et al. [9] introduced a blockchain-based green energy model supported by nature-inspired algorithms to optimize communication and energy distribution, thus improving both reliability and sustainability. Veeramsetty et al. [10] demonstrated the effectiveness of lightweight learning algorithms such as Stochastic Gradient Descent (SGD) in short-term load forecasting, highlighting the potential of Green Machine Learning approaches that balance

computational efficiency and predictive accuracy. Musengimana et al. [11] addressed the stability of photovoltaic inverters connected to weak grids, proposing control mechanisms to prevent voltage collapse and enhance energy resilience. Similarly, Benbouhenni et al. [12] applied higher-order sliding mode control to minimize torque and power ripples in wind systems, ensuring dynamic stability with reduced energy consumption. Dubey et al. [13] further explored multi-objective optimization through the Equilibrium Optimizer, achieving a balance between cost, emissions, and performance. Finally, Lee et al. [14] utilized reinforcement learning for intelligent energy storage scheduling, integrating degradation and lifecycle costs to achieve sustainable and efficient energy management. In general, these studies highlight the capabilities of AI-powered energy management as the cornerstone for developing stable and sustainable smart grid systems.

2.2. Approaches for Grid Stability Prediction based ML

Machine Learning has emerged as a powerful tool to predict and enhance smart grid stability, enabling early detection of potential instabilities due to renewable fluctuations and variable demand. Using the Electrical Grid Stability Simulated Dataset from the Karlsruhe Institute of Technology, Ezzahra et al. [15] demonstrated that the Extreme Gradient Boosting (XGBoost) model achieved superior results (95.23% accuracy) when combined with the `f_classif` feature selection technique, confirming its robustness for stability prediction and sustainable grid management. Similarly, Kumar Reddy et al. [16] evaluated classical models such as Logistic Regression, SVM, Naïve Bayes, Decision Tree, KNN, and Neural Networks, finding that Decision Tree Classifiers offered the most effective results after hyperparameter tuning. Mohsen et al. [17] proposed an Artificial Neural Network (ANN) model for Decentralized Smart Grid Control (DSGC) systems, achieving remarkable results with a 97.36% testing accuracy, 98.02% weighted F1-score, and 100% AUC, highlighting ANN's potential for real-time grid stability forecasting. Franović et al. [18] extended this line of research by analyzing decentralized smart grid stability using multiple ML models (MLP, XGBoost, SVM, Genetic Programming) on a dataset of 30,000 samples. Their findings confirmed that XGBoost achieved the best classification results, even without time-response variables, emphasizing its efficiency in data-driven grid modeling. Additionally, Wang et al. [19] reinforced the importance of AI in intelligent grid prediction by applying advanced ML models to the UCI Smart Grid Stability Dataset, confirming that intelligent classification systems play a critical role in ensuring sustainable energy operation.

2.3. Green Machine Learning and Sustainable Prediction Frameworks

The growing complexity of modern electrical networks, intensified by the integration of renewable energy sources and the increasing demand for sustainable energy, has underscored the critical role of smart grids in achieving stability and energy efficiency. However, predicting and maintaining grid stability remains a persistent challenge, as power systems exhibit nonlinear dynamics influenced by fluctuations in generation, consumption, and environmental conditions. To address these challenges, Green Machine Learning (GML) has emerged as a promising approach that combines high predictive performance with reduced computational and energy costs. Unlike conventional ML methods, GML emphasizes algorithmic efficiency, employing techniques such as pruning, quantization, and lightweight architectures to achieve energy-aware computation while preserving accuracy.

Several studies have demonstrated the application of ML to grid stability prediction. Rai and De [20] implemented regression-based forecasting using real-time smart meter data, demonstrating the effectiveness of preprocessing in enhancing model performance. Alazab et al. [21] introduced an enhanced LSTM architecture that improved prediction accuracy over traditional recurrent models. Comparative analyses by Ghosh and Koley [22] and Bashir et al. [23] identified ensemble models like XGBoost and Decision Trees as robust classifiers for grid stability assessment. Ahmed et al. [24] proposed a hybrid energy management model integrating Gaussian Process Regression to handle renewable energy variability, outperforming classical optimization techniques. Wang et al. [25] employed Bayesian optimization with LightGBM, achieving fast and accurate learning for large-scale datasets. Ma et al. [26] developed a Grid Stability Awareness System (GSAS) for real-time monitoring, while Malbasa et al. [27] highlighted Random Forest as the most effective classifier for voltage stability prediction. More recent works introduced sustainability considerations, such as Panda and Das [28], who linked decentralized control with energy resilience, and Gorzaczany et al. [29], who applied fuzzy inference for interpretable and computationally efficient prediction. The ReSGPC framework proposed by Dayananda et al. [30] further integrated Kalman filters for energy-efficient and cyber-resilient grid protection. Recent research has introduced composite sustainability metrics that integrate energy consumption, execution time, and carbon footprint, such as the Python GreenScore proposed by Turja et al. [31]. These approaches primarily focus on software-level energy profiling and aim to optimize code execution efficiency across different runtime environments. However, such metrics do not incorporate predictive performance, which is a fundamental requirement in Machine Learning applications, particularly in smart grid stability prediction where both accuracy and computational

efficiency are critical. Furthermore, these approaches are often tightly coupled with specific programming environments and hardware configurations, limiting their applicability for fair and reproducible comparison between heterogeneous learning models. To address these limitations, this work proposes a model-level sustainability evaluation framework specifically designed for Machine Learning. Unlike existing approaches, the proposed framework enables a consistent and hardware-agnostic comparison of predictive models under identical experimental conditions. In addition, this study introduces an enhanced composite metric, GreenScore*, which extends the classical GreenScore by integrating both predictive quality and discriminative capability while stabilizing the impact of computational cost. This contribution provides a more robust and unbiased assessment of the trade-off between performance and efficiency in smart grid applications.

2.4. Synthesis and Research Gap

The reviewed literature confirms that intelligent control and data-driven optimization are key to improving the resilience and sustainability of smart grids. However, while traditional ML models provide strong predictive performance, their computational cost and carbon footprint remain underexplored in most studies. Recent efforts in Green Machine Learning address this limitation by emphasizing lightweight models and energy-aware evaluation metrics. Building upon these foundations, the present study aims to conduct a comprehensive performance and energy-efficiency evaluation of multiple ML algorithms, including Logistic Regression, Random Forest, XGBoost, CatBoost, LightGBM, and MLP, in order to identify the most sustainable and accurate approach for Smart Grid Stability Prediction. Although several studies have applied Machine Learning models such as Random Forest, CatBoost, and Gradient Boosting to smart grid stability prediction, most of these works focus exclusively on maximizing predictive accuracy. The computational cost and energy efficiency of these models remain largely underexplored, particularly in the context of sustainable AI. Therefore, the novelty of this study lies in reframing model evaluation under Green Machine Learning principles, introducing sustainability-aware metrics and analyzing performance–efficiency trade-offs. This perspective is essential for transitioning from purely theoretical models to practical, deployable solutions in modern energy systems.

3. RESEARCH METHOD

In this article, we present a comparative study of application of Green Machine Learning techniques for the prediction of smart grid stability by integrating performance accuracy and energy efficiency criteria. The analysis includes a comparative evaluation of several models, ranging from lightweight algorithms such as logistic regression to more advanced and computationally efficient methods, including Random Forest, Extra Trees, LightGBM, CatBoost and MLP. Each model has different characteristics, advantages, and disadvantages in terms of predictive power, computational cost, and energy consumption, which directly affect its suitability for real-time stability assessment. This work emphasizes the growing importance of combining high predictive accuracy with low environmental impact and proposes a new perspective on sustainable artificial intelligence for energy systems. By evaluating the predictive and environmental dimensions of machine learning, this study highlights the respective strengths and limitations of each approach and contributes to the development of intelligent and environmentally efficient solutions for next-generation smart grids.

3.1 Model selection criteria

The selection ML models in this study was guided by a set of rigorous scientific and environmental criteria designed to ensure both predictive reliability and computational sustainability [32].

- Modeling linear and nonlinear relationships: The inclusion of Logistic Regression as a baseline linear model enables the analysis of fundamental stability patterns, while ensemble-based and gradient boosting models such as Extra Trees, Random Forest, LightGBM, and CatBoost capture complex nonlinear interactions inherent in smart grid dynamics.
- Energy-aware computational efficiency: Models were selected not only for their accuracy but also for their execution time and energy footprint. Algorithms like LightGBM and Extra Trees are particularly suitable for large-scale grid data, offering an optimal trade-off between precision and energy efficiency.
- Robustness and stability: Ensemble techniques, including Random Forest and CatBoost, provide strong generalization capabilities while minimizing overfitting, which is critical for maintaining reliable stability prediction across variable operational conditions.
- Adaptability to smart grid data characteristics: CatBoost effectively manages categorical and heterogeneous variables, while MLP (Multilayer Perceptron) excels in modeling nonlinear temporal dependencies, making it valuable for understanding dynamic grid fluctuations.

- Sustainability-oriented methodological diversity: By combining models of different computational complexities and learning paradigms, this study ensures a comprehensive and interpretable evaluation framework that balances predictive performance, energy efficiency, and environmental responsibility.

This methodological diversity establishes a robust foundation for Green Machine Learning evaluation, enabling the identification of models that not only predict smart grid stability with high precision but also align with sustainable and energy-efficient AI practices.

3.2. Description of Dataset

The dataset used in this research is a fundamental element for evaluating the performance and energy efficiency of Green ML models applied to predicting the stability of intelligent grids. It is a simulated and structured dataset comprising 60,000 samples representing various scenarios of grid stability and instability, collected from dynamic parameters of the electrical system. Each record is defined by 14 main attributes describing the instantaneous operating conditions of the grid, as well as a stability label (stab or stabf) indicating whether the system is stable or unstable. The attributes included such as τ_1 to τ_4 (time constants), p_1 to p_4 (electrical powers), and g_1 to g_4 (coupling coefficients or conductances) represent physical and dynamic variables of the grid, enabling the modelling of interactions between electrical nodes, load and system voltage. These parameters are essential for capturing the non-linearity and temporal complexity inherent in Smart Grid systems.

Table 1. Description of the dataset attributes used for Smart Grid stability prediction

Column	Example	Description	Use in Modeling
$\tau_1, \tau_2, \tau_3, \tau_4$	2.95, 3.07, 8.38, 9.78	Voltage delay parameters (tau) representing the temporal response of the electrical system	Continuous explanatory variables used to model system dynamics
p_1, p_2, p_3, p_4	3.76, -0.78, -1.25, -1.72	Active power parameters reflecting generator state and system load	Input variables influencing energy stability
g_1, g_2, g_3, g_4	0.65, 0.85, 0.88, 0.95	Coupling or gain coefficients indicating correlation between system units	Continuous variables reflecting inter-generator dependency
stab	0.055	Numeric value indicating the degree of system stability	Intermediate variable used to compute the final stability index
stabf	stable / unstable	Output label representing the stability class of the grid	Target variable for binary classification (stable vs. unstable)

3.3 Dataset preprocessing

In this study, the dataset has been preprocessed to guarantee quality, coherence, and suitability for machine learning analysis. The steps of preprocessing included the following:

- Feature normalization: The dataset contains 13 numerical features and a single categorical output variable, stabf, which indicates the stability of the system (stable or unstable) (Table 1).
- Missing data and noise handling: The data was checked for missing values and inconsistencies to ensure statistical consistency and uniform scaling.
- Target definition: The categorical variable stabf was encoded into binary values (0 for unstable, 1 for stable) to facilitate supervised learning.
- Feature scaling: All numerical features were normalized to improve model convergence and numerical stability, especially for gradient-based algorithms.
- Data splitting: The dataset has been split into 70% for training with 30% for testing, to ensure balanced representation of both stability classes.

This pipeline ensures that the dataset is statistically consistent and optimized for different learning algorithms, thereby improving prediction reliability and model generalization.

3.4 Implimentation

The proposed application follows a systematic pipeline designed to evaluate Green Machine Learning (GML) models for Smart Grid Stability Prediction, emphasizing both predictive accuracy and energy efficiency. As illustrated in Figure 1, the process begins with data preprocessing, which involves cleaning and normalizing the dataset, handling missing or inconsistent entries, performing feature selection, and dividing the data into training and testing subsets to ensure model reliability. Next, a diverse set of algorithms is trained, including traditional Machine Learning models (Logistic Regression, Random Forest, Extra Trees) [33], gradient boosting methods (LightGBM, CatBoost), and a deep learning approach

(Multilayer Perceptron, MLP).

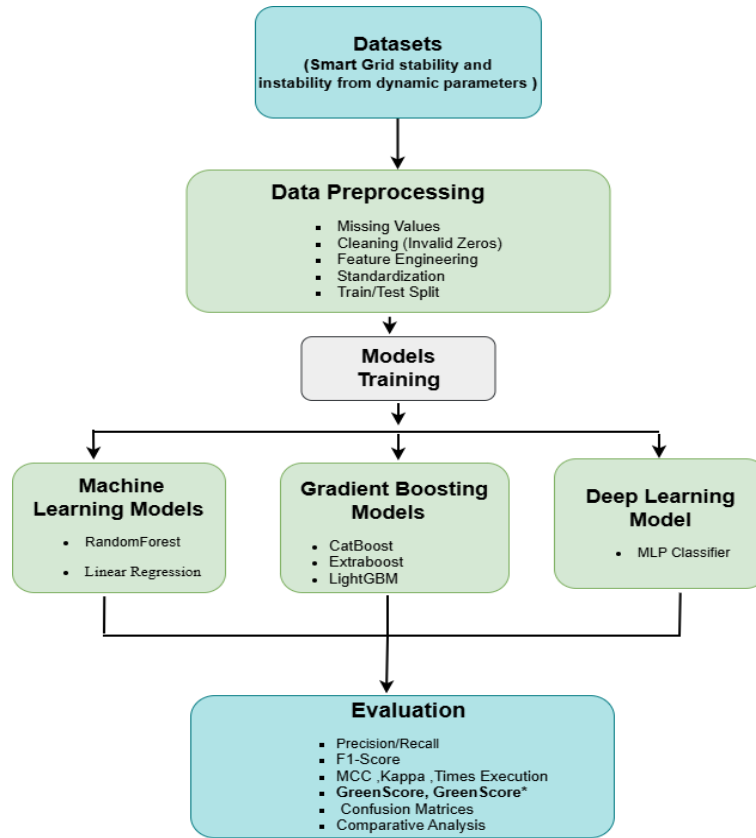


Figure 1. Steps for the proposed method

This comprehensive modeling strategy enables a balanced evaluation across different paradigms of learning, focusing on both accuracy and sustainability. The trained models are then assessed through a dual evaluation process combining performance metrics (MCC, Kappa, AUC, Accuracy, Precision, Recall and F1-score,) and energy-oriented indicators (execution time and GreenScore). Such an integrated methodology provides an in-depth understanding of each model's computational behavior, allowing the identification of algorithms that achieve an optimal trade-off between predictive capability and energy consumption. Ultimately, this pipeline supports the advancement of sustainable and intelligent smart grid management systems, aligning high performance with environmental responsibility.

3.5 Performance Evaluation Measures

To evaluate and compare the performance of our models, we utilize commonly used metrics, including Precision, Recall, F1-score, MCC, Kappa, Time, and GreenScore [34,35].

- **Precision** : indicates how many of the instances identified as positive are truly positive.

$$\text{Precision} = \frac{\text{Correct}}{\text{Correct} + \text{Spurious}} \quad (1)$$

- **Recall** : measures how many of the actual positive instances are correctly detected by the model.:

$$\text{Recall} = \frac{\text{Correct}}{\text{Correct} + \text{Missing}} \quad (2)$$

- **F-measure** : combines precision and recall into a single value, reflecting their balance through the harmonic mean.

$$\text{F1} = \frac{2 * \text{Precision} * \text{Recall}}{(\text{Precision} + \text{Recall})} \quad (3)$$

- **Matthews Correlation Coefficient (MCC)** : Evaluates the quality of binary classifications by

considering all outcomes in the confusion matrix (TP, TN, FP, FN). It measures the correlation between predicted and actual classes, providing a balanced assessment even with imbalanced data.

$$MCC = \frac{(TP*TN)-(FP*FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FN)}} \quad (4)$$

- MCC equal 1 then perfect prediction.
 - MCC equal 0 then random prediction
 - MCC= equal -1 then total disagreement.
- **Kappa** : Cohen's Measures the level of agreement between predicted and actual classifications while accounting for chance agreement. It is particularly valuable for imbalanced datasets.

$$K = \frac{Po-Pe}{1-Pe} \quad (5)$$

where:

- Po equal to observed agreement (empirical accuracy)
 - Pe equal to expected agreement by chance
- **AUC (Area Under the Curve)** : Indicates the model's ability to separate positive and negative classes; higher values mean better performance.

$$AUC = \int_0^1 TPR(FPR^{-1}(x)) dx \quad (6)$$

Interpretation:

- AUC=1 equal to perfect classifier
 - AUC=0.5 equal to random classifier
 - Higher AUC indicates stronger class separability and better predictive reliability.
- **Execution Time (s)**: measures the total computational duration (in seconds) required to train and test the model. It is a crucial metric for evaluating **computational cost** and **energy efficiency** in Green Machine Learning.

Interpretation:

- Lower time : lightweight, energy-efficient model
- Higher time : computationally expensive model

It is important to note that execution time is used in this study as a **proxy indicator for computational cost**, rather than a direct measurement of energy consumption. While time is strongly correlated with energy usage under controlled conditions, actual energy consumption remains **hardware-dependent**, influenced by factors such as processor architecture, memory usage, and system load.

- Therefore, the results presented in this study should be interpreted as **relative comparisons between models under identical experimental settings**, rather than absolute measurements of energy consumption.
- Future work will incorporate **hardware-level energy profiling tools**, such as Intel RAPL and external power measurement devices, to provide more precise and reproducible energy evaluations.
- **GreenScore**: is a composite metric designed to evaluate the **environmental efficiency** of Machine Learning models by integrating predictive performance and computational energy cost. It reflects the balance between model accuracy and sustainability.

$$\text{GreenScore} = \frac{F1}{\text{Time (s)}} \times \alpha \quad (7)$$

where α (alpha) is a normalization constant to maintain comparability between models.

Interpretation:

- High GreenScore : strong performance with low energy cost (ideal balance)
- Low GreenScore : accurate but energy-intensive, or energy-efficient but less accurate;

Unlike system-level energy metrics, it focuses on comparative evaluation under identical experimental conditions, ensuring fairness across models with varying complexities. This formulation provides a simple and interpretable measure of efficiency, reflecting how much predictive performance is achieved per unit of computational time. However, relying solely on execution time may introduce a bias in favor of extremely fast models, even when their predictive capability is limited. To overcome this limitation, this study introduces an enhanced metric, denoted as GreenScore*,

- **GreenScore***: is a novel composite metric designed to assess the trade-off between predictive accuracy and computational efficiency defined as:

$$\text{GreenScore}^* = \frac{(\text{F1} \times \text{AUC})}{\text{Time (s)} \times \log(1 + \text{Time})} \quad (8)$$

The proposed GreenScore* improves the evaluation process in three key aspects. First, it integrates the AUC metric to better capture the model's discriminative ability beyond the F1-score alone. Second, it introduces a logarithmic penalization term that stabilizes the influence of execution time and prevents disproportionate penalization of moderately slower models. Third, it reduces the bias toward overly simplistic yet fast models by promoting a more balanced consideration of predictive quality and computational efficiency. As a result, GreenScore* provides a more robust and balanced assessment of sustainability, particularly in complex and nonlinear environments such as smart grids, where both accuracy and efficiency are critical.

The combination of GreenScore and GreenScore* establishes a dual-metric evaluation framework that captures complementary aspects of model performance: basic efficiency and [36]. optimization. To the best of our knowledge, this represents one of the first attempts to introduce such a sustainability-aware evaluation framework specifically tailored for model-level comparison in smart grid stability prediction.

Although the present study focuses on comparative evaluation, it is important to note that model optimization techniques such as pruning, quantization, and knowledge distillation constitute promising strategies for further improving energy efficiency. These approaches can significantly reduce model complexity, memory consumption, and inference time, thereby enhancing GreenScore-based performance. While not implemented in this work, they are fully compatible with the proposed framework and represent a natural extension for future research.

4. RESULTS AND EVALUATION

In this part, the research results are presented (Table 2, Table 3) and then discussed in detail. The results may be presented in the form of graphs, figures, and other formats to facilitate the reader's understanding. The discussion may be divided into several subsections. It is strongly recommended to provide a comparison with the results of other published articles to give more context and reinforce the novelty.

Table 2. Results of performance models

Model	Accuracy	Precision	Recall	F1-score
L R	0.8027	0.8250	0.8752	0.8494
RF	0.9312	0.9332	0.9604	0.9466
Extra-Trees	0.9380	0.9247	0.9824	0.9527
LightGBM	0.9597	0.9608	0.9764	0.9685
CatBoost	0.9485	0.9506	0.9693	0.9599
MLP	0.9663	0.9708	0.9764	0.9736

Table 3. Performance Metrics of models

Model	MCC	Kappa	AUC	Time (s)	GreenScore	GreenScore*
L R	0.5662	0.5641	0.8826	0.0313	28.2349	533.8422
RF	0.8505	0.8498	0.9846	2.3713	0.4152	1.5570
Extra-Trees	0.8663	0.8630	0.9898	0.7957	1.2438	0.9449
LightGBM	0.9126	0.9124	0.9941	1.5000	0.6627	0.2646
CatBoost	0.8883	0.8880	0.9909	2.8279	0.3504	0.2171
MLP	0.9272	0.9272	0.9957	17.8762	0.0557	0.0161

In this study, we used five-fold cross-validation (Table 4) to robustly evaluate model performance. Consistent results across folds and comparison with final tests (Table 2) confirm dataset quality and reproducibility. LightGBM and MLP showed stable, high performance (<0.3% deviation). From a Green ML perspective, MLP had the highest F1 (0.9736) and accuracy (0.9663) but high computational cost ($\approx 121 \rightarrow 17.9$ s), resulting in low GreenScore (0.0082–0.0557) and GreenScore* (0.0161). LightGBM achieved similar predictive power ($\text{AUC} \approx 0.9941$, $\text{F1} = 0.9685$) with faster runtime (≈ 8.37 to 1.50 s), higher GreenScore (0.119 to 0.663), and moderate GreenScore* (0.2646). CatBoost was stable but slower, with

GreenScore* = 0.2171; Random Forest and Extra Trees balanced accuracy (≈ 0.93 – 0.94) and efficiency, with GreenScore* of 1.5570 and 0.9449, respectively. Logistic Regression remains lightweight and suitable for real-time deployment, despite a high GreenScore* of 533.8422 due to low predictive performance. Overall, the agreement between cross-validation and test results confirms the findings' stability and validity. Including GreenScore emphasizes energy-aware, sustainable Machine Learning, illustrating that cross-validation supports both methodological rigor and computational sustainability.

Table 4. Results of performance for cross-validation (5 folds)

Model	Accuracy	F1-score	MCC	Kappa	AUC	Time (s)	GreenScore
LR	0.8108	0.8248	0.5852	0.5838	0.8890	0.2344	28.2349
RF	0.9307	0.9461	0.8495	0.8491	0.9845	15.4156	0.4152
Extra-Trees	0.9438	0.9567	0.8783	0.8767	0.9901	5.3427	1.2438
LightGBM	0.9627	0.9708	0.9193	0.9191	0.9708	8.3697	0.6627
CatBoost	0.9522	0.9628	0.8964	0.8960	0.9912	16.2565	0.3504
MLP	0.9700	0.9764	0.9353	0.9352	0.9965	121.3686	0.0557

5. ANALYSIS AND DISCUSSION OF RESULTS

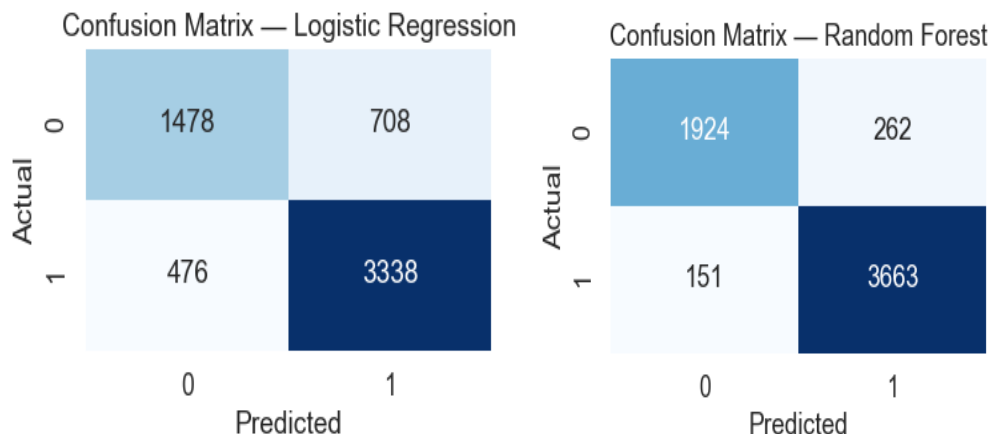
In this section, the results obtained from multiple evaluation metrics are analyzed and discussed. Together, these metrics provide a comprehensive assessment of the models' predictive performance, reliability, and energy efficiency, offering insights into both classification accuracy and computational efficiency.

5.1 Classification Metrics

- **Precision, Recall, and F1-Score Metrics**

The analysis of precision, recall, and F1-score provides a comprehensive understanding of the predictive reliability and classification quality of each model. These three metrics are essential in evaluating the trade-off between false positives and false negatives, which is particularly relevant in applications where misclassification may have significant implications, such as energy stability prediction in smart grids.

In contrast, Logistic Regression (Figure 2.a) displays relatively moderate scores (precision = 0.8250, recall = 0.8752, F1 = 0.8494), revealing its limited ability to model non-linear dependencies between features. While it remains computationally efficient and interpretable, its linear nature restricts its predictive capacity for complex systems such as dynamic smart grid environments. The Random Forest (Figure 2.b) and Extra Trees (Figure 3.a) algorithms also exhibit solid and consistent results (F1 = 0.9466 and 0.9527, respectively). These ensemble methods leverage randomization and aggregation to achieve robust generalization, ensuring stability even in the presence of data variability or noise. Their slightly lower precision values compared to LightGBM and MLP (Figure 4.b) may indicate marginally higher false-positive rates, yet their recall remains excellent, confirming their reliability in recognizing relevant patterns.



The LightGBM (Figure 3.b) model follows closely (precision = 0.9608, recall = 0.9764, F1 =

0.9685), demonstrating a strong equilibrium between underfitting and overfitting due to its efficient gradient-boosting mechanism. Its architecture allows the model to optimize feature interactions effectively, leading to a nearly optimal balance between detection capacity and false alarm reduction.

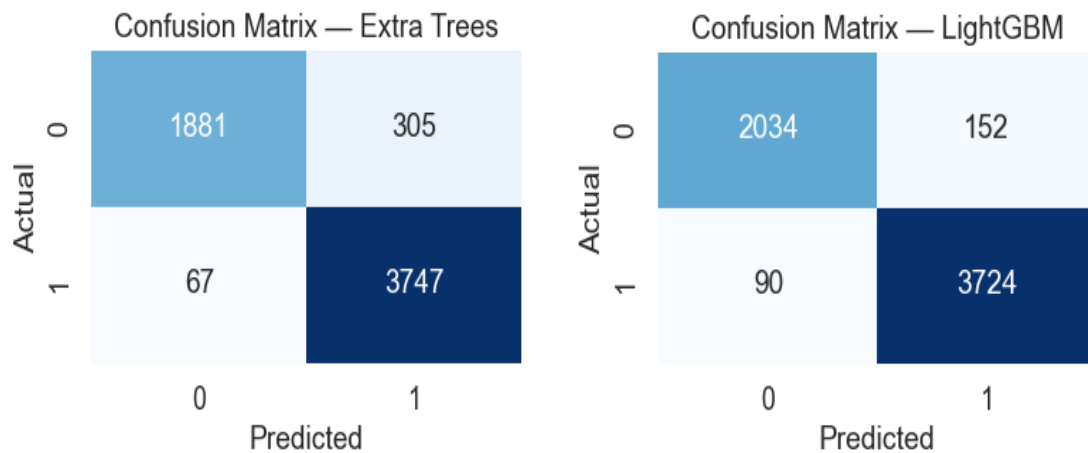


Figure 3. (a) Matrix Confusion of Extrat Tree ;(b) Matrix Confusion of LighGBM

The CatBoost (Figure 4.a) achieves competitive performance (precision = 0.9506, recall = 0.9693, F1 = 0.9599), although slightly below LightGBM and MLP. This marginal difference might be due to a more conservative regularization process or sensitivity to categorical feature encoding, inherent to its ordered boosting technique. Finally, the Multilayer Perceptron (MLP) achieved the highest performance across all three indicators, with precision = 0.9708, recall = 0.9764, and F1-score = 0.9736. This consistency highlights the ability of neural networks to effectively capture complex, non-linear patterns within the data while maintaining a balance between sensitivity and specificity. The high F1-score confirms that MLP minimizes both types of classification errors, making it particularly effective in critical predictive environments where both precision and recall are essential.

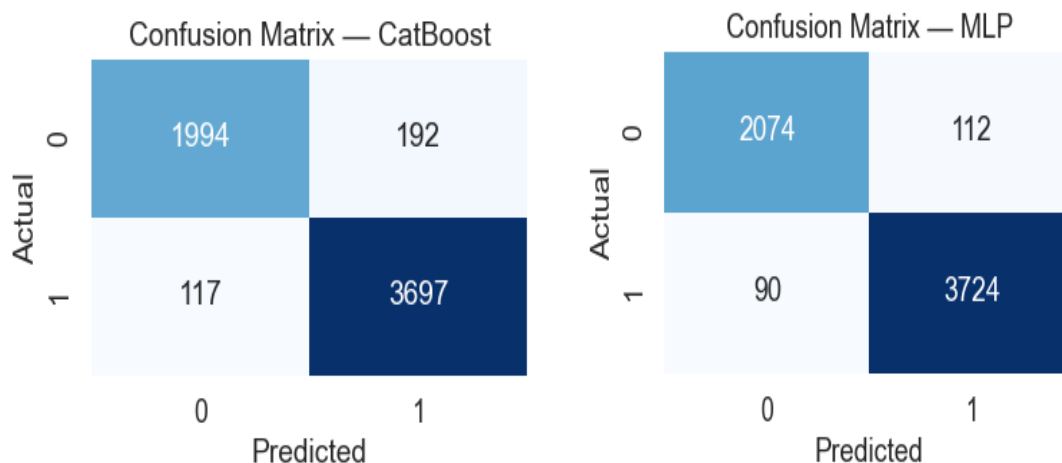


Figure 4. (a) Matrix Confusion of CatBoost ; (b) Matrix Confusion of MLP model

In summary, the comparison reveals that MLP and LightGBM consistently outperform other models in balancing precision and recall (See Figure 5), thereby achieving the highest F1-scores. This demonstrates their capacity to maintain robustness in identifying true positives while minimizing false detections. From a practical standpoint, these characteristics are crucial for smart energy management systems, where maintaining prediction reliability while avoiding unnecessary alarms contributes directly to operational efficiency and sustainability.

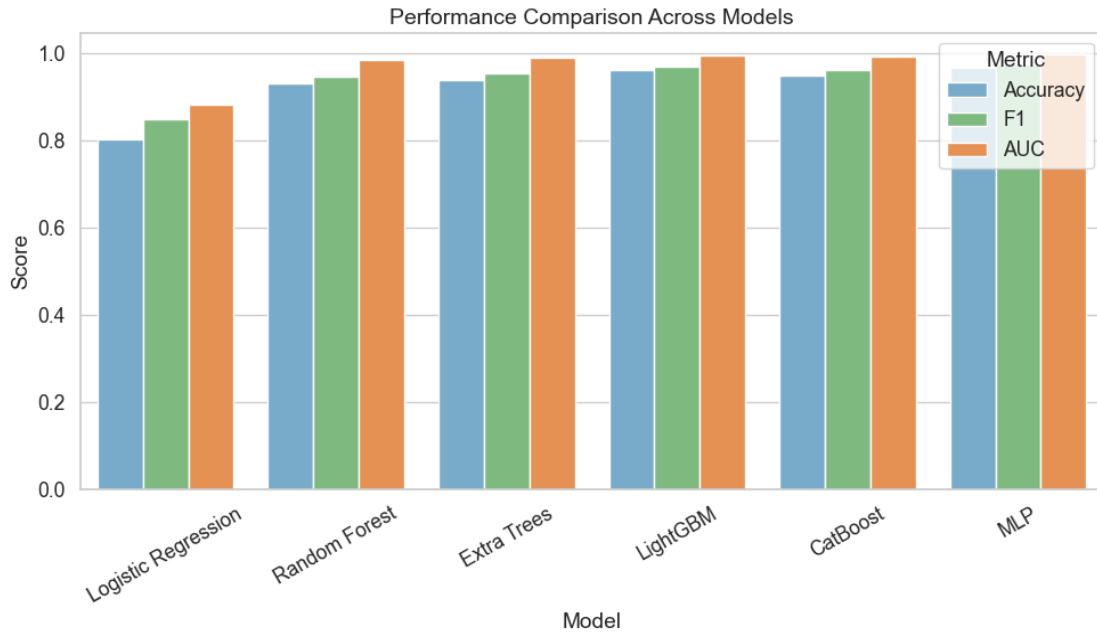


Figure 5. Comparison of Performance Metrics of Models

- **Matthews Correlation Coefficient (MCC) and Cohen's Kappa**

The Matthews Correlation Coefficient (MCC) and Cohen's Kappa are robust evaluation metrics that provide a more balanced assessment of model performance compared to accuracy, especially in the presence of class imbalance. In this study, both metrics were employed to evaluate the reliability and consistency of the models used for smart grid stability prediction. The results reveal a strong correlation between MCC and Kappa values, confirming the consistency of classification performance across models. The MLP (Multi-Layer Perceptron) achieved the highest scores (MCC = 0.9272; Kappa = 0.9272), demonstrating its ability to capture complex nonlinear relationships within the electrical system. However, this comes at the cost of a relatively longer computation time (17.87 s). The LightGBM model also performed exceptionally well (MCC = 0.9126; Kappa = 0.9124) while maintaining higher computational efficiency (1.5 s), making it a strong candidate for energy-efficient and high-performance applications. Similarly, Extra Trees and CatBoost achieved competitive results (MCC and Kappa above 0.86), indicating reliable classification but slightly lower consistency compared to LightGBM and MLP. In contrast, Logistic Regression obtained lower values (MCC = 0.5662; Kappa = 0.5641), highlighting its limited ability to handle the nonlinear dynamics of smart grid data.

Taken together, both MCC and Kappa confirm that MLP and LightGBM are the most robust and consistent models, with LightGBM offering a superior balance between predictive accuracy, computational efficiency, and energy sustainability—aligning well with the principles of Green Machine Learning.

5.2 ROC Curves and AUC

The ROC curves illustrate (Figure 6) the classification capability of all models through the balance between the true positive and false positive rates. The MLP achieves the highest AUC (0.996), indicating exceptional discriminative power and robustness in distinguishing between classes. LightGBM and CatBoost follow closely (AUC = 0.994 and 0.991), confirming their strong generalization capacity and consistent performance across thresholds. Extra Trees and Random Forest also show high AUC values (0.990 and 0.985), reflecting reliable ensemble behavior and stable prediction quality. In contrast, Logistic Regression (AUC = 0.883) demonstrates a clear performance gap, limited by its linear nature and inability to capture complex feature interactions.

In conclusion, these results confirm that gradient boosting and neural network models provide superior separability and are better suited for complex, non-linear datasets, while simpler models trade predictive accuracy for computational efficiency.

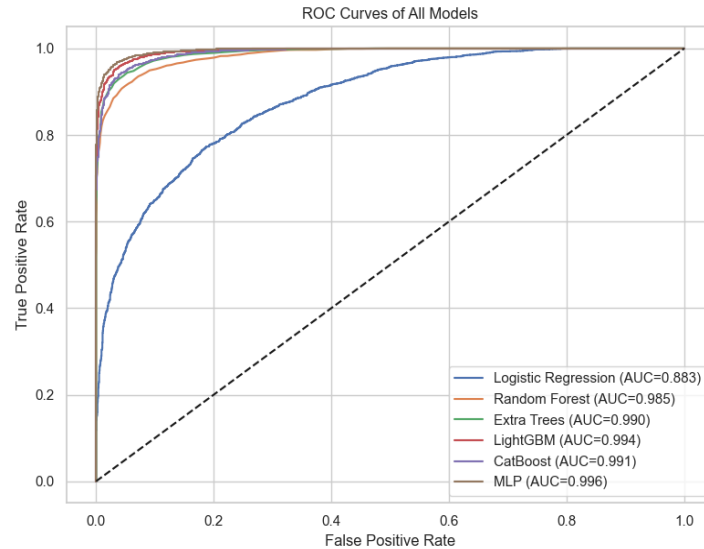


Figure 6. ROC Curve of Models

5.3 Computational Performance and Sustainability

- **Execution Time**

Execution time represents a key factor in assessing the computational efficiency and real-world applicability of Machine Learning models. In the current analysis, the observed times (Figure7) vary significantly from 0.03 s for Logistic Regression to 17.87 s for MLP illustrating the impact of algorithmic complexity on temporal performance. Lightweight models, such as Logistic Regression, achieve minimal execution times due to their simple linear architecture, making them suitable for real-time applications. However, this speed comes at the cost of reduced representational capacity. Ensemble models like Random Forest, Extra Trees, and LightGBM show moderate execution times (0.79–2.37 s), reflecting a balance between complexity and efficiency. Notably, LightGBM stands out with an optimized runtime (1.50 s) thanks to histogram-based learning and parallel computation, ensuring both high accuracy and computational efficiency. Conversely, the MLP exhibits the highest execution time (17.87 s), mainly due to its iterative training process and numerous parameters, leading to greater energy demand. CatBoost (2.83 s) provides an intermediate compromise, though it remains slower than LightGBM due to its ordered boosting mechanism.

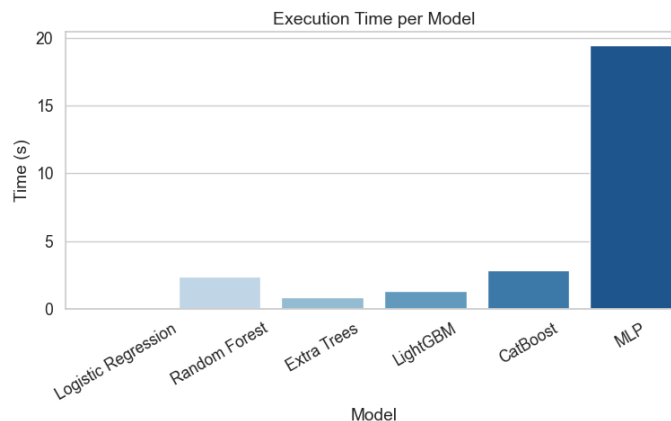


Figure 7. Execution Time per Model

In summary, these results highlight a trade-off between accuracy and computational speed. Models like LightGBM achieve an optimal equilibrium, making them ideal candidates for green and scalable AI systems that prioritize both performance and energy efficiency.

- **GreenScore (AUC/Time) Comparison**

The figure 8 illustrates the comparative evaluation of model sustainability through the GreenScore, which reflects the balance between predictive performance (AUC) and computational cost (execution time).

The results reveal a striking disparity among models. Logistic Regression achieves an exceptionally high GreenScore, confirming its minimal energy consumption and rapid execution. However, this performance comes at the expense of lower predictive accuracy, highlighting the classic trade-off between computational efficiency and learning capacity. In contrast, ensemble methods such as Random Forest, Extra Trees, and LightGBM exhibit significantly lower GreenScores. Despite their strong predictive performance, their higher computational complexity and longer training times reduce their energy efficiency. CatBoost and particularly the MLP (Multilayer Perceptron) show the lowest GreenScores, indicating substantial energy costs associated with their training and inference processes.

Overall, this analysis emphasizes that simpler models, like Logistic Regression, remain the most energy-efficient, while advanced models, although more accurate, demand more computational resources. This trade-off underscores the necessity of developing energy-aware algorithms that optimize both predictive quality and environmental impact, a key objective in the emerging field of Green Machine Learning. Finally, while MLP delivers high accuracy, it exhibits slightly higher energy consumption due to intensive training requirements. Nevertheless, its ability to learn deep nonlinear representations makes it well-suited for modeling the complex temporal dynamics of smart grids.

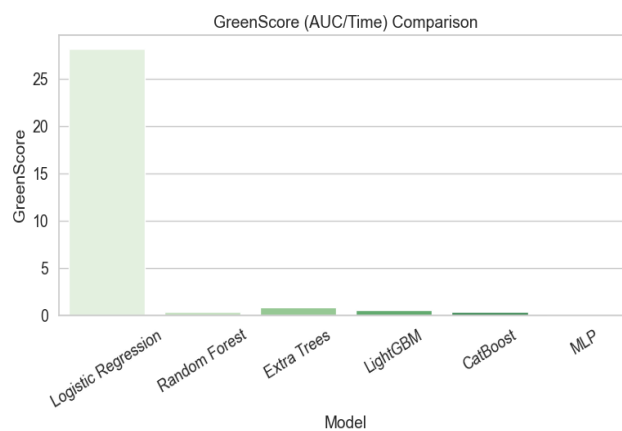


Figure 8. Green Score of Models

5.4 Edge Deployment and Real-Time Constraints

In practical smart grid applications, stability prediction must often operate under low-latency and real-time conditions, particularly in edge computing environments with limited computational resources. Under such constraints, model selection cannot rely solely on predictive performance; inference speed, memory footprint, and energy efficiency are equally critical factors. The findings of this study highlight the following insights:

- LightGBM achieves a favorable trade-off between accuracy and computational efficiency, making it highly suitable for deployment on edge devices.
- Logistic Regression provides extremely low latency, but its predictive capability is limited, which may reduce its effectiveness in complex scenarios.
- MLP, although demonstrating high predictive accuracy, requires additional optimization techniques such as pruning or quantization to meet real-time deployment requirements.
- Within this framework, GreenScore and GreenScore* serve as practical, latency-aware sustainability indicators. They facilitate the identification of models that balance predictive accuracy with operational feasibility, ensuring energy-efficient and reliable deployment in real-world edge computing contexts.

A primary limitation of this study is the use of execution time as a proxy for energy consumption. While this approach allows for consistent and reproducible comparisons across models, it does not fully reflect hardware-level energy variations. This limitation underscores the importance of incorporating direct energy measurement techniques, such as power meters or hardware-level profiling (e.g., Intel RAPL), in future work to enhance the validity of Green Machine Learning evaluations.

5.5 Trade-off Between Model AUC and GreenScore

The Figure 9 illustrates the trade-off between the predictive performance of Machine Learning models, measured by AUC (Area Under the Curve), and their energy efficiency, represented by the GreenScore. This metric highlights the inverse relationship between accuracy and computational cost in

sustainable computing contexts. The Logistic Regression model shows an exceptionally high GreenScore (above 25), indicating minimal energy consumption and fast execution. However, its relatively low AUC (~0.88) reflects limited predictive capability, emphasizing the classic trade-off between computational simplicity and the ability to capture complex nonlinear relationships in smart grid data. In contrast, ensemble learning models Random Forest, Extra Trees, LightGBM, and CatBoost along with the MLP (Multilayer Perceptron), occupy an optimal region of the chart. They achieve AUC values above 0.98, demonstrating excellent classification accuracy and robustness, while maintaining low GreenScores (<5), reflecting efficient energy use despite higher algorithmic complexity. Among them, LightGBM and CatBoost stand out for their strong balance between accuracy and energy efficiency, confirming their suitability for eco-efficient AI applications. Their gradient boosting architectures enable near-optimal performance with reduced computational energy demand.

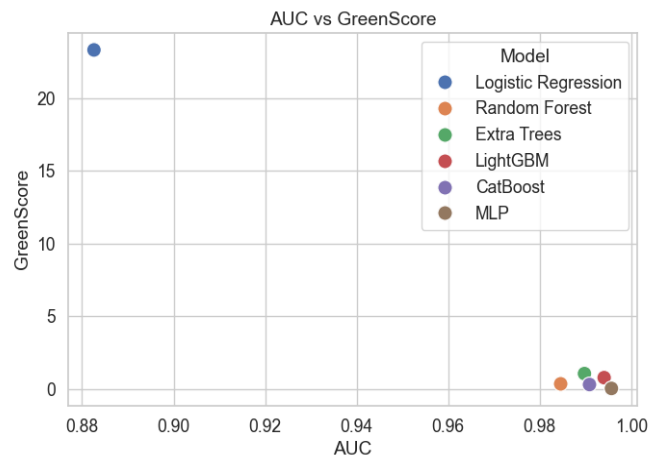


Figure 9. Trade-off Between Model AUC and GreenScore

5.6 Trade-off Between GreenScore and GreenScore*

The analysis highlights the trade-off between predictive performance (F1, AUC) and computational efficiency (GreenScore, GreenScore*), as illustrated in Figure 10. Logistic Regression achieves a very high GreenScore* despite a moderate GreenScore, reflecting strong discriminative ability (AUC) even with non-optimal execution time. Ensemble models—LightGBM, CatBoost, Random Forest, and Extra Trees—show high F1 but lower GreenScore* due to higher computational cost. The inclusion of AUC and the logarithmic time adjustment in GreenScore* balances speed and accuracy, differentiating models with similar F1 but varying robustness. For fast models, GreenScore and GreenScore* are similar; for slower yet robust models, GreenScore* provides a more realistic performance/time trade-off. Logistic Regression is ideal for rapid deployment on resource-constrained systems, while ensemble models may require optimization to be viable on edge devices. Overall, GreenScore* offers a reliable metric for selecting models that balance accuracy and efficiency in real-world smart grid applications.

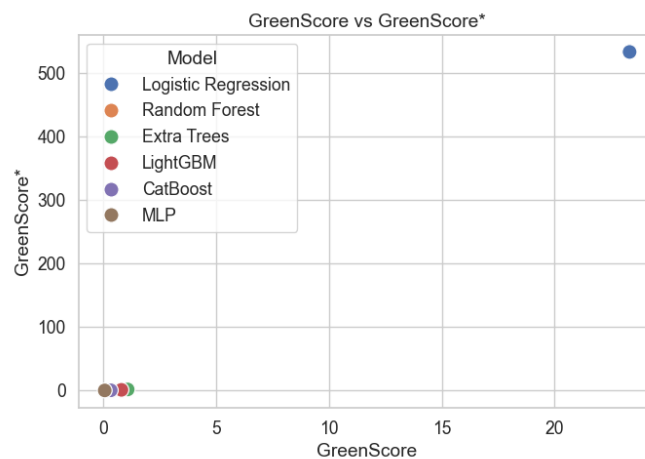


Figure 10. Trade-off Between GreenScore and GreenScore *

5.7 Multi-Metric Visualization

• Correlation Heatmap

The correlation heatmap (Figure 11) illustrates the relationships between performance and sustainability metrics. A strong positive correlation ($r > 0.98$) is observed among Accuracy, Precision, Recall, F1, MCC, Kappa, and AUC, indicating that models performing well in one metric tend to perform well across all others. This coherence reflects consistent and stable model behavior. Execution Time shows a moderate positive correlation ($\approx 0.42\text{--}0.49$) with performance metrics, suggesting that higher accuracy often requires more computation, highlighting the trade-off between precision and efficiency. Conversely, the GreenScore and GreenScore* metrics exhibit a strong negative correlation with all performance indicators ($r \approx -0.95$ to -1.00), highlighting a clear environmental trade-off: higher predictive accuracy generally leads to increased energy consumption and reduced ecological efficiency. Furthermore, the weak negative correlation observed between GreenScore and execution time ($r = -0.33$), as well as between GreenScore* and execution time ($r = -0.30$), suggests that computational time alone is not a sufficient indicator of energy impact, as algorithmic and hardware-level optimizations can significantly influence overall efficiency.

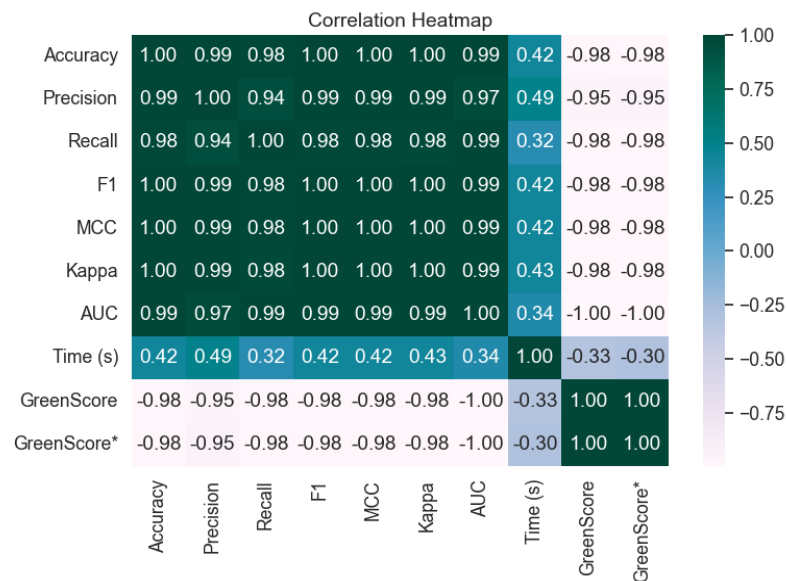


Figure 11. Correlation Heatmap Between Metrics

In conclusion, the analysis confirms the dual challenge of balancing predictive performance and environmental sustainability, emphasizing the need for energy-efficient and green-aware Machine Learning approaches.

• Radar Chart (Multi-Metric Comparison)

Figure 12 presents a radar chart that provides a comparative visualization of the performance of six Machine Learning models—Logistic Regression, Random Forest, Extra Trees, LightGBM, CatBoost, and MLP—based on multiple evaluation metrics. The purpose of this visualization is to highlight the trade-offs among models in terms of accuracy, robustness, and energy efficiency, all of which are critical for smart grid stability prediction under green computing constraints. From the chart, it is evident that Logistic Regression shows lower performance across most dimensions, reflecting its limited capacity to capture the nonlinear dependencies inherent in dynamic smart grid data. Conversely, ensemble-based methods such as Random Forest, Extra Trees, and LightGBM demonstrate superior and more balanced performance, indicating their strength in managing complex data interactions and minimizing prediction variance. Among the evaluated models, LightGBM and CatBoost exhibit particularly consistent and strong results across nearly all metrics, suggesting that gradient boosting frameworks are well-suited for achieving both high prediction accuracy and computational efficiency. This aligns with previous studies emphasizing the scalability and low resource consumption of these models in energy-aware environments. The MLP (Multi-Layer Perceptron) model, while achieving competitive accuracy, presents slightly higher variability across metrics, likely due to its sensitivity to parameter tuning and training cost. Nevertheless, its ability to learn deep nonlinear representations remains an advantage when dealing with temporal dependencies in smart grid data;

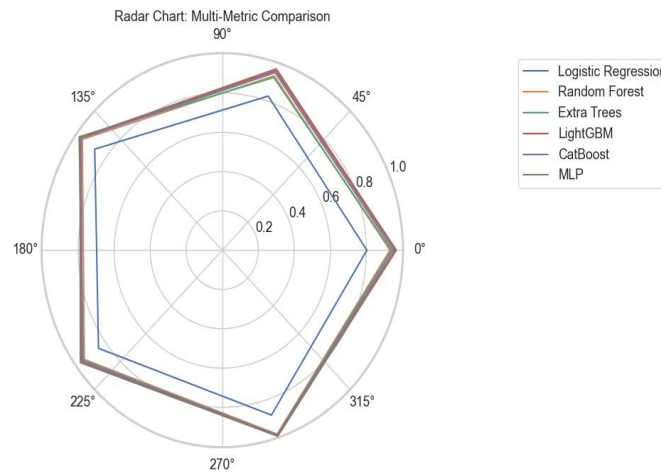


Figure 12. Radar Multi-Metric Comparison

Taken together, the radar chart emphasizes that while traditional models like Logistic Regression provide interpretability and computational simplicity, modern ensemble and neural approaches achieve a superior balance between performance and energy efficiency. This balance is a fundamental aspect of green Machine Learning, where the goal is not only predictive accuracy but also minimization of computational energy footprint, contributing to more sustainable smart grid management strategies.

5.8 Toward a Sustainable Smart Grid Prediction Architecture

Beyond Building on the evaluation of individual models, the results of this study enable the design of a conceptual architecture for sustainable smart grid prediction systems. We propose a hybrid approach that leverages the complementary strengths of different algorithms:

- LightGBM is employed for real-time prediction, offering low latency and high computational efficiency suitable for edge deployment.
- MLP is used for offline analysis, capable of capturing complex nonlinear patterns and modeling long-term system behavior.

This hybrid architecture delivers several key benefits:

1. Efficient real-time decision-making: LightGBM ensures rapid predictions with minimal computational cost, aligning with energy-aware deployment requirements.
2. Enhanced offline learning: MLP supports deeper pattern extraction, enabling improved understanding of grid dynamics and system behavior over time.
3. Improved reliability and robustness: By combining real-time responsiveness with offline analytical depth, the system provides a balanced solution for operational and predictive requirements.

Building on the Green AI insights discussed in Section 5.6, the proposed hybrid architecture combines LightGBM for real-time prediction with MLP for offline analysis, balancing predictive performance and computational efficiency in a sustainable framework.

Overall, this framework bridges the gap between theoretical evaluation and practical deployment, providing a pathway toward energy-efficient, intelligent smart grid controllers. Furthermore, metrics such as GreenScore and GreenScore* can be directly applied within this architecture to guide model selection, ensuring a sustainable balance between predictive accuracy and computational efficiency. From a Green Machine Learning standpoint, advanced optimization techniques including model pruning and quantization could further enhance the sustainability of high-performing models such as MLP. By reducing the number of parameters or lowering numerical precision, these methods can significantly decrease computational cost while maintaining acceptable predictive performance, thus achieving a better balance between accuracy and energy efficiency.

6. CONCLUSION

The increasing complexity of modern smart grids requires intelligent and energy-efficient predictive models capable of ensuring system stability under operational constraints. This study demonstrates that Green Machine Learning (GML), through the proposed dual-metric framework (GreenScore and GreenScore*), enables a multi-objective evaluation that jointly considers predictive performance and computational efficiency.

The experimental results highlight clear trade-offs among models: MLP achieves the highest predictive performance ($F1 = 0.9736$, $AUC = 0.9957$) but with low energy efficiency (GreenScore =

0.0161*), whereas LightGBM provides the best balance between accuracy and efficiency ($F1 = 0.9685$, $AUC = 0.9941$; $GreenScore = 0.66$, $GreenScore^* = 0.2646$). Ensemble models such as Extra Trees also demonstrate strong sustainability performance ($GreenScore = 1.24$, $GreenScore^* = 0.9449$). In contrast, Logistic Regression, despite its minimal execution time, exhibits limited predictive capability, leading to an inflated $GreenScore^*$ (533.8422).

Overall, the findings confirm that GML supports multi-objective optimization, guiding the selection of models that are both accurate and energy-aware. Future work will extend this framework toward real-time and edge deployment scenarios, incorporate hardware-level energy measurements, and explore model optimization techniques such as pruning, quantization, and lightweight architectures to further enhance energy efficiency and practical applicability.

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