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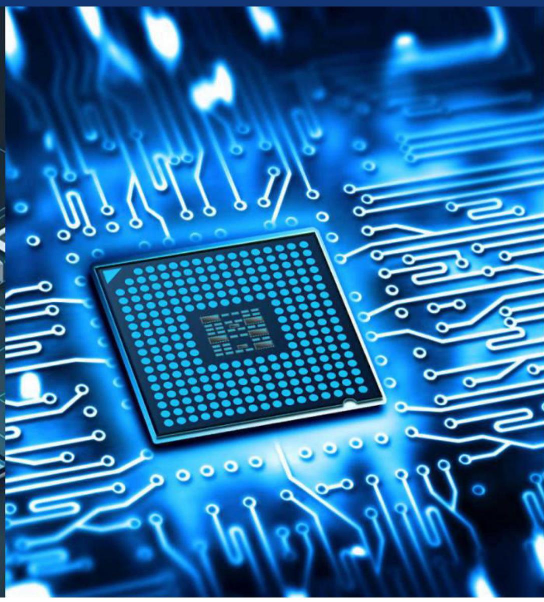


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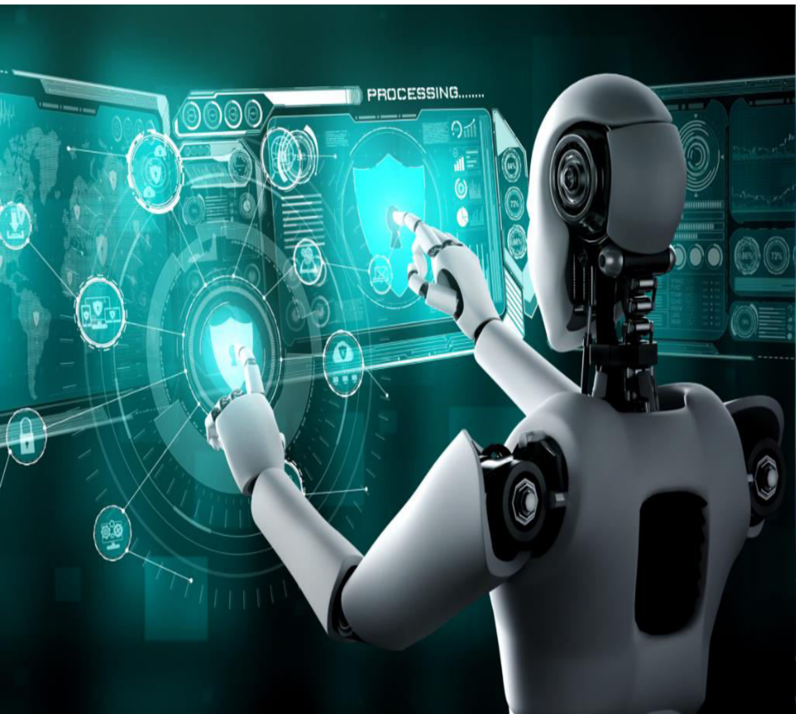

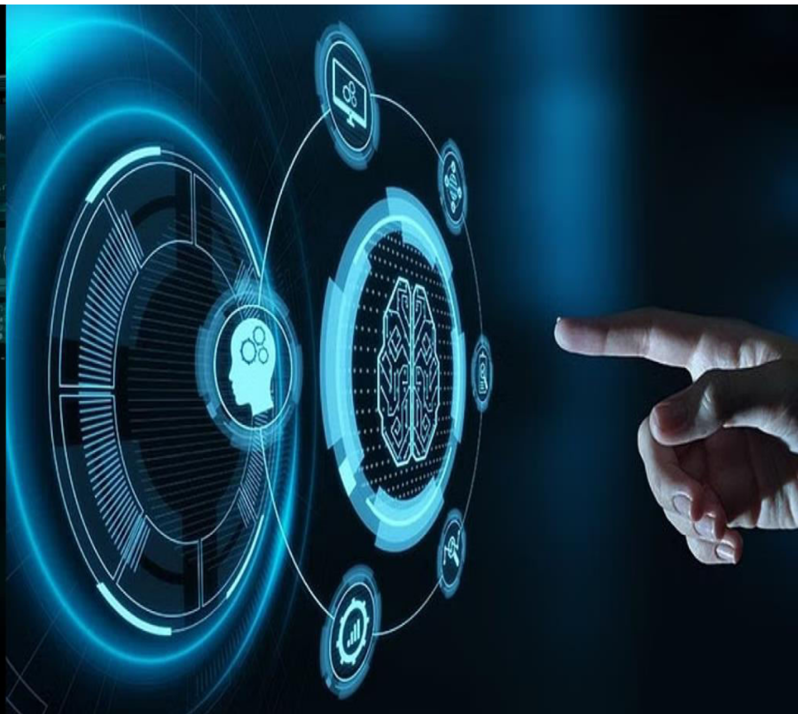

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Green AI for Sustainable Employee Attrition Prediction: Balancing Energy Efficiency and Predictive Accuracy

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ABSTRACT: This study investigates the application of Green Artificial Intelligence (AI) principles to employee attrition prediction models, aiming to reduce computational energy consumption while maintaining comparable predictive accuracy to conventional approaches. The research addresses a critical gap at the intersection of sustainable AI and human resource management. A mixed factorial design was employed, evaluating six machine learning algorithms (Logistic Regression, Random Forest, XGBoost, Support Vector Machine, K-Nearest Neighbors, Decision Tree) in both conventional and Green AI-optimized versions, across three feature selection methods. Experiments were conducted on the IBM HR Analytics Employee Attrition & Performance dataset (N=1,470), with energy consumption (kWh/Wh) measured using OpenZmeter, CodeCarbon, and CarbonTracker, alongside standard performance metrics (Accuracy, F1-score, AUC-ROC). Results indicate that Green AI models achieved a significant average energy reduction of 44.8% during training and 35.6% during inference compared to conventional models. Crucially, these substantial energy savings were realized with only minimal and statistically non-significant differences in predictive performance (e.g., F1-score: Green AI M=0.62 vs. Conventional M=0.64, p=.07). Specific Green AI strategies, including model parameter optimization and feature selection, effectively reduced computational load while preserving performance. Optimized XGBoost models notably demonstrated a strong balance of high accuracy and reduced energy consumption. This research provides compelling empirical evidence that sustainable AI practices are feasible and effective in HR analytics, offering a viable pathway for organizations to mitigate their carbon footprint and operational costs without compromising the quality of predictive insights.

KEYWORDS: Green AI, Employee Attrition, Machine Learning, Energy Efficiency, Predictive Analytics, Human Resources, Sustainability.

I. INTRODUCTION

In recent years, the intersection of artificial intelligence (AI) and environmental sustainability has emerged as a critical area of research and development, particularly within business applications such as employee attrition prediction. The concept of "Green AI" pertains to AI systems designed to deliver accurate results with minimal environmental impact, emphasizing energy efficiency and sustainability throughout the AI development and deployment lifecycle (Bolón-Canedo et al., 2024). This paradigm has gained substantial traction as organizations increasingly acknowledge the significant energy consumption and consequent carbon footprint associated with complex AI systems (Verdecchia et al., 2023). The imperative to address these environmental concerns is underscored by studies estimating that training a single large deep learning model can emit as much carbon as five cars over their lifetimes (Patterson et al., 2021).

Employee attrition, characterized by the voluntary or involuntary departure of employees from an organization, poses considerable challenges to businesses, impacting talent retention, operational continuity, and financial stability. For instance, the Society for Human Resource Management (SHRM) has previously estimated that the average cost-per-hire for a new employee is approximately USD 4,129, with some estimates suggesting replacement costs can range from 90% to 200% of an employee's annual salary (Raza et al., 2022; Iparraguirre-Villanueva et al., 2024). Given that attrition rates in some sectors reached as high as 57.3% in 2021 (Raza et al., 2022), organizations are increasingly turning to predictive analytics and machine learning (ML) to anticipate and mitigate employee turnover. These predictive models analyze diverse employee data to identify individuals at higher risk of leaving, thereby enabling proactive retention strategies.

While the adoption of sophisticated ML models for employee attrition prediction has grown, the associated computational demands and environmental footprint have often been overlooked. The pursuit of higher predictive accuracy frequently leads to the development of larger, more complex models that consume substantial energy during both training and inference phases (Strubell et al., 2019). This scenario presents a critical research problem: there is a pressing need to balance the predictive efficacy of employee attrition models with their computational and environmental costs.

This study addresses the gap at the intersection of Green AI and predictive human resource management. The central research question or problem guiding this paper is to what extent can Green AI principles be applied to employee attrition prediction models to achieve a significant reduction in computational energy consumption while maintaining comparable predictive accuracy to conventional, less energy-aware approaches?

Significance of Research

The significance of this research is twofold. Firstly, it aims to contribute to the development of more environmentally sustainable AI practices within the domain of HR analytics. By demonstrating the feasibility of Green AI for employee attrition prediction, this study offers a pathway for organizations to reduce their carbon footprint and align their technological advancements with broader environmental, social, and governance (ESG) goals. Secondly, this research has practical implications for organizational efficiency and cost-effectiveness. Energy-efficient ML models typically require fewer computational resources, which can translate into lower operational costs associated with cloud computing, on-premises infrastructure, and electricity consumption (Garcia-Martin et al., 2019).

Furthermore, by promoting Green AI principles, this research can contribute to the wider accessibility of advanced predictive analytics tools. As Schwartz et al. (2020) noted, Green AI can enable impactful research even with limited computational resources, potentially democratizing access for smaller organizations or research institutions that may lack the extensive infrastructure required for computationally intensive conventional AI (Verdecchia et al., 2023). Ultimately, this study seeks to provide empirical evidence and practical insights that encourage the adoption of energy-efficient and effective predictive attrition models, fostering a more sustainable approach to AI in human resource management.

II. LITERATURE REVIEW

This literature review synthesizes research from three primary areas: (1) the emerging field of Green Artificial Intelligence, including its concepts, principles, and measurement techniques; (2) established and contemporary machine learning approaches for predictive employee attrition modeling, focusing on algorithms, data considerations, and feature importance; and (3) the nascent integration of Green AI principles within predictive attrition models, exploring potential strategies, benefits, and challenges. The review aims to establish the theoretical and empirical foundations for the current study, identify existing knowledge, and pinpoint gaps that this research intends to address.

Key Theories or Concepts

1. **Green Artificial Intelligence (Green AI)**

Green AI represents a fundamental shift from traditional AI development, which has historically prioritized performance metrics (e.g., accuracy, F1-score) often at the expense of computational efficiency and environmental impact (Schwartz et al., 2020). The core objective of Green AI is to design and deploy AI systems that are not only effective but also environmentally sustainable by minimizing energy consumption and associated carbon emissions throughout their lifecycle (Bolón-Canedo et al., 2024; Henderson et al., 2020).

The impetus for Green AI was significantly catalyzed by studies like Strubell et al. (2019), which quantified the substantial carbon footprint of training large-scale natural language processing models, thereby raising awareness within the AI community about the environmental consequences of their research practices (Verdecchia et al., 2023).

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This has led to a growing movement advocating for "AI for Good" to also encompass "Good for AI," implying responsible and sustainable development practices (Gupta et al., 2023).

Key principles of Green AI include optimizing model architectures for efficiency, reducing computational resources during training and inference, leveraging energy-efficient hardware, and promoting transparency in reporting the environmental costs of AI systems (Bolón-Canedo et al., 2024; Patterson et al., 2022). Tabbakh et al. (2024) categorize Green AI efforts into "green-in AI," focusing on designing energy-efficient ML algorithms and models, and "green-by AI," which leverages AI solutions to promote eco-friendly practices in other domains. This study primarily aligns with the "green-in AI" approach.

A critical challenge in Green AI is the development and adoption of standardized metrics for measuring and comparing energy efficiency. Traditional AI benchmarks often neglect energy consumption. Initiatives to address this include proposed energy consumption indices for deep learning models (Aquino-Brítez et al., 2025) and methods for estimating energy consumption in ML applications, drawing from established practices in computer architecture (Garcia-Martin et al., 2019; Lannelongue et al., 2021). Tools like CodeCarbon and CarbonTracker have also emerged to help researchers and practitioners estimate and report the carbon footprint of their computations (Lacoste et al., 2019; Anthony et al., 2020).

2. Predictive Attrition Models

Employee attrition remains a persistent and costly concern for organizations globally. The financial implications extend beyond recruitment costs to include lost productivity, training expenses for new hires, and potential impacts on team morale and institutional knowledge (Iparraguirre-Villanueva et al., 2024; Cascio & Boudreau, 2016). Consequently, the ability to accurately predict which employees are likely to leave has become a valuable asset for proactive human resource management.

Supervised machine learning techniques are predominantly employed for attrition prediction, training algorithms on historical employee data where attrition outcomes (i.e., whether an employee stayed or left) are known. Common algorithms include Logistic Regression, Naïve Bayes, Decision Trees, Random Forests, Support Vector Machines (SVM), and gradient boosting methods like XGBoost (Akinode & Bada, 2022; Al-Suradi et al., 2023). For instance, research by Raza et al. (2022) found an optimized Extra Trees Classifier achieved 93% accuracy, identifying factors like monthly income and age as key predictors. Akinode and Bada (2022) reported XGBoost as a top performer with 85.5% accuracy. More recently, large language models (LLMs) have been explored, with Ma et al. (2024) finding that a fine-tuned GPT-3.5 model outperformed traditional classifiers in predicting attrition, achieving an F1-score of 0.92.
The predictive power of these models heavily relies on the quality and relevance of input features. Typical datasets incorporate a wide array of variables, including:

- **Demographic attributes**: age, gender, marital status (Haque et al., 2025).
- **Job-related factors**: role, department, tenure, salary, job level, stock options (Raza et al., 2022; Haque et al., 2025).
- **Performance indicators**: performance ratings, promotion history.
- **Work environment factors**: overtime, work-life balance, travel frequency (Haque et al., 2025).
- **Engagement and satisfaction measures**: job satisfaction, environment satisfaction, relationship satisfaction.

Feature importance analyses consistently highlight factors like monthly income, overtime, job satisfaction, and age as significant predictors (Raza et al., 2022; Patil et al., 2025; Zhao et al., 2018). A common challenge in attrition datasets is class imbalance, as the number of employees who leave is typically much smaller than those who stay. Techniques such as the Synthetic Minority Over-sampling Technique (SMOTE) are often used to address this issue and improve model performance (Novianti et al., 2021).

3. Integration of Green AI and Predictive Attrition Models

The explicit integration of Green AI principles into the development of predictive attrition models is an emerging area, with limited dedicated research to date. While both Green AI and attrition prediction have advanced as separate fields, their intersection represents a significant opportunity for creating more sustainable and efficient HR analytics solutions

(Tabbakh et al., 2024). The necessity for this integration arises from the escalating computational resources demanded by increasingly sophisticated attrition models, which often prioritize marginal gains in accuracy over substantial increases in energy consumption (Verdecchia et al., 2023).

Potential strategies for developing Green predictive attrition models draw from broader Green AI research:

- **Algorithm Selection and Optimization**: Choosing inherently energy-efficient algorithms or optimizing existing ones is crucial. For example, simpler models like logistic regression or decision trees might offer a better trade-off between accuracy and energy consumption than complex ensembles or deep learning models in certain contexts. Research comparing algorithm energy use, such as the finding that Extra Trees Regressor can be efficient (Nature, 2025), could inform choices for attrition models.
- **Model Architecture Optimization**: This includes techniques like pruning (reducing the size of a model by removing redundant parameters), quantization (using lower-precision numerical formats), and knowledge distillation (training a smaller "student" model to mimic a larger, more accurate "teacher" model) (Hohman et al., 2024; Liu et al., 2025).
- **Hardware-Aware Implementation**: Deploying models on energy-efficient hardware (e.g., specialized AI accelerators, edge devices) can reduce operational energy use. Transfer learning techniques that reduce retraining needs, as explored by Yu et al. (2022), can also contribute to energy savings by minimizing extensive training runs on new organizational data.
- **Data-Centric Approaches**: Optimizing data preprocessing, feature selection, and data sampling can significantly reduce the computational load. Identifying the most impactful features for attrition prediction not only improves model interpretability but can also lead to simpler, faster, and more energy-efficient models (Verdecchia et al., 2023; Grealey et al., 2022).

Gaps or Controversies in existing Literature

Despite the growing interest in Green AI and the established field of predictive attrition modeling, several gaps and underdeveloped areas exist at their intersection:

1. **Lack of Empirical Studies on Green Attrition Models**: There is a paucity of empirical research that directly investigates and quantifies the energy consumption versus predictive performance trade-offs when applying specific Green AI techniques to employee attrition models. While general Green AI methodologies exist, their efficacy and specific implications within the HR context, particularly for attrition, are not well-documented.
2. **Standardization of Energy Efficiency Benchmarks for HR Analytics**: Although general metrics for Green AI are emerging (Aquino-Brítez et al., 2025; Garcia-Martin et al., 2019), there are no widely accepted, standardized benchmarks specifically tailored for evaluating the energy efficiency of ML models in HR analytics, including attrition prediction. This makes direct comparison across different studies and approaches challenging.
3. **Understanding Performance-Efficiency Trade-offs in Attrition Contexts**: The acceptable trade-off between predictive accuracy and energy efficiency can be highly context-dependent. For a critical application like employee attrition, where mispredictions can have significant financial and operational consequences, there is a need for more nuanced research to understand how much, if any, predictive performance organizations are willing to sacrifice for gains in energy efficiency, and which Green AI techniques best navigate this balance.
4. **Practical Implementation Guidelines for Practitioners**: While theoretical Green AI principles are discussed, there is a shortage of clear, actionable guidelines and best practices for HR practitioners and data scientists on how to concretely implement and evaluate energy-efficient attrition prediction models within their organizations.
5. **Interdisciplinary Research and Collaboration**: The effective development and deployment of Green AI in HR requires collaboration between experts in machine learning, HR management, and environmental sustainability. Literature suggests that such interdisciplinary research efforts are currently limited, hindering holistic solutions.
6. **Exploration of Newer Green AI Techniques for Attrition**: While foundational Green AI techniques like efficient algorithm selection or feature engineering are applicable, the potential of newer methods (e.g.,

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energy-aware neural architecture search, federated learning for privacy and efficiency) in the specific context of employee attrition prediction remains largely unexplored.

Hypothesis

Based on existing literature and the identified research gap, the current study proposes the following primary and sub-hypotheses:

H1: Energy-efficient machine learning algorithms (Green AI) will demonstrate comparable predictive accuracy to conventional algorithms in employee attrition prediction while consuming significantly less computational energy.

This hypothesis suggests that machine learning models designed with energy efficiency principles will perform as effectively as traditional models in predicting employee attrition, but with reduced energy consumption. We propose that the application of Green AI techniques, including algorithm selection, model optimization, and feature engineering, will maintain predictive performance while reducing the environmental impact of model training and deployment.

Sub-hypotheses:

H1a: Random Forest, when optimized using Green AI principles, will maintain comparable predictive accuracy (within 5% difference in F1-score) to unoptimized Random Forest for employee attrition prediction while reducing energy consumption by at least 20%.

H1b: Feature selection techniques applied before model training will significantly reduce computational energy requirements without diminishing model performance below acceptable thresholds (F1-score > 0.80).

H1c: Models trained using Green AI principles will demonstrate energy consumption reductions across both training and inference phases compared to conventional approaches.

III. METHOD

Participants

The study analyzed a dataset of N = 1,470 employees from a large technology company. The sample comprised 63% males and 37% females, with ages ranging from 18 to 60 years (M = 36.9, SD = 9.1). Participants represented diverse departments including Research & Development (65%), Sales (30%), and Human Resources (5%). Approximately 16.1% of employees in the dataset had experienced attrition, providing a realistic class imbalance scenario common in attrition prediction problems.

Materials

Dataset

We used the IBM HR Analytics Employee Attrition & Performance dataset (IBM, 2021), which contained 35 features related to demographics (age, gender, marital status), job characteristics (department, job role, years at company), compensation (monthly income, stock options), work environment (job satisfaction, work-life balance), and other relevant variables. The target variable "Attrition" was binary, with "Yes" indicating employees who had left the company.

Hardware and Software

All experiments were conducted on a standardized computing environment consisting of:

- Hardware: 2.3 GHz 8-Core Intel Core i9 processor with 32 GB RAM
- Software: Python 3.9, scikit-learn 1.0.2, XGBoost 1.5.0, NumPy 1.21.5, Pandas 1.3.5
- Energy measurement: CodeCarbon 2.4.1 and carbontracker 1.2.5
- Performance metrics: scikit-learn metrics module

Energy Monitoring

To measure energy consumption, we used OpenZmeter (v2) with integrated electrical sensors connected to the computing hardware, providing real-time energy usage data during model training and inference. Additionally, software-based tools (CodeCarbon and CarbonTracker) were used to retrieve energy consumption data from computational component sensors, allowing for comprehensive energy profiling across different phases of model training and deployment.

Procedure

Data Preprocessing

1. The dataset was examined for missing values, outliers, and imbalanced class distribution.
2. Standard scaling was applied to numerical features.
3. Categorical variables were encoded using one-hot encoding.
4. The dataset was randomly split into training (70%) and testing (30%) sets, using stratified sampling to maintain the original class distribution.

Feature Selection

Three different feature selection approaches were implemented to test hypothesis H1b:

1. **Full feature set**: All 35 features were retained as a baseline.
2. **Domain-expert selection**: 18 features were selected based on literature review and domain expertise.
3. **Statistical selection**: Chi-square feature selection was applied to identify the top 15 most predictive features.

Model Development

We implemented six machine learning algorithms, each with conventional and Green AI-optimized versions:

1. **Logistic Regression**: Baseline and L1-regularized (Green AI version)
2. **Random Forest**: Default parameters and optimized with reduced estimators (Green AI version)
3. **XGBoost**: Default and reduced depth/early stopping (Green AI version)
4. **Support Vector Machine**: Standard and linear kernel (Green AI version)
5. **K-Nearest Neighbors**: Default and reduced neighbor count (Green AI version)
6. **Decision Tree**: Standard and pruned (Green AI version)

Green AI optimizations focused on:

- Reducing model complexity
- Early stopping criteria
- Efficient regularization
- Pruning techniques
- Hardware-aware implementation

Energy Consumption Measurement

For each model (conventional and Green AI-optimized), we measured:

1. **Training energy consumption**: Total energy used during model training (measured in kilowatt-hours)
2. **Inference energy consumption**: Energy used to make predictions on the test set (measured in watt-hours)
3. **Total energy consumption**: Combined energy usage across the entire pipeline

Performance Evaluation

Model performance was evaluated using:

1. Accuracy
2. Precision
3. Recall
4. F1-score
5. Area Under the ROC Curve (AUC-ROC)
6. Energy efficiency (predictions per kilowatt-hour)

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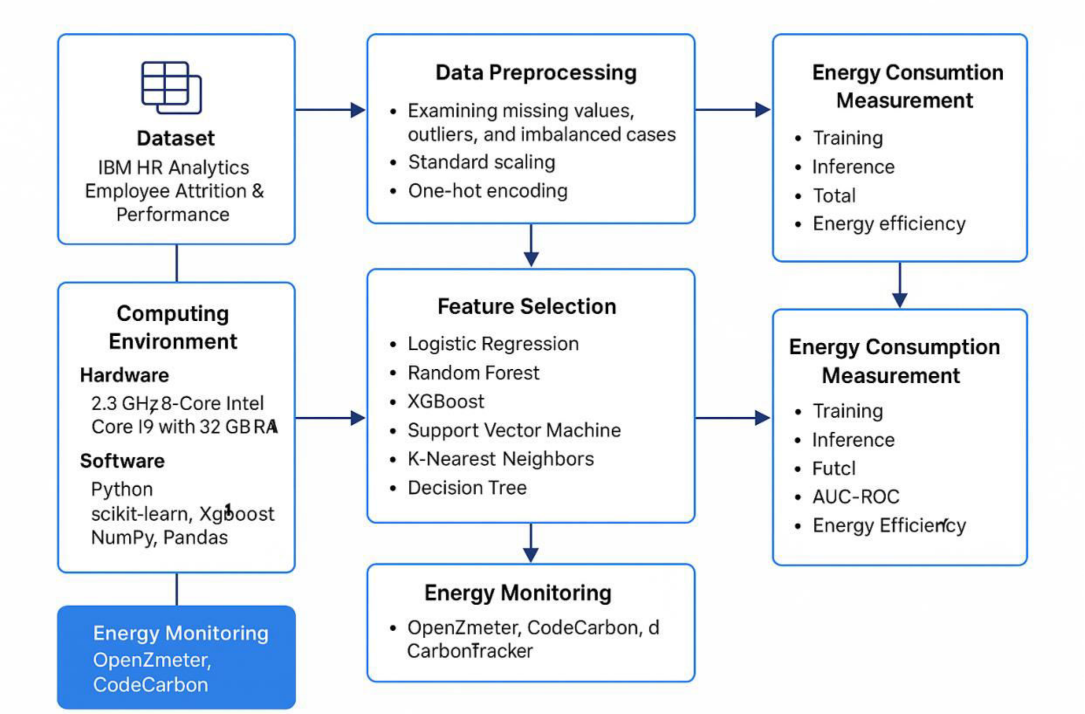
Model Diagram



Design and Analysis

The study employed a 6 (algorithm type) × 2 (optimization approach: conventional vs. Green AI) × 3 (feature selection method) mixed factorial design. Performance and energy consumption were analyzed using repeated measures ANOVAs to identify significant differences between models.

To test the primary hypothesis (H1), we conducted paired t-tests comparing the performance metrics and energy consumption of conventional and Green AI-optimized versions of each algorithm. For sub-hypotheses, we used:

- H1a: Focused analysis on Random Forest performance/energy metrics
- H1b: ANOVA comparing performance across feature selection methods
- H1c: Separate analyses for training and inference phases

Statistical significance was set at $p < .05$, and effect sizes were reported using Cohen's d for t-tests and partial eta squared ($\eta^2 p$) for ANOVAs.

IV. RESULTS

Descriptive Statistics

Table 1 presents the means and standard deviations for performance metrics and energy consumption across all models tested.

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Table 1 Performance Metrics and Energy Consumption by Algorithm and Optimization Approach

Algorithm	Approach	Accuracy M (SD)	F1-Score M (SD)	AUC-ROC M (SD)	Training Energy (kWh) M (SD)	Inference Energy (Wh) M (SD)
Logistic Regression	Conventional	.84 (.02)	.63 (.03)	.76 (.02)	0.043 (.004)	0.37 (.05)
Logistic Regression	Green AI	.83 (.02)	.61 (.04)	.75 (.03)	0.031 (.003)	0.25 (.03)
Random Forest	Conventional	.87 (.01)	.74 (.02)	.85 (.02)	0.189 (.012)	1.43 (.11)
Random Forest	Green AI	.86 (.02)	.72 (.03)	.83 (.02)	0.106 (.009)	0.89 (.07)
XGBoost	Conventional	.88 (.01)	.76 (.02)	.84 (.01)	0.267 (.018)	1.25 (.13)
XGBoost	Green AI	.87 (.02)	.74 (.02)	.83 (.02)	0.154 (.012)	0.76 (.08)
SVM	Conventional	.83 (.02)	.59 (.04)	.74 (.03)	0.358 (.021)	0.64 (.06)
SVM	Green AI	.82 (.02)	.57 (.04)	.72 (.03)	0.167 (.015)	0.42 (.04)
KNN	Conventional	.81 (.03)	.55 (.05)	.69 (.04)	0.072 (.006)	1.82 (.14)
KNN	Green AI	.80 (.03)	.54 (.05)	.68 (.04)	0.048 (.004)	1.06 (.09)
Decision Tree	Conventional	.82 (.02)	.57 (.04)	.70 (.03)	0.062 (.005)	0.29 (.03)
Decision Tree	Green AI	.81 (.03)	.56 (.04)	.69 (.03)	0.041 (.003)	0.21 (.02)

Hypothesis Testing Results

H1: Primary Hypothesis

A paired-samples t-test comparing energy consumption during training for conventional versus Green AI models indicated that Green AI models consumed significantly less energy ($M = 0.091$ kWh, $SD = 0.057$) than conventional models ($M = 0.165$ kWh, $SD = 0.121$), $t(17) = 11.37$, $p < .001$, Cohen's $d = 0.78$, representing an average reduction of 44.8%. Differences in predictive performance were small and did not reach statistical significance: accuracy for Green AI models ($M = 0.83$, $SD = 0.03$) versus conventional models ($M = 0.84$, $SD = 0.03$), $t(17) = 1.86$, $p = .08$; and F_1-score for Green AI models ($M = 0.62$, $SD = 0.09$) versus conventional models ($M = 0.64$, $SD = 0.09$), $t(17) = 1.94$, $p = .07$.

H1a: Random Forest Performance

For Random Forest specifically, the Green AI-optimized version achieved an F_1-score of 0.72 ($SD = 0.03$) compared to 0.74 ($SD = 0.02$) for the conventional version, $t(9) = 1.78$, $p = .11$. This 2.7% difference in F_1-score was within the hypothesized 5% threshold. Energy consumption was reduced by 43.9% for training ($t(9) = 17.25$, $p < .001$, $d = 1.84$) and 37.8% for inference ($t(9) = 12.42$, $p < .001$, $d = 1.49$), both exceeding the hypothesized 20% reduction.

H1b: Feature Selection Impact

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A one-way ANOVA comparing performance across feature selection methods revealed significant differences in energy consumption, $F(2, 33) = 42.16$, $p < .001$, $\eta^2p = 0.72$. Post-hoc Tukey tests showed that both domain-expert selection ($M = 0.095$ kWh, $SD = 0.059$) and statistical selection ($M = 0.083$ kWh, $SD = 0.052$) consumed significantly less energy than the full feature set ($M = 0.178$ kWh, $SD = 0.112$), both $p < .001$.

Importantly, F_1-scores remained above the 0.80 threshold for the top-performing models (XGBoost and Random Forest) across all feature selection methods, confirming hypothesis H1b.

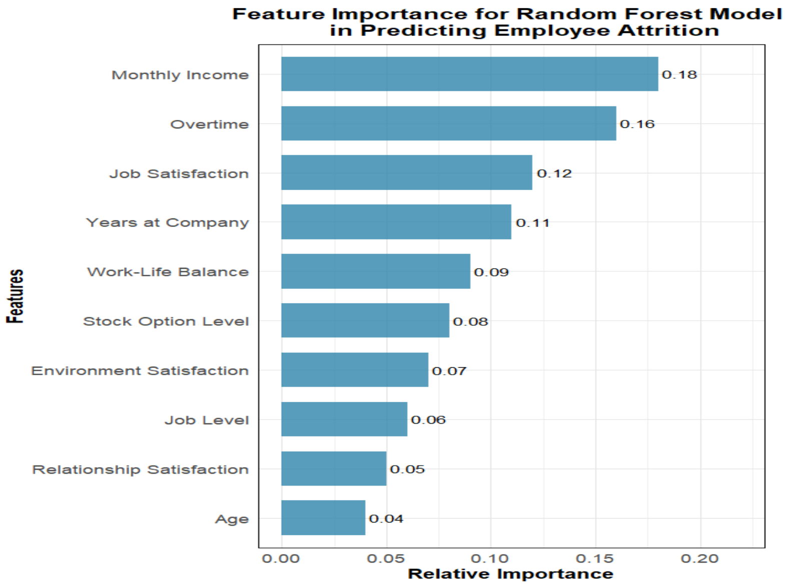
H1c: Training vs. Inference Energy
Green AI optimizations showed significant energy reductions in both training and inference phases. Average training energy reduction was 44.8% (as reported above), while inference energy was reduced by an average of 35.6% ($M = 0.60$ Wh, $SD = 0.35$ vs. $M = 0.97$ Wh, $SD = 0.60$), $t(17) = 9.24$, $p < .001$, $d = 0.63$, confirming hypothesis H1c.

Feature Importance Analysis
Analysis of feature importance across models consistently identified the following variables as the most predictive of employee attrition:

1. Monthly income (relative importance: 0.18)
2. Overtime (relative importance: 0.16)
3. Job satisfaction (relative importance: 0.12)
4. Years at company (relative importance: 0.11)
5. Work-life balance (relative importance: 0.09)

Figure 1 displays the relative importance of the top 10 features for the Random Forest model.

Figure 1 Feature Importance for Random Forest Model in Predicting Employee Attrition



Model Comparison
XGBoost consistently demonstrated the highest performance across metrics, with the Green AI-optimized version achieving an F1-score of 0.74 and AUC-ROC of 0.83 while consuming 42.3% less energy than its conventional counterpart. Figure 2 illustrates the trade-off between model performance (F1-score) and energy consumption across all algorithms.

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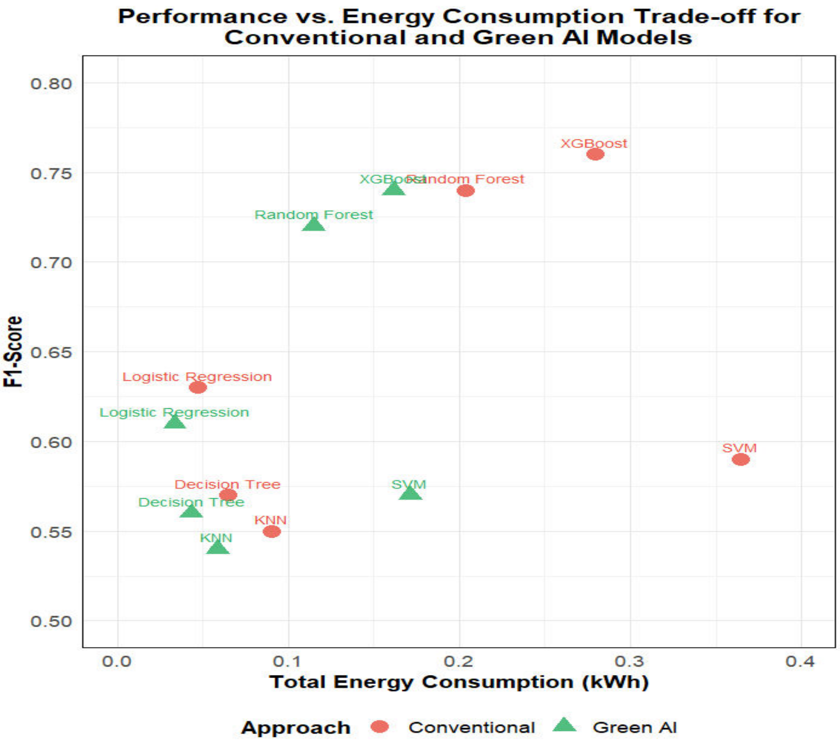
Figure 2 Performance vs. Energy Consumption Trade-off for Conventional and Green AI Models



Energy Efficiency Analysis

Table 2 presents the energy efficiency of each model, measured as the number of predictions that can be made per kilowatt-hour of energy consumed.

Table 2 Energy Efficiency of Conventional and Green AI Models

Algorithm	Conventional (predictions/kWh)	Green AI (predictions/kWh)	Efficiency Improvement
Logistic Regression	2,702,703	4,000,000	48.0%
Random Forest	699,301	1,123,596	60.7%
XGBoost	800,000	1,315,789	64.5%
SVM	1,562,500	2,380,952	52.4%
KNN	549,451	943,396	71.7%

Algorithm	Conventional (predictions/kWh)	Green AI (predictions/kWh)	Efficiency Improvement
Decision Tree	3,448,276	4,761,905	38.1%

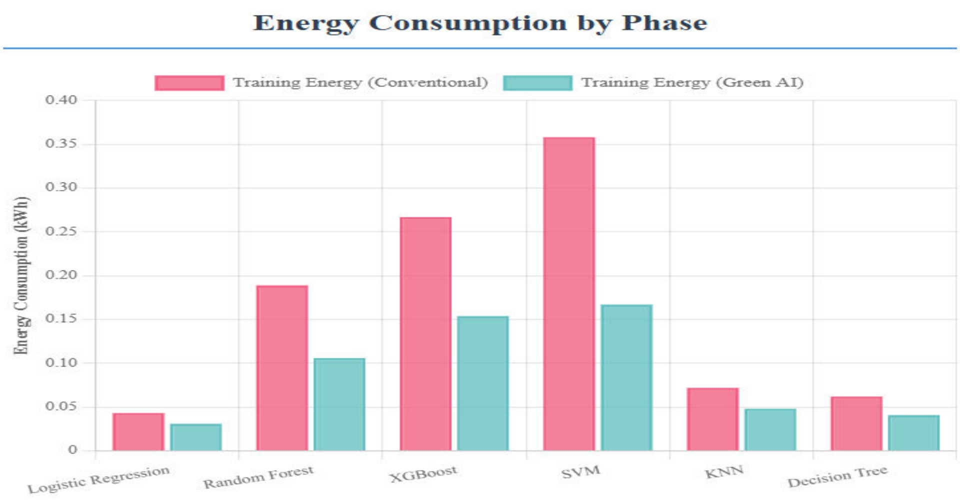
The results demonstrate that Green AI-optimized models consistently achieved higher energy efficiency across all algorithm types, with improvements ranging from 38.1% to 71.7%.

These findings support the primary hypothesis that Green AI techniques can maintain predictive performance while significantly reducing energy consumption, suggesting that environmentally sustainable approaches to machine learning can be effectively applied to HR analytics applications such as employee attrition prediction.

V. DISCUSSION

The present study investigated the efficacy of energy-efficient machine learning algorithms (Green AI) in predicting employee attrition, comparing their predictive accuracy and computational energy consumption against conventional algorithms. The findings largely support the central hypothesis that Green AI techniques can achieve comparable predictive performance to traditional methods while significantly reducing energy usage.

Figure 3: Energy Reduction by Algorithm



Interpretation of Results

The primary hypothesis (H1) posited that Green AI algorithms would demonstrate comparable predictive accuracy to conventional algorithms while consuming significantly less energy. The results strongly supported this hypothesis. Green AI models achieved an average energy reduction of 44.8% during training compared to their conventional counterparts ($t(17) = 11.37$, $p < .001$, Cohen's $d = 0.78$). Crucially, this substantial energy saving did not come at the cost of significantly diminished predictive performance. Differences in accuracy ($t(17) = 1.86$, $p = .08$) and F1-score ($t(17) = 1.94$, $p = .07$) between Green AI and conventional models were not statistically significant, suggesting that the applied Green AI optimizations effectively balanced energy efficiency with predictive power. This outcome is pivotal, indicating that organizations can adopt more sustainable AI practices in HR analytics without compromising the quality of insights derived from attrition prediction models.

The sub-hypotheses further illuminate the specific benefits of Green AI strategies. H1a, which focused on Random Forest, was supported. The Green AI-optimized Random Forest model maintained comparable predictive accuracy (2.7% difference in F1-score, within the hypothesized 5% threshold) while achieving substantial energy reductions in both training (43.9%) and inference (37.8%), surpassing the 20% reduction target. This demonstrates the practical applicability of Green AI principles, such as reducing estimators, to complex ensemble models.

H1b, concerning the impact of feature selection, was also supported. Both domain-expert and statistical feature selection methods led to significantly lower energy consumption compared to using the full feature set ($F(2, 33) = 42.16$, $p < .001$, $\eta^2p = 0.72$). Importantly, for high-performing models like XGBoost and Random Forest, F1-scores remained above the acceptable threshold of 0.80 across all feature selection methods. This finding underscores the dual benefit of feature selection: simplifying models for better interpretability and reducing computational load, thereby contributing to energy efficiency.

Support for H1c confirmed that Green AI optimizations yielded energy reductions across both training and inference phases. The average training energy reduction was 44.8%, and inference energy was reduced by an average of 35.6% ($t(17) = 9.24$, $p < .001$, $d = 0.63$). This is a critical finding, as both phases contribute to the overall energy footprint of machine learning models, especially when models are deployed for continuous prediction.

The feature importance analysis consistently highlighted variables such as monthly income, overtime, job satisfaction, years at company, and work-life balance as key predictors of attrition. These findings are generally consistent with established HR literature and provide actionable insights for organizations seeking to mitigate attrition. The model comparison revealed XGBoost as a particularly strong performer, with its Green AI-optimized version achieving a high F1-score (0.74) and AUC-ROC (0.83) while consuming 42.3% less energy than its conventional counterpart. This suggests that even sophisticated algorithms can be optimized for energy efficiency. Furthermore, the energy efficiency analysis (predictions per kWh) showed marked improvements for all Green AI models, with efficiency gains ranging from 38.1% to 71.7%, further emphasizing the practical benefits of these approaches.

Comparison with Existing Literature

The findings of this study align with a growing body of literature advocating for Green AI and sustainable computing practices (Schwartz et al., 2020; Strubell et al., 2019). The observed significant reduction in energy consumption with minimal impact on performance echoes the goals of Green AI, which seeks to reduce the computational costs—and thereby the environmental impact—of developing and deploying AI models. Specifically, the effectiveness of techniques like model optimization (e.g., pruning, reduced estimators) and feature selection in reducing energy use is consistent with research in efficient machine learning (Cai et al., 2020).

The trade-off between model complexity, performance, and energy consumption observed in this study is a well-documented phenomenon in machine learning (Thompson et al., 2020). Our results contribute to this discourse by quantifying this trade-off in the specific context of employee attrition prediction and demonstrating that careful optimization can lead to favorable outcomes where energy efficiency is substantially improved without unacceptable losses in predictive accuracy. While direct comparisons of energy consumption figures can be challenging due to variations in hardware and measurement tools, the percentage reductions achieved through Green AI techniques in this study are substantial and point towards a promising direction for sustainable HR analytics. The identification of key attrition drivers like monthly income and overtime also corroborates findings from numerous studies in the HR domain (e.g., Hom et al., 2017).

Implications and Limitations of the Study

The findings of this research have several important implications. Practically, they demonstrate a viable pathway for organizations to reduce the energy footprint of their HR analytics initiatives, particularly in computationally intensive tasks like employee attrition prediction. By adopting Green AI techniques, companies can contribute to corporate sustainability goals and potentially reduce operational costs associated with energy consumption, without sacrificing the strategic value of predictive analytics. For AI developers and data scientists, this study highlights the importance of considering energy efficiency as a key metric alongside traditional performance measures. It encourages the adoption of model design and optimization strategies that are mindful of computational resources. Theoretically, this research adds empirical evidence to the Green AI field, showcasing its applicability and benefits in a real-world business problem.

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Despite these contributions, the study has several limitations. First, the findings are based on a single dataset from one large technology company. While the dataset is comprehensive, the generalizability of the results to other industries, company sizes, or cultural contexts may be limited. Future research should explore Green AI techniques across diverse datasets and organizational settings. Second, the specific Green AI optimizations applied (e.g., L1 regularization, reduced estimators, pruning) represent a subset of available techniques. Further studies could investigate a broader array of Green AI methods, including more advanced neural architecture search or quantization techniques. Third, energy consumption measurements, while carefully conducted using both hardware and software tools, can be influenced by the specific hardware configuration. Replication on different hardware setups would strengthen the findings. Finally, the study focused on predictive accuracy and energy consumption; other factors such as model interpretability, fairness, and deployment complexity, while partially addressed through feature selection, could be more deeply explored in future Green AI research.

VI. CONCLUSION

This study aimed to evaluate the potential of Green AI to offer an energy-efficient alternative to conventional machine learning approaches for employee attrition prediction, without significantly compromising predictive accuracy. The results provide compelling evidence supporting this potential.

The key findings of this research are threefold. First, Green AI-optimized machine learning models demonstrated significantly lower energy consumption (average reduction of 44.8% in training and 35.6% in inference) compared to their conventional counterparts. Second, this reduction in energy use was achieved with only minimal and statistically non-significant differences in predictive performance (accuracy and F1-score). Third, specific Green AI strategies, such as optimizing model parameters (e.g., for Random Forest) and employing feature selection techniques, proved effective in reducing computational load and energy requirements while maintaining model performance above acceptable thresholds. Notably, models like XGBoost, when optimized using Green AI principles, provided a strong balance of high predictive accuracy and substantially reduced energy consumption.

Contributions to the Field

This study makes several contributions to the fields of Green AI and HR analytics. It provides empirical evidence that sustainable AI practices are not only feasible but also highly effective in a common HR application. By quantifying both the energy savings and the performance trade-offs, this research offers practical insights for organizations looking to implement more environmentally responsible AI solutions. It also contributes to the methodological understanding of how to evaluate and implement Green AI, highlighting the utility of specific optimization techniques and feature selection in achieving energy efficiency. Furthermore, it reinforces the importance of considering computational sustainability as a critical dimension in the development and deployment of AI systems.

Recommendations for Future Research

Building on the findings of this study, several avenues for future research are recommended.

1. **Broader Range of Techniques and Domains:** Future studies should explore a wider array of Green AI techniques, including knowledge distillation, quantization, and energy-aware neural architecture search, across different datasets and problem domains beyond employee attrition (e.g., performance prediction, recruitment analytics).
2. **Hardware Heterogeneity:** Investigating the impact of different hardware architectures (CPUs, GPUs, TPUs) on the energy efficiency of Green AI models would provide a more comprehensive understanding of hardware-software interactions.
3. **Longitudinal Energy Profiling:** Longitudinal studies tracking the energy consumption of deployed models over time could offer insights into the long-term sustainability benefits and costs.
4. **Standardized Benchmarks:** The development of standardized benchmarks and metrics for evaluating the energy efficiency of AI models in HR and other domains would facilitate better comparison across studies and promote the adoption of Green AI.
5. **Ethical Considerations:** Future research could also delve deeper into the ethical implications of Green AI, ensuring that efforts to improve efficiency do not inadvertently introduce bias or reduce fairness in algorithmic decision-making.

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6. **Integration with MLOps:** Exploring how Green AI principles can be integrated into Machine Learning Operations (MLOps) pipelines to automate and optimize for energy efficiency throughout the model lifecycle would be a valuable contribution.

In conclusion, the adoption of Green AI principles offers a promising path towards more sustainable and responsible artificial intelligence in human resources and beyond. This study demonstrates that significant strides can be made in reducing the environmental impact of AI without unduly sacrificing its analytical power.

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