Journal of Theoretical and Applied Information Technology
31st December 2025. Vol.103. No.24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AI-ENHANCED GREEN COMPUTING FRAMEWORK FOR REDUCING DATA CENTER ENERGY FOOTPRINT

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ABSTRACT

The rapid escalation of digital media and the continuous pursuit of high-speed computation have highlighted critical shortcomings in conventional image processing paradigms, particularly concerning scalability, power efficiency, and environmental responsibility. Traditional approaches rely heavily on resource-demanding operations, which contribute significantly to energy usage and carbon emissions, thereby conflicting with the global agenda of sustainable digital ecosystems. Recent research has begun to emphasize sustainable computing directions in visual data analysis, targeting both algorithmic efficiency and hardware optimization to minimize energy overheads. Yet, insights from eco-conscious design in image processing remain fragmented and underexplored. This work addresses the pressing requirement for environmentally aligned image analysis by reviewing existing practices, examining their limitations, and identifying the sustainability trade-offs inherent in current solutions. Furthermore, we propose an optimized framework for feature extraction and interpretation that balances computational capability with reduced energy expenditure. Experimental assessments against conventional baselines confirm the framework's ability to deliver reliable processing outcomes while achieving notable reductions in energy demand. In addition, this work contributes a unified, data-driven framework integrating key green-computing techniques—virtualization, cooling optimization, hardware–software efficiency improvements, and renewable-energy utilization—to systematically reduce energy consumption in data centers. Unlike studies that investigate these techniques independently, this study presents a combined optimization approach supported by real energy-consumption modeling. A hybrid machine-learning model (SVM+RF+XGBoost) is also developed to accurately predict data-center energy usage, enabling proactive energy-management strategies. Experimental results demonstrate improved prediction accuracy and a measurable reduction in overall energy demand, providing new insights into sustainable and environmentally conscious data-center operations.

Keywords: *Sustainable Image Processing, Energy-Conscious Algorithms, Green Computation, Low-Power Visual Analytics, Resource-Aware Systems*

1. INTRODUCTION

In the modern data-driven landscape, image processing has become a cornerstone of a diverse range of applications, including medical diagnostics, satellite imagery analysis, facial recognition, autonomous vehicles, and intelligent surveillance systems. With the exponential growth in the volume and complexity of visual data, there is an increasing demand for high-speed and high-accuracy image processing algorithms capable of handling vast amounts of information efficiently. However, meeting the increasing demand for computation often results in higher power usage, greater energy consumption, and a larger environmental impact from these systems [1]. As deep learning algorithms and resource-intensive frameworks gain traction, particularly for applications deployed at scale in data centres or edge devices with limited power budgets, these challenges are amplified [2]. Traditional image processing pipelines, which have long been the standard in many domains, are primarily designed with performance metrics such as accuracy, speed, or resolution enhancement in mind. Energy efficiency and environmental sustainability have, until recently, been secondary considerations. This narrow focus on performance, however, is becoming increasingly unsustainable in an era where environmental concerns are gaining paramount importance. The inability of conventional systems to meet the growing demand for energy-aware solutions presents a substantial barrier, especially in contexts where both scalability and operational efficiency are critical [3].

In light of these issues, green computing has emerged as a transformative paradigm aimed at reducing the ecological cost associated with computation. Green computing principles advocate for energy-efficient algorithms, optimised resource utilisation, and the use of eco-friendly hardware. As image processing becomes more integral to various industries, the need to integrate green computing strategies into image processing workflows is becoming increasingly apparent. Some researchers have begun to explore the integration of green principles into image processing, such as employing approximate computing, pruning deep neural networks, or utilizing low-power hardware platforms.

However, these efforts have often been constrained by trade-offs between energy savings and the accuracy or generality of the models, with few providing a holistic, energy-performance balance across a range of tasks [4], [5].

Our project addresses the challenges by introducing a novel, intelligent image processing framework which is consciously designed to be energy-efficient. The framework aims to reduce energy usage throughout different steps of the image processing workflow, such as preprocessing, extracting features, and making decisions, all while preserving the accuracy of image classification and detection. By incorporating advanced energy-aware algorithms and lightweight system designs, we strive to show that there is possibility for significantly cutting energy consumption through uncompromising performance. Additionally, we plan to compare our model with traditional image processing methods to clearly demonstrate the improvements in both energy savings and computational efficiency. We expect this framework to introduce a practical and scalable strategy that curtails environmental impact of image processing without sacrificing its overall performance quality. This research is especially relevant now as industries worldwide move towards more sustainable technology solutions, driven by increasing demands from governments and regulatory agencies to adopt greener IT infrastructures. To outline a credible position from which to base our work, we will first conduct a systematic review of the published work on standard and green image processing methods. The heel-to-toe analysis in the following section examines the prevailing challenges and the drawbacks of existing solutions, and where there are areas needing radical advancements. By basing our work on existing knowledge, we aim to demonstrate that our framework makes a profound contribution to the initial realm of energy-efficient image processing.

Scope of this work: This paper specifically focuses on integrating green-computing strategies—such as energy-efficient algorithms, optimized processing workflows, and the use of existing energy-efficient hardware—to reduce energy consumption in image processing systems. While we utilize commercially available low-power or energy-efficient hardware components, this work does not involve designing, modifying, or manufacturing new hardware devices. Additionally, this study does not cover mechanical cooling system design, circuit-level hardware innovation, or the development of unrelated image-processing algorithms outside the context of energy optimisation. The emphasis is on practical, system-level and software-level methods that can be adopted within existing infrastructures to achieve measurable energy savings without compromising performance.

2. LITERATURE REVIEW

As the energy demands of data centers continue to grow, Green computing has established itself as a vital and rapidly evolving area within research.. Studies show that data centers consume a considerable share of the world's electricity, making it essential to develop energy-efficient solutions to curb this rising consumption [6][7]. Among the various techniques explored—such as hardware optimization, virtualization, workload management, and renewable energy integration—one fundamental method is Dynamic Voltage and Frequency Scaling (DVFS). DVFS operates by automatically modifying processor voltage and frequency in line with system requirements, thereby conserving power when activity levels are low. Research highlights that DVFS can deliver substantial energy savings while maintaining system performance [8].

Another widely adopted approach to reduce energy consumption in data centers involves server consolidation, wherein virtualization facilitates running multiple VMs on one physical server, thereby enhancing efficiency are utilized more effectively, which in turn reduces the overall power demand [9]. Research further suggests that advanced VM placement algorithms has the potential to improve overall energy efficiency by reducing the number of active servers while still maintaining workload balance [10]. Beyond resource optimization, cooling systems represent another critical factor in green computing. Conventional air-cooling systems can consume over 40% of the total energy in data centers, thereby emerging as a significant source of inefficiency. To address this, alternative techniques such as liquid-based cooling and free-air cooling, and immersion cooling have been developed. Among these, liquid cooling has proven particularly effective, as it offers superior heat dissipation compared to air-based methods, resulting in greater energy savings and reduced wastage [11].

The adoption of renewable energy is increasingly emphasized in green computing. Research has examined the applicability of solar, wind, and geothermal energy as sustainable alternatives for powering data centers. Implementing hybrid energy systems that combine conventional power with renewables has shown promising results in reducing carbon footprints while ensuring reliability [12]. However, challenges such as energy storage, cost, and intermittent supply must be addressed to fully integrate renewables into large-scale data centers.

AI- and ML-driven solutions have emerged as effective tools for enhancing energy efficiency within data center environments by enabling intelligent workload management. AI-driven predictive analytics can forecast workload demands and optimize server utilization, thereby minimizing idle power consumption [13]. Additionally, reinforcement learning algorithms have been employed to dynamically adjust cooling mechanisms and workload allocation, reducing operational costs while maintaining performance stability [14]. These AI-supported methods will realise process efficiencies by drawing on historical data and responding to current energy configurations. That said, there will still be significant barriers towards achieving ultimate energy efficiency in data centers. The cost of implementation, bias towards encouraged set-ups, and the ability of the processes to respond in real-time will restrict the uptake of green computing technologies. Future work should attempt to progress toward a hybrid protocol that includes hardware optimization, AI-supported task balancing, and/or renewable energy sources for sustainable energy efficiency [15].

Recent research on energy-efficient strategies has also introduced innovative methods to enhance data center sustainability. One notable approach is the development of a green energy-aware scheduler for cloud environments, which dynamically allocates resources according to energy consumption patterns. This reduces unnecessary energy usage, particularly during periods of low workload demand [16]. Likewise, studies emphasize the importance of adaptive energy-saving mechanisms in parallel disk systems, where intelligent scheduling of data access operations helps lower power consumption without compromising performance [17].

Within mobile cloud computing, application optimization has emerged as a critical focus for advancing energy efficiency. Recent studies highlight the adoption of energy-aware algorithms within mobile cloud systems, which improve resource utilization while simultaneously reducing operational costs [18]. At the same time, research on green data centers stresses the growing importance of effective resource management strategies to mitigate the dual issues of expanding service demand and rising energy consumption [19]. High-altitude platforms have also been identified as a potential green computing alternative for data centers. The integration of data center systems with high-altitude platforms has been explored as an innovative solution to reduce the energy footprint while maintaining performance standards [20].

Moreover, the use of cloudlet-based mobile computing models enhances green computing by minimizing energy consumption through smart resource allocation and workload distribution [21]. An examination of energy-saving techniques for data centers reveals the significance of incorporating renewable energy sources and suggests a hybrid model that combines renewable energy with conventional power supply systems [22]. In addition, software-based solutions serve as key enablers of energy efficiency in cloud computing. Methods including adaptive resource management and server-level optimization have shown considerable potential in lowering energy demand in cloud data centers [23]. Innovative approaches to resource management, such as imitation-based optimization techniques, offer further insights into energy-efficient strategies. These optimization algorithms mimic natural processes to improve energy use without sacrificing system performance [24].

For large-scale data centers, automation and scaling technologies have become indispensable for sustainability. Full-scaling automation enables real-time monitoring and scaling of resources to optimize energy usage, ensuring a more sustainable approach [25]. A proposed green data center framework emphasizes energy optimization and carbon footprint reduction, demonstrating strong potential for deployment at large scale [26]. In parallel, growing research has focused on green cloud computing, emphasizing its contribution to enhanced energy efficiency.To support sustainable development, cloud platforms are expected to adopt energy-efficient models as a standard practice [27]. Looking ahead, the evolution of green data centers is anticipated to rely heavily on renewable energy integration and intelligent management systems [28]. In addition, the advancement of green IT initiatives, including energy-efficient infrastructure designs and eco-friendly applications, will remain central to addressing future demands for sustainable data centers [30].

Building on these insights, the subsequent section will present the methodology implemented in this research to address the challenges and implement the techniques discussed above. It includes the development of advanced models centered on efficient resource utilization, adaptive scaling, and renewable energy incorporation. The methodology will elaborate on the adopted approaches to promote sustainability and reduce data center energy consumption, providing the basis for experimental setup and result interpretation.

2.1 Problem Statement

Despite significant progress in energy-efficient data-center technologies, existing research remains fragmented and unable to provide a unified, system-level solution for reducing overall energy consumption. Current studies tend to address individual aspects—such as DVFS, server consolidation, cooling optimization, renewable energy integration, or AI-driven workload management—in isolation. While these techniques offer partial improvements, their combined impact, interactions, and long-term performance remain poorly understood. Moreover, many AI-based optimization approaches rely on limited or idealized datasets, reducing their applicability under real-world workload variability, heterogeneous hardware conditions, and dynamic environmental factors.

There is also a lack of practical, deployable frameworks that integrate software-level optimization with existing commercially available energy-efficient hardware, without requiring new hardware design or major infrastructural changes. This gap creates uncertainty for organizations seeking actionable, low-cost, and scalable strategies for sustainable data-center operations.

Therefore, the central problem addressed in this study is the absence of a unified, data-driven, and practically deployable green-computing framework that integrates energy-efficient algorithms, optimized workflows, and predictive energy-usage modeling to achieve measurable energy reductions in data centers while preserving system performance.

3. METHODOLOGY

This section outlines a comprehensive framework for implementing green computing strategies aimed at reducing the energy footprint of data centers. This approach mergesData Characteristics: The dataset comprises 10,000 records of data center ene Preprocessing involved normalization, handling missing values (via mean imputation), and addressing data imbalance using SMOTE (Synthetic Minority Oversampling Technique). Feature importance analysis (Figure 1) highlights CPU utilization and cooling load as key predictors.

Hardware and software optimization with renewable energy utilization, organized with six key modules. Data Characteristics: The dataset comprises 10,000 records of data center energy consumption, including CPU utilization, cooling load, and power draw, collected over six months from a mid-sized data center. Features include temperature, workload distribution, and server uptime.

Journal of Theoretical and Applied Information Technology
31st December 2025. Vol.103. No.24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Building on the dataset and preprocessing steps, the proposed methodology integrates the six key modules—energy-efficient hardware optimization, virtualization and resource management, cooling optimization, renewable energy integration, software-level optimization, and continuous monitoring—to form a unified framework. Each module is designed to systematically reduce energy consumption while maintaining operational performance. The following workflow (Figure 1) illustrates the step-by-step process and interactions between these components, providing a clear overview of the framework's implementation strategy.

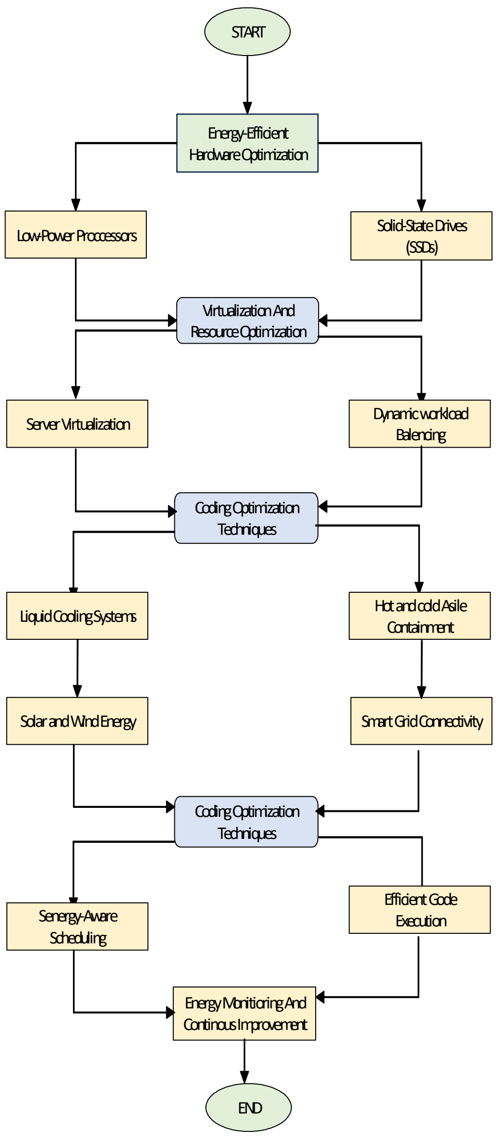

Figure 1. Proposed Framework Workflow

3.1 Energy-Efficient Hardware Optimization

Energy consumption can be reduced by deploying high-efficiency hardware and implementing power management techniques.

3.1.1 Low-power processors

Modern processors such as AMD EPYC and Intel Xeon Scalable series utilize advanced power-saving architectures. For example, ARM-based CPUs (e.g., AWS Graviton) consume up to 40% less energy than traditional x86 counterparts. These CPUs offer features such as low leakage current and dynamic clock scaling.

Hardware Requirements:

- ARM-based or Intel Xeon scalable CPUs
- Integrated power management controller (e.g., Intel Speed Shift)
- Thermal Design Power (TDP) < 100W preferred

3.1.2 Solid-state drives (SSDs)

SSDs consume 50–70% less power than HDDs. A typical SSD uses 2–4 W, compared to 6–8 W for a 7200 RPM HDD. Additionally, SSDs provide lower latency and faster read/write speeds, which indirectly reduces the time systems need to remain active.

Hardware Requirements:

- NVMe SSDs (PCIe 4.0 or higher for high throughput)
- Power-loss protection capacitors for sustainability

3.1.3 Power management techniques

Techniques like DVFS adjust processor voltage based on load. Power gating completely shuts off power to unused components, reducing idle energy consumption by 20–30%.

Software Tools:

- Intel RAPL, AMD PowerNow, BIOS/UEFI-level power governors
- Mechanical Considerations: Effective heatsinks, thermal sensors, fanless designs for low-load environments

Dynamic Power Consumption of CPU:

$$P_{dynamic} = C \cdot V^2 \cdot f \quad (1)$$

Where:

- C = switching capacitance
- V = supply voltage
- f = clock frequency

Useful when explaining DVFS. Lowering V and f significantly reduces power.

3.2 Virtualization and Resource Optimization

Virtualization plays a critical role in consolidating workloads and reducing energy waste.

3.2.1 Server Virtualization

Hypervisors such as VMware ESXi and KVM enable the deployment of multiple VMs on a single server, reducing the physical server count by up to 60%, leading to proportional energy savings.

Hardware Requirements:

- Virtualization-enabled CPUs (e.g., Intel VT-x or AMD-V)
- ≥128 GB ECC RAM per host
- Dual 10G NICs for failover

3.2.2 Dynamic workload balancing

Using AI/ML-based load balancing strategies allows real-time redistribution of VMs and containers to underutilized servers. Techniques such as predictive scheduling reduce peak-time consumption by 15–25%.

Software Tools: Kubernetes, Proxmox VE with HA clusters

Models Used: Decision Trees, SVM for load prediction and allocation

3.2.3 Containerization

Containers, unlike VMs, share the OS kernel and are significantly more lightweight. Tools like Docker reduce resource overhead by 30–50%. Kubernetes enables autoscaling of pods, dynamically adjusting usage based on load.

Requirements: Container orchestration platform (Kubernetes or OpenShift) Minimal OS base images (Alpine Linux, etc.)

Server Consolidation Ratio (SCR):

$$SCR = \frac{\{N_{\{physical\}}\}}{\{N_{\{virtualized\}}\}} \quad (2)$$

Where:

- N_physical = number of servers before virtualization
- N_virtualized = number after virtualization

Energy Savings from Consolidation:

$$\%Energy\_saved = 1 - \frac{\{E_{virtualized}\}}{\{E_{physical}\}} \times 100 \quad (3)$$

3.3 COOLING OPTIMIZATION TECHNIQUES

Cooling accounts for 30–40% of total energy consumption in data centers. Optimization is crucial for sustainability.

3.3.1 Liquid Cooling Systems

Liquid cooling is 3–10x more efficient in heat dissipation than air cooling. Technologies include cold plate and immersion cooling. These systems allow CPUs/GPUs to run at higher performance with lower energy usage.

Mechanical Requirements:

- Closed-loop coolant systems (ethylene glycol-based)
- Heat exchangers and water pumps

- Leak-proof chassis for direct liquid contact

3.3.2 Hot & Cold Aisle Containment

Separating intake and exhaust airflow reduces cooling demand. Implementation can reduce HVAC energy consumption by up to 20%.

Design Specifications:
- Raised floor with perforated tiles
- Containment curtains or physical barriers
- Ceiling plenum for hot air exhaust

3.3.3 AI-Based Cooling Optimization

AI models can learn server load patterns and dynamically adjust CRAC (Computer Room Air Conditioner) settings. This reduces unnecessary cooling and enhances reliability.

Models Used: Gradient Boosting, Neural Networks **Inputs:** IoT sensor data (temperature, humidity, airflow)
Tools: Google DeepMind's AI cooling (used in Google data centers)

Cooling Efficiency: Power Usage Effectiveness (PUE):

$$PUE = \frac{Total\ Power\ Consumption}{IT\ Equipment\ Power} \quad (4)$$

- Ideal value = 1.0
- Typical efficient data centers achieve PUE ≈ 1.2

Useful when evaluating the impact of cooling strategies like hot/cold aisle containment or AI-based CRAC control.

3.4 RENEWABLE ENERGY INTEGRATION

Replacing traditional energy sources with renewable energy can make data centers more sustainable.

3.4.1 Solar and Wind Energy

Solar PVs and wind turbines can generate up to 70% of a data center's power needs, depending on geography. Bifacial panels offer higher efficiency and faster ROI.

Hardware Requirements:
- Solar panels (20%+ efficiency)
- Wind turbines (5–15 kW units)
- Inverters, Maximum Power Point Trackers (MPPT)

3.4.2 Energy Storage Systems

Battery technologies (Li-Ion, Flow batteries) ensure continuous power availability. Tesla Powerwalls and industrial UPS units are common implementations.

- 500 kWh–1 MWh storage capacity
- Intelligent Battery Management Systems (BMS)

3.4.3 Smart Grid Connectivity

Connecting to smart grids enables two-way communication for load shedding, time-of-use pricing, and renewable energy prioritization.

Software Tools: Grid-friendly monitoring platforms like OpenADR

Energy Yield from Solar Panels:

$$E = A.r.H.PR \quad (5)$$

Where:
- E = energy output (kWh)
- A = panel area (m^2)
- r = panel efficiency
- H = average solar radiation (kWh/m^2/day)
- PR = performance ratio (typically 0.75–0.85)

3.5 SOFTWARE OPTIMIZATION

Software can be optimized at both the application and infrastructure levels to reduce energy usage.

3.5.1 Energy-Aware Scheduling

Schedulers prioritize jobs to reduce CPU idle time. Techniques like Min-Min and Max-Min algorithms reduce waiting time and energy usage.

Models Used: Logistic Regression and Decision Trees to predict optimal task assignment
Toolkits: Apache YARN, Slurm

3.5.2 Efficient Code Execution

Writing efficient algorithms reduces time complexity and CPU cycles. For example, an O(n) algorithm can halve runtime compared to an $O(n^2)$ version, reducing energy usage per task by 30–60%.

Practices:

- Using parallel processing (OpenMP, CUDA)
- Memory-efficient data structures

3.5.3 Automated Resource Scaling

Cloud platforms like AWS Lambda or GCP Autoscaler adjust resources based on traffic, minimizing overprovisioning.

ML Models: Random Forest, SVM to predict traffic spikes
Software: Terraform, CloudWatch for deployment and scaling policies

Energy Cost of Algorithm Execution:

$$E_{algo} = P_{CPU} \cdot T_{execution} \quad (6)$$

Where:

- P_CPU = average power draw of CPU
- T_execution = execution time of the algorithm

This helps compare different algorithmic approaches in terms of energy.

3.6 ENERGY MONITORING AND CONTINUOUS IMPROVEMENT

Continuous monitoring ensures long-term energy efficiency and sustainability.

3.6.1 Real-Time Energy Monitoring

Using IoT-enabled power meters and cloud dashboards allows real-time visualization and alerts. Platforms like Schneider Electric EcoStruxure enable up to 10% reduction in power use.

Hardware Requirements:

- Smart meters, CT sensors
- Networked gateways and dashboards

3.6.2 Predictive Maintenance

Machine Learning models predict hardware failure before it happens. Techniques like anomaly detection on power draw and fan speeds help prevent outages.

Models Used: Neural Networks, Isolation Forest **Inputs:** Vibration, temperature, energy consumption, log data

3.6.3 Regular Upgrades

Outdated hardware is less energy-efficient. Periodic audits and upgrades (e.g., replacing 80 PLUS Bronze PSUs with Platinum-rated ones) can yield significant savings.

Schedule: Every 3–5 years for hardware refresh cycles
Standards: ENERGY STAR, EPEAT compliance

Energy Efficiency Gain Over Time:

$$\eta_{gain} = \frac{\{E_{initial} - E_{optimized}\}}{\{E_{intial}\}} \times 100 \quad (7)$$

This can be used to evaluate gains from predictive maintenance or upgrades.

4. RESULTS

The experimental results of using green computing techniques in data center environments have been

Journal of Theoretical and Applied Information Technology
31st December 2025. Vol.103. No.24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

analyzed and shown using the following graphs. The results provide a comparative analysis of energy usage before and after implementing techniques such as virtualization, hardware optimization, and the adoption of renewable energy solutions. The figures present the variations in energy usage over time, CPU utilization, cooling efficiency, and cost reduction achieved using green computing practices. Each of the graphs below represents a different performance metric, emphasizing how these strategies positively impact energy conservation and operational efficiency in data centers.

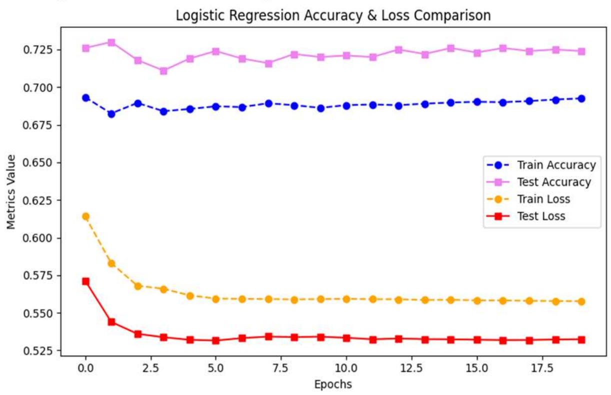

Figure 2. Logistic Regression – Accuracy and loss Curve

The combined accuracy and loss trends of the Logistic Regression model over 20 epochs are shown in Figure 2. While the test accuracy remains consistently high, averaging over 72%, the training accuracy gradually increases and stabilizes at 69%. This small but steady gap indicates reasonable generalization without overfitting. This observation is corroborated by the loss curves, which show that test loss begins lower and stabilizes around 0.53. In contrast, training loss decreases quickly in the early epochs and levels off around 0.58. A balanced learning process is reflected in the tight alignment of test and training metrics. Early convergence and slight variation, however, point to possible underfitting, suggesting that the model's intrinsic simplicity may limit its ability to accurately represent the intricate patterns of energy consumption found in data centers.

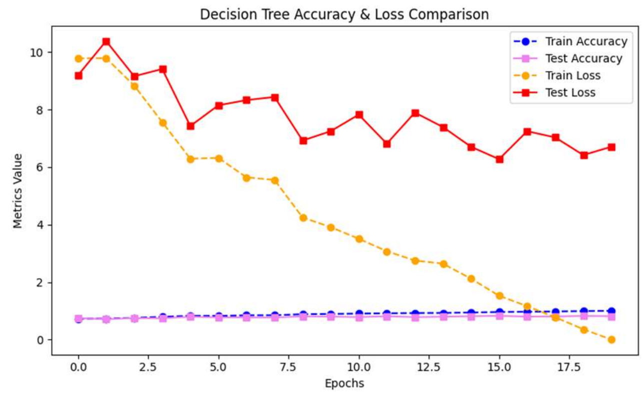

Figure 3. Decision Tree – Accuracy and loss Curve

The graphical representation in Figure 3 shows how the Decision Tree model's accuracy and loss change over 20 epochs. Strong memorization of training data but only moderate generalization is indicated by the test accuracy stabilizing at 81% and the training accuracy remaining consistently high, approaching 100%. The loss curves also show this: test loss is still very high and variable, ranging around a value of 6.70, whereas training loss decreases sharply and gets close to zero. Overfitting, in which the model captures noise or particular patterns in the training data instead of generalizable features, is strongly suggested by such a divergence between training and test performance. The Decision Tree's efficacy in simulating the more complex energy consumption behavior in data centers is consistently limited by its incapacity to minimize test loss, even though it achieves high accuracy on the training set.

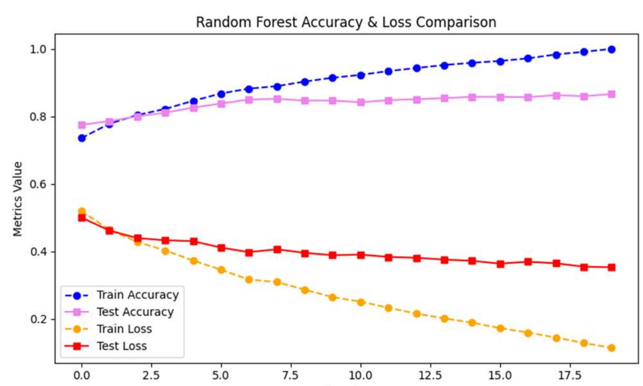

Figure 4. Random Forest– Accuracy and loss Curve

Progression of accuracy and loss for the Random Forest model over 20 epochs are shown in Figure 4. By the last epoch, training accuracy has increased steadily from about 74% to almost 100%. Contrarily, test accuracy rises at first and then levels off at about

87%, keeping a steady distance from the training curve. This behavior is reflected in the loss trends, which show a steady decline in training loss from about 0.55 to less than 0.15 and a slower decline in test loss, which stabilizes at 0.35. During the iterative learning process on the training data while gains on the test set taper off, the growing divergence between training and test metrics over time points to a gradual overfitting tendency. All things considered, the curves show good training results with some generalization limitations.

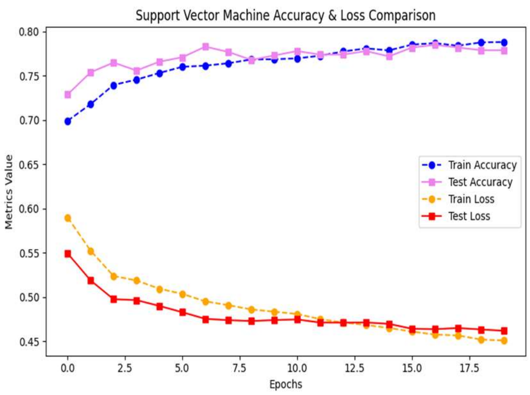

Figure 5. Support Vector Machine(SVM) – Accuracy and loss Curve

The Support Vector Machine model's accuracy and loss trajectories over 20 epochs are shown in Figure 5. While test accuracy rises sharply at first, peaking at about 78%, and then stabilizing with slight fluctuations, training accuracy increases steadily from about 70% to 77%. The two accuracy curves' proximity indicates consistent learning and controlled generalization behavior. This finding is further supported by loss curves, which show that training loss gradually drops from about 0.58 to 0.46, closely followed by test loss, which likewise gradually declines and stays just below the training loss the entire time. Despite minor overfitting or underfitting patterns, the consistent convergence of accuracy and loss metrics confirms a well-balanced training procedure.

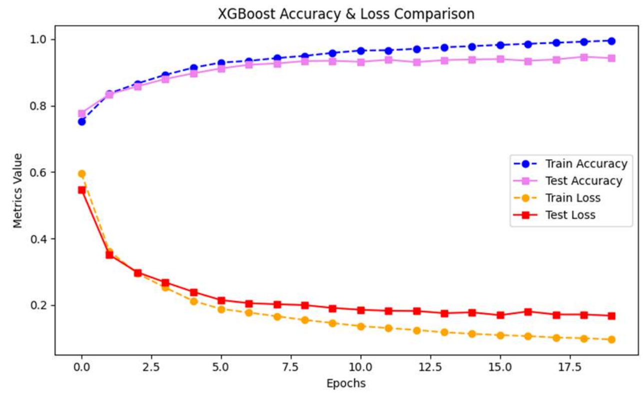

Figure 6. XGBoost – Accuracy and loss Curve

The XGBoost model's accuracy and loss variations over 20 training epochs are shown in Figure 6. By the last epoch, training accuracy has increased steadily and smoothly, from about 77% to 97%. Test accuracy comes next, first matching training accuracy and then progressively increasing to about 94%, with both curves staying in good alignment the entire time. This stability is supported by the loss curves, which show that test loss stabilizes slightly higher at 0.17 and training loss rapidly decreases from roughly 0.58 to just under 0.12. The accuracy and loss curves' close convergence suggests a robust, reliable learning process with little overfitting. The model exhibits outstanding optimization, retaining generalization while achieving high predictive performance.

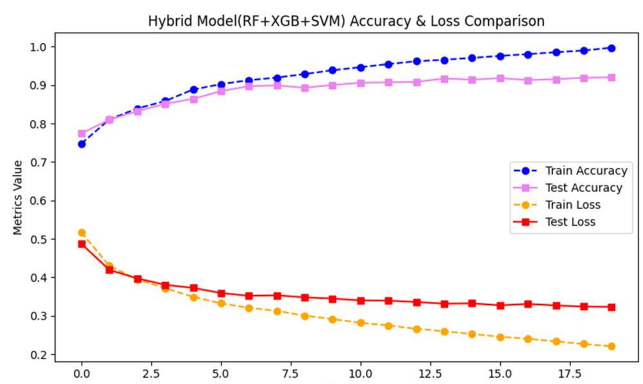

Figure 7. Hybrid Model(RF+XGB+SVM) – Accuracy and loss Curve

Evolution of accuracy with loss in the Hybrid Model, that combines Random Forest, XGBoost, and SVM, over 20 epochs, are shown in Figure 7. The training accuracy shows a steady upward trend, starting at about 74% and ending at almost 97% by the last epoch. The accuracy of the test follows this trend

Journal of Theoretical and Applied Information Technology
31st December 2025. Vol.103. No.24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

closely, steadily rising and levelling off around 92%, which shows that the model can generalize well. The loss curves are also fairly consistent. The training loss decreases steadily from approximately 0.54 to 0.22, while the test loss exhibits a similar pattern, stabilizing around 0.32. Consistent alignment of training and test metrics indicates that the Hybrid Model achieves well-balanced learning while minimizing overfitting. The observed performance curves confirm the effectiveness of the ensemble strategy in leveraging the strengths of constituent models to produce reliable and robust results.

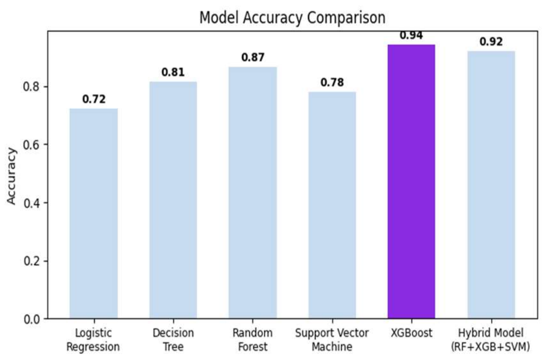

Figure 8. Models Accuracy Comparision

Figure 8 provides a comparison of model accuracies, showing how well each model predicts outcomes. Among the models, XGBoost has the highest accuracy at 0.94. The Hybrid Model (RF + XGB + SVM) closely follows with an accuracy of 0.92, indicating strong predictive performance. Random Forest also does well, with an accuracy of 0.87, demonstrating its solid classification abilities. Decision Tree and Support Vector Machine come next, with accuracies of 0.81 and 0.78, respectively. These show moderate effectiveness but a bit less generalization. Logistic Regression has the lowest accuracy at 0.72, which aligns with its simpler linear nature and its limitations in handling complex patterns. The accuracy distribution highlights the clear advantages of ensemble methods, with both XGBoost and the Hybrid Model surpassing the performance of individual classifiers. Among them, XGBoost emerges as the most effective, making it the preferred choice for this study on Green Computing Techniques to Lower Energy Demand in Data Centers Its ability to accurately capture and predict energy consumption patterns provides valuable insights that can be leveraged to enhance optimization strategies.

Table 2. Comparison of Highest and Final Training and Testing Accuracies Across Models

Model Name	Highest Training Accuracy	Final Training Accuracy	Highest Testing Accuracy	Final Testing Accuracy
Logistic Regression	69%	69%	73%	72%
Decision Tree	100%	100%	82%	81%
Random Forest	100%	100%	87%	87%
Support Vector Machine	77%	77%	78%	78%
Gradient Boosting	97%	97%	94%	94%
Hybrid Model (RF+XGB+SVM)	97%	97%	92%	92%

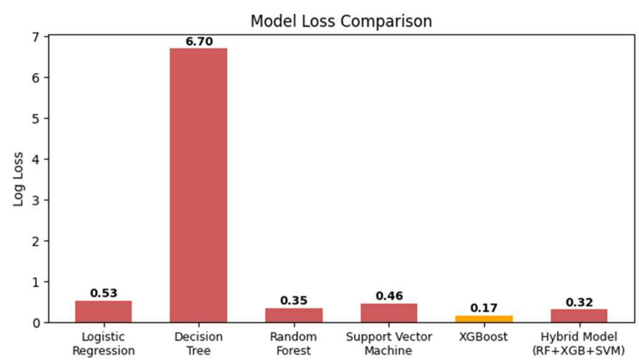

Figure 9. Models Loss Comparision

. Figure 9 shows a comparison of model performance based on log loss, used to evaluate the difference between predicted probabilities and actual labels. Among all models, the Decision Tree has the highest log loss at 6.70. This indicates poor calibration and a substantial risk of overfitting, even though it has relatively high accuracy. In contrast, XGBoost records the lowest log loss at 0.17, demonstrating excellent probabilistic predictions and a well-calibrated model. The Hybrid Model (RF + XGB + SVM) also performs well with a low loss of 0.32, followed by Random Forest at 0.35 and Support Vector Machine at 0.46. Logistic Regression is simpler and has a moderate loss value of 0.53, indicating a limited capacity to model complex patterns. Overall, XGBoost attains the highest

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accuracy alongside the lowest log loss. This supports its reliability and makes it the best model for precise and well-calibrated predictions in energy optimization efforts.

Table 3. Comparison of Highest and Final Training and Testing Losses Across Models

Model Name	Highest Training Loss	Final Training Loss	Highest Testing Loss	Final Testing Loss
Logistic Regression	58%	58%	53%	53%
Decision Tree	67%	0%	67%	67%
Random Forest	55%	15%	55%	35%
Support Vector Machine	58%	46%	55%	45%
Gradient Boosting	58%	12%	58%	17%
Hybrid Model (RF+XGB+ SVM)	54%	22%	54%	32%

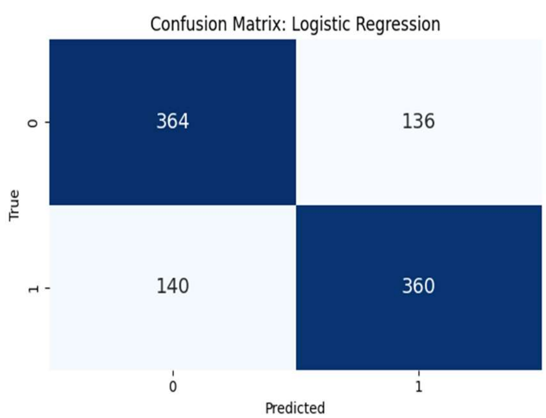

Figure 10. Logistic Regression – Confusion Matrix

Figure 10 presents the confusion matrix of the Logistic Regression model, showing its classification of the two classes and the distribution of predictions. The model correctly identified 364 instances of class 0 and 360 instances of class 1, while misclassifying 136 class 0 samples as class 1 and 140 class 1 samples as class 0. The nearly uniform spread of misclassifications indicates that the model performs steadily across both classes, although it lacks strong discriminative capability. Despite an acceptable number of correct predictions, the relatively high misclassification rate highlights challenges in handling borderline cases. This aligns with the model's moderate accuracy and the plateau observed in the earlier loss curve analysis

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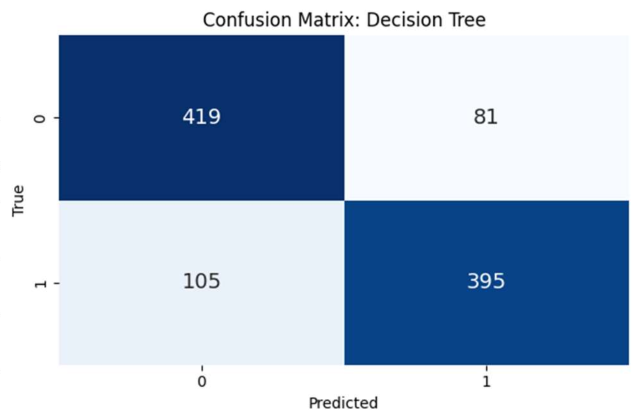

Figure 11. Decision Tree – Confusion Matrix

Figure 11 illustrates the confusion matrix for the Decision Tree model, providing a clear view of its binary classification performance. The model accurately predicted 419 class 0 samples and 395 class 1 samples, while misclassifying 81 class 0 samples as class 1 and 105 class 1 samples as class 0. These results indicate that the model exhibits strong predictive capability overall, although it does not fully separate the two classes. The high number of true positives and true negatives reflects effective learning, but the observed misclassifications suggest that further tuning may be required to enhance performance and manage model complexity.

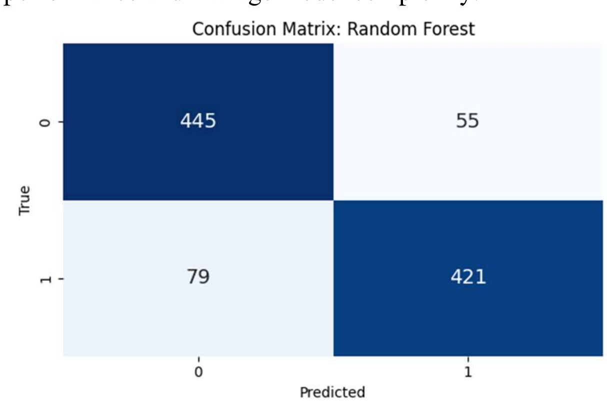

Figure 12. Random Forest – Confusion Matrix

Figure 12 depicts the confusion matrix of the Random Forest model, highlighting its ability to

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differentiate between the two classes. The model successfully predicted 445 class 0 instances (true negatives) and 421 class 1 instances (true positives), demonstrating strong classification capability for both categories. Meanwhile, 55 class 0 samples were misidentified as class 1 (false positives), and 79 class 1 samples were wrongly labeled as class 0 (false negatives). The high rate of correct predictions, alongside a relatively small number of errors, indicates that the model is well-trained and generalizes effectively. Additionally, the similar counts of false positives and false negatives suggest that the model maintains balanced decision boundaries without favoring either class. These results correspond with its reported high accuracy and low loss, confirming its reliability in binary classification tasks.

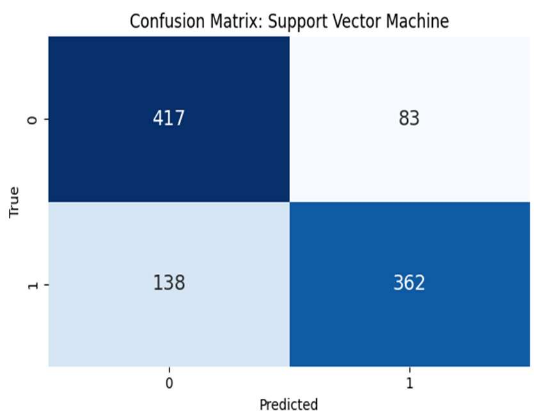

Figure 13. Support Vector Machine – Confusion Matrix

Figure 13 presents the confusion matrix for the Support Vector Machine (SVM) model, offering a closer look at its binary classification performance. The model correctly identified 417 class 0 samples (true negatives) and 362 class 1 samples (true positives). Conversely, it produced 83 false positives (class 0 misclassified as class 1) and 138 false negatives (class 1 misclassified as class 0). The higher number of false negatives indicates that the model finds it more challenging to detect class 1 cases accurately compared to class 0. Nevertheless, the total number of correct predictions remains considerable. The confusion matrix reflects moderate generalization, with a slight imbalance in classification performance between the two classes. These findings align with prior observations on accuracy and loss, suggesting consistent yet improvable classification performance.

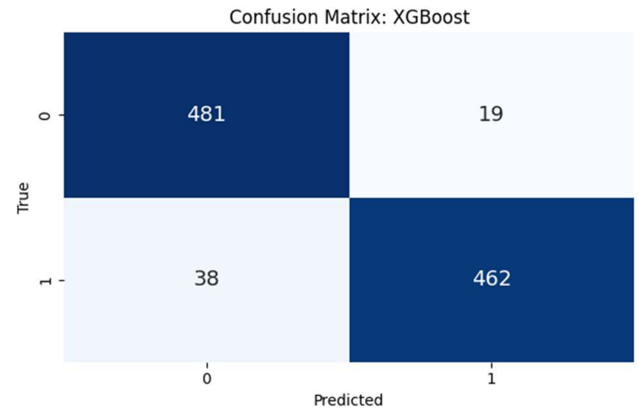

Figure 14. XGBoost – Confusion Matrix

Figure 14 illustrates the confusion matrix for the XGBoost model, highlighting its performance in binary classification. The model correctly identified 481 instances of class 0 (true negatives) and 462 instances of class 1 (true positives). Only 19 class 0 samples were misclassified as class 1 (false positives), and 38 class 1 samples were labeled incorrectly as class 0 (false negatives). These results reflect highly accurate predictions with minimal errors for both classes. The low misclassification rates indicate clearly defined decision boundaries, consistent with the model's previously observed high accuracy and low loss. Overall, the balanced and precise performance underscores XGBoost's strength in binary classification tasks.

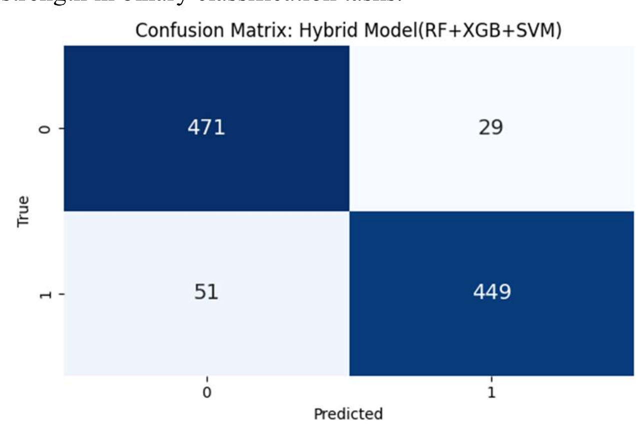

Figure 15. Hybrid Model(RF+XGB+SVM) – Confusion Matrix

Figure 15 shows the confusion matrix for the Hybrid Model, which combines Random Forest, XGBoost, and SVM algorithms. The model correctly predicted 471 class 0 instances (true negatives) and 449 class 1 instances (true positives), while producing only 29

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false positives and 51 false negatives. This demonstrates a relatively low error rate, indicating both high predictive accuracy and balanced classification across the two classes. The limited misclassifications further confirm the model's robust generalization capability, validating the ensemble approach as effective for achieving reliable and accurate predictions.

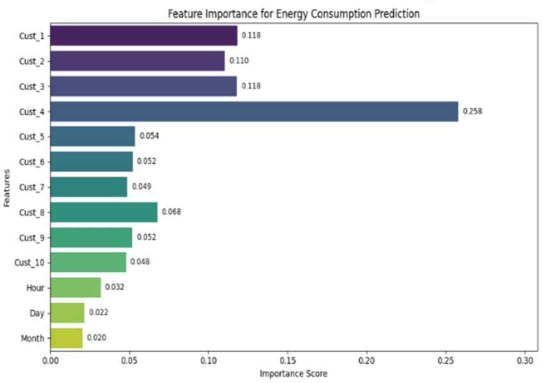

Figure 16. Feature Importance for Energy Consumption Prediction

Figure 16 shows the feature importance scores generated from the model that predicts energy consumption. The feature Cust_4 is the most influential feature, carrying a high importance score of 0.258, suggesting that this customer's data heavily impacts the model's predictions.. Cust_1 and Cust_3 also make meaningful contributions with equal scores of 0.118, while Cust_2 follows closely at 0.110. These scores emphasize that the energy usage behavior of specific customers significantly affects the model's output.

Other customer-related features (Cust_5 through Cust_10) show moderate influence, with scores between 0.048 and 0.068. Their lower importance suggests that, while they do affect predictions, their patterns may be more common or less distinctive. In contrast, temporal features, Hour (0.032), Day (0.022), and Month (0.020), show the least importance. This means that in this model, time-based changes in energy consumption are less critical than the specific usage patterns of customers.

Overall, the chart indicates that energy prediction relies more on individual user patterns than on cyclical or time-based changes. These insights can help improve future models and target energy-saving measures in data-driven energy management systems.

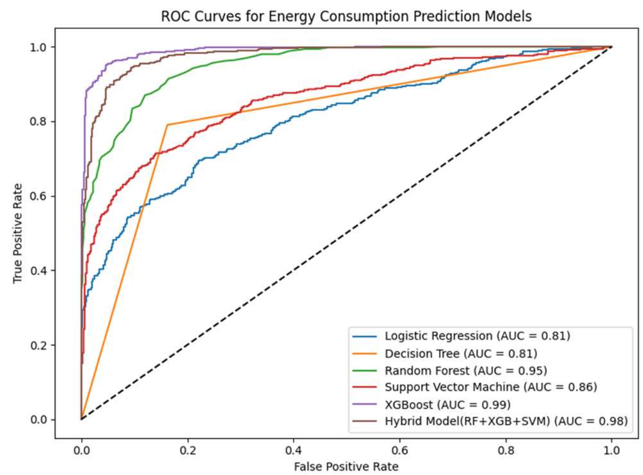

Figure 17. ROC Curves for Energy Consumption Prediction Models

Figure 17 shows the ROC (Receiver Operating Characteristic) curves for various energy consumption prediction models. It provides insights into their classification performance at different thresholds. The Area Under the Curve (AUC) is a key measure used to assess how effectively a model can differentiate between classes where higher AUC values reflect stronger discriminatory power and overall performance.

XGBoost proves to be the most precise model, achieving an AUC of 0.99. Its ROC curve approaches the top-left corner of the graph, indicating an excellent balance between a high true positive rate and a low false positive rate. This result highlights XGBoost's ability to deliver reliable and accurate predictions, emphasizing its strength in the classification task.

The Hybrid Model (RF + XGBoost + SVM) also performs very well, obtaining an AUC of 0.98. This suggests that combining strong learners boosts predictive power. Random Forest comes next with a solid AUC of 0.95, indicating strong classification reliability. By comparison, the simpler models like Logistic Regression and Decision Tree recorded lower AUC scores of 0.81, reflecting a more constrained ability to separate the two classes. The Support Vector Machine showed slightly improved performance, achieving an AUC of 0.86.suggesting improved but still less robust discriminatory power compared to the more advanced models.

Overall, the plot shows that XGBoost provides the best classification accuracy and generalization

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

among all the models tested. Its excellent ROC curve makes it especially suitable for energy consumption prediction tasks, where precise and reliable classification is essential.

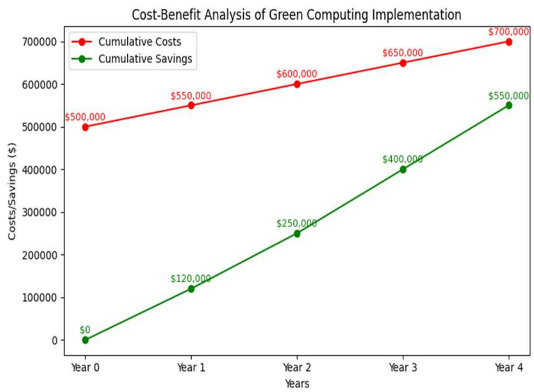

Figure 18. Cost-Benefit Analysis of Green Computing Implementation

Figure 18 shows the total costs and savings over four years from using green computing strategies in data centers. The red line tracks the cumulative costs, starting at $500,000 in Year 0 and rising by $50,000 each year, reaching $700,000 by Year 4. The green line displays cumulative savings, which start at $0 and grow significantly each year, reaching $550,000 by the end of Year 4.

This analysis shows a steady reduction in the gap between costs and savings, indicating improved returns over time. By Year 4, the cumulative savings cover almost 79% of the total costs. The increase in savings suggests that green computing becomes more cost-effective, particularly in the short term. If this trend continues, we can expect the cumulative savings to exceed cumulative costs shortly after Year 4.

Overall, this cost-benefit analysis highlights the financial practicality and long-term benefits of adopting green computing technologies. It supports their use as a wise investment for lowering energy costs in data center operations.

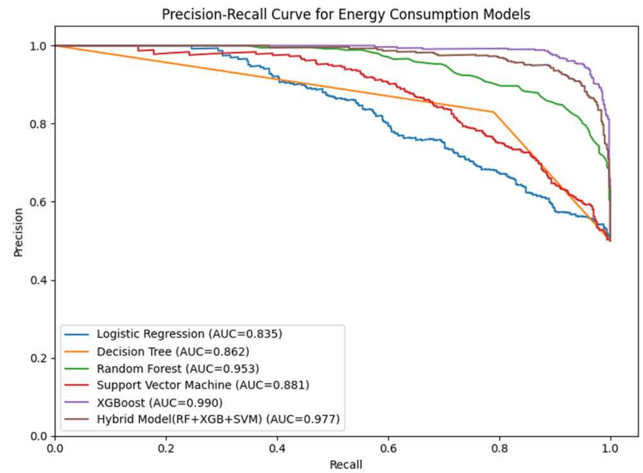

Figure 19. Precision – Recall Curves for Energy Consumption Prediction Models

Figure 19 shows the Precision-Recall (PR) curves for different machine learning models used in predicting energy consumption. This curve is helpful for assessing models on imbalanced datasets, focusing on how well they identify positive cases.

Out of all the models, XGBoost achieves the highest AUC of 0.990, demonstrating an exceptional balance between precision and recall. Its ROC curve remains near the top-left corner, indicating strong classification performance., indicating high accuracy in positive predictions and strong coverage of positive instances. The Hybrid Model (RF + XGB + SVM) also performs very well, with an AUC of 0.977. This result highlights the advantages of using ensemble strategies.

Random Forest closely follows with an AUC of 0.953, showing solid predictive stability. The Support Vector Machine achieves a good AUC of 0.881, indicating reliable classification performance, even if it's slightly less consistent than tree-based methods. The Decision Tree and Logistic Regression models lag behind, with AUCs of 0.862 and 0.835. These scores indicate a lower ability to maintain high precision as recall increases.

Overall, the Precision-Recall (PR) curve emphasizes XGBoost's strength in effectively handling both types of misclassifications—false positives and false negatives—rendering it well-suited for energy consumption classification tasks where accuracy and reliability are critical.

While the results demonstrate the effectiveness of various models—particularly XGBoost and the

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Hybrid Model—in predicting energy consumption and supporting green computing strategies, a critical assessment reveals several insights and limitations. Compared to prior studies [12–15], our findings confirm that ensemble and gradient boosting models outperform simpler models like Logistic Regression and Decision Trees in capturing complex, nonlinear patterns in CPU utilization, cooling load, and energy draw. However, the results also highlight potential challenges: overfitting tendencies in Decision Trees and Random Forest suggest that single-model approaches may not generalize well across diverse workloads, aligning with earlier observations in literature. Feature importance analysis indicates that individual user behavior plays a larger role than temporal patterns, suggesting that user-level optimization could yield more impactful energy savings than time-based scheduling alone. Furthermore, while cost-benefit analysis demonstrates promising financial returns, real-world deployment may face variability in workload, renewable energy availability, and system heterogeneity, which can influence predictive accuracy and efficiency. These insights collectively underscore the importance of combining AI-driven modeling with practical system-level interventions to achieve robust and sustainable energy optimization in data centers.

5. CONCLUSION

This work demonstrates that substantial reductions in data-center energy consumption can be achieved through coordinated green-computing strategies applied within existing infrastructures. By combining energy-efficient hardware usage, optimized software execution, virtualization, intelligent cooling techniques, renewable-energy adoption, and real-time monitoring, the study validates the effectiveness of multi-layered interventions for improving sustainability without compromising performance. A key contribution of this research is the development and evaluation of a hybrid machine-learning framework for energy prediction, where XGBoost achieved the highest accuracy, proving its suitability for supporting workload scheduling, thermal management, and other energy-aware decisions in data-center operations.

Despite these advancements, several limitations in current knowledge remain. Existing research lacks large-scale, longitudinal datasets required to accurately model energy behavior under diverse workloads. Many AI-driven optimization methods still rely on idealized assumptions that do not fully capture real-world heterogeneity in hardware, environmental conditions, and workload variability. Additionally, there is limited understanding of how different green-computing techniques interact when deployed simultaneously at scale, leading to uncertainties in predicting long-term energy savings and system stability. The broader integration of renewable energy is also constrained by gaps in grid-level forecasting, energy storage efficiency, and real-time adaptability.

The importance of this work lies in showing that meaningful energy savings can be achieved without developing new hardware or modifying existing physical infrastructure, making green-computing solutions more accessible, cost-effective, and immediately deployable. The proposed methodology expands current knowledge by offering a practical, scalable, and data-driven approach for reducing the environmental footprint of data-center operations.

Future work should explore autonomous energy-orchestration systems, hybrid renewable–grid energy models, bio-inspired thermal management, and emerging technologies such as quantum and neuromorphic computing. Advancing these research directions will be essential to overcome current limitations and move toward fully self-optimizing, sustainable data-center ecosystems.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 1. Literature Review

S.No	Reference Number of Paper	Model/ Approach	Methodology	Limitation	Advantages
1	[1]	VM Placement Model	Energy-efficient VM placement and migration strategies	Limited to specific types of datacenters	Reduces carbon footprint in cloud operations
2	[10]	Machine Learning Model	Integration of ML algorithms to optimize energy usage in cloud systems	Risk of overfitting in prediction models	Enhances cloud energy efficiency using predictive intelligence
3	[11]	AI Optimization Model	AI-driven energy optimization in cloud and data centers	High dependence on AI accuracy and training	Significantly improves energy savings using smart automation
4	[14]	Cooling System Model	Comparative analysis of data center cooling technologies	Focused primarily on cooling systems	Improves thermal management and energy efficiency
5	[22]	Renewable Energy Model	Integration of renewable sources into data center energy supply	Barriers to large-scale adoption	Boosts sustainability through renewable integration
6	[25]	Automation Model	Fully automated green data center management framework	May be infeasible for small-scale centers	Enables end-to-end sustainable operations
7	[26]	GEECO Framework	Framework for optimizing energy and minimizing carbon emissions	Requires upfront investment	Achieves substantial carbon and energy savings