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Energy-Efficient Machine Learning Algorithms for Sustainable AI Systems

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Abstract

The rapid expansion of Artificial Intelligence (AI) systems across enterprise and industrial domains has led to a substantial increase in energy consumption, raising concerns about sustainability and operational efficiency. This research presents a comprehensive method for energy-efficient machine learning (ML) algorithms to develop sustainable AI systems while maintaining high predictive performance. Min-Max normalization normalizes feature ranges to improve model stability and efficiency, while Principal Component Analysis (PCA) reduces dimensionality, removing redundancy to enhance computational efficiency and energy-aware learning aligned with sustainable AI objectives. ML models, including Dynamic Raven Roosting Optimized Enriched Support Vector Machines (DRRO-En-SVM) for robust classification and complex pattern recognition, are integrated to address diverse analytical tasks while optimizing energy usage. The primary purpose of these ML techniques is to enhance prediction accuracy, automate intelligent decision-making, and reduce computational overhead through optimized model design. The proposed method incorporates energy-aware strategies such as model pruning, quantization, and adaptive learning mechanisms to minimize power consumption during both training and inference stages. An optimization approach is employed to balance energy efficiency and model accuracy, identifying Pareto-optimal solutions for different deployment scenarios. Experimental evaluation on large-scale datasets demonstrates that the DRRO-En-SVM (Proposed) achieved 98.9% accuracy, 3.1% error rate, 98.5% F1 score, 98.7% precision, 98.2% recall, and 1.05 seconds of training time. The results highlight the effectiveness of integrating energy-efficient ML techniques in enabling scalable, cost-effective, and environmentally sustainable AI systems, and providing insights for future advancements in green AI technologies.

Keyword: Energy-Efficient, Machine Learning, Model Pruning, Resource Optimization, Artificial Intelligence

Introduction

Artificial Intelligence (AI) has emerged as an essential tool in improving decision-making capabilities in numerous fields owing primarily to the increased availability of high computational powers, and not due to improvements in algorithms [1]. Besides, the fast proliferation of Internet of Things (IoT) involving around 35 billion connected devices has facilitated the use of AI technology in fields such as healthcare, consumer electronics, and smart cities, thereby collecting extensive data from these fields for intelligent processing [2]. The increased application of AI has caused increased energy usage. Data centers using AI consume 5-9% of global energy usage while causing nearly 2% carbon dioxide emissions. Additionally, ICT is expected to produce up to 14% of greenhouse gas emissions in the coming years [3]. The need for an environmentally friendly AI technology is increasingly felt by researchers today. Several techniques for optimizing energy consumption in the field of AI have been studied, both in low-level and high-level approaches. Examples of low-level techniques include hardware optimization, reduced precision arithmetic operations, and compiler-based optimization techniques. High-level optimizations involve choosing algorithms carefully, hyperparameter tuning, and minimization of computational complexity [4]. ML technology has revolutionized enterprise software applications like Salesforce Customer Relationship Management (CRM), where ML allows for automatic decision-making capabilities and reduced development time through data analysis [5, 6]. However, there are still some issues that exist, such as the problem of balancing energy efficiency versus accuracy, lack of practical application outside edge and IoT settings, and the absence of standardized benchmarks [7, 8]. This emphasizes the need for full-stack solutions.

Research Aim: The objective of this research is to design and test energy-efficient machine learning algorithms for sustainable AI, specifically those that will enable highly accurate predictions with the use of the DRRO-En-SVM model. This would involve the construction and optimization of models by employing energy-efficient practices like pruning, quantization, and adaptive learning.

Research organization: Research focuses on developing energy-efficient machine learning algorithms that maintain high prediction accuracy while reducing computational cost. Section 2 reviews related work in energy-efficient ML, green AI, and optimization techniques. Section 3 presents the proposed method, including Min-Max normalization, PCA, DRRO-En-SVM, and energy-saving strategies like pruning and quantization. Section 4 discusses experiments and trade-offs, while Section 5 concludes the research.

Related Works

Table 1 summarizes the literature on AI-based methods of energy efficiency, which show improvement but still lack generalization, scalability, and consistency.

Table 1: Existing research methodology, limits and their findings

Ref	Objective	Method	Results	Limitations
[9]	Develop an energy-efficient visual inspection system for Printed Circuit Board (PCB) defect detection	AI with a Convolutional Neural Network (CNN) integrated with Dynamic Voltage Scaling (DVS)	20% energy savings, 95.4% accuracy, 30% reduction in downtime	Limited dataset size, low generalizability
[10]	Analyze energy-efficient algorithms for sustainable and green computing systems.	Empirical research using heuristic search algorithm evaluation.	Algorithms showed varied energy efficiency across simple and complex tasks	Limited focus on the large-scale industrial environments.
[11]	Develop predictive green building models for sustainable, efficient design.	Applied Exploratory Data Analysis(EDA), Z-score normalization, ML, and DL predictive techniques.	Graph Neural Network (GNN) and Long Short-Term Memory(LSTM) achieved the highest accuracy.	High computational complexity and dependency on large labeled datasets.
[12]	Enhance industrial energy efficiency using ML	ML-based prediction, monitoring, and optimization	Reduced energy use, cost savings	Poor data quality, high cost, limited scalability
[13]	Improve energy management in smart buildings	IoT-enabled CNN using Gene Expression Programming (GEP) III dataset	88% prediction accuracy	Dataset dependency, scalability issues
[14]	Optimize energy efficiency in old buildings using IoT and DL.	IoT sensors, DL–Enhanced Predictive Energy Modeling (DL-PEM) model.	Improved forecasting, reduced energy use, and better thermal comfort.	High retrofit cost and integration challenges in historic buildings.
[15]	Optimize building operations using AI techniques	AI-based HVAC optimization, lighting control, and predictive maintenance	20–50% energy savings, up to 35% maintenance cost reduction	Requires interdisciplinary integration, scalability challenges
[16]	To enhance Energy-conscious IT governance inference	Standard ML techniques	High-accuracy ML classification	Dataset dependency, limited generalization

Methodology

With the intention of normalizing the features and reducing computational cost, data preprocessing using Min–Max normalization is performed first, followed by the application of PCA for feature extraction by transforming high-dimensional data into orthogonal and uncorrelated subspaces. The DRRO-En-SVM model consists of SVMs for high-accuracy, low-energy classification and IRRO for efficient parameter tuning. Energy-efficient AI techniques and sustainable learning algorithms enable the development of environmentally sustainable AI technologies due to their power efficiency without compromising forecasting precision, and their processes are shown in Figure 1.

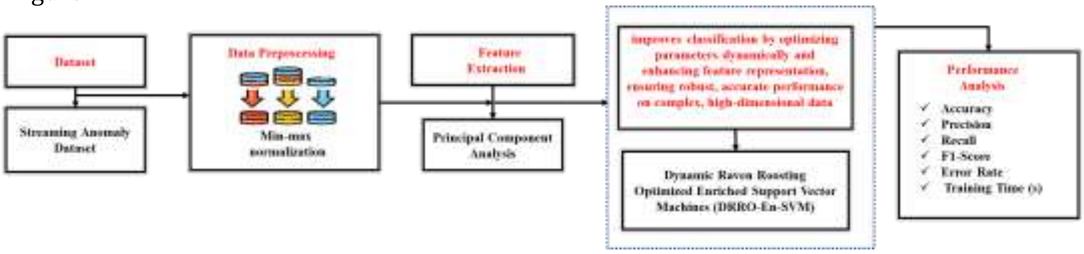

Figure 1: General workflow of data preprocessing, feature extraction, and model evaluation

Data collection

This dataset comprises 7,167 records capturing system-level energy usage, computational performance, and resource utilization metrics across diverse operating conditions. The dataset is intended for facilitating analysis of efficiency, performance, and behavioral patterns in artificial intelligence systems, with each row representing a particular state of the system characterized by factors such as energy usage, execution process, and efficiency. The dataset contains 12 variables that allow an in-depth analysis of the relationship between energy usage and processing speed among others. **Kaggle Source: https://www.kaggle.com/datasets/colabsss/energy-efficient-ai-system-performance-dataset**

Data feature exploration: Figure 2 includes two subgraphs that demonstrate the dynamics of the system's operation at different parameters. In particular, Figure 2 (a) demonstrates the efficiency classes that exhibit various dynamics and trends depending on the index's magnitude. Figure 2 (b) depicts the distribution of system values over time, which demonstrates erratic deviations and peaks, thus showing the dynamic processes occurring in the system's performance and energy efficiency. Figure 3(a) depicts the correlation between system variables, revealing the interconnection between different metrics associated with the system's performance and energy efficiency. Figure 3(b) is a comparison of the distribution of the system's performance depending on the efficiency level, illustrating differences in dispersion and central tendency.

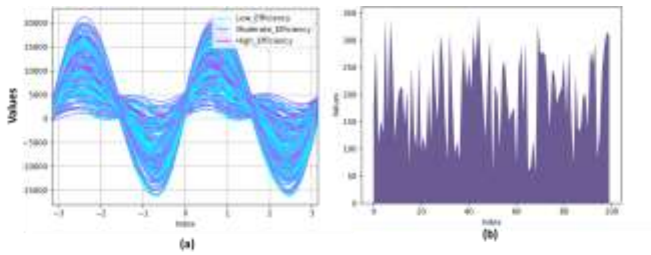

Figure 2: Temporal efficiency patterns and dataset distribution (a) Variations corresponding to the efficiency levels and (b) Dataset distribution with their process.

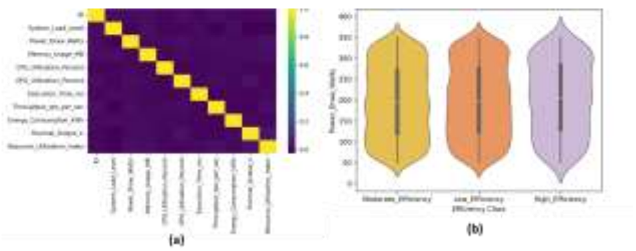

Figure 3: Graphical presentation of (a) Correlation feature analysis and (b) Efficiency-based power consumption distribution

Data preprocessing using Min-Max normalization

Min–max normalization minimizes variation in the input by scaling features to a standard range, ensuring that no specific feature dominates the learning process. In line with the objective of developing energy-efficient and high-accuracy AI models, this normalization improves learning speed and reduces computational cost, thereby contributing to sustainable system performance. One of the most common approaches is to transform feature values into a specified range, typically [0–1]. Importantly, the relationships within the data are preserved during this process. The following expression shows how each value of the considered feature is mapped into a normalized value.

$$U^p = \overline{max_B - min_B}^{u-min} B\left[new_{max_B} - new_{min_B}\right] + new_{min_B} \quad (1)$$

Equation (1) represents a linear normalization or scaling formula. U^p is the normalized value of u in the new range, max B, the maximum value in dataset B, and min_B, the minimum value in dataset B. It represents the smallest observed value of the feature, $u - min$ represents the Shifts data, so the minimum becomes 0

Removes baseline offset. Represents the largest observed value of the feature $B\left[new_{max_B} - new_{min_B}\right]$. It maps a value for u from its original range $[\min_{B}, \max_{B}]$ to a new range $[\text{new\_min}_{B}, \text{new\_max}_{B}]$. The term normalizes u relative to the original range, while multiplying by $(\text{new_max}_B - \text{new_min}_B)$scales it to the new range, and adding new_min_Bshifts the result into the desired output interval.

Feature extraction using PCA

The PCA aims to maximize the variance of high-dimensional data and transform it into lower-dimensional subspaces using a linear approach. In line with the development of energy-efficient and high-accuracy AI models, PCA reduces data complexity, thereby lowering computational cost and improving processing efficiency. The resulting components are orthogonal and uncorrelated, as they are derived from the eigenvectors of the covariance matrix, representing the most significant patterns in the dataset. This transformation retains essential information while eliminating redundancy, enabling faster learning, reduced energy consumption, and improved model performance in large-scale AI applications.

$$T = \frac{1}{l}\sum_{j=1}^{l}(w_j - \mu)(w_j - \mu)^s \quad (2)$$

In Equation (2), T can be expressed using this formula: l means the average value, converts the sum into a mean, and j is the indexing range. Start from the first data point (j = 1) and go up to last data point (j = l) whereby T is the mean of the outer products of deviations of vectors w_j from the mean vector μ. Each of the terms $(w_j - \mu)(w_j - \mu)^s$ expresses the correlation between the elements of wj in relation to the mean, resulting in a form of matrix that resembles the covariance matrix.

$$z_l = b_{l1w1} + b_{l2w2} + \cdots + b_{llwl} \quad (3)$$

In equation (3), z_l is represented as a linear combination of the vectors, $w1, w2 \ldots wl$. Each of these vectors is multiplied by a respective weight b_{llwl}, and then their sum is computed. This is a very common operation in linear algebra and ML applications, where a quantity is computed from several other variables in equation (4).

$$\gamma_l = \frac{\lambda_1 + \lambda_2 + \cdots + \lambda_n}{\lambda_1 + \lambda_2 + \cdots + \lambda_n + \cdots + \lambda_l} \geq 80\% \quad (4)$$

γ_l is defined as the sum of the first neigenvalues $\lambda_1, \lambda_2 \ldots \lambda_n$ divided by the sum of the first leigenvalues $\lambda_1, \lambda_2 \ldots \lambda_n$. This equation is often employed in Principal Component Analysis to determine the proportion of variance captured in the selected components, and λ_l Represents eigenvalues. Each eigenvalue shows the amount of variance captured by a principal component. In particular, $\gamma_l \geq 80\%$ means that the selected l components account for 80% or more of the variance in equation (4).

Energy-Efficient for a sustainable AI system using DRRO-En-SVM

To increase prediction capability, the proposed DRRO-En-SVM model integrates the En-SVM classification technique with the DRRO algorithm, aligning aligned with the goal of developing energy-efficient and high-accuracy AI models. While En-SVM combines multiple SVM classifiers to enhance classification performance, the DRRO algorithm identifies optimal SVM parameters. By reducing overfitting and improving convergence rates, the DRRO-En-SVM approach ensures optimal hyperparameter selection through the combined strengths of ensemble learning and DRRO optimization.

En-SVM model for robust classification in energy efficiency: En-SVM is a supervised learning algorithm widely used for classification and regression tasks. It constructs an optimal hyperplane that maximizes the margin between data classes, ensuring strong generalization on unseen data. In alignment with the development of energy-efficient ML algorithms for sustainable AI systems, SVM effectively handles high-dimensional data while reducing overfitting risk. The use of kernel functions helps to learn nonlinear relationships through computation at reasonable costs. The new approach is developed by employing energy-efficient techniques like pruning, quantization, and adaptive learning schemes for ensuring low-power operations in training as well as inference.

$$\min_{x} -^{1} ||\omega||^{2}$$
$$s.z_j(< \omega, w_j > +a) \geq 1 \quad (5)$$

In equation (5) is the optimization constraint for En-SVM. It seeks the weight vector ω that minimizes the squared norm $\| \omega \|^2$, which corresponds to maximizing the margin between classes. The constraint $(< \omega, w_j > +a) \geq 1$ensures that each training sample w_j, with its label z_j, is the correctly classified and lies outside the margin, enforcing a hard-margin separation between classes.

$$-||\omega||^{2} + D \sum_{j=1} \epsilon_j^m \quad (6)$$
$$min_{\omega,a,t^{1}2}$$

Equation (6) represents the objective function of a soft-margin En-SVM. It minimizes a combination of two terms: the squared norm of the weight vector ω, which maximizes the margin, and a penalty term $D \sum_{j=1} \epsilon_j^m$ that accounts for misclassifications or margin violations (ϵ_j are slack variables). The minimization is performed over ω, a(bias), and ϵ_j, balancing margin width and classification errors.

$$(w) = sign(\sum_{j} \alpha_j z_j \langle \Phi(w_j), \Phi(w) \rangle_E + a)_{\ class} \quad (7)$$

Equation (7) defines the predicted class of a new input w in an SVM. The term $\sum_j \alpha_j z_j \langle \Phi(w_j), \Phi(w) \rangle_E$ computes a weighted sum of the training points $w_j$in the feature space Φ, with z_j being their labels and α_j is the learned coefficients. Adding a is a shift to the decision boundary. Finally, the sign function determines the class label, producing +1 or -1.

Dynamic Raven Roosting Optimized (DRRO) for parameter tuning: The optimization technique is employed to ensure energy efficiency while maintaining an optimal level of accuracy through the identification of Pareto-optimal points. The use of a nature-inspired metaheuristic technique is employed to perform parameter tuning to facilitate efficient implementation of the proposed DRRO methodology. The method utilizes a modeling of the raven bird behavior to exploit the SVM hyperparameters in an exploration and exploitation manner. DRRO improves RRO by using a time-based $Food_{st}^{t+1,j}$ parameter and dividing ravens into weak and greedy based on their personal best.

$$Food_{st}^{t+1,j} = Food_{Max} \frac{MaxIt-i}{MaxIt} \quad (8)$$

$Food$ is a control parameter that influences how long a raven continues searching before stopping, Equation (8) defines the time-based update of the $Food_{st}$ parameter. Here, $Food_{Max}$ is the initial maximum value, $MaxIt$ is the total number of iterations, and i is the current iteration. At each iteration $t + 1$, the parameter decreases linearly according to $(MaxIt - i)/MaxIt$, gradually reducing the “stopping tendency” of ravens. This mechanism is intended to balance exploration and exploitation over time, with higher values early on promoting wider search and smaller values later encouraging convergence near promising solutions.

Algorithm 1:BO-ACNN for robust anomaly detection

1. Load Input dataset D
2. Apply Z-score normalization to D
3. Extract features using PCA → obtain W^j
4. Initialize En-SVM model with initial parameters

```
Initialize DRRO population A^old for SVM parameters
Evaluate initial fitness   using SVM performance
For iteration t = 1to max_iter do
   a. Update DRRO solution A^new
   b. Train SVM with A^new and compute E^new
   c. If E^new < E^old then
      i. A^old = A^new
      ii. E^old = E^new
   d. Else retain A^old
End For
Train the final SVM with optimized A^old
For each x_i ∈ D do
   a. Predict ŷ_i = f(x_i)
   b. If ŷ_i ≥ θ, label = Anomaly
   c. Else label = Normal
End For
Output: Return predicted labels
```

Explanation of Algorithm 1 provides the framework for the new algorithm that includes the steps of preprocessing, feature extraction, classification, and optimization in order to ensure accuracy and efficiency. Firstly, the data is normalized and then compressed through PCA, and the classification step is initiated using En-SVM. DRRO then fine-tunes the parameters of the En-SVM model to enhance its fitness function and prevent premature convergence.

Result and discussion

Performance results of the proposed DRRO-En-SVM algorithm are discussed in the Results section with the aim to meet the accuracy objective in an energy-efficient manner. Implementation of the algorithm is done in Python and testing of the results is done on a Windows machine using the Intel® Core™ i7-10875H CPU @ 2.30 GHz processor. **Accuracy (%):** It calculates the percentage of correctly classified instances in the testing dataset and hence indicates whether a model can have accurate prediction capabilities as per the objectives of creating AI systems **Error Rate (%):** It shows the percentage of misclassification (100 – accuracy) which reflects the shortcomings of the model while helping to build a better and more efficient one. F1 Score (%): It is used to balance precision and recall, which leads to consistent performance even when the distribution of classes in the data is uneven, and hence results in dependability. Precision (%): It denotes the fraction of the total number of correctly classified positives among the total positives. Recall (%): It shows the proportion of positively classified cases in the entire population. Training Time (s): This metric shows the amount of time needed to develop the model, hence allowing evaluation of computational efficiency.

Performance evaluation using existing dataset: DRRO-En-SVM was developed and tested using the generated system level energy dataset [16], which has a total of 7,167 records in order to understand the relationship between energy and performance issues in AI environment. Instead of relying on survey based approaches for organization-level studies, the present work is based on computing experimentation for the purpose of realizing efficient and accurate AI model development. Comparative performance results obtained by analyzing DRRO-En-SVM against common classification algorithms such as SVM, Logistic Regression (LR), Decision Tree (DT), Neural Network (NN) and k-Nearest Neighbor (KNN) [16] reveal that DRRO-En-SVM attains highest accuracy (95%) along with least error rate (5%). These results confirm the effectiveness of the proposed approach in developing sustainable, high-performance AI systems, as presented in Table 2 and Figure 4(a, b).

Table 2: Comparative Performance Metrics of Proposed DRRO-En-SVM and Standard ML Models

Model	Accuracy (%)	Error Rate (%)	F1 Score (%)	Precision (%)	Recall (%)	Training Time (s)
SVM [16]	90.0	10.0	89.8	89.9	90.0	1.2578
LR [16]	86.7	13.3	86.1	86.6	86.7	1.1949
DT [16]	86.7	13.3	85.3	88.8	86.7	2.3509
NN [16]	86.7	13.3	85.3	88.8	86.7	7.4872
KNN [16]	83.3	16.7	82.2	83.3	83.3	2.1084
DRRO-En-SVM[Proposed]	95.0	5.0	94.8	95.0	95.0	1.0508

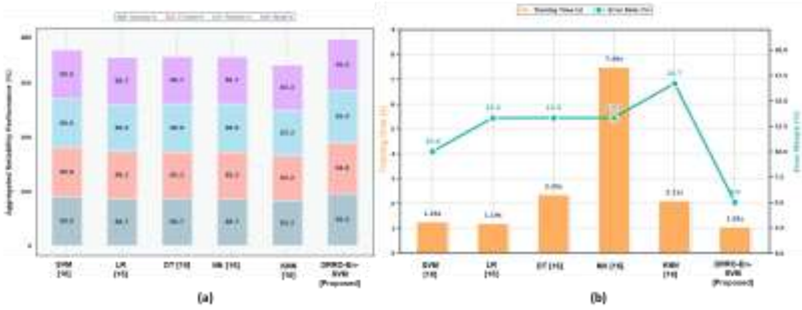

Figure 4: Graphical representation of (a) Training time and Error rate, (b) Classification metrics in existing dataset

Performance evaluation using proposed dataset: Performance evaluation is conducted using the Energy-Efficient AI System Performance Dataset, incorporating CPU, GPU, memory, and energy metrics to analyze performance–energy trade-offs. The existing models like SVM, LR, DT, NN, and KNN [16], which were retrained on the proposed dataset, compared to the proposed DRRO-En-SVM model, effectively capture relationships between system behavior and energy efficiency, aligning with the objective of sustainable AI. It outperforms baseline models with 98.9% accuracy and a 3.1 error rate. High F1-score, precision, and recall indicate stable predictions. Additionally, the model requires less training time than Neural Network-based approaches, demonstrating improved computational and energy efficiency, it is highly suitable for energy-aware and scalable AI systems, as shown in Table 3 and Figure 5 (a, b).

Table 3: Comparison of the standard model with suggested model in the proposed dataset

Model	Accuracy (%)	Error Rate (%)	F1 Score (%)	Precision (%)	Recall (%)	Training Time (s)
SVM	93.8	6.2	91.0	91.2	91.0	1.26
LR	89.5	10.5	88.7	88.9	88.8	1.19
DT	88.3	11.7	87.5	88.2	87.6	2.35
NN	90.7	9.3	90.1	90.3	90.2	7.49
KNN	87.2	12.8	86.5	86.9	86.6	2.11
DRRO-En-SVM [Proposed]	98.9	3.1	98.5	98.7	98.2	1.05

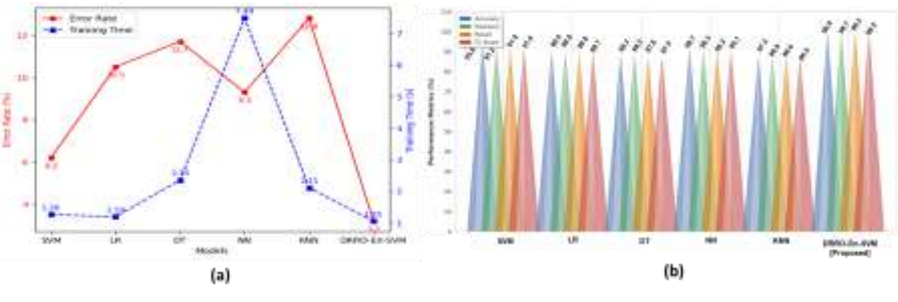

Figure 5: Graphical representation of (a) Training time and Error rate, (b) Classification metrics in proposed dataset

Conclusion

The evaluation process for the proposed DRRO-En-SVM model is done using the Energy-Efficient AI System Performance Dataset, whose features are CPU, GPU, memory, and energy consumption-related parameters to efficiently measure and predict performance-energy tradeoffs in AI systems. The model performs excellently and attains an accuracy of 98.9%, while its error is low at 3.1. Besides, other measures such as F1-score, precision, and recall were achieved, which indicate that the proposed model has strong capabilities for classification tasks. Notably, the model has higher computational efficiency since training time has been minimized than NN-based models, hence fulfilling the research objective to design energy-efficient and sustainable AI systems without compromising accuracy. It can be concluded that the adoption of DRRO optimization technique and incorporation into the En-SVM significantly improves the model performance and reduces energy consumption. Nonetheless, limitations are experienced because of the reliance on a single and narrow dataset whose data is limited to certain conditions and does not have wide coverage. Further research should be focused on increasing the diversity of the training datasets, applying IoT-based real-time energy consumption measures, and designing adaptable and contextual algorithms.

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