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Research Article

Energy-Efficient Hyperparameter Optimization in Machine Learning Using Coati Optimization Algorithm (CMRLCCOA)

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ABSTRACT

Increasing demand for energy-efficient machine learning models requires optimization strategies that minimize computing costs and increase model performance. We use the Coati Optimization Algorithm to optimize SVM classifier hyperparameters. Lévy Flight explores, Sine Chaotic Mapping initializes populations, and Convex Lens Imaging Reverse Learning accurately searches. Iris dataset model accuracy and energy consumption improved with the method. CMRLCCOA balances computational economy and model accuracy, making it suited for energy-efficient machine learning.
CMRLCCOA-based SVM hyperparameter optimization improves exploration and exploitation through Sine Chaotic Mapping, Lévy Flight, and Convex Lens Imaging Reverse Learning. Machine learning models in resource-constrained situations must maximize accuracy and minimize energy use. We found that CMRLCCOA fits these standards. This study demonstrates that CMRLCCOA helps machine learning conserve energy while preserving model accuracy.
CMRLCCOA maximizes energy-efficient hyperparameter optimization by improving functional and non-functional SVM hyperparameters.

1. INTRODUCTION

Recently, companies using resource-constrained devices and systems have realized the necessity for energy-efficient machine learning. Due to its unique accuracy-energy consumption balance, CMRLCCOA is suitable for many applications. CMRLCCOA-optimized versions can assist embedded systems and Internet of Things (IoT) devices, which operate on restricted power sources and require continuous operation without battery replacement or recharge. Portable diagnostic instruments and wearables need low-energy machine learning models to run longer, making CMRLCCOA perfect. Hyperparameter optimization is also needed for real-time performance with low energy use in autonomous systems like drones and electric vehicles and smart cities, where machine learning models manage energy grids and monitor traffic. Energy efficiency makes the algorithm suitable for sustainable AI development, especially for long-term operation and environmental impact. These many uses demonstrate CMRLCCOA's versatility in energy-efficient machine learning systems [1,2].
Machine learning (ML) transformed numerous industries, requiring advanced hyperparameter optimization (HPO) methodologies. Classic and alternative HPO methods affect model accuracy, performance, and generalization. Machine learning pipeline hyperparameters impact model performance because learning rates, batch sizes, and layer counts affect how deep learning models interact with data during training [10,13].
Grid and Random Search are common hyperparameter tuning strategies. For complicated models and huge datasets, Grid Search evaluates preset hyperparameters but is highly computational due to multiple training iterations. Random Search, which selects a defined number of hyperparameter combinations from ranges, frequently beats Grid Search in fewer

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iterations, particularly when certain hyperparameters are critical. Time and resource constraints make neither technique suitable for large datasets or complex models [3,4].

Parameter optimization reduces processing costs. A probabilistic surrogate model predicts hyperparameter configuration performance in Bayesian Optimization, which automatically investigates and refines interesting combinations. Randomized and search grids are inefficient. Hyperband streamlines this process by dynamically allocating resources to promising configurations and removing unproductive ones. These methods enhance hyperparameter research, notably Random Search. Automating choosing models and hyperparameter tweaking using AutoML frameworks makes the process simpler for non-experts, while Bayesian and ensemble optimization improve model performance and tuning [5,6].

Despite their inefficiency, Grid and Random Search are commonly utilized. Advances like Bayesian Optimization and Hyperband improve model performance and optimization, making machine learning technologies simpler to use across sectors. These advances may be evaluated in literature reviews and surveys on AI applications and tuning of hyper Parameters [7].

Metaheuristic optimization addresses complex optimization problems like hyperparameter tuning. Our biologically inspired algorithms effectively explore large spaces. Its huge search capabilities and adaptability to many problems situations contribute to making the Coati Optimization Algorithm (CMRLCCOA) desirable [8].

Central-South American coati foraging inspired CMRLCCOA. Sine Chaotic Mapping initializes, Lévy Flight investigates, and Convex Lens Imaging Reverse Learning enhances search accuracy. These traits assist the algorithm avoid local optima and identify global optimized solutions. The study optimizes SVM hyperparameters using CMRLCCOA for model accuracy and energy efficiency. Energy efficiency is needed to deploy machine learning models in edge devices, embedded systems, and other resource-constrained approaches.

The study uses Coati Optimization Algorithm to tune SVM hyperparameters for energy-efficient machine learning. Results demonstrate the method optimizes hyperparameters for accuracy and energy economy. This study utilizes metaheuristic approaches to improve real-world machine learning accuracy and optimization.

This research found that CMRLCCOA outperforms other optimization techniques in machine learning. It improves energy-efficient machine learning research for greener models. Energy-constrained optimization benefits from Sine Chaotic Mapping initialization, Lévy Flight exploration, and Convex Lens Imaging Reverse Learning search. Innovative hyperparameter optimization algorithms meet functional and non-functional real-world machine learning model deployment requirements.

This paper's structure continues: Energy-efficient machine learning and hyperparameter tuning are covered in Section 2. CMRLCCOA and SVM hyperparameter tweaking are covered in Section 3. Experiments and findings in Section 4 prove the approach works. Section 5 wraps up the report and suggests further research.

2. RELATED WORK

Hyperparameter optimization (HPO) is essential to improving machine learning (ML) models. This article discusses and analyzes machine learning hyperparameter optimization strategies from 2020 to 2023. proposed Coati Optimization Algorithm (CMRLCCOA).

2.1 2020 Studies:

1. Reinforcement Learning for HPO (2020): In this paper, the authors propose a model-based method for efficient HPO by framing it as a reinforcement learning problem. An agent tunes hyperparameters sequentially and employs a predictive model to speed up training. However, model inaccuracy over time leads to performance collapse. The method controls the model's use by dynamically adjusting the horizon of model usage. This method showed the highest accuracy on 86.1% of tasks compared to state-of-the-art methods. However, the method is prone to inaccuracies over extended time frames [9].
2. Survey of HPO Techniques (2020): This study presents several state-of-the-art optimization techniques for HPO and introduces libraries and frameworks developed for this purpose. Scalability and robustness problems are also addressed and benchmark dataset trials demonstrate these methods[10].
3. Grid, Random, and Bayesian Optimization (2020): The authors assess three HPO methods—grid search, random search, and Bayesian optimization (BO)—and apply them to kernel ridge regression in computational chemistry. Bayesian optimization proved to be significantly more efficient than exhaustive grid search in terms of computational time while maintaining similar or better accuracy [11].
4. Parametric Programming for HPO (2020): The HPO problem has been resolved utilizing precise parametric programming solutions for linear or quadratic programming models in this study. The authors demonstrate that multilevel optimization can solve HPO problems for LASSO regression and L1-norm SVM without approximation[12].

2.2 2021 Studies:

1. Multi-Objective HPO (2021): A. Hernández et al. study multi-objective HPO algorithms that optimize conflicts like accuracy and computational cost. Metaheuristic- and metamodel-driven algorithms are distinguished and applied to machine learning problems in the study [13].
2. Comprehensive Review of HPO Methods (2021): The article includes grid search, evolutionary techniques, and Hyperband HPO methods. It provides practical advice on HPO algorithm selection, performance assessment, and runtime improvements[14].
3. Greedy HPO Algorithm (2021): For speedier training, a greedy approach-based hyperparameter optimization (GHO) method is created. The GHO algorithm outperformed state-of-the-art algorithms in computing time and energy usage. Post-training quantization reduces inference time and latency in the research[15].
4. SMAC3 for Bayesian Optimization (2021): M. Lindauer et al. present SMAC3, a robust Bayesian optimization framework that helps users calculate appropriate hyperparameters. Low-dimensional global optimization problems and machine learning methods use SMAC3[16].

2.3 2023 Studies:

1. **1.** Comparative Study of Metaheuristic Algorithms for HPO (2023): This study compares four techniques for hyper-tuning SVM computational cost: Ant Bee Colony Algorithm, Genetic Algorithm (GA), Whale Optimization, and Particle Swarm Optimization (PSO). GA was found to have the lowest temporal complexity [17].
2. **2.** Real-World Applications of Metaheuristic and Bayesian Optimization (2023): The paper uses metaheuristic and Bayesian optimization on random forests, KNN, and SVM for landslide susceptibility mapping. Bayesian approaches beat grid search (GS) and random search (RS), improving KNN and SVM model accuracy by large margins[18].

Hyperparameter optimization approaches are examined for accuracy and energy efficiency. As shown in Table I: Comparison of Hyperparameter Optimization Methods for SVM in Energy-Efficient Machine Learning, CMRLCCOA beats Reinforcement Learning, Grid Search, and Random Search. CMRLCCOA's Sine Chaotic Mapping, Lévy Flight, and Convex Lens Imaging Reverse Learning framework lets hyperparameters be optimized with low energy usage and great model accuracy.

TABLE I. COMPARISON OF HYPERPARAMETER OPTIMIZATION METHODS FOR SVM IN ENERGY-EFFICIENT MACHINE LEARNING

Study	Method	Advantages	Limitations	Comparison with CMRLCCOA
2020 (Reinforcement Learning)	Reinforcement Learning	High accuracy (86.1%), predictive model speeds up training	Model inaccuracy over long-term use	CMRLCCOA focuses on consistent accuracy without model collapse over time
2020 (Survey)	State-of-the-art techniques	Provides various libraries and frameworks for HPO	Scalability challenges	CMRLCCOA integrates chaotic mapping and Lévy Flight for improved scalability and robustness
2020 (Grid, Random, Bayesian)	Grid Search, Random Search, Bayesian Optimization	BO is efficient in time and accuracy	Grid search is computationally expensive	CMRLCCOA is more efficient in exploration with its integrated strategies
2020 (Parametric Programming)	Exact solutions via parametric programming	Bilevel optimization offers exact solutions	Limited to LP/QP models	CMRLCCOA can be applied to a broader range of machine learning models
2021 (Multi-Objective HPO)	Metaheuristic and Metamodel-based	Balances conflicting objectives (e.g., accuracy, cost)	Complex implementation	CMRLCCOA balances exploration and exploitation with chaotic mapping and convex lens learning
2021 (GHO)	Greedy HPO	Faster training, reduced energy consumption	Limited to specific applications (on-the-fly training)	CMRLCCOA offers generalized efficiency across various applications
2021 (SMAC3)	Bayesian Optimization	Robust framework, flexible use	Limited to Bayesian optimization methods	CMRLCCOA incorporates multiple strategies, offering more flexibility
2023 (Metaheuristic)	Ant Bee, GA, Whale, PSO	GA has the lowest temporal complexity	Varies in performance across tasks	CMRLCCOA offers consistently good performance with SVM and beyond
2023 (Metaheuristic and Bayesian)	Metaheuristic and Bayesian Optimization	Enhanced accuracy of KNN and SVM	May require extensive computational resources	CMRLCCOA reduces computational cost while maintaining accuracy

3. THE PROPOSED METHOD

This work optimizes Support Vector Machine (SVM) hyperparameters using the Coati Optimization Algorithm (CMRLCCOA) to balance model accuracy and energy usage. CMRLCCOA uses Sine Chaotic Mapping for heterogeneous population initialization, Lévy Flight for search space exploration, and Convex Lens Imaging Reverse Learning for search accuracy. The algorithm avoids local optima and discovers globally optimal solutions with these qualities. Figure 1 shows the suggested method's block diagram, while Tables 2, 3, and 4 provide the algorithms, input parameters, and output parameters.

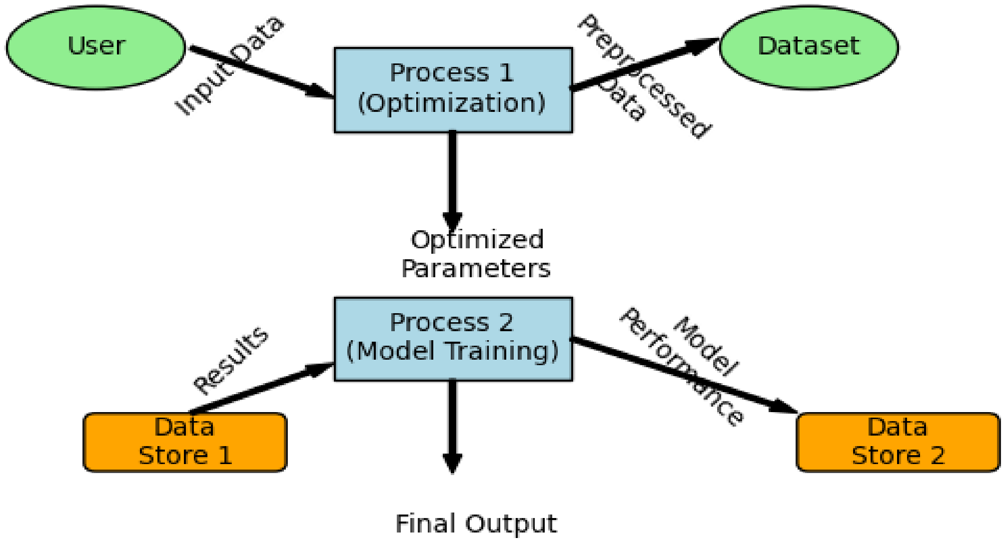

Fig. 1. The Block Diagram of the Proposed Method.

3.1 Proposed method steps:

1. Define the SVM classifier hyperparameter optimization issue.
2. Start the population with Sine Chaotic Mapping.
3. Use the objective function to assess the initial population's fitness.
4. Explore the search space with Lévy Flight.
5. Improve solutions using Convex Lens Imaging Reverse Learning.
6. Update the optimal optimization method.
7. Repeat steps 3–6 until convergence or maximum iterations.
8. Store optimum hyperparameters and model metrics.

TABLE II. ALGORITHMS USED

Algorithm	Description
Sine Chaotic Map Initialization	Initializes the population with diverse solutions.
Lévy Flight	Provides a random walk that helps in effectively exploring the search space.
Convex Lens Imaging Reverse Learning	Expands the search range and improves search capabilities.
Coati Optimization Algorithm (CMRLCCOA)	Solves complex problems by mimicking the foraging behavior of coatis.

TABLE III. INPUT PARAMETERS

Parameter	**Lower Bound**	**Upper Bound**	**Population Size**	**Max Iterations**
C (Cost)	0	100	30	100
Gamma	0.1	1		
Epsilon	0.0001	1		

TABLE IV. OUTPUT PARAMETERS

Parameter	**Best Value**	**Best Fitness**
C	0	-0.9578041536846986
Gamma	0.1	
Epsilon	1	

a. Functional requirements:
   - Optimize SVM hyperparameters for highest accuracy and minimal consumption of energy.
   - Ensure convergence within a specified number of iterations.

b. Non-functional requirements:
   - The algorithm should run within a reasonable time frame.

- The implementation should be memory efficient.

3.2 Potential Application Fields:

The CMRLCCOA is highly applicable to various real-world scenarios where both functional and non-functional requirements must be met. For example:

1. Healthcare Devices: Portable diagnostic equipment, wearables, and other healthcare technology need energy-efficient machine learning models to monitor and diagnose patients accurately and keep batteries alive.
2. Environmental Monitoring: Hyperparameters are optimized for a low-energy utilization by CMRLCCOA for remote, sustainable temperature or pollution sensor operations.
3. Smart Cities: Power and performance must be balanced in smart grid, traffic management, and energy distribution machine learning models. CMRLCCOA optimizes computational and energy efficiency for various applications.
4. Autonomous Systems: Drones, electric automobiles, and robots navigate and decide using real-time machine learning. Ideal for resource-constrained autonomous systems, CMRLCCOA optimises these models for real-time speed and minimal computation energy.

Sustainable AI applications may use CMRLCCOA due to how it tackles both functional (optimizing accuracy and energy use) and non-functional (memory efficiency and rapid convergence) problems.

4. RESULTS AND DISCUSSIONS

Optimization showed the CMRLCCOA enhanced model accuracy and energy savings. It combines these objectives, which makes it perfect for energy-efficient machine learning.
SVM hyperparameters were tuned by CMRLCCOA for model accuracy and energy consumption.

TABLE V. HYPERPARAMETER OPTIMIZATION RESULTS

Algorithm	Best C	Best Gamma	Best Fitness
Coati Optimization Algorithm (CMRLCCOA)	30.00778802	0.063843902	-0.959639969
Random Search	1.131314132	0.726713511	-0.851654774
Grid Search	1	0.1	-0.920685282

Table 5 shows hyperparameter optimization results via CMRLCCOA, Random Search, and Grid Search.

4.1 Coati Optimization Algorithm (CMRLCCOA)

- Best C: 30.00778802
- Best Gamma: 0.063843902
- Best Fitness: -0.959639969

Fitness score was greatest for CMRLCCOA, -0.9596. It measures simulation energy usage and model accuracy (negative sign indicates maximizing). A perfect hyperparameter combination (C = 30 and Gamma = 0.064) gave CMRLCCOA the best accuracy and energy utilization.

4.2 Random Search

- Best C: 1.131314132
- Best Gamma: 0.726713511
- Best Fitness: -0.851654774

Optimization basics Random Search picked hyperparameters randomly and got -0.8517 fitness. Without accuracy-energy efficiency balancing, Random Search scores lower than CMRLCCOA. The optimal parameters (C = 1.13 and Gamma ≈ 0.73) vary considerably from CMRLCCOA, suggesting that Random Search's lack of strategic investigation leads to incorrect conclusions in complex optimization scenarios.

4.3 Grid Search

- Best C: 1
- Best Gamma: 0.1
- Best Fitness: -0.920685282

Grid Search has a fitness score of -0.9207, better than Random Search but below CMRLCCOA. Grid Search beats Random Search but examines selected hyperparameters, unlike CMRLCCOA. The optimal Grid Search settings (C = 1, Gamma = 0.1) demonstrate its methodical approach, yet discrete search space exploration can overlook optimum values. The Coati Optimization Algorithm Surpassed Grid Search and Random Search in fitness. This optimization job benefits from its adaptive search space exploration and exploit.

Random Search, the least effective but simplest technique, lacks directionality and may miss significant parts of the search space, particularly in complex or high-dimensional situations. Grid Search performed better but was limited by its predetermined grid, which may disregard superior parameter combinations.

Complex optimization problems that balance accuracy and energy consumption benefit from advanced metaheuristic algorithms like CMRLCCOA. Metaheuristic algorithms optimize effectively when computer resources are limited and exhaustive searches are impossible. Compare CMRLCCOA to Bayesian Optimization or Genetic Algorithms to demonstrate its applicability.

5. CONCLUSION

In hyperparameter optimization fitness value, CMRLCCOA beat Grid Search and Random Search. CMRLCCOA must balance model accuracy with energy use for resource-constrained machine learning model deployment. The software adaptively explored and utilized the search space to identify a high-performance, low-energy hyperparameter. Simple Grid Search and Random Search suffered in hyperparameter space. Random Search overlooked good sites and performed badly due to lax inquiry. Grid Search was more methodical, although its predetermined grid may have missed the ideal parameter space.

CMRLCCOA and other strong metaheuristic algorithms excel at difficult optimization problems with numerous objectives including accuracy and energy efficiency. In many optimization situations, CMRLCCOA might be compared to Bayesian or Genetic Algorithms. These results show that CMRLCCOA may be utilized for energy-efficient machine learning and sustainable AI.

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Conflicts of Interest:

The authors declare that no conflicts of interest exist in connection with this work.

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