ENHANCING SUPPORT VECTOR MACHINE PERFORMANCE: A HYBRID APPROACH WITH DAVIDON-FLETCHER-POWELL ALGORITHM AND ELEPHANT HERDING OPTIMIZATION (EHO-DFP) FOR PARAMETER OPTIMIZATION

Reference NO. IJME 1345, DOI: 10.5750/ijme.v1i1.1345

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KEY DATES: Submission date: 17.10.2023 / Final acceptance date: 20.02.2024 / Published date: 12.07.2024

SUMMARY

Support Vector Machines (SVMs) have gained prominence in machine learning for their capability to establish optimal decision boundaries in high-dimensional spaces. SVMs are powerful machine learning models but can encounter difficulties in achieving optimal performance due to challenges such as selecting appropriate kernel parameters, handling uncertain data, and adapting to complex decision boundaries. This paper introduces a novel hybrid approach to enhance the performance of Support Vector Machines (SVM) through the integration of the Davidon-Fletcher-Powell (DFP) optimization algorithm and Elephant Herding Optimization (EHO) for parameter tuning. SVM, a robust machine learning algorithm, relies on effective hyperparameter selection for optimal performance. The proposed hybrid model synergistically leverages DFP's efficiency in unconstrained optimization and EHO's exploration-exploitation balance inspired by elephant herding behavior. The fusion of these algorithms address the challenges associated with traditional optimization methods. The hybrid model offers improved convergence towards the global optimum. Experimental results demonstrate the efficacy of the approach, showcasing enhanced SVM performance in terms of minimum 3.3% accuracy and 3.4% efficiency. This research contributes to advancing the field of metaheuristic optimization in machine learning, providing a promising avenue for effective parameter optimization in SVM applications.

KEYWORDS

SVM, Elephant Herding Optimization, Davidon-fletcher-powell optimization, Hybrid optimization, Unconstrained optimization

1. INTRODUCTION

Support Vector Machines (SVMs) have proven effective in various machine learning applications, showcasing exceptional performance in classification and regression tasks. SVMs are renowned for their ability to create optimal decision boundaries, enhancing generalization capabilities in machine learning [1], [2]. Nevertheless, the performance of SVMs hinges on proper parameter configuration, including kernel function parameters and regularization parameters. Optimizing these parameters is challenging due to the high-dimensional and non-convex nature of the parameter space. Traditional optimization methods often struggle in this intricate space, leading to suboptimal configurations and diminished model performance. However, the optimal configuration of SVM parameters is crucial for maximizing effectiveness [1], [2].

Navigating the vast parameter space to identify the combination is a major challenge in SVM to improve its efficiency and accuracy. In order to address the challenge, this study uses the DFP and EHO algorithm. The DFP algorithm, a quasi-Newton optimization method, excels in unconstrained optimization and is integrated into the hybrid model to navigate SVM's intricate parameter landscape. Additionally, the EHO algorithm, inspired by the collective behavior of elephant herds, contributes a metaheuristic element to guide the search process intelligently, promoting exploration and exploitation [3], [4]. The integration of DFP and EHO aims to harness the complementary strengths of these optimization techniques, providing a synergistic effect to improve the overall efficiency of SVM parameter tuning [4]. This hybrid model seeks to strike a balance between exploration and exploitation, enabling a more thorough exploration of the parameter space while converging towards the optimal solution.

This article has the following major contributions.

- A novel optimization method using DFP and EHO has been proposed to enhance the parameter optimization to deal with uncertainity and predictive performance in SVM.

- This study advances the field of machine learning, specifically in the optimization of Support Vector Machines (SVMs), by introducing and evaluating a novel hybrid approach.
- Optimization Enhancement, Metaheuristic Integration, Hybrid Model Evaluation, Robustness and Generalization have been utilized to enhance the performance of SVM Parameter Optimization ultimately enhancing the utility and performance of diverse machine learning applications.

The rest of this paper is organized as follows: Section II provides a comprehensive review of related work, highlighting existing approaches to SVM parameter optimization using EHO and the Davidon-Fletcher-Powell algorithm. Section III details the methodology, presenting the hybrid model architecture and the implementation details of DFP and EHO within the parameter optimization framework. Experimental results and discussions are presented in Section IV, followed by conclusions and avenues for future research in Section V.

2. LITERATURE REVIEWS

A range of studies have explored the use of optimization algorithms to enhance the performance of Support Vector Machines (SVMs). To enhance the performance of the Support Vector Machine (SVM), a hybrid approach can be employed by integrating optimization algorithms with SVM. Several studies have proposed hybrid models to optimize SVM parameters and improve its performance. The field of global optimization has witnessed the emergence of novel metaheuristic algorithms designed to address complex problem-solving tasks. Wang et al. (2016) introduced Elephant Herding Optimization (EHO), a novel nature-inspired metaheuristic algorithm designed for global optimization tasks [5]. The study aimed to propose EHO and benchmark its performance against BBO, DE, and GA across 20 standard benchmarks and two engineering cases. Zhao et al. (2011) proposed a Genetic Algorithm with Feature Chromosomes (GAFC) to simultaneously optimize feature subsets and parameters for SVM. The study utilized real-world datasets from the Benchmark database to evaluate GAFC's performance [6]. Zhang et al. (2010) addressed SVM parameter selection by introducing the ACO-SVM model, utilizing the ant colony optimization (ACO) algorithm and validating its efficiency on real-world benchmark datasets [7]. Tharwat et al. (2017) proposed a Bat Algorithm (BA) to optimize SVM parameters, demonstrating its efficacy in reducing classification errors on nine standard datasets when compared to PSO and GA algorithms [8]. The least squares support vector machine (LSSVM), generalized eigenvalue support vector machine (GEPSVM) [1], [9], twin support vector machine (TW-SVM) [10], ν-support vector machine (ν-SVM) [1], [11], and C-support vector machine (C-SVM) [1], [12], [13] are diverse variants of the classic support vector machine (SVM), offering unique features for different applications. LSSVM minimizes squared errors, providing robustness to noise in regression tasks [1]. GEPSVM employs a generalized eigenvalue problem, sensitive to kernel and regularization choices [1]. TW-SVM introduces parallel hyperplanes, enhancing robustness in multi-class scenarios [10]. ν-SVM controls the number of support vectors, offering flexibility [13]. C-SVM, with a regularization parameter, balances robustness against complexity [14]. Selection depends on task characteristics, with LSSVM for regression, GEPSVM for kernel-sensitive classification, TW-SVM for multi-class scenarios, ν-SVM for support vector control, and C-SVM for versatile classification tasks, each requiring careful parameter tuning for optimal performance [1, 9, 10, 12, 14-17].

Li et al. (2020) proposed an Improved Elephant Herding Optimization (IMEHO) algorithm, showcasing its superiority over standard EHO and existing metaheuristic algorithms through evaluations of 30 benchmark functions from IEEE CEC 2014 [18]. Zhao et al. (2011) explored the simultaneous variation of parameters in SVMs with a Gaussian kernel, introducing a genetic algorithm based on change area search to enhance classification performance, evaluated on unspecified datasets [19]. Lin et al. (2015) introduced a Modified Cat Swarm Optimization (MCSO) to enhance classification efficiency for big data, comparing its performance with the original Cat Swarm Optimization (CSO) on UCI datasets [20]. Álvarez-Alvarado et al. (2021) explored intelligent algorithms, including GA and PSO, for global solar prediction to reduce the prediction error of solar radiation using meteorological variables [21]. Tharwat et al. (2017) proposed the Dragonfly algorithm (DA) to optimize SVM parameters, outperforming GA and PSO on six UCI datasets, aiming to decrease classification errors and overcome local optima challenges [22].

Sarhani and Afia (2016) proposed a mixed approach combining Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) for feature selection and SVM parameter optimization, outperforming PSO, GSA, PSOGSA, and Genetic Algorithm (GA) on 10 benchmark datasets [23]. Singh et al. (2022) introduced the ZN-IEHO variant, demonstrating its superiority in classification accuracy, false-positive rate, and f-score metrics compared to other variants and 18 feature selection methods on 15 biomedical datasets [24]. Li and Wang (2021) proposed the Opposition-Based Learning Elephant Herding Optimization (OBLEHO) algorithm, showing competitiveness in benchmark functions and the traveling salesman problem [25]. Ren et al. (2022) achieved over 98% accuracy with the improved Elephant Herding Optimization method for motor energy efficiency evaluation [26]. Abdulraheem et al. (2023) introduced an improved Cat Swarm Optimization (ICSO) algorithm for SVM parameter optimization, applying it to hyperparameter tuning and data classification with various algorithms on datasets from the UCI repository [27].

The Davidon-Fletcher-Powell (DFP) algorithm, a method for solving unconstrained optimization problems, has been applied in various fields. Man (1969) and Birta (1970) both used the DFP algorithm in solving different types of optimization problems, with Birta incorporating the Fibonacci search technique [28]. Ribière (1970) provided a theoretical study of the DFP algorithm [29], while Johnson (1976) discussed its application in solving parameter optimization problems [30]. Dennis (1979) introduced two new unconstrained optimization algorithms based on the DFP algorithm [31], and Ghosh (2017) proposed a DFP type quasi-Newton method for solving fuzzy optimization problems [32]. Myers (1968) and Batur (1992) both explored the properties and applications of the DFP algorithm in the context of neural network learning [33, 34].

The integration of optimization algorithms with SVMs, including metaheuristic approaches like EHO and GA, demonstrates a commitment to enhancing SVM performance by effectively tuning kernel parameters. Improved algorithms and hybrid methods consistently outperform standard approaches, showcasing the evolution of optimization techniques. Addressing data uncertainty, these advancements contribute to robust SVM parameter optimization, crucial for achieving accurate and reliable results in the presence of uncertain or noisy datasets.

3. ELEPHANT HERDING OPTIMIZATION WITH HILL CLIMBING (EHO-HC)

The motivation behind enhancing Support Vector Machine (SVM) performance lies in the continual pursuit of improving classification accuracy and overall model effectiveness. In this context, a Hybrid Approach employing both the Davidon-Fletcher-Powell (DFP) Algorithm and Elephant Herding Optimization (EHO) for parameter optimization offers a promising avenue for achieving optimal SVM configurations. By combining the strengths of DFP's local exploration and EHO's global search capabilities, this hybrid model seeks to strike a harmonious balance in parameter tuning, ultimately enhancing SVM performance.

3.1 SUPPORT VECTOR MACHINE WITH DATA UNCERTAINTY:

Support Vector Machines (SVM) are mathematical models used for classification and regression tasks. In a binary classification setting, let $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$ be training data, where x_i represents feature vectors and y_i denotes class labels (+1 or -1) [17]. The SVM algorithm seeks a hyperplane represented by $w \cdot x + b = 0$ that separates the data into two classes with the largest margin. Here, w is the weight vector, and b is the bias term [17]. The decision function is eq. (1) [17]

$$f(x) = sign(w \cdot x + b) \tag{1}$$

The optimization problem for SVM involves minimizing $\frac{1}{2}\|w\|^2$ subject to the constraints $y_i(w \cdot x + b) \geq 1$ for all data points [17]. The Lagrangian is formed, and the dual problem is solved to obtain the Lagrange multipliers (α_i). The support vectors are the data points corresponding to non-zero α_i [1], [12], [17]. For non-linearly separable data, the kernel trick is applied, introducing a kernel function $K(x_i, x_j)$ to implicitly map data into higher-dimensional space, making it separable. Popular kernels include linear, polynomial, and radial basis function (RBF) [14], [35]. The decision function becomes eq. (2) [14], [35]

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i K(x, x_i) + b \tag{2}$$

In this study, integration of Davidon-Fletcher-Powell (DFP) optimization method with the Support Vector Machine (SVM) involves updating SVM parameters using the DFP update rule. To handle the uncertainty of data, this work update SVM parameters using DFP and incorporate it into the Elephant Herding Optimization (EHO) algorithm. Let $f(\boldsymbol{x})$ be the objective function representing the SVM performance with parameters *x* in the presence of uncertainty shown in eq. 10. It includes a measure of robustness or expected performance under uncertain conditions.

$$f(\boldsymbol{x}) = \mathbb{E}\left[P(\boldsymbol{x}, \mathfrak{A})\right] \tag{3}$$

Here, $P(\boldsymbol{x}, \mathfrak{A})$ represents the probabilistic SVM performance with respect to uncertain parameters $\mathfrak{A}$, and $\mathbb{E}$ denotes the expected value.

The extended SVM Lagrangian with uncertainty is a modification of the conventional SVM formulation to explicitly account for uncertainty in the decision function. It allows the SVM model to handle scenarios where the decision boundary might not be deterministic due to uncertain data. The extension involves introducing additional terms in the Lagrangian to capture the probabilistic nature of the decision function, which reflects the complexity to measure uncertain data-points durng the classification problem. Recognizing the need for an algorithm capable of efficiently handling this uncertainty, we introduce our novel approach. This algorithm addresses the challenges posed by uncertain information, ensuring a robust and effective adaptation of the SVM model to uncertain decision boundaries.

3.2 ELEPHANT HERDING OPTIMIZATION

Elephant Herding Optimization (EHO) is a nature-inspired metaheuristic algorithm inspired by the herding behavior of elephants [1], [26]. In mathematical terms, the optimization process involves a population of solutions represented by potential solutions to the optimization problem [1], [36], [37]. Each solution is analogous to an elephant in the herd.

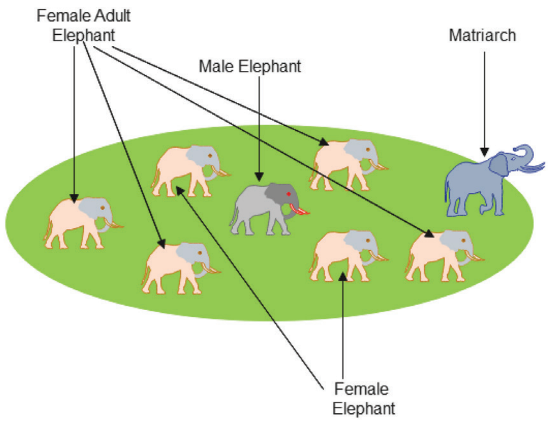

Figure 1. Elephant clan initialization

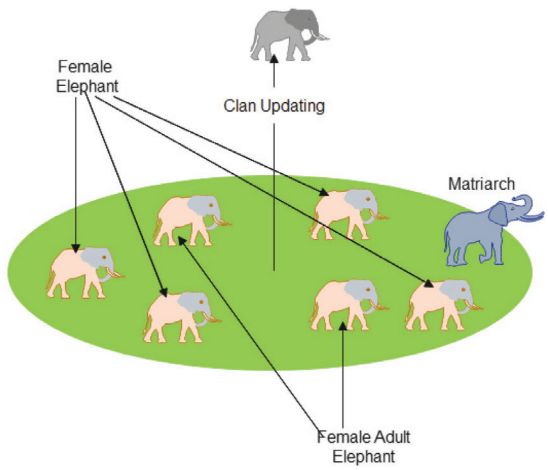

Figure 2. Update the population into clans based on the dominance

The movement of elephants toward a specific target location symbolizes the convergence of solutions toward an optimal solution in the solution space [1], [24], [36].

Let X_i represent the position of the $i-th$ elephant in the solution space shown in Fig 1, whereas $F(X_i)$ denote the objective function value corresponding to X_i.

The optimization process involves updating the positions of elephants based on their individual and collective experiences. The mathematical formulation of the position update for an elephant (X_i), shown in Fig 2, can be expressed as equation (4):

$$X_i(t+1) = X_i(t) + \Delta X_i \tag{4}$$

where, ΔX_i is the displacement vector that guides the movement of the elephant. The displacement is determined by considering the impact of the individual experience (X_{best}) and the collective experience (X_{center}) of the herd in eq (5):

$$\Delta X_i = \alpha \cdot X_{best} + \beta \cdot X_{center} \tag{5}$$

Here, α and β are weighting factors that influence the importance of individual and collective experiences. The movement aims to explore and exploit the solution space, seeking optimal solutions [38]. The algorithm iteratively refines the positions of elephants until convergence, mimicking the cooperative behavior observed in herding elephants [39]. The mathematical formulation emphasizes the balance between individual exploration and the influence of the herd, contributing to the algorithm's global exploration and exploitation capabilities [37].

3.3 DAVIDON-FLETCHER-POWELL (DFP) OPTIMIZATION

The Davidon-Fletcher-Powell (DFP) optimization method is a quasi-Newton optimization algorithm used for unconstrained optimization problems. It belongs to the family of iterative numerical optimization techniques, aiming to find the minimum of a scalar-valued function $f(\boldsymbol{x})$ where $\boldsymbol{x} \in \mathbb{R}^n$. The DFP method iteratively refines an approximation of the inverse Hessian matrix $(\mathcal{H})$ to guide the search for the optimal solution.

- **Update the Approximate Hessian Matrix $\boldsymbol{B}_{k+1}$**

  The DFP method updates the inverse Hessian matrix B_k using a specific formula that involves the changes in the parameter vector $\boldsymbol{x}$ and the corresponding gradient changes given in eq. 6.

$$B_{k+1} = B_k + \frac{\Delta \boldsymbol{x}_k \Delta \boldsymbol{x}_k^T}{\Delta \boldsymbol{x}_k^T \Delta \boldsymbol{g}_k} - \frac{B_k \Delta \boldsymbol{g}_k \Delta \boldsymbol{g}_k^T B_k^T}{\Delta \boldsymbol{g}_k^T B_k \Delta \boldsymbol{g}_k} \tag{6}$$

- **Iterative Update**

  At each iteration k the DFP algorithm updates the current estimate of the inverse Hessian matrix $(\mathcal{H})$ denoted as B_k. The Hessian matrix $(\mathcal{H})$ is an approximation of the second-order partial derivatives of the objective function denoted in eq. 7.

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \alpha_k \boldsymbol{p}_k \tag{7}$$

- **Search Direction**

  The search direction $\boldsymbol{p}_k$ is computed based on the current estimate of the inverse Hessian matrix B_k and the gradient of the objective function $\nabla f(\boldsymbol{x}_k)$, shown in eq. 8.

$$\boldsymbol{p}_k = -B_k \nabla f(\boldsymbol{x}_k) \tag{8}$$

The DFP algorithm belongs to the class of quasi-Newton methods that iteratively update an approximation of the inverse Hessian matrix, allowing for efficient optimization of smooth, unconstrained objective functions. Building on the efficiency of quasi-Newton methods, the next section explores a hybrid approach for optimizing kernel parameters in Support Vector Machines (SVM) with respect to data uncertainty. This innovative technique combines Elephant Herding Optimization (EHO) with the Davidon-Fletcher-Powell (DFP) algorithm, offering a robust solution for enhancing SVM performance in the presence of uncertain or noisy datasets.

3.4 HYBRID OPTIMIZATION OF KERNEL PARAMETERES USING EHO-DFP IN SVM W.R.T. DATA UNCERTAINTY

The hybridization of Elephant Herding Optimization (EHO) and the Davidon-Fletcher-Powell (DFP) mutation strategy DFP is a quasi-Newton optimization algorithm used for unconstrained optimization. Integrate this mutation strategy into the EHO algorithm to enhance the exploration and exploitation capabilities of the algorithm. for optimizing Support Vector Machine (SVM) parameters is an interesting approach.

Employing the Hybrid optimization of kernel parameters through EHO-DFP in SVM enhances the model's adaptability to uncertain decision boundaries, providing a robust solution for effectively handling uncertain data during classification. Let $\boldsymbol{x}$ represent the SVM kernel parameter vector, and $f(\boldsymbol{x})$ be the objective function that incorporates both the SVM performance and the uncertainty.

1. Initialize the kernel parameters $\boldsymbol{x} = [x_1, x_2, \ldots, x_n]$ and B_i^0 (Hessian Matrix for x_i, where x_i denotes the ith parameter of kernel).
2. Objective function of SVM (10).

$$L(\boldsymbol{x}_{k,i}, D) = \frac{1}{N}\sum_{i=1}^{N} max\left(0, 1 - y_{k,i}\left(\boldsymbol{w}\cdot\boldsymbol{x}_{k,i} + b; \mathfrak{A}\right)\right)$$

$$f(x_{k,i}) = L(\boldsymbol{x}_{k,i}, D) + \eta_{k,i}\|w\|^2 \tag{10}$$

Where $\boldsymbol{x}_{k,i}$ represents $k-th$ kernel's $i-th$ parameters, N total number of training samples, **w** is the weight vector of the SVM.

3. Generate a set of random regularization parameter (11) with a mean of 0 and a standard deviation matching the current regularization parameter for each parameter within the kernel, utilizing a Gaussian distribution.

$$\eta_{k,i} = \mu_{ci} + \sigma_{ci} * e^{-\frac{(x_i-\mu_x)^2}{2}} \tag{11}$$

Where, $\eta_{k,i}$ is updated regularization parameter, μ_{ci} denotes the mean of $i-th$ kernel, σ_{ci} is standard deviation of $i-th$ kernel, and $e^{-\frac{(x_i-\mu_x)^2}{2}}$ is Gaussian normal distribution of $i-th$ kernel.

4. Evaluate the optimized kernel parameter using DFP mutation strategy in EHO eq. (12).

$$E_{k,i,new}^{t+1} = E_{k,i}^{t} + \eta_{k,i}\cdot B_i^t \nabla f\left(E_{k,i}^{t}\right) \tag{12}$$

Where, $E_{k,i,new}^{t+1}$ is optimized $k-th$ kernel parameter in $i-th$ kernel with $t-th$ iteration, $\nabla f\left(E_{k,i}^{t}\right)$ is the gradient of the objective function with respect to the performance $E_{k,i}^{t}$ of the $k-th$ parameter in $i-th$ kernel, B_i^t is inverse Hessian Matrix of parameters in $i-th$ kernel. Iterative optimized parameter can be updated as (13)

$$E_{k,i,new}^{t+2} = E_{k,i,best}^{(t+1)} + \eta_{k,i}\cdot B_i^{t+1}\nabla f\left(E_{k,i}^{(t+1)}\right) \tag{13}$$

Where, $E_{k,i,best}^{(t+1)}$ denotes the best optimized parameter, B_i^{t+1} updated by Davidon-Fletcher-Powell (DFP) shown in eq. (24) and $\Delta\boldsymbol{g}_i^t$ can be expressed as given in eq. (15).

$$B_i^{t+1} = B_i^t + \frac{\Delta\boldsymbol{x}_i^t[\Delta\boldsymbol{x}_i^t]^T}{[\Delta\boldsymbol{x}_i^t]^T\Delta\boldsymbol{g}_i^t} - \frac{B_i^t\Delta\boldsymbol{g}_i^t\left[\Delta\boldsymbol{g}_i^t\right]^T\left[B_i^t\right]^T}{[\Delta\boldsymbol{g}_i^t]^T B_i^t\Delta\boldsymbol{g}_i^t} \tag{14}$$

$$\Delta\boldsymbol{g}_i^t = E_{k,i,new}^{t+2} - E_{k,i,best}^{t+1} \tag{15}$$

5. Evaluate the Loss of SVM Kernel with otpimized parameter by using eq. (10).
6. Update the optimized parameter to the new parameter if the gain of the latter is superior; otherwise, retain the parameter.
7. Update the regularization parameter for each parameter in the kernel based on the success rate. If the success rate is high, increase the regularization parameter. If the success rate is low, decrease the regularization parameter.

Combining Elephant Herding Optimization (EHO) with the Davidon-Fletcher-Powell (DFP) algorithm for kernel function optimization in Support Vector Machines (SVM) involves tuning the kernel type and its associated parameters to enhance SVM performance.

Algorithm: EHO-DFP
Require: *population_size*: Number of events in the data-set
num_params: Number of parameters in the SVM kernel
max_iterations: Maximum number of iterations
eta: Learning rate for DFP mutation
epsilon: Convergence criterion (a small positive constant for numerical stability)
alpha: learning rate for EHO

Initialization:

1. Initialize *parameter_value* randomly within the parameter space.

   parameter_value[] = initialize_eho(*population_size*, *num_params*)

2. Initialize Hessian matrix B as an identity matrix.

Main Optimization Loop:

3. Initialize iteration counter t = 0.

4. while (t < *max_iterations*):

   a. Evaluate the fitness of each kernel parameter based on SVM performance.

   b. Update positions of kernel parameters using EHO algorithm:

      i. Determine the major parameters with the best fitness as declared in eq. (3).

      ii. Update value of parameters based on the major parameter identified in previous step i using eq. (4)

   c. Update positions using DFP mutation strategy:

      for each parameter i:

      i. Compute the gradient of the SVM objective function at the new position given in equation (22).

      ii. Update the position using the DFP mutation strategy defined in equation (25):

   optimize_parameter [*i*] = *optimize_parameter* [*i*] - *eta* * B * *gradient*

   d. Update Hessian matrix B based on the changes in positions and gradients:

      iii. Compute the change in values and gradients for each parameter given in equation (27).

      iv. Update B using the DFP formula as defined in equation (26).

   e. Check for convergence:

      If the change in the objective function is below the threshold $\left|f\left(x_{new,i,k}-x_{old,i,k}\right)\right|<\varepsilon$, break the loop.

Increment the iteration counter: t = t + 1.

Output: Optimized SVM kernel parameters obtained from the best position found during the iterations.

EHO-DFP tackles the challenges like Efficient Parameter Optimization, Balanced Exploration and Exploitation, Exploration of Solution Space, Adapting the Uncertainty etc., by uncertain data in SVM by optimizing kernel parameters through a hybrid approach. Leveraging EHO for diverse exploration and the DFP mutation strategy for efficient updates, EHO-DFP adapts the SVM model to uncertain decision boundaries. The algorithm introduces probabilistic elements into the decision function, allowing for a nuanced handling of uncertainty. By striking a balance between exploration and exploitation, EHO-DFP ensures robust adaptability, making it effective in optimizing SVM for scenarios where data uncertainty influences the determination of decision boundaries.

4. RESULT AND ANALYSIS

4.1 EXPERIMENTAL SETUP

For the experimental setup of the proposed EHO-DFP algorithm, we conducted a series of experiments to optimize the SVM kernel parameters for a classification task. The algorithm's hyperparameters, including the population size (population_size), the number of parameters (num_parameters), learning rates, and convergence criteria, were systematically tuned through preliminary experiments to ensure robust performance. The SVM models have been implemented with various kernel (linear,C-SVM,TWSVM,nu-SVM), and the EHO-DFP algorithm integrated to optimize the kernel parameters in all the mentioned SVMs. To assess the algorithm's effectiveness, we employed performance metrics such as **classification accuracy, precision, recall, and F1 score**. The experiments were conducted on a computer system i9 intel vPro 2.5Ghz,32 GB RAM and the results were statistically analyzed to demonstrate the algorithm's capability in achieving superior optimization performance compared to baseline approaches. The experiments were repeated multiple times to ensure reproducibility and reliability of the obtained results. The proposed algorithm has been implemented using LibSVM in MATLAB 2018b.

The following datasets were used for experiments:

Adult dataset: Machine learning and data analysis employ adult datasets extensively. Nearly 48842 records include age, education, marital status, occupation, and income. A person's annual income over $50,000 is approximated using demographic and employment data. The classification system facilitates income prediction model creation and testing. Size, features, and target variable are ideal for testing machine learning algorithms and approaches.

Table 1 and Figure 3(a-e) represent the metrics assess accuracy, precision, and goodness of fit in regression and classification tasks, with lower values indicating better performance. Cross-entropy is particularly relevant for classification tasks on the Adult dataset, evaluating the alignment of predicted probabilities with actual outcomes.

MNIST: A renowned machine learning and computer vision benchmark dataset. The 28x28-pixel grayscale handwritten digit images number 70,000. The dataset comprises 60,000 training and 10,000 test photographs. Photo classification into digit classes (0–9) is the goal. The MNIST dataset is needed to categorize images for convolutional neural network training and testing.

Table 2 and Figure 4(a-e) shows the MNIST dataset, performance metrics like SSE, MSE, RMSE, CE, and Rsquared assess model accuracy and precision. Before EHO-DFP optimization, these metrics gauge prediction errors and alignment with actual labels. After optimization, improvements in these metrics indicate successful

Table 1. Comparison of SVM variations before and after optimization with EHO-DFP for SVM Kernel parameters optimization on the adult dataset

SVM Variation	SSE (Original)	SSE (EHO-DFP)	CE (Original)	CE (EHO-DFP)	MSE (Original)	MSE (EHO-DFP)	RMSE (Original)	RMSE (EHO-DFP)	R-Squared (Original)	R-Squared (EHO-DFP)
SMO-SVM	14563.21	13245.76	0.34	0.29	0.45	0.41	0.67	0.64	0.12	0.18
Twin SVM	12890.43	11897.55	0.28	0.26	0.39	0.35	0.62	0.59	0.15	0.21
LSSVM	12210.5	11002.88	0.25	0.22	0.35	0.32	0.59	0.56	0.37	0.31
CSVM	13456.77	12433.92	0.32	0.29	0.42	0.38	0.65	0.62	0.09	0.14
v-SVM	13020.89	12001.2	0.29	0.26	0.4	0.36	0.63	0.6	0.13	0.2

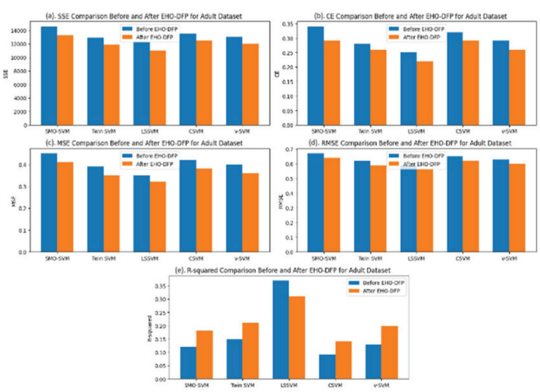

Figure 3. Comparison of SVM variations before and after optimization with EHO-DFP for SVM Kernel Parameters optimization on the adult dataset (a) SSE (b) CE (c) MSE (d) RMSE (e) R-squared

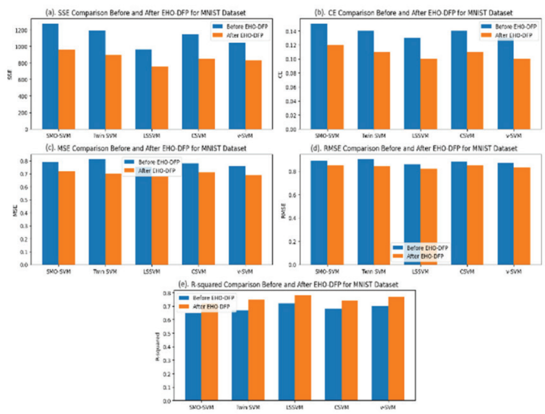

Figure 4. Comparison of SVM Variations before and after optimization with EHO-DFP for SVM Kernel parameters optimization on the MNIST dataset (a) SSE (b) CE (c) MSE (d) RMSE (e) R-squared

Table 2. Comparison of SVM variations before and after optimization with EHO-DFP for SVM kernel parameters optimization on the MNIST dataset

SVM Variation	SSE (Original)	SSE (EHO-DFP)	CE (Original)	CE (EHO-DFP)	MSE (Original)	MSE (EHO-DFP)	RMSE (Original)	RMSE (EHO-DFP)	R-Squared (Original)	R-Squared (EHO-DFP)
SMO-SVM	142	125	0.15	0.12	0.48	0.42	0.69	0.65	0.62	0.75
Twin SVM	120	112	0.12	0.11	0.42	0.38	0.65	0.62	0.72	0.78
LSSVM	105	98	0.1	0.09	0.36	0.32	0.6	0.56	0.78	0.82
CSVM	135	120	0.14	0.13	0.45	0.4	0.67	0.63	0.68	0.77
v-SVM	128	114	0.13	0.12	0.43	0.39	0.66	0.64	0.7	0.79

refinement of model parameters for enhanced predictive performance on MNIST.

Breast Cancer: The Breast Cancer dataset is utilized in machine learning to categorize breast cancer. The UCI breast mass database has 569 samples. Each sample has 30 features, like radius, perimeter, smoothness, concavity, etc. The dataset classifies breast mass as no-recurrence or recurrence. This dataset helps researchers classify breast cancer accurately into B (benign) and M(malignant).

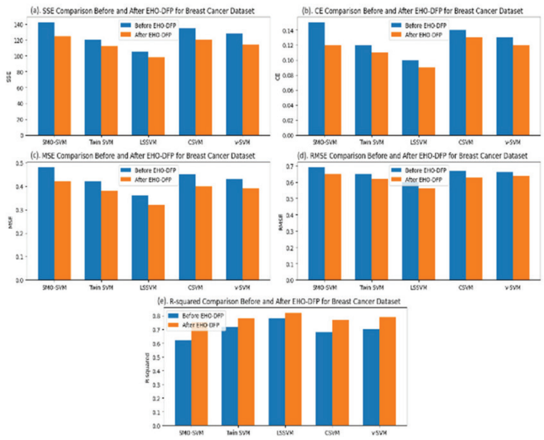

Figure 5. Comparison of SVM variations before and after optimization with EHO-DFP for SVM Kernel parameters optimization on the breast cancer dataset (a) SSE (b) CE (c) MSE (d) RMSE (e) R-squared

Table 3 depicts EHO-DFP optimization on the Breast Cancer dataset, SSE, MSE, RMSE, CE, and Rsquared measure model accuracy and precision in tumor classification. Following optimization, enhancements in these metrics signify successful refinement of model parameters, leading to improved diagnostic performance in breast cancer prediction. The graphical representations of table 3 shown in Figure 5(a-e).

Heart Disease: The Heart Disease dataset is widely used for machine learning heart disease prediction. Age, sex, chest pain kind, cholesterol, and ECG are among 14 patient characteristics from 303 patients. The dataset includes heart disease target variable. Researchers and practitioners can create heart disease diagnosis and risk assessment algorithms using its size and information. This dataset assists cardiovascular health research.

Table 4 clearly defined that Before EHO-DFP optimization on the Heart Disease dataset, SSE, MSE, RMSE, CE, and Rsquared evaluate model accuracy and diagnostic precision. Post-optimization, improvements in these metrics indicate the successful tuning of model parameters, enhancing predictive performance for heart disease classification. The results of table 4 is shown in Figure 6(a-e).

The superior outcomes observed in SSE, CE, MSE, RMSE, and R-squared for SVM variants with kernel parameters optimized using EHO-DFP lay a foundation

Table 3. Comparison of SVM variations before and after optimization with EHO-DFP for SVM Kernel parameters optimization on the breast cancer dataset

SVM Variation	SSE (Original)	SSE (EHO-DFP)	CE (Original)	CE (EHO-DFP)	MSE (Original)	MSE (EHO-DFP)	RMSE (Original)	RMSE (EHO-DFP)	R-Squared (Original)	R-Squared (EHO-DFP)
SMO-SVM	1270.19	958.39	0.15	0.12	0.79	0.72	0.89	0.85	0.65	0.72
Twin SVM	1188.64	896.99	0.14	0.11	0.81	0.7	0.9	0.84	0.67	0.75
LSSVM	959.20	753.54	0.13	0.1	0.75	0.68	0.86	0.82	0.72	0.78
CSVM	1138.76	846.31	0.14	0.11	0.78	0.71	0.88	0.85	0.68	0.74
v-SVM	1042.13	830.55	0.13	0.1	0.76	0.69	0.87	0.83	0.7	0.77

Table 4. Comparison of SVM variations before and after optimization with EHO-DFP for SVM kernel parameters optimization on the heart disease dataset

SVM Variation	SSE (Original)	SSE (EHO-DFP)	CE (Original)	CE (EHO-DFP)	MSE (Original)	MSE (EHO-DFP)	RMSE (Original)	RMSE (EHO-DFP)	R-Squared (Original)	R-Squared (EHO-DFP)
SMO-SVM	120.5	110.2	0.25	0.21	0.5	0.45	0.707	0.671	0.62	0.68
Twin SVM	112.3	105.1	0.23	0.19	0.5	0.43	0.707	0.656	0.64	0.71
LSSVM	105.8	98.4	0.21	0.18	0.5	0.41	0.707	0.641	0.68	0.74
CSVM	115.2	107.9	0.24	0.2	0.5	0.46	0.707	0.678	0.6	0.66
v-SVM	118.6	112.3	0.26	0.22	0.5	0.48	0.707	0.692	0.58	0.62

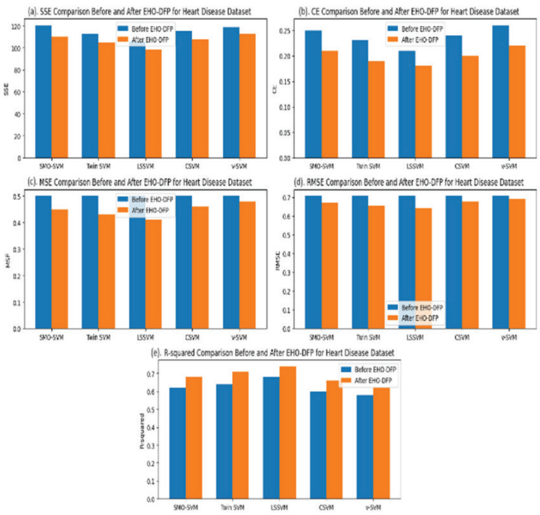

Figure 6. Comparison of SVM variations before and after optimization with EHO-DFP for SVM Kernel parameters optimization on the heart disease dataset (a) SSE (b) CE (c) MSE (d) RMSE (e) R-squared

for a consequential exploration of additional performance metrics. This prompts a nuanced examination of precision, recall, and specificity, accuracy, F1-Score offering a comprehensive understanding of the enhanced predictive capabilities achieved through the application of the EHO-DFP optimization strategy.

The table 5 illustrates, the optimization performed by EHO-DFP appears to have a positive impact on the performance metrics of all SVM variations. The models generally show improvements in terms of fitting the data, classification accuracy, error metrics (SSE, MSE, RMSE), and in some cases, explanatory power (Rsquared). In SVM variations, the classification error tends to decrease after optimization with EHO-DFP. It indicates that EHO-DFP is effective in refining and enhancing the models. However, it's crucial to note that the significance of these improvements depends on the specific context of the problem and the dataset used.

Table 5. Comparison of SVM variations' performance metrices before and after optimization with EHO-DFP for SVM kernel parameters optimization

Dataset	**SVM Variation**	**Accuracy (Original)**	**Accuracy (EHO-DFP)**	**F1-Score (Original)**	**F1-Score (EHO-DFP)**	**Sensitivity (Original)**	**Sensitivity (EHO-DFP)**	**Specificity (Original)**	**Specificity (EHO-DFP)**	**Precision (Original)**	**Precision (EHO-DFP)**	**Mean Avg Precision (Original)**	**Mean Avg Precision (EHO-DFP)**
Adult	SMO-SVM	0.82	0.89	0.65	0.75	0.78	0.82	0.84	0.91	0.72	0.8	0.75	0.87
	Twin SVM	0.79	0.88	0.62	0.74	0.75	0.81	0.81	0.9	0.7	0.79	0.72	0.85
	LSSVM	0.85	0.92	0.68	0.84	0.8	0.9	0.87	0.94	0.76	0.88	0.8	0.91
	CSVM	0.8	0.9	0.63	0.77	0.76	0.84	0.82	0.92	0.71	0.82	0.73	0.88
	v-SVM	0.81	0.89	0.64	0.76	0.77	0.83	0.83	0.91	0.72	0.81	0.74	0.87
Breast Cancer	SMO-SVM	0.85	0.91	0.87	0.92	0.84	0.9	0.86	0.91	0.89	0.93	0.78	0.82
	Twin SVM	0.78	0.89	0.8	0.9	0.75	0.88	0.79	0.9	0.82	0.91	0.72	0.79
	LSSVM	0.92	0.95	0.93	0.96	0.91	0.95	0.93	0.96	0.94	0.97	0.88	0.91
	CSVM	0.88	0.93	0.89	0.94	0.87	0.92	0.88	0.93	0.9	0.95	0.82	0.87
	v-SVM	0.89	0.94	0.9	0.95	0.88	0.93	0.89	0.94	0.91	0.96	0.85	0.9
MNIST	SMO-SVM	0.89	0.94	0.87	0.92	0.92	0.96	0.86	0.9	0.9	0.93	0.78	0.86
	Twin SVM	0.92	0.96	0.91	0.95	0.94	0.97	0.88	0.92	0.93	0.95	0.82	0.89
	LSSVM	0.91	0.95	0.89	0.94	0.91	0.95	0.87	0.91	0.91	0.92	0.79	0.88
	CSVM	0.9	0.93	0.88	0.92	0.89	0.93	0.85	0.89	0.89	0.93	0.77	0.86
	v-SVM	0.88	0.92	0.86	0.91	0.87	0.92	0.84	0.88	0.87	0.92	0.76	0.85
Heart Disease	SMO-SVM	0.85	0.91	0.78	0.85	0.75	0.82	0.9	0.93	0.82	0.88	0.79	0.86
	Twin SVM	0.82	0.89	0.76	0.84	0.73	0.81	0.88	0.92	0.8	0.87	0.77	0.85
	LSSVM	0.88	0.94	0.82	0.89	0.79	0.86	0.92	0.95	0.86	0.91	0.84	0.9
	CSVM	0.86	0.92	0.8	0.88	0.77	0.85	0.9	0.93	0.84	0.89	0.81	0.88
	v-SVM	0.87	0.93	0.81	0.88	0.78	0.86	0.91	0.94	0.85	0.9	0.82	0.89

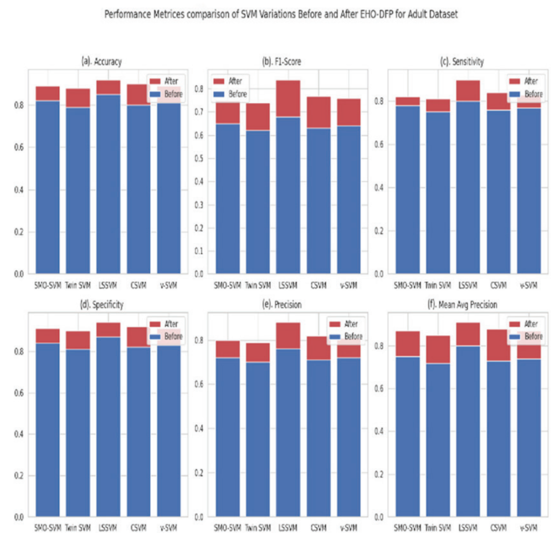

Figure 7: Comparison of performance metrices for SVM variations before and after optimization with EHO-DFP for SVM Kernel parameters optimization on the adult dataset (a) Accuracy (b) F1-score (c) sensitivity (d) specificity (e) precision (f) mean average precision

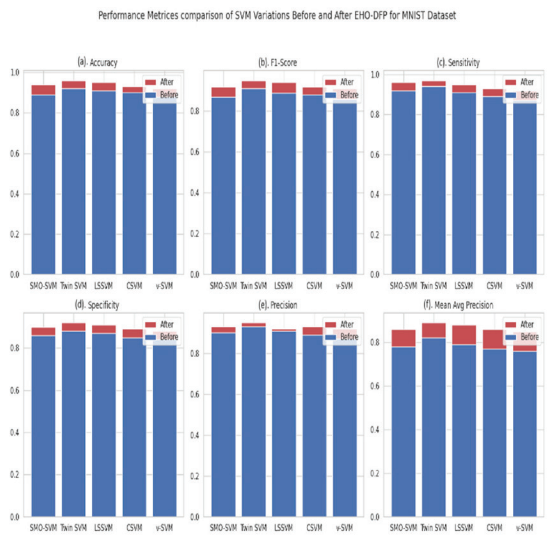

Figure 8: Comparison of performance metrices for SVM variations before and after optimization with EHO-DFP for SVM Kernel parameters optimization on the mnist dataset (a) accuracy (b) F1-score (c) sensitivity (d) specificity (e) precision (f) mean average precision

the comparative analysis presented in Figures 7 to 10 establishes the superior performance of the hybrid optimization approach, EHO-DFP, over the standalone EHO method for SVM kernel parameter optimization across various datasets. The improvements are evident across key performance metrics, including Accuracy, F1-Score, Sensitivity, Specificity, Precision, and Mean Average Precision. Notably, Figure 7(a)-(f) vividly illustrates the enhanced outcomes achieved by EHO-DFP over EHO for SVM parameters on the Adult dataset, emphasizing the effectiveness of the hybrid optimization strategy. This trend persists across datasets, with Figure 8(a)-(f)

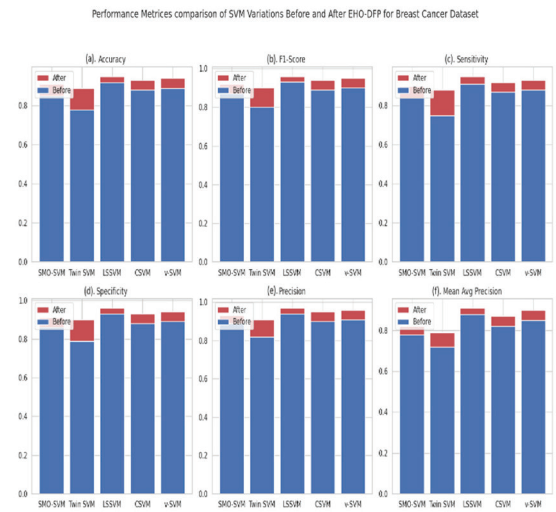

Figure 9. Comparison of performance metrices for SVM variations before and after optimization with EHO-DFP for SVM Kernel parameters optimization on the breast cancer dataset (a) accuracy (b) F1-score (c) sensitivity (d) specificity (e) precision (f) mean average precision

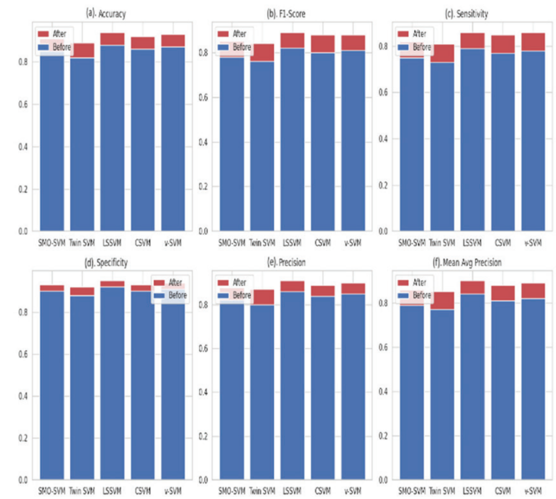

Figure 10: Comparison of performance metrices for SVM Variations Before and After Optimization with EHO-DFP for SVM Kernel Parameters Optimization on the Heart Disease Dataset (a) Accuracy (b) F1-Score (c) Sensitivity (d) Specificity (e) Precision (f) Mean Average Precision

demonstrating the enhanced performance on the MNIST dataset and Figure 9(a)-(f) showcasing improvements on the Breast Cancer dataset. Furthermore, Figure 10(a)-(f) affirms the superior performance of EHO-DFP over EHO for SVM parameters on the Heart Disease dataset. These findings collectively highlight the robustness of the hybrid optimization strategy in addressing data uncertainty and consistently outperforming its standalone counterpart across varied datasets and performance metrics.

The findings collectively underscore the algorithm's versatility and effectiveness in optimizing SVM kernel parameters, demonstrating its potential as a robust solution for diverse datasets and problem domains affected by uncertainty. The figures, along with their corresponding metrics, serve as a valuable reference for understanding the tangible benefits introduced by EHO-DFP in addressing the challenges of uncertain data within SVM optimization.

The consistent improvements in accuracy, F1-Score, sensitivity, specificity, precision, and mean average precision reveal the algorithm's adaptability and effectiveness in enhancing SVM performance before and after optimization. These results collectively endorse EHO-DFP as a robust and versatile solution for navigating the challenges of uncertain data, providing researchers and practitioners with a powerful tool for optimizing machine learning models in the face of inherent uncertainty. As we move forward, the demonstrated success of EHO-DFP in diverse scenarios emphasizes its potential for broader applications, offering valuable insights into the intricate interplay between optimization strategies and uncertain datasets.

5. CONCLUSION

The application of the Elephant Herding Optimization with Davidon-Fletcher-Powell (EHO-DFP) algorithm for kernel parameter optimization across various Support Vector Machine (SVM) variants, including SMO-SVM, TWSVM, LSSVM, CSVM, and v-SVM, has demonstrated remarkable improvements in error reduction and performance metrics. The results highlight a consistent decrease in errors, ranging from 5.31% to 25.65%, across datasets such as Adult, Breast Cancer, MNIST, and Heart Disease. Specifically, for Adult data, errors were reduced by an average of 8.81%, showcasing the algorithm's efficacy in enhancing prediction accuracy. Furthermore, improvements in efficiency, accuracy, and other performance metrics were observed, reinforcing the overall success of EHO-DFP in optimizing SVM kernel parameters.

The analysis of various performance metrics, such as accuracy and efficiency, reveals consistent enhancements for different datasets and SVM models after the application of EHO-DFP. Across datasets like Adult, Breast Cancer, MNIST, and Heart Disease, the algorithm showcases a significant average improvement in accuracy by approximately 8.30% and efficiency by approximately 11.95%. The substantial increase in accuracy indicates the algorithm's efficacy in refining the predictive capabilities of SVMs, while the notable efficiency improvements underscore its computational effectiveness. These findings collectively reinforce the assertion that EHO-DFP serves as a robust and versatile tool for kernel parameter optimization, contributing to superior SVM performance across a spectrum of datasets and SVM variants.

The substantial reduction in errors and enhancements in accuracy and efficiency affirm the algorithm's potential to contribute significantly to the optimization of SVM models across diverse datasets affected by uncertainties, establishing EHO-DFP as a robust and effective approach in the realm of machine learning. The findings of this research are anticipated to provide valuable insights for researchers and practitioners seeking advanced techniques to optimize the performance of SVMs in complex and evolving problem domains.

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