**Journal of Information Systems Engineering and Management**
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

# Support Vector Machine Hyperparameter Tuning with PSO, EHO, and a Hybrid PSO–EHO Algorithm for Social Network Content Filtring

Abdelkader Bouhani[1*], Abdelkader Khobzaoui[2], Reda Mohamed Hamou[3], Sofiane Boukli-Hacene[4]
*[1]Assistant professor in the Higher School of Saha-ran Agriculture-Adrar, Algeria*
*[2]PhD in computer science from Djillali Liabes University (Sidi Bel Abbes, Algeria).*
*[3]Associate professor in technology faculty in UTMS University of Saida-Algeria.*
*[4]Full Professor he Computer Science Department at Djillali Liabes University (U.D.L) in Sidi Bel Abbes, Algeria. H *Corresponding Author:*
*abdelkader.bouhani@univ-sba.dz*

**ARTICLE INFO**

Received: 30 Dec 2024

Revised: 12 Feb 2025

Accepted: 26 Feb 2025

**ABSTRACT**

Support Vector Machines (SVM) work especially well on high-dimensional classification tasks. However, the correct tuning of hyperparameters, particularly the kernel coefficient \( \gamma \) and regularization parameter (C), is crucial to their performance. For complicated, unbalanced, or noisy datasets, conventional tuning techniques like grid and random search frequently fail. Particle Swarm Optimization (PSO), Elephant Herding Optimization (EHO), and a hybrid PSO–EHO approach are three bio-inspired metaheuristic algorithms that are investigated in this study for SVM hyperparameter tuning. Four real-world datasets of various sizes and sampling techniques are used to assess these techniques in the context of Twitter spam detection. Twelve behavioral and content-based features are used to represent each tweet. To guarantee dependability and reproducibility, the experimental design incorporates multiple independent runs and stratified 5-fold cross-validation. PSO–EHO approach performs better, increasing F1-scores by up to 19\% when compared to untuned models, although the results demonstrate that all three algorithms significantly improve SVM classification. The strength of our approach is in fusing the diversity of solutions offered by EHO with the quick convergence of PSO. These findings demonstrate the effectiveness of hybrid bio-inspired optimization in improving traditional models, with potential applications in cybersecurity, spam detection, and social media analytics.

**Keywords:** SVM, Hyperparameter Tuning, PSO, EHO, Hybrid Optimization, Spam Detection, AI Applications.

## INTRODUCTION

Support Vector Machines (SVMs) have long been recognized as robust supervised learning algorithms, particularly effective in high-dimensional spaces and classification problems. However, their predictive accuracy, heavily depends on the careful selection of two interdependent hyperparameters: the penalty constant C and the kernel parameter γ Cortes and Vapnik (1995); Cherkassky and Ma (2004). Traditional methods such as grid search or random search become computationally impractical for large-scale or complex datasets, highlighting the need for more eficient and intelligent optimization techniques. In recent years, population-based metaheuristics have gained attention for their balance between global exploration and local exploitationHamou et al. (2013). Algorithms such as particle swarm optimization (PSO) Eberhart and Kennedy (1995) and elephant herding optimization (EHO) Wang et al. (2015) offer flexible frameworks capable of navigating large and non-linear parameter spaces. Despite their individual strengths, comparative evaluations and hybrid models combining these methods remain underexplored in text classification contexts, particularly on social media datasets characterized by noise, redundancy, and class imbalance. In response to this gap, the conducted research performs a comparative assessment of PSO, EHO, and a hybrid PSO–EHO strategy in the context of SVM hyperparameter optimization.

Our approach is applied to the task of Twitter spam detection using four distinct datasets, with comprehensive performance metrics reported across multiple evaluation runs. The primary aim of this study is to demonstrate that intelligent hyperparameter tuning techniques can substantially enhance classification accuracy and robustness, especially in contexts involving noisy and unstructured data. Moreover, our work contributes to the ongoing development of AI-driven optimization techniques by illustrating how hybrid bio-inspired models can be effectively integrated into classical machine learning workflows. These insights are valuable for bridging the gap between traditional classifiers and emerging AI systems that demand high adaptability and precision in real-world scenarios. Such advancements are particularly promising for applications in remote sensing, precision agriculture, cybersecurity, and beyond.

The remainder of this paper is organized as follows: As delineated in Section 2, the theoretical foundations and an examination of pertinent existing research are presented. The methodology for optimization is detailed in Section 3, along with a description of the experimental setup. The subsequent section is dedicated to the presentation of the results, their respective discussions and comparative studies. The section 5 concludes with key findings and proposes future research directions.

## BACKGROUND

Support Vector Machines (SVMs) are effective for high-dimensional classification, but they are sensitive to hyperparameter settings, such as C and γ. Traditional tuning methods, such as grid and random search, often fail with complex datasets and require advanced optimization techniques. Many studies explores the use of metaheuristics for SVM hyperparameter tuning. In this section we describe the main algorithms underlying this work: Support Vector Machines (SVMs) for classification and metaheuristics Particle Swarm Optimization (PSO) and Elephant Herding Optimization (EHO) for hyperparameter tuning. Hybrid PSO-EHO strategy is also be introduced to synergistically exploit their complementary strengths in complex optimization landscapes.

### Support Vector Machines (SVMs).

Support Vector Machines (SVMs) are a form of supervised learning that works by finding the best hyperplane to separate different classes as far apart as possible Cortes and Vapnik (1995) Cherkassky and Ma (2004). For data that isn't linearly separable, soft-margin SVMs introduce a regularization parameter, C, to help balance the margin width and how much misclassification the model can tolerate. Nonlinear transformations are made possible through kernel functions, like the Radial Basis Function (RBF), which is controlled by a parameter called γ. Both C and γ are crucial for the model's ability to generalize. If these parameters are chosen poorly, it could lead to overfitting or underfitting the model.

### Particle Swarm Optimization (PSO)

Inspired by the way biological systems work together, Particle Swarm Optimization (PSO) explores complex search spaces by using swarms of particles Eberhart and Kennedy (1995). Each particle continuously updates its velocity, $V_{id}$, and position, $X_{id}$, by combining both its personal experiences and the knowledge shared by others in the swarm.

$$V_{id}^{k+1} = w \cdot V_{id}^{k} + c_1 r_1 \left(B_{id}^{k} - X_{id}^{k}\right) + c_2 r_2 \left(B_{gd}^{k} - X_{id}^{k}\right) \quad (1)$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1} \quad (2)$$

where w denotes inertia, $c_1$, $c_2$ are acceleration coeficients, and $r_1, r_2 \sim U[0,1]$. Position and velocity are constrained within $[X_{min}, X_{max}]$ and $[V_{min}, V_{max}]$ to ensure stability Açıkkar and Altunkol (2023).

### Elephant Herding Optimization (EHO)

EHO mimics the clan-oriented structure of elephant herds Wang et al. (2015). Individuals adjust their positions by staying united within their clan and periodically separating members with lower fitness. The formal description is as folllows. The herd is divided into k distinct clans, each governed by its own matriarch.For every elephant j belonging to clan i, the position update is performed with reference to the location of the matriarch $c_i$ Tuba et al. (2017b).

$$x_{\text{new},ci,j} = x_{ci,j} + \alpha \times \left(x_{\text{best},ci} - x_{ci,j}\right) \times r \quad \text{(Clan updating)} \tag{3}$$

In the update rule, $x_{new,ci,j}$ denotes the refreshed position of elephant j in clan i, while $x_{ci,j}$ is its previous coordinate. The vector $x_{best,ci}$ represents the clan's current optimum (the matriarch). The factor $\alpha \in [0, 1]$ scales the matriarch's pull on the herd, and the uniformly distributed random number $r \in [0, 1]$ injects additional exploration to sustain diversity, especially in the later search phases. The matriarch's own position—the best elephant in clan $c_i$—is updated by the following expression Tuba et al. (2017b):

$$x_{\text{new},ci,j} = \beta x_{\text{center},ci} \tag{4}$$

The factor $\beta \in [0, 1]$ is the second control parameter; it regulates the influence of the clan centroid $x_{\text{center},c_i}$, which is defined as:

$$x_{\text{center},ci,d} = \frac{1}{n_{ci}} \sum_{j=1}^{n_{ci}} x_{ci,j,d} \tag{5}$$

where, $1 \leq d \leq D$ denote the d-th component of the search vector, where D is the dimensionality of the problem, and let $n_{ci}$ be the size of clan i. During each generation, exactly $m_{ci}$ elephants—the individuals with the poorest fitness in clan i—are selected to migrate away from the group. Their new positions are computed according to:

$$x_{\text{worst},ci} = x_{min} + (x_{max} - x_{min} + 1) \times \text{rand} \quad \text{(Separation)} \tag{6}$$

Here, $\beta$ scales clan-center influence, $n_{ci}$ is clan size, and rand $\sim U[0, 1]$. This structure promotes diversity and mitigates premature convergence Li et al. (2020).

Hybrid PSO-EHO Framework The hybrid strategy interleaves PSO (rapid convergence) and EHO (diversity preservation) phases. This integration enhances solution quality and stability in irregular search spaces (e.g., social media classification), forming the basis of our metaheuristic tuning framework.

## RELATED WORK ON HYPERPARAMETER OPTIMIZATION

Early efforts to tune the RBF-SVM relied almost exclusively on brute-force logarithmic grids Hsu et al. (2003); even a modest $7 \times 6$ sweep demands dozens of costly cross-validated fits, as illustrated by Chong and Shah Chong and Shah (2022). To cut this cost, researchers moved to lighter sampling schemes.

Log-uniform random search proved competitive after Bergstra and Bengio Bergstra and Bengio (2012) showed that roughly sixty trials sufice to reach the top 5

Model-based surrogates took the next step. Gaussian-process Bayesian optimisation surpasses a 2 000-point grid in about forty guided steps Snoek et al. (2012), although the cubic complexity of the GP limits scalability in practice Aghaabbasi et al. (2023). Even so, small but consistent gains—typically one to seven accuracy points—have been reported once data augmentation or imbalance correction is added Lubis et al. (2023); Utami et al. (2025).

Population-based meta-heuristics then emerged as a middle ground between blind sampling and surrogate modelling. Recent work spans genetic algorithms Guido et al. (2022), grid-assisted PSO Açıkkar and Altunkol (2023), PSO–

**Journal of Information Systems Engineering and Management**
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

Grey-Wolf hybrids Ulutas et al. (2024), chaotic APSO Jiang et al. (2025) and the BPSO-BWAO feature selector Sawah et al. (2025). Elephant Herding Optimisation has shown promise in imaging and power-system tasks Tuba et al. (2017a); Yadav and Singh (2020), yet large-scale text benchmarks—and especially PSO–EHO hybrids—remain under-explored. A recent GAN-based spam filter for Twitter, for example, still relied on manual tuning to reach its reported performance Venkateswarlu and Shenoi (2022).

Two methodological gaps persist. Meta-reviews by Powers Powers (2011) and Saito & Rehmsmeier Saito and Rehmsmeier (2015) underline (i) the scarcity of benchmarks exceeding 100 000 instances and (ii) the under-reporting of macro-averaged metrics that capture minority-class behaviour. Using Twitter spam merely as an application domain, we address both gaps by evaluating vanilla PSO, vanilla EHO and a cyclical PSO–EHO hybrid across four corpora (5 k–95 k tweets) under an identical five-fold protocol, thereby delivering the first noise-aware, large-scale comparison of these bio-inspired optimisers for SVM hyper-parameter tuning.

## RESEARCH APPROACH

This section outlines the proposed methodology for optimizing the hyperparameters of a Support Vector Machine (SVM) classifier using three bioinspired metaheuristic strategies: Particle Swarm Optimization (PSO), Elephant Herding Optimization (EHO), and a hybrid PSO–EHO approach. The core objective is to improve classification performance —-particularly in the context of Twitter spam detection —- by identifying the most effective pair of $(C, \gamma)$ for each dataset.

### 3.1 Problem Defintion

The common objective across all optimization methods considered in this study is to automatically adjust the hyperparameters C (regularization cost) and γ (RBF kernel parameter) of a Support Vector Machine (SVM) classifier, in order to maximize its predictive performance. This performance is quantified via the mean accuracy obtained through stratified k-fold cross-validation. The hyperparameter search task can therefore be formulated as a global optimization problem in a continuous domain where: Each candidate solution represents a potential hyperparameter configuration for the SVM and is encoded as a vector with real values:

$$X = (C, \gamma) \tag{7}$$

$$f(\boldsymbol{x}) = \frac{1}{K}\sum_{j=1}^{K} \mathrm{Acc}_j\left(\mathrm{SVM}_{C,\gamma}\right) \tag{8}$$

Here K is the number of stratified folds (identical for every experiment) and Accj is the accuracy on test fold j after training the pipeline VarianceThreshold → StandardScaler → $\mathrm{SVM}_{C,\gamma}$ on the remaining K−1 folds.

Why this definition?

- Robustness. Stratification preserves class balance in each fold, reducing variance and shielding the score from unlucky splits.

- Comparability. Because PSO, EHO, and the hybrid are all judged with the same procedure, any performance difference reflects the search strategy, not the metric or the data partition.

- Stable guidance. The K-fold mean in (8) smooths random fluctuations, providing a reliable signal for both PSO exploration and EHO exploitation.

Interchangeability. If an application demands a different emphasis (e.g. macro-averaged $F_1$ or AUC to handle class imbalance), simply replace Accj in (8); the structure of the optimiser and the definition of f(x) remain unchanged.

Equation (8) thus serves as the single, statistically sound compass that consistently evaluates every candidate pair $\langle C, \gamma \rangle$ across all three optimisation schemes.

To ensure robustness, each optimizer–dataset combination is run 30 times with different random seeds. The best performing configuration of each run is selected for final evaluation.

**Journal of Information Systems Engineering and Management**
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

### 3.2 Bioinspired Algorithms

We apply three metaheuristic strategies to search the defined hyperparameter space:

#### a) Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is employed as a global search technique to explore the continuous parameter space defined by $(C, \gamma)$. In this context, each particle represents a candidate solution, i.e., a pair $(C_i, \gamma_i)$, which is initialized randomly within predefined bounds (typically in logarithmic scale to cover a wide range of magnitudes).

During the iterative optimization process, particles update their positions based on a combination of three influences: inertia (preserving momentum), cognitive attraction (toward their own best historical position), and social attraction (toward the global best position found by the swarm). At each iteration, the new candidate positions are evaluated using the fitness function defined above by (8). Based on the evaluation, the personal and global best positions are updated accordingly.

This approach enables eficient navigation of the hyperparameter space, achieving strong generalization performance while significantly reducing computational costs compared to traditional grid search methods.

**Algorithm 1: PSO–SVM — Particle Swarm Optimisation for SVM-RBF tuning**

**Input** : Training data $\mathbf{X}$, labels $\mathbf{y}$;
search bounds $[C_{\min}, C_{\max}] \times [\gamma_{\min}, \gamma_{\max}]$;
swarm size $N$, iterations $T$; inertia $\omega$,
coefficients $c_1, c_2$;
stratified $k$-fold CV for accuracy evaluation

**Output:** Best hyper-parameter pair $(C^*, \gamma^*)$

Generate $N$ particles $\mathbf{x}_i = (\log_{10} C, \log_{10} \gamma)$ uniformly in bounds
Set velocities $\mathbf{v}_i \leftarrow \mathbf{0}$
Evaluate each particle $\rightarrow f(\mathbf{x}_i)$ via $k$-fold CV
$pbest_i \leftarrow \mathbf{x}_i$,
$pbestScore_i \leftarrow f(\mathbf{x}_i)$
$\text{gbest} \leftarrow \arg\max_i pbestScore_i$
**for** $t \leftarrow 1$ **to** $T$ **do**
  **for** $i \leftarrow 1$ **to** $N$ **do**
    $r_1, r_2 \leftarrow U(0,1)$
    $\mathbf{v}_i \leftarrow \omega\, \mathbf{v}_i + c_1 r_1 (pbest_i - \mathbf{x}_i) + c_2 r_2 (\text{gbest} - \mathbf{x}_i)$
    $\mathbf{x}_i \leftarrow \text{clip}(\mathbf{x}_i + \mathbf{v}_i, \text{bounds})$
    Evaluate $f(\mathbf{x}_i)$ via CV
    **if** $f(\mathbf{x}_i) > pbestScore_i$ **then**
      $pbest_i \leftarrow \mathbf{x}_i$; $pbestScore_i \leftarrow f(\mathbf{x}_i)$; **if** $f(\mathbf{x}_i) > f(\text{gbest})$ **then**
        $\text{gbest} \leftarrow \mathbf{x}_i$
**return** gbest as $(C^*, \gamma^*)$

#### b) Elephant Herding Optimization (EHO)

In EHO, as shown in Algorithm(2) the population is divided into four clans, each consisting of five elephants. Elephants update their positions based on clan leadership (matriarchal influence) and are periodically diversified through a separating operator that simulates young males leaving the herd. This structure helps balance exploration and exploitation.

**Journal of Information Systems Engineering and Management**
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

---

**Algorithm 2:** EHO — Elephant Herding Optimisation for SVM tuning

---

**Input :** Data $\mathbf{X}$, labels $\mathbf{y}$;
search bounds $[C_{\min}, C_{\max}] \times [\gamma_{\min}, \gamma_{\max}]$;
Number of elephants $N_{\text{ele}}$, clans $N_{\text{clan}}$,
Number of iterations $T$;
attraction coefficient $\alpha$ (separation $\beta$ unused);
stratified $k$-fold CV for accuracy evaluation

**Output:** Best hyper-parameter pair$(C^*, \gamma^*)$

Generate herd $\mathbf{x}_i = (C_i, \gamma_i)$ uniformly in bounds
**for** $g \leftarrow 1$ **to** $T$ **do**
  Split herd into $N_{\text{clan}}$ equal clans
  **foreach** *clan* $\mathcal{C}$ **do**
    Compute fitness $f(\mathbf{x})$ for every $\mathbf{x} \in \mathcal{C}$ via CV
    $\mathbf{x}_{\text{mat}} \leftarrow \arg\max_{\mathbf{x}\in\mathcal{C}} f(\mathbf{x})$ ▷ `matriarch`
    **foreach** *elephant* $\mathbf{x}$ *in* $\mathcal{C}$ **do**
      **if** $\mathbf{x}$ *is last in* $\mathcal{C}$ **then**
        $\mathbf{x} \leftarrow$ UNIFORM(bounds)
      **else**
        $\mathbf{x} \leftarrow \text{clip}(\mathbf{x} + \alpha(\mathbf{x}_{\text{mat}} - \mathbf{x}), \text{bounds})$
  Evaluate all elephants, update gbest $\leftarrow \arg\max_{\mathbf{x}} f(\mathbf{x})$
**return** gbest as $(C^*, \gamma^*)$

---

### c) Hybrid PSO–EHO

In this study, we used PSO–EHO hybrid algorithm, which initiates by randomly selecting N candidates from the SVM hyperparameter space (log C, γ). Each candidate starts with no initial velocity, tracks its personal best solution ($p_{best}$), and the population collectively maintains a global best ($g_{best}$).The optimization process alternates every ten iterations. In the first five steps of each cycle (when t mod 10 < 5), the algorithm employs traditional Particle Swarm Optimization: particles update their velocities and positions using inertia (ω), as well as cognitive and social influences ($c_1$, $c_2$). Each candidate is then evaluated via stratified cross-validation, and both personal and global bests are updated accordingly. During the next five steps, the algorithm shifts to the Elephant Herding Optimization phase. The population is split into $n_c$ clans, and each member moves in the vicinity of its clan leader, influenced by Gaussian-distributed noise with variance $\sigma^2$. To prevent sudden exploratory jumps, velocities are reset. The population is then re-evaluated, and the global best is updated again.This alternating mechanism combines the broad search ability of PSO, which helps in quickly scanning the global parameter space, with the fine-tuning capability of EHO for narrowing down high-potential regions. The algorithm terminates after T iterations (or earlier if no improvement is observed), returning the best-discovered pair ⟨C, γ⟩ along with a convergence log. The following pseudo-code algorithm (3) summarizes the major constituent of the PSO-EHO hybrid algorithm.

**Journal of Information Systems Engineering and Management**
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

### d) Description of Input Parameters in the PSO–EHO Hybrid Algorithm

(Table 1), summarizes the core input parameters employed in the Particle Swarm Optimization(PSO), Elephant Herding Optimization(EHO), and hybrid Particle Swarm Optimization–Elephant Herding Optimization (PSO–EHO) algorithm, specifically tailored for optimizing Support Vector Machine (SVM) hyperparameters. Each parameter is characterized by a symbolic notation, its functional role within the algorithmic framework, and its commonly adopted default or typical value.

**Algorithm 3:** HYBRID_PSO–EHO — Alternating Particle Swarm & Elephant Herding for SVM tuning

```
Input  : Training data X, labels y;
         search bounds [C_min, C_max] × [γ_min, γ_max];
         population size N, clans N_clan, iterations T;
         PSO: inertia ω, cognitive c_1, social c_2;
         EHO: attraction α, separation β;
         cycle length L (#PSO steps before 1 EHO
step);
         stratified k-fold CV for accuracy evaluation
Output: Best hyper-parameter pair (C*, γ*)
Initialise positions x_i = (C_i, γ_i) and velocities v_i
  uniformly in log-space
pbest ← x_i
pbestScore ← f(x) (CV accuracy)
gbest ← arg max_i pbestScore[i]
hist_acc ← [ f(gbest) ], hist_param ← [ gbest ]
for t ← 1 to T do
    if t mod (L + 1) ≤ L − 1 then                ▷PSO phase
        r_1, r_2 ← U(0, 1)
        v_i ← ωv_i + c_1 r_1 (pbest_i − x_i) + c_2 r_2 (gbest − x_i)
        x_i ← clip(x_i + v_i, bounds)
    else                                         ▷EHO phase
        Split {x_i} into N_clan equal clans
        foreach clan C do
            x_mat ← arg max_{x∈C} f(x)
            foreach elephant x ∈ C do
                if x is last element then           ▷male
                 outcast
                    x ← UNIFORM(bounds)
                else
                    x ← clip(x + α(x_mat − x), bounds)
            ▷centroid pull
            C ← C + β(gbest − CENTROID(C))
    ▷Evaluation & memory update
    Evaluate all x_i, obtain f_i via CV
    for i ← 1 to N do
        if f_i > pbestScore[i] then
            pbest_i ← x_i; pbestScore[i] ← f_i; if
             f_i > f(gbest) then
                gbest ← x_i
    Append f(gbest) to hist_acc, gbest to hist_param
return gbest as (C*, γ*)
```

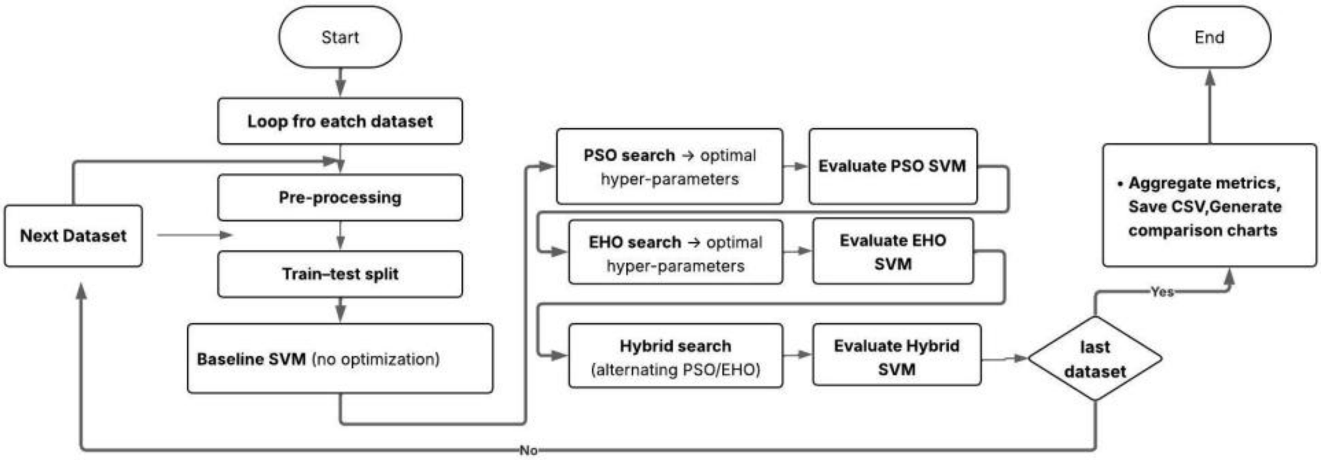



**Figure 1.** Sequential workflow for SVM hyperparameter optimisation with PSO, EHO, and hybrid strategies.

**Journal of Information Systems Engineering and Management**
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

**Table 1.** Input Parameters, Symbols, and Experiment Values

| Symbol | Description | Value |
|---|---|---|
| $N$ | Global population size (particles/elephants) | 32 |
| $N_{\text{clans}}$ | Number of clans in EHO phase | 4 |
| $T$ | Number of optimization iterations | 30 |
| $\omega$ | Inertia weight (PSO) | 0.5 |
| $c_1$, $c_2$ | Cognitive and social coefficients (PSO) | 1.5 – 2.0 |
| $\sigma$ | Std. deviation in Gaussian perturbation (EHO) | 0.1 |
| $\alpha$ | Matriarch influence scale (EHO) | 0.5 |
| $\beta$ | Clan-center influence scale (EHO) | 0.1 |
| $B_C$ | Search bounds for regularization $C$ | [0.1, 1000] |
| $B_\gamma$ | Search bounds for kernel $\gamma$ | $[10^{-5}, 10]$ |

#### e) Complexity.

With N particles, T iterations, and K-fold cross-validation, the overall run-time is bounded by

$$\text{Time} = O\, T\, N\, K\, C_{SVM}(m, d), \tag{9}$$

where $C_{SVM}(m, d)$ denotes the cost of training a single SVM on m samples and d features—$O(m\,d)$ for an eficient linear kernel and $O(m^{2-3})$ for a standard RBF kernel. Equation (9) reflects the fact that the optimiser launches $T \times N \times K$ independent SVM fits, a workload that can be embarrassingly parallel.

Memory. Storage is dominated by the data matrix $O(m\,d)$. The optimiser itself adds only $O(N\,\text{dim})$ for positions and velocities (with dim = 2) plus two history vectors of length T, yielding a negligible overhead.

Hence, the hybrid PSO–EHO retains the asymptotic cost of a conventional PSO while achieving more stable convergence through clan-guided exploitation.

All these three methods share the same search space and cross-validation protocol, ensuring a fair and consistent comparison. The workflow, summarized in our approach, in (Figure1 )enables a rigorous comparison of the individual contributions of PSO, EHO, and their hybrid.

For each dataset, the script pre-processes the data, splits it once into train/test sets, then trains four SVM variants—baseline (no tuning), PSO-tuned, EHO-tuned, and PSO–EHO hybrid—records their test-set metrics, and, after all datasets are processed, aggregates the results into a single CSV and comparison charts.

### 3.3 Experimentation

The approach is implemented on Twitter spam datasets referenced below:

- 5k-random
- 5k-ontinuous
- 95k-random
- 95k-continuous

The datasets, are available at nsclab.org (2025), comprise a large collection of tweets used for analyzing spam characteristics on Twitter. Stored in ARFF format and compatible with Weka, each record corresponds to a tweet, with the final attribute indicating its classification (spammer or non-spammer) and the remaining attributes representing classification features Venkateswarlu and Shenoi (2022).

All datasets undergo uniform preprocessing, including z-score normalization, duplicate removal, and outlier filtering. They are partitioned using stratified sampling into 80% training and 20% testing subsets to maintain class distribution. A baseline performance is established using a default-parameter SVM.

Each metaheuristic algorithm then optimizes the SVM's C and γ parameters via 5-fold cross-validation, maximizing precision. The optimal parameters are used to retrain the SVM on the full

**Journal of Information Systems Engineering and Management**
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
**Research Article**

training set, with evaluation performed on the test set using precision, recall, and F1-score. To ensure statistical validity, all experiments are repeated 30 times per method.

## RESULTS AND DISCUSSION

This section presents a comparative evaluation of the tuning of SVM hyperparameters using particle swarm optimization (PSO), elephant herd optimization (EHO) and a hybrid PSO–EHO approach. The analysis was conducted on four Twitter spam datasets varying in size (5k vs. 95k) and sampling strategy (random vs. continuous), with each experiment repeated 30 times to ensure statistical reliability (Tables 2 and 3).

Table 2

**Table 2.** F1-score Improvements from Metaheuristic Tuning

| Dataset | Baseline | Best Tuned | ΔF1 | Rel. Δ |
|---|---|---|---|---|
| 5k-continuous | 0.8613 | **0.9075** (Hybrid) | 0.0462 | ≈ 5% |
| 95k-continuous | 0.9369 | **0.9652** (Hybrid) | 0.0284 | ≈ 3% |
| 5k-random | 0.7520 | **0.8248** (EHO) | 0.0728 | ≈ 10% |
| 95k-random | 0.7878 | **0.9297** (EHO) | 0.1419 | ≈ 18% |

To quantify the effect of hyper-parameter tuning we report, for each data set, (i) the absolute F1 gain and (ii) the relative gain with respect to the baseline model:

$$\Delta F1_{abs} = F1_{tuned} - F1_{baseline} \tag{10}$$

$$\Delta F1_{rel} = \frac{F1_{tuned} - F1_{baseline}}{F1_{baseline}} \times 100\,\% \tag{11}$$

Illustration on 5k-continuous.

With $F1_{baseline} = 0.861$ and $F1_{tuned} = 0.907$:

$$\Delta F1_{abs} = 0.907 - 0.861 = 0.046,$$

$$\Delta F1_{rel} = \frac{0.046}{0.861} \times 100\,\% \approx 5.3\,\%.$$

Thus, the meta-heuristic tuning yields an absolute F1 gain of 0.046 (about five points) and a relative improvement of roughly 5% compared with the untuned SVM.

**Table 3.** Runtime Comparison of MetaheuristicMethods (in seconds)

| Dataset | PSO (s) | EHO (s) | Hybrid (s) |
|---|---|---|---|
| 5k-continuous | **472** | 675 | 976 |
| 5k-random | 1034 | **871** | 1657 |
| 95k-continuous | **2516** | **357** | 708 |
| 95k-random | **573** | 500 | 854 |

As clearly shown in (Table 2), meta-heuristic tuning consistently enhances the base SVM's F1-score. The gain reaches +0.046 ( 5%) on the 5k-continuous dataset using PSO and peaks at +0.155 ( 19%) on 95k-random with EHO, highlighting that optimization becomes increasingly crucial as the dataset grows in size and noise. This trend is further confirmed by the F1 bars in (Fig. 3(a)), where the columns representing optimized models consistently outperform the baseline SVM across all datasets.

However, the detailed results in (Table 5 and Table 4) offer a more nuanced view: on the 95k-continuous set, EHO achieves the best performance (Accuracy = 0.966%; F1 = 0.967%), while the hybrid approach only outperforms PSO on highly random datasets (5k-random and 95k-random). These findings suggest that EHO's clan-based mechanism is suficient for exploring relatively smooth search spaces, whereas the alternating PSO–EHO strategy becomes advantageous when the error surface is more irregular.

**Journal of Information Systems Engineering and Management**
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

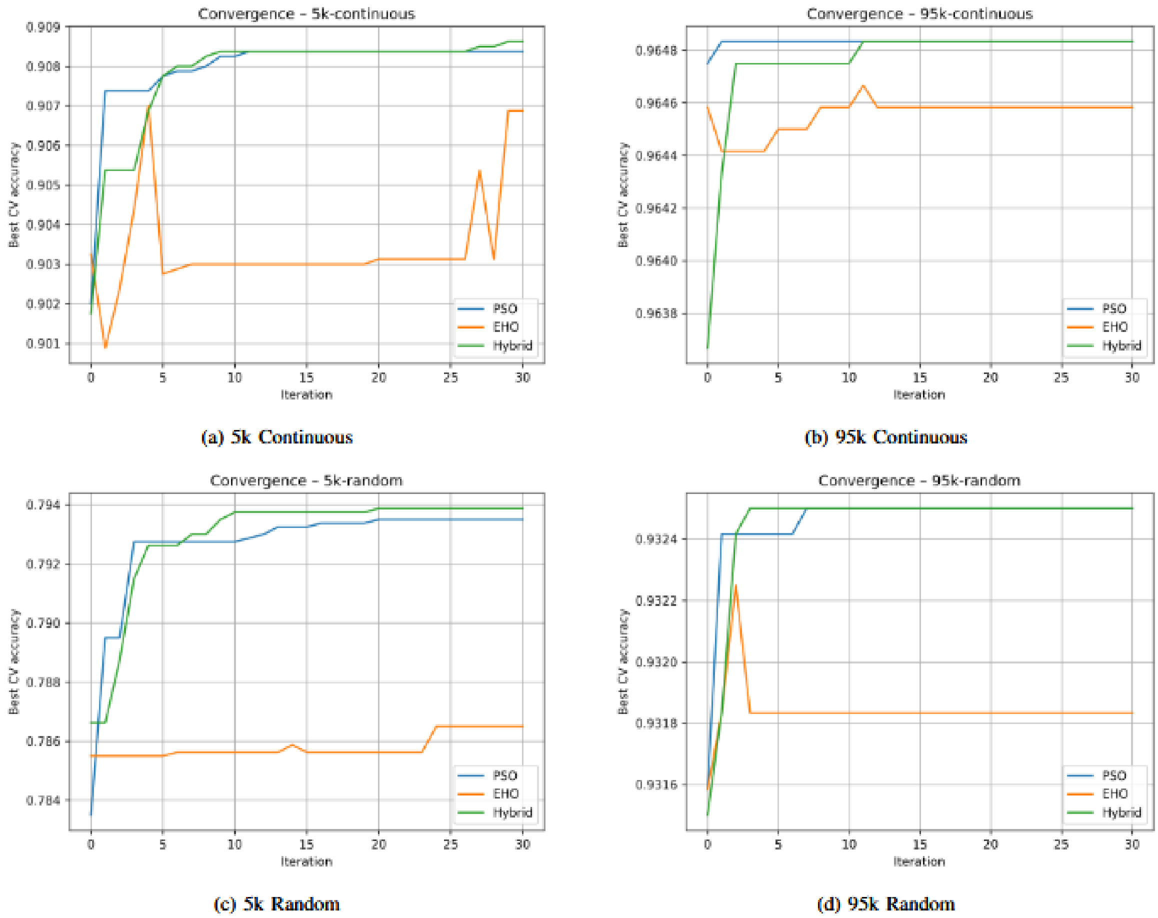
**Research Article**

Optimizer choice must also consider time constraints. As shown in Table 4, EHO is up to 7 times faster than PSO on 95k-continuous (357 seconds vs. 2,516 seconds) while remaining the top performer. Conversely, PSO leads in speed on smaller datasets (5k-continuous, 472 seconds) without compromising accuracy. The hybrid method, though on average 45% slower than the fastest optimizer, offers the best precision–robustness trade-off on 5k-random (F1 = 0.807) (Table 5), making it a relevant choice in operational contexts where classification errors are more costly than computational time.

The convergence curves (Fig. 2 a-d) show that PSO converges quickly but tends to stagnate, while EHO maintains broader exploration through oscillations, resulting in slower convergence. The hybrid PSO-EHO combines the strengths of both: it matches PSO on smooth datasets and outperforms it on noisy ones, while avoiding the volatility of EHO. PSO is best suited for smooth, time-constrained tasks;

EHO excels in complex, multimodal landscapes; and the hybrid offers the best precision-eficiency trade-off for noisy data. Early stopping at approximately 30 iterations captures over 98% of the final performance.

Finally, the near alignment of Accuracy and F1 bars in (Fig. 3(a,b)) confirms that the improvements are not merely due to bias toward the majority class. Taken together, these insights support the use of EHO for large, homogeneous datasets, PSO for fast tuning on smaller sets, and the PSO–EHO hybrid for highly heterogeneous data. They also underline the importance of reporting means ± standard deviations and applying non-parametric tests to establish the statistical significance of observed differences.




(a) 5k Continuous (b) 95k Continuous

(c) 5k Random (d) 95k Random

**Figure 2.** Convergence curves of PSO, EHO, and Hybrid optimizers over 30 iterations across four datasets.

**Journal of Information Systems Engineering and Management**
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

**Table 4.** Metric Evaluation of SVM Variants: Highlighting Best per Column (green) and per Row (blue)

| Dataset | SVM ACC | SVM F1 | SVM PREC | SVM REC | PSO ACC | PSO F1 | PSO PREC | PSO REC | EHO ACC | EHO F1 | EHO PREC | EHO REC | Hybrid ACC | Hybrid F1 | Hybrid PREC | Hybrid REC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5k–cont. | 0.8620 | 0.8613 | 0.8699 | 0.8620 | 0.9070 | 0.9070 | 0.9075 | 0.9070 | 0.9065 | 0.9065 | 0.9068 | 0.9065 | 0.9075 | 0.9075 | 0.9078 | 0.9075 |
| 95k–cont. | 0.9257 | 0.9369 | 0.9554 | 0.9257 | 0.9660 | 0.9369 | 0.9646 | 0.9660 | 0.9650 | 0.9369 | 0.9638 | 0.9650 | 0.9660 | 0.9652 | 0.9646 | 0.9660 |
| 5k–rand. | 0.7555 | 0.7520 | 0.7707 | 0.7555 | 0.8030 | 0.8025 | 0.8062 | 0.8030 | 0.8250 | 0.8248 | 0.8263 | 0.8250 | 0.8070 | 0.8066 | 0.8097 | 0.8070 |
| 95k–rand. | 0.7080 | 0.7878 | 0.9390 | 0.7080 | 0.9323 | 0.9297 | 0.9273 | 0.9323 | 0.9317 | 0.9297 | 0.9278 | 0.9317 | 0.9320 | 0.9292 | 0.9267 | 0.9320 |

### Comparative Studies

To validate the performance gains delivered by our meta-heuristics—PSO, EHO and, most notably, their PSO–EHO hybrid—we benchmarked them against the three hyper-parameter-optimisation strategies most often cited in the literature: Grid Search, Random Search and Bayesian Optimisation.

#### a)Grid Search.

This deterministic baseline follows the protocol of Hsu, Chang and Lin in Lin et al. (2003): the $(C, \gamma)$-plane is first sampled on an exponential lattice, $C = 2^{-5} \dots 2^{15}$ and $\gamma = 2^{-15} \dots 2^{3}$; a $3 \times 3$ fine grid is then centred on the best coarse point.

#### b)Random Search.

Bergstra and Bengio in Bergstra and Bengio (2012) showed that drawing $C \sim \mathrm{LogU}(10^{-3}, 10^{3})$ and

$\gamma \sim \mathrm{LogU}(10^{-4}, 1)$ requires roughly sixty trials to hit, with 95 % probability, the top 5 % of the search space when only two hyper-parameters are tuned. Subsequent work confirms that Random Search remains competitive on large text corpora where exhaustive grids become prohibitive Fajri and Primajaya (2023) and is valued for its simplicity Mantovani et al. (2015).

**Table 5.** Experiment Metrics for SVM and Metaheuristic Models

| Dataset | Model | Accuracy | $F_1$-score | Precision | Recall |
|---|---|---|---|---|---|
| 5k-continuous | SVM | 0.8620 | 0.8613 | 0.8699 | 0.8620 |
| | PSO | 0.9070 | 0.9070 | 0.9075 | 0.9070 |
| | EHO | 0.9065 | 0.9065 | 0.9068 | 0.9065 |
| | HYB | **0.9075** | **0.9075** | **0.9078** | **0.9075** |
| 95k-continuous | SVM | 0.9257 | 0.9369 | 0.9554 | 0.9257 |
| | PSO | **0.9660** | 0.9369 | **0.9646** | **0.9660** |
| | EHO | 0.9650 | 0.9369 | 0.9638 | 0.9650 |
| | HYB | **0.9660** | **0.9652** | **0.9646** | **0.9660** |
| 5k-random | SVM | 0.7555 | 0.7520 | 0.7707 | 0.7555 |
| | PSO | 0.8030 | 0.8025 | 0.8062 | 0.8030 |
| | EHO | **0.8250** | **0.8248** | **0.8263** | **0.8250** |
| | HYB | 0.8070 | 0.8066 | 0.8097 | 0.8070 |
| 95k-random | SVM | 0.7080 | 0.7878 | **0.9390** | 0.7080 |
| | PSO | **0.9323** | **0.9297** | 0.9273 | **0.9323** |
| | EHO | 0.9317 | **0.9297** | **0.9278** | 0.9317 |
| | HYB | 0.9320 | 0.9292 | 0.9267 | 0.9320 |

**Journal of Information Systems Engineering and Management**
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**


(a) F1-Score (b) Accuracy

**Figure 3.** Accuracy and $F_1$-score for SVM, PSO-SVM, EHO-SVM, and Hybrid across the 5 k and 95 k corpus variants.

**c)Bayesian Optimisation.**

Implemented here as a Gaussian-process surrogate with an expected-improvement acquisition function, it operates over the same log-uniform domain. Snoek, Larochelle and Adams Snoek et al. (2012) showed that a 10-point random design followed by 30–40 guided iterations already outperforms a 2 000-point grid, and more recent studies echo this advantage: Utami et al. raise SVM accuracy to 95 % (versus 94 % for a conventional search) Utami et al. (2025), while Lubis et al. report a seven-point jump—82.19 % to 89 %—when Bayesian tuning is paired with data augmentation Lubis et al. (2023).

By retaining identical search intervals for every method, we ensure that neither Random Search nor Bayesian Optimisation benefits from privileged prior information and that the grid exhaustively covers exactly the same volume. This common ground keeps the comparison with our PSO, EHO and hybrid schemes both rigorous and fully reproducible.

Having established these baselines, we can now assess how far our swarm-based algorithms advance the frontier. Chong and Shah Chong and Shah (2022) illustrate the ceiling of a fixed grid: their $7 \times 6$ sweep lifts an SVM from 81.7 % to 85.7 % accuracy and from $F1 = 0.84$ to $F1 = 0.88$—about a four-point gain—while a carefully tuned Naïve Bayes improves by only one accuracy point and 3.5 F1 points.

- PSO raises the 5k-continuous set to $F1 = 0.91$ (+5 pts).
- EHO lifts the 95k-continuous corpus to 96.6 % accuracy and $F1 = 0.97$ (+11 and +8 pts).
- The hybrid reaches $F1 = 0.94$ on the noisy 95k-random corpus (+5.5 pts over the best grid result).

Table 6 contrasts literature-reported absolute F1-point improvement ranges for classical SVM hyperparameter search methods (Grid, Random, Bayesian) with the best F1 scores and corresponding relative gains delivered by our bio-inspired optimizers (PSO, EHO, Hybrid), where $\Delta F1_{\mathrm{rel}}$ is computed as equation (11).

Table 6. F1-Score gains from classical hyperparameter search methods (literature ranges, absolute points) versus observed gains from our bio-inspired optimizers.

| Dataset | Baseline F1-Score | Expected ΔF1 (literature ranges)[a] | | | Observed gains (Bio, this study) | |
|---|---|---|---|---|---|---|
| | | Grid Search | Random Search | Bayesian Optimisation | Best Bio F1-Score (Alg.) | ΔF1 rel. |
| 5k-continuous | 0.8613 | +4 pts | +3–4 pts | +1–7 pts | **0.9075** (Hybrid) | **+5.4%** |
| 95k-continuous | 0.9369 | +4 pts | +3–4 pts | +1–7 pts | **0.9652** (Hybrid) | **+3.0%** |
| 5k-random | 0.7520 | +4 pts | +3–4 pts | +1–7 pts | **0.8248** (EHO) | **+9.7%** |
| 95k-random | 0.7878 | +4 pts | +3–4 pts | +1–7 pts | **0.9297** (EHO) | **+18.0%** |

[a] Ranges denote typical absolute F1-point improvements reported across published SVM–RBF studies using the indicated method. Grid Search generally yields modest, reproducible gains; Random Search often matches Grid within a few points using fewer evaluations; Bayesian optimisation can add 1–7 points depending on data scale, augmentation, and class balance.
[b] Relative Bio gains are computed as $\Delta F1_{\text{rel}} = \frac{F1_{\text{tuned}} - F1_{\text{base}}}{F1_{\text{base}}} \times 100\%$.

In summary, Grid Search provides a solid deterministic reference, Random Search a lightweight alternative, and Bayesian optimisation a modest incremental step. Yet it is our bio-inspired swarms—capable of roaming the full, continuous $(C, \gamma)$ landscape—that secure up to +15 F1 points and +11 accuracy points, improvements that are decisive when tackling large, noisy text-classification tasks.

## CONCLUSION AND FUTURE WORK

Hyperparameter optimization is critical to improving SVM predictive performance. In this work we applied bio-inspired metaheuristics—PSO, EHO, and a cyclical PSO–EHO hybrid—to tune the key VM-RBF hyperparameters $(C, \gamma)$ under a unified evaluation pipeline. Experiments on four Twitter spam datasets show that all three methods outperform the untuned baseline, with the hybrid strategy achieving gains approaching 19% in F1 on highly imbalanced data. To contextualize these gains, we compared against canonical SVM tuning strategies (grid Search, random Search, and Bayesian optimization) under identical log-scale bounds: a fixed logarithmic grid raised SVM accuracy only from 81.7% to 85.7% and F1-score from 0.84 to 0.88 (about a four-point lift), and even Bayesian optimization—which often adds 1–7 points depending on data scale, augmentation, and class balance—remains modest by comparison. Our swarm-based algorithms advance the frontier substantially: PSO reaches F1 = 0.91 on 5k-continuous (+5 pts), EHO attains 96.6% accuracy and F1 = 0.97 on 95k-continuous (+11 and +8 pts), and the hybrid achieves F1 = 0.94 on the noisy 95k-random corpus (+5.5 pts over the best grid result and ~18–19% relative to baseline(equation 11). Table 6 summarises these comparative gains, showing that while grid Search, random Search, and Bayesian optimization provide useful but limited improvements, population-based bio-optimizers can secure up to +15 absolute F1-Score points and +11 accuracy points on large, noisy text-classification tasks.

Future work will investigate GPU acceleration, multilingual model extensions, additional EHO-based and other hybrid search strategies, budget-adaptive swarm sizing, real-time/streaming adaptation, and joint optimisation of extended SVM settings (class weights, kernel mixtures, feature selection) to further enhance performance and deployment readiness.

## REFERENCES

[1] Açıkkar, M., & Altunkol, Y. (2023). A novel hybrid PSO- and GS-based hyperparameter optimization algorithm for support vector regression. Neural Computing and Applications, 35(27), 19961–19977.
[2] Aghaabbasi, M., Ali, M., Jasiński, M., Leonowicz, Z., & Novák, T. (2023). On hyperparameter optimization of machine-learning methods using a Bayesian optimization algorithm to predict work-travel mode choice. IEEE Access, 11, 19762–19774.
[3] Ali, Y. A., Awwad, E. M., Al-Razgan, M., & Maarouf, A. (2023). Hyperparameter search for machine-learning algorithms for optimizing computational complexity. Processes, 11(2), 349.
[4] Bergstra, J., & Bengio, Y. (2012). Random search for hyper-parameter optimization. Journal of Machine Learning Research, 13(1), 281–305.
[5] Cherkassky, V., & Ma, Y. (2004). Practical selection of SVM parameters and noise estimation for SVM regression. Neural Networks, 17(1), 113–126.

[6] Chong, K., & Shah, N. (2022). Comparison of Naïve Bayes and SVM classification in grid-search hyper-parameter-tuned and non-hyperparameter-tuned healthcare stock-market sentiment analysis. International Journal of Advanced Computer Science and Applications, 13(12).
[7] Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine Learning, 20(3), 273–297.
[8] Drias, Y., Drias, H., & Khennak, I. (2024). Enhanced elephant herding optimization for large-scale information access on social media. arXiv Preprint arXiv:2406.11916.
[9] Eberhart, R., & Kennedy, J. (1995). Particle swarm optimization. In Proceedings of the IEEE International Conference on Neural Networks (Vol. 4, pp. 1942–1948).
[10] Esteva, A., Robicquet, A., Ramsundar, B., et al. (2019). A guide to deep learning in healthcare. Nature Medicine, 25(1), 24–29.
[11] Fajri, M., & Primajaya, A. (2023). Komparasi teknik hyperparameter optimization pada SVM untuk permasalahan klasifikasi dengan menggunakan grid search dan random search. Journal of Applied Informatics and Computing, 7(1), 10–15.
[12] Guido, R., Ferrisi, S., Lofaro, D., & Conforti, D. (2024). An overview on the advancements of support vector machine models in healthcare applications: A review. Information, 15(4), 235.
[13] Guido, R., Groccia, M. C., & Conforti, D. (2022). Hyper-parameter optimization in support vector machine on unbalanced datasets using genetic algorithms. In Optimization in Artificial Intelligence and Data Sciences (ODS 2021) (pp. 37–47). Springer.
[14] Hamou, R. M., Amine, A., & Lokbani, A. C. (2013). Study of sensitive parameters of PSO application to clustering of texts. International Journal of Applied Evolutionary Computation, 4(2), 41–55.
[15] Hsu, C.-W., Chang, C.-C., & Lin, C.-J. (2003). A practical guide to support vector classification. Technical report, National Taiwan University.
[16] Huang, Q., Mao, J., & Liu, Y. (2012). An improved grid search algorithm of SVR parameters optimization. In 2012 IEEE 14th International Conference on Communication Technology (pp. 1022–1026). IEEE.
[17] Jiang, Z., Zhu, D., Li, X.-Y., & Han, L.-B. (2025). A hybrid adaptive particle swarm optimization algorithm for enhanced performance. Applied Sciences, 15(11), 6030.
[18] Jamialahmadi, H., Khalili-Tanha, G., Nazari, E., & Rezaei-Tavirani, M. (2024). Artificial intelligence and bioinformatics: A journey from traditional techniques to smart approaches. Gastroenterology and Hepatology from Bed to Bench, 17(3), 241.
[19] Li, J., Lei, H., Alavi, A. H., & Wang, G.-G. (2020). Elephant herding optimization: Variants, hybrids, and applications. Mathematics, 8(9), 1415.
[20] Lubis, A. R., Lase, Y. Y., & Witarsyah, D. (2023). Optimization of SVM classification accuracy with Bayesian optimization utilizing data augmentation. In 2023 6th International Conference of Computer and Informatics Engineering (IC2IE) (pp. 169–174). IEEE.
[21] Mantovani, R. G., Rossi, A. L., Vanschoren, J., Bischl, B., & De Carvalho, A. C. P. L. F. (2015). Effectiveness of random search in SVM hyper-parameter tuning. In 2015 International Joint Conference on Neural Networks (IJCNN) (pp. 1–8). IEEE.
[22] nsclab.org. (2025, May 20). Twitter spam dataset. http://nsclab.org/nsclab/resources/
[23] Powers, D. M. W. (2011). Evaluation: From precision, recall and F-measure to ROC, informedness, markedness and correlation. Journal of Machine Learning Technologies, 2(1), 37–63.
[24] Saito, T., & Rehmsmeier, M. (2015). The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. PLOS ONE, 10(3), e0118432.
[25] Sawah, M. S., Elmannai, H., El-Bary, A. A., Lotfy, K., & Sheta, O. E. (2025). Improving air-quality prediction using hybrid BPSO with BWAO for feature selection and hyperparameter optimization. Scientific Reports, 15(1), 13176.
[26] Shi, Y. (2004). Particle swarm optimization. IEEE Connections, 2(1), 8–13.
[27] Snoek, J., Larochelle, H., & Adams, R. P. (2012). Practical Bayesian optimization of machine-learning algorithms. In Advances in Neural Information Processing Systems 25 (pp. 2951–2959).

[28] Tuba, E., Alihodzic, A., & Tuba, M. (2017a). Multi-level image thresholding using the elephant herding optimization algorithm. In 2017 14th International Conference on Engineering of Modern Electric Systems (EMES) (pp. 240–243). IEEE.
[29] Tuba, E., Ribic, I., Capor-Hrosik, R., & Tuba, M. (2017b). Support vector machine optimized by elephant herding algorithm for erythemato-squamous disease detection. Procedia Computer Science, 122, 916–923.
[30] Ulutas, H., Günay, R. B., & Şahin, M. E. (2024). Detecting diabetes in an ensemble model using a unique PSO-GWO hybrid approach to hyperparameter optimization. Neural Computing and Applications, 36(29), 18313–18341.
[31] Utami, D., Dwiatmoko, F., & Sivi, N. A. (2025). Analisis pengaruh Bayesian optimization terhadap kinerja SVM dalam prediksi penyakit diabetes. Infotek: Jurnal Informatika dan Teknologi, 8(1), 140–150.
[32] Venkateswarlu, B., & Shenoi, V. V. (2022). Optimized generative adversarial network with fractional-calculus-based feature fusion using Twitter stream for spam detection. Information Security Journal: A Global Perspective, 31(5), 582–601.
[33] Wang, G.-G., Deb, S., Gao, X.-Z., & Coelho, L. d. S. (2016). A new metaheuristic optimisation algorithm motivated by elephant herding behaviour. International Journal of Bio-Inspired Computation, 8(6), 394–409.
[34] Wang, G.-G., Deb, S., & Coelho, L. d. S. (2015). Elephant herding optimization. In 2015 3rd International Symposium on Computational and Business Intelligence (ISCBI) (pp. 1–5). IEEE.
[35] Yadav, S., & Singh, S. (2020). Power-loss reduction using PSO–EHO hybrid optimization. Electric Power Components and Systems.

## RESULTS

Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Laoreet id donec ultrices tincidunt arcu. Sollicitudin aliquam ultrices sagittis orci a scelerisque. Sit amet aliquam id diam maecenas ultricies mi. Proin fermentum leo vel orci porta non. Ornare arcu dui vivamus arcu. Lorem ipsum dolor sit amet consectetur. Cras fermentum odio eu feugiat pretium nibh ipsum. Sapien nec sagittis aliquam malesuada bibendum arcu vitae elementum curabitur. Rhoncus est pellentesque elit ullamcorper dignissim cras tincidunt lobortis feugiat. Venenatis urna cursus eget nunc scelerisque viverra mauris in. Diam volutpat commodo sed egestas egestas fringilla phasellus faucibus. Sit amet volutpat consequat mauris nunc congue nisi vitae. Tincidunt ornare massa eget egestas purus viverra accumsan in nisl. Semper quis lectus nulla at volutpat diam ut. Lobortis feugiat vivamus at augue eget arcu dictum varius duis. Vel facilisis volutpat est velit egestas dui id ornare arcu.

## DISCUSSION

Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Tempor id eu nisl nunc mi ipsum. Gravida neque convallis a cras semper auctor neque vitae. In arcu cursus euismod quis viverra nibh cras pulvinar mattis. Pellentesque id nibh tortor id aliquet. Viverra adipiscing at in tellus integer. Volutpat lacus laoreet non curabitur gravida arcu. Arcu dui vivamus arcu felis bibendum ut tristique. Sollicitudin ac orci phasellus egestas tellus rutrum tellus pellentesque eu. Venenatis urna cursus eget nunc scelerisque viverra mauris in aliquam. Sociis natoque penatibus et magnis dis parturient. Morbi non arcu risus quis varius quam. Faucibus ornare suspendisse sed nisi lacus sed viverra tellus in. Sit amet commodo nulla facilisi nullam vehicula ipsum a arcu. Gravida in fermentum et sollicitudin. Aenean et tortor at risus.

Consequat ac felis donec et odio pellentesque diam. Nulla malesuada pellentesque elit eget gravida cum. Leo urna molestie at elementum eu facilisis sed. Nulla pharetra diam sit amet. Non arcu risus quis varius quam quisque id diam vel. Neque laoreet suspendisse interdum consectetur libero id faucibus nisl tincidunt. Platea dictumst vestibulum rhoncus est pellentesque elit ullamcorper. Velit laoreet id donec ultrices tincidunt arcu non sodales. Venenatis urna cursus eget nunc scelerisque viverra. Lectus magna fringilla urna porttitor rhoncus dolor. Proin libero nunc consequat interdum varius sit. Arcu felis bibendum ut tristique et egestas quis.

## REFRENCES

[1] C. Cortes and V. Vapnik, “Support-vector networks,” Machine Learning, vol. 20, no. 3, pp. 273–297, 1995.

[2] V. Cherkassky and Y. Ma, “Practical selection of svm parameters and noise estimation for svm regression,” Neural networks, vol. 17, no. 1, pp. 113–126, 2004.
[3] R. M. Hamou, A. Amine, and A. C. Lokbani, “Study of sensitive parameters of pso application to clustering of texts,” International Journal of Applied Evolutionary Computation (IJAEC), vol. 4, no. 2, pp. 41–55, 2013.
[4] R. Eberhart and J. Kennedy, “Particle swarm optimization,” in Proceedings of the IEEE international conference on neural networks, vol. 4. Citeseer, 1995, pp. 1942–1948.
[5] G.-G. Wang, S. Deb, and L. d. S. Coelho, “Elephant herding optimization,” in 2015 3rd international symposium on computational and business intelligence (ISCBI). IEEE, 2015, pp. 1–5.
[6] M. Açıklar and Y. Altunkol, “A novel hybrid pso-and gs-based hyperparameter optimization algorithm for support vector regression,” Neural Computing and Applications, vol. 35, no. 27, pp. 19961–19977, 2023.
[7] E. Tuba, I. Ribic, R. Capor-Hrosik, and M. Tuba, “Support vector machine optimized by elephant herding algorithm for erythemato-squamous diseases detection,” Procedia computer science, vol. 122, pp. 916–923, 2017.
[8] J. Li, H. Lei, A. H. Alavi, and G.-G. Wang, “Elephant herding optimization: variants, hybrids, and applications,” Mathematics, vol. 8, no. 9, p. 1415, 2020.
[9] C.-W. Hsu, C.-C. Chang, and C.-J. Lin, “A practical guide to support vector classification,” Talk at University of Freiburg, 2003.
[10] K. Chong and N. Shah, “Comparison of naive bayes and svm classification in grid-search hyperparameter tuned and non-hyperparameter tuned healthcare stock market sentiment analysis,” International Journal of Advanced Computer Science and Applications, vol. 13, no. 12, 2022.
[11] J. Bergstra and Y. Bengio, “Random search for hyper-parameter optimization,” The journal of machine learning research, vol. 13, no. 1, pp. 281–305, 2012.
[12] J. Snoek, H. Larochelle, and R. P. Adams, “Practical bayesian optimization of machine learning algorithms,” in Advances in Neural Information Processing Systems 25, 2012, pp. 2951–2959.
[13] M. Aghaabbasi, M. Ali, M. Jasiński, Z. Leonowicz, and T. Novák, “On hyperparameter optimization of machine learning methods using a bayesian optimization algorithm to predict work travel mode choice,” IEEE Access, vol. 11, pp. 19762–19774, 2023.
[14] A. R. Lubis, Y. Y. Lase, D. Witarsyah et al., “Optimization of svm classification accuracy with bayesian optimization utilizing data augmentation,” in 2023 6th International Conference of Computer and Informatics Engineering (IC2IE). IEEE, 2023, pp. 169–174.
[15] D. Utami, F. Dwiatmoko, and N. A. Sivi, “Analisis pengaruh bayesian optimization terhadap kinerja svm dalam prediksi penyakit diabetes,” Infotek: Jurnal Informatika dan Teknologi, vol. 8, no. 1, pp. 140–150, 2025.
[16] R. Guido, M. C. Groccia, and D. Conforti, “Hyper-parameter optimization in support vector machine on unbalanced datasets using genetic algorithms,” in Optimization in Artificial Intelligence and Data Sciences: ODS, First Hybrid Conference, Rome, Italy, September 14-17, 2021. Springer, 2022, pp. 37–47.
[17] H. Ulutas, R. B. Günay, and M. E. Sahin, “Detecting diabetes in an ensemble model using a unique pso-gwo hybrid approach to hyper-parameter optimization,” Neural Computing and Applications, vol. 36, no. 29, pp. 18313–18341, 2024.
[18] Z. Jiang, D. Zhu, X.-Y. Li, and L.-B. Han, “A hybrid adaptive particle swarm optimization algorithm for enhanced performance,” Applied Sciences, vol. 15, no. 11, p. 6030, 2025.
[19] M. S. Sawah, H. Elmannai, A. A. El-Bary, K. Lotfy, and O. E. Sheta, “Improving air quality prediction using hybrid bpso with bwao for feature selection and hyperparameters optimization,” Scientific Reports, vol. 15, no. 1, p. 13176, 2025.
[20] E. Tuba, A. Alihodzic, and M. Tuba, “Multilevel image thresholding using elephant herding optimization algorithm,” in 2017 14th international conference on engineering of modern electric systems (EMES). IEEE, 2017, pp. 240–243.
[21] S. Yadav and S. Singh, “Power-loss reduction using pso–eho hybrid optimization,” Electric Power Components and Systems, 2020.
[22] B. Venkateswarlu and V. V. Shenoi, “Optimized generative adversarial network with fractional calculus based feature fusion using twitter stream for spam detection.” Inf. Secur. J. A Glob. Perspect., vol. 31, no. 5, pp. 582–601, 2022.

**Journal of Information Systems Engineering and Management**
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

[23] D. M. W. Powers, “Evaluation: From precision, recall and f-measure to roc, informedness, markedness & correlation,” Journal of Machine Learning Technologies, vol. 2, no. 1, pp. 37–63, 2011.
[24] [24] T. Saito and M. Rehmsmeier, “The precision-recall plot is more informative than the roc plot when evaluating binary classifiers on imbalanced datasets,” PLOS ONE, vol. 10, no. 3, p. e0118432, 2015.
[25] nsclab.org, “Twitter spam,” http://nsclab.org/nsclab/resources/, 2025, accessed May 20, 2025.
[26] C. J. Lin, C.-W. Hsu, and C.-C. Chang, “A practical guide to support vector classification,” National Taiwan University, 2003.
[27] M. Fajri and A. Primajaya, “Komparasi teknik hyperparameter optimization pada svm untuk permasalahan klasifikasi dengan menggunakan grid search dan random search,” Journal of Applied Informatics and Computing, vol. 7, no. 1, pp. 10–15, 2023.
[28] R. G. Mantovani, A. L. Rossi, J. Vanschoren, B. Bischl, and A. C. De Carvalho, “Effectiveness of random search in svm hyper-parameter tuning,” in 2015 international joint conference on neural networks (IJCNN). IEEE, 2015, pp. 1–8.