Enhancing Classification Performance of k-NN and SVM with Firefly Algorithm

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***Abstract*—In the realm of machine learning, optimal parameter selection plays a critical role in determining classification performance. Two widely adopted algorithms Support Vector Machine (SVM) and k-Nearest Neighbors (k-NN) are highly sensitive to specific parameters. Manual tuning of these parameters is often time-consuming and may not yield optimal outcomes. This study proposes the use of the Firefly Algorithm (FA), a swarm intelligence method inspired by the flashing behavior of fireflies, to automatically determine optimal parameter values. A set of datasets from the UCI Machine Learning Repository is utilized to evaluate the effectiveness of the proposed approach. For SVM, the parameters tuned include C and gamma, while for k-NN, the optimal number of neighbors (k) is determined. The results demonstrate that FA enhances classification accuracy and produces more stable models due to reduced performance variance. The findings suggest that FA is a viable and efficient solution for parameter tuning in SVM and k-NN, particularly valuable for researchers seeking to construct reliable classification models without the burden of manual configuration.**

Keywords—Firefly Algorithm, Parameter Optimization, Support Vector Machine (SVM), k-Nearest Neighbors (k-NN)

I. INTRODUCTION

Classification is a fundamental component of machine learning[1]. Its applications are ubiquitous in everyday life, including spam detection systems, customer segmentation, disease prediction, and movie recommendation engines. Among the various classification algorithms, Support Vector Machine (SVM) and k-Nearest Neighbors (k-NN) are among the most frequently utilized due to their proven efficacy and ease of implementation[2][3]. However, the performance of both algorithms is highly dependent on appropriate parameter selection[4][5].

Improper parameter configuration can significantly compromise classification accuracy. For instance, SVM performance is influenced by the selection of C and gamma parameters[6][7], while k-NN depends critically on the number of nearest neighbors (k)[8][9]. Manually determining these parameters can be both time-consuming and suboptimal, particularly as the complexity of the data increases.

Conventional techniques such as grid search, which explores all possible combinations within a predefined parameter range, are commonly employed[10][11]. While effective, these methods are computationally intensive and impractical for high-dimensional parameter spaces. Consequently, alternative optimization techniques that are more automated and efficient have gained traction. Swarm Intelligence-based optimization algorithms offer a promising solution by mimicking collective behaviors observed in nature[12][13]. These include Particle Swarm Optimization (PSO), Firefly Algorithm (FA), Bat Algorithm (BA), Cuckoo Search (CS), and Ant Colony Optimization (ACO). Among these, FA, inspired by the attraction mechanism of fireflies via bioluminescent signals, has demonstrated strong potential in solving complex optimization tasks[14]. Although previous studies have applied FA to optimize either SVM or k-NN parameters individually[15][16], few have simultaneously evaluated its efficacy across both algorithms and multiple datasets. This study addresses this gap by applying FA to jointly optimize parameters for SVM and k-NN across fifteen distinct datasets sourced from the UCI Machine Learning Repository. The classification performance before and after tuning is systematically compared, with an emphasis on accuracy and model stability.

The main contributions of this study are as follows demonstrating the effectiveness of FA in enhancing classification performance through automated parameter tuning. Comparing FA-tuned and default models on various datasets to assess generalizability. Highlighting the practical advantages of FA, particularly its capacity to balance global exploration and local exploitation in the search space. This research aspires to provide a practical and accessible framework for students and researchers aiming to develop accurate classification models without relying on manual parameter configuration.

II. METHOD

A. Research Method

This study employs an experimental research methodology, involving systematic performance evaluations of SVM and k-NN classifiers before and after parameter optimization via the Firefly Algorithm. The primary objective is to measure improvements in classification accuracy and stability (measured by standard deviation) resulting from FA-based tuning.

The research process includes several essential stages. Initially, data preprocessing is conducted, which encompasses feature normalization, data splitting, and class-balanced validation using Stratified K-Fold Cross Validation[17]. The baseline performance of the models is established using default parameter settings. Subsequently, the Firefly Algorithm is employed to identify the optimal parameter combinations. For SVM, this involves tuning the regularization parameter C and the kernel coefficient gamma[6][7]. For k-NN, the number of neighbors k is optimized[8][9]. The tuning process aims to maximize average cross-validation accuracy.

Once optimal parameters are identified by FA, the models are retrained and evaluated against the baseline models. Each experiment is repeated multiple times to ensure consistency and validity. Additionally, the approach is tested across fifteen classification datasets from the UCI Machine Learning Repository to verify generalizability.

The datasets selected for experimentation exhibit diverse levels of complexity and varying numbers of features and classes, ensuring comprehensive evaluation of FA's optimization capabilities. These datasets are presented in Table 1.

TABLE I. DATASETS

No	Dataset Names	Number of Records	Number of Attributes	Number of Classes
1	Lung Cancer	32	56	3
2	Lymphography	148	18	4
3	Iris	150	4	3
4	Wine	178	13	3
5	Parkinson's	195	22	2
6	Heart Disease	303	13	2
7	Ionosphere	351	34	2
8	Thoracic Surgery Data	470	17	2
9	Wisconsin Diagnostic Breast Cancer	569	30	2
10	Breast Cancer (Wisconsin Original)	699	9	2
11	Scene	2407	294	6
12	Page Blocks Classification	5473	10	5
13	Amphibians	7240	29	2
14	Diabetic	101766	50	2
15	Covertype	581012	54	7

B. *Firefly Algorithms*

The Firefly Algorithm, introduced by Xin-She Yang in 2008, is a nature-inspired metaheuristic optimization technique that mimics the flashing behavior of fireflies[5][16][18]. In FA, each firefly represents a potential solution and emits a brightness determined by its fitness value.

The attractiveness of a firefly is proportional to its brightness and inversely related to the distance between two fireflies by the following equation 1[19][20]:

$$\beta(r) = \beta_0 . e^{-\gamma r^2} \quad (1)$$

Where:

β_0 is the maximum attractiveness,

γ is the light absorption coefficient,

r is the Euclidean distance between firefly i and j,

The movement of firefly i toward a more attractive firefly j is governed by the following equation 2[19][20]:

$$x_i^{t+1} = x_i^t + \beta_0 . e^{-\gamma r^2}(x_j^t - x_i^t) + \alpha.(rand - 0.5) \quad (2)$$

Where:

β_0 is the maximum attractiveness,

γ is the light absorption coefficient,

r is the Euclidean distance between firefly i and j,

α is the randomization parameter,

rand is a uniformly distributed random number in [0,1].

In this study, the fitness function is defined as the average accuracy obtained from Stratified K-Fold Cross Validation (k=5). The optimization process continues iteratively until the stopping condition is met (e.g., maximum number of generations).

C. *k-Nearest Neighbors (k-NN)*

The k-Nearest Neighbors algorithm is a simple yet effective classification method that assigns a label to a new data point based on the majority class of its k closest neighbors. The distance between data points is typically measured using the Euclidean metric by the following equation 3[21]:

$$d(x, x_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{ij})^2} \quad (3)$$

The value of k significantly affects the classification result. A smaller k may lead to overfitting due to sensitivity to noise, whereas a larger k may cause underfitting by smoothing class boundaries excessively. Hence, determining the optimal value of k is crucial and in this study, it is optimized using the Firefly Algorithm.

D. *Support Vector Machine (SVM)*

Support Vector Machine is a supervised learning algorithm that constructs a hyperplane or set of hyperplanes in a high-dimensional space to classify data. For non-linear classification, SVM employs kernel functions such as the radial basis function (RBF), defined as equation 4 [6][7]:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) \quad (4)$$

Key parameters influencing SVM performance include C (Regularization parameter) Controls the trade-off between achieving a low error on the training data and minimizing model complexity. γ (Gamma) Determines the influence of a single training example; a low value implies a broad influence while a high value implies a narrow influence. Improper tuning of these parameters can result in either overfitting or underfitting. In this research, both parameters are optimized using the Firefly Algorithm to enhance classification effectiveness.

The range of values for both C and gamma (γ), spanning from 10^{-3} to 10^3, is considered adequate. A gamma value that is excessively high results in the influence of a Support Vector being limited solely to itself, rendering the value of C ineffective in preventing overfitting. Conversely, when gamma is too low, the model becomes overly constrained and fails to capture the complexity of the data structure. Increasing the value of C under such circumstances offers no benefit, as there are no longer error margins to adjust or superior solutions to be uncovered. Furthermore, an overly small C value may lead to extended prediction times. Therefore, careful tuning of C and γ is crucial to achieving optimal model performance. In this study, both parameters will be optimized using the Firefly Algorithm (FA).

E. *Proposed Model*

The proposed model is an automated parameter optimization framework for k-Nearest Neighbors (k-NN) and Support Vector Machine (SVM) classification algorithms, utilizing the Firefly Algorithm (FA) as a metaheuristic search strategy to identify optimal parameter settings. The primary objective is to enhance classification accuracy and model stability while eliminating the need for manual tuning, which is often time-consuming and error-prone.

This hybrid model integrates the Firefly Algorithm as a parameter optimization engine for both SVM and k-NN classifiers. Model performance is evaluated using Stratified k-Fold Cross-Validation to ensure the robustness of the accuracy measurements. Experiments are conducted on ten classification datasets obtained from the UCI Machine Learning Repository.

In general, the workflow of the proposed method includes: dataset preprocessing (normalization, encoding, etc.); initial evaluation of SVM and k-NN using default parameters (serving as the baseline); parameter tuning via FA with the objective of maximizing average accuracy; retraining the models with the optimized parameters; and finally, comparing the models’ performance before and after the tuning process.

The following block diagram illustrates the operational flow of the proposed model (Figure 1):

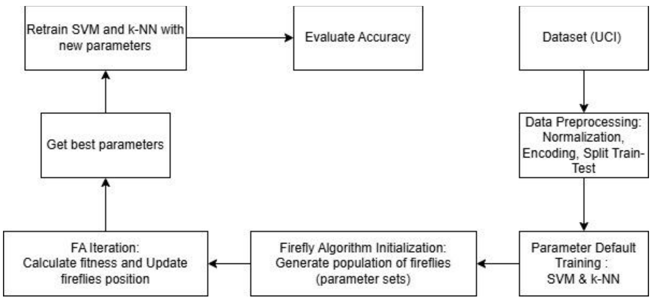

Fig. 1. Workflow Diagram of the Proposed Model

1. Solution Representation (Firefly Position)

Each firefly in the Firefly Algorithm (FA) represents a potential solution, corresponding to a set of parameters for the classification model. For the k-NN classifier, a firefly's position is defined by the value of k, which denotes the number of nearest neighbors. For the SVM classifier with an RBF kernel, a firefly's position is represented as a pair (C, γ), where:

$C \in [C_{min}, C_{max}]$ is the regularization parameter,
$\gamma \in [\gamma_{min}, \gamma_{max}]$ is the kernel parameter.

2. Fitness Function

The fitness function evaluates the quality of each solution by measuring the classification performance using the specified parameters. It is defined as the average classification accuracy obtained through Stratified k-Fold Cross-Validation, as shown in Equation (5):

$$\text{fitness}(x) = \frac{1}{k}\sum_{i=1}^{k} \text{Accuracy}_i \qquad (5)$$

Where:
Accuracy denotes the classification accuracy on the i-th fold, and k is the total number of folds (e.g., 5 or 10)..

3. Firefly Movement

A firefly with lower fitness is attracted to and moves toward a brighter (higher fitness) firefly. The movement is governed by Equation (2), which simulates attractiveness and distance-based displacement.

4. Evaluation and Iteration

After movement, the fitness of each firefly is re-evaluated using the defined fitness function. This iterative process continues until a stopping criterion is met, such as a maximum number of iterations or convergence threshold.

5. Optimal Parameters

At the conclusion of the optimization process, the firefly with the highest fitness value represents the best solution. The corresponding parameters are selected as the optimal values for either k-NN or SVM. The final model is retrained using these optimized parameters and evaluated on the test data.

III. Experimental Results

This study successfully applied the Firefly Algorithm (FA) as a parameter optimization method for the k-Nearest Neighbors (k-NN) and Support Vector Machine (SVM) classification algorithms, aiming to enhance classification performance across various multidimensional datasets. Experiments conducted on fifteen distinct datasets from the UCI Machine Learning Repository demonstrated a notable improvement in classification accuracy after implementing FA-based parameter tuning, compared to the use of default parameters.

In general, the k-NN model, when optimized by FA for the k value, exhibited accuracy improvements ranging from 3% to 10%, depending on the complexity and characteristics of the dataset under evaluation. Similarly, SVM models tuned by FA—specifically in optimizing the C and γ parameters—achieved consistently better accuracy, with improvements exceeding 8% in certain cases. These findings suggest that manual parameter tuning or conventional grid search methods can be effectively replaced by more efficient and adaptive metaheuristic optimization techniques such as FA.

The results of FA-based tuning on k-NN across several UCI ML datasets are summarized in Table 2. The parameter settings used for the FA include: population size = 10, maximum generations = 20, $\alpha = 0.2$, $\beta_0 = 1$, and $\gamma = 1$. The experimental outcomes indicate that FA tuning successfully identified near-optimal k values for the k-NN model. The tuning process was particularly effective for small to medium-sized datasets, especially those with minimal noise. However, the method is less suitable for small datasets without imposing a maximum limit on k, and it may require substantial computational resources for large datasets. Additionally, care should be taken with small datasets, which tend to be more susceptible to overfitting.

TABLE II. Experimental Results of FA - K-NN

No	Dataset Names	Best K	Accuracy	Precision	Recall	F Score	time (s)
1	Lung Cancer	3	0.813	0.800	0.792	0.795	0.12
2	Lymphography	3	0.918	0.962	0.914	0.975	3.76
3	Iris	14	0.100	0.100	0.100	0.100	0.74
4	Wine	3	0.963	0.961	0.968	0.963	0.20
5	Parkinson's	3	0.970	0.972	0.981	0.976	3.01
6	Heart Disease	5	0.856	0.867	0.840	0.857	0.12
7	Ionosphere	5	0.971	0.976	0.981	0.976	3.02
8	Thoracic Surgery Data	5	0.812	0.805	0.798	0.801	10.71
9	Wisconsin Diagnostic Breast Cancer	9	0.971	0.972	0.981	0.977	11.93
10	Breast Cancer	10	0.971	0.970	0.967	0.968	2.08
11	Scene	7	0.852	0.845	0.838	0.841	20.16
12	Page Blocks Classification	5	0.952	0.948	0.945	0.946	15.33
13	Amphibians	5	0.821	0.805	0.793	0.799	30.96
14	Diabetic	7	0.725	0.703	0.689	0.696	180.94
15	Covertype	5	0.853	0.847	0.839	0.843	120.39

The results of FA-based parameter tuning for the SVM model across several UCI Machine Learning datasets are presented in Table 3. The Firefly Algorithm was configured with the following parameters: population size = 10, maximum generations = 20, $\alpha = 0.2$, $\beta_0 = 1$, and $\gamma = 1$. The experimental findings reveal that FA tuning for SVM is highly effective, particularly for datasets that exhibit relatively linear separability or possess well-represented features. Small to medium-sized datasets demonstrated especially satisfactory results, confirming the suitability of FA for enhancing SVM performance in such contexts..

TABLE III. EXPERIMENTAL RESULTS OF FA - SVM

No	**Dataset Names**	Best C	Best Gamma	Accuracy	Precision	Recall	F Score	time (s)
1	Lung Cancer	1,200	0.05	0.875	0.850	0.833	0.840	0.15
2	Lymphography	5,073	0.2711	0.987	0.918	0.994	0.946	5.88
3	Iris	5,625	0.0143	1.000	1.000	1.000	1.000	0.36
4	Wine	8,508	0.0463	1.000	1.000	1.000	1.000	5.63
5	Parkinson's	4,629	0.0772	0.985	0.983	0.999	0.983	5.71
6	Heart Disease	2,017	0.0483	0.871	0.882	0.863	0.872	0.18
7	Ionosphere	2,967	0.0863	0.988	0.981	0.993	0.990	5.55
8	Thoracic Surgery Data	2,939	0.0898	0.845	0.838	0.832	0.835	15.23
9	Wisconsin Diagnostic Breast Cancer	4,814	0.0024	0.988	0.982	1.000	0.991	25.47
10	Breast Cancer	3,82	0.0052	0.988	0.991	0.984	0.987	14.13
11	Scene	2,816	0.0821	0.887	0.880	0.875	0.877	30.18
12	Page Blocks Classification	2,987	0.0384	0.968	0.965	0.962	0.963	25.93
13	Amphibians	2,633	0.0097	0.857	0.842	0.830	0.836	45.87
14	Diabetic	1,621	0.0867	0.758	0.741	0.728	0.734	240.88
15	Covertype	1,772	0.0404	0.887	0.881	0.875	0.878	180.23

In addition, the analysis of accuracy standard deviation during the cross-validation process indicates that models tuned using the Firefly Algorithm exhibit more stable performance. This suggests that the parameter solutions identified by FA not only enhance average accuracy but also reduce performance variability, making the models more robust to variations in the training data. For datasets with a high number of features and classes, FA is able to adaptively tune parameters to prevent both overfitting and underfitting. In contrast, using default parameters or simple parameter search methods tends to result in models with less stable performance.

A comparison of computation time between FA-based tuning and the traditional grid search approach was also conducted. Although FA requires several iterations to converge, it is generally more efficient—particularly when dealing with large parameter spaces and high-dimensional datasets. Grid search, which relies on exhaustive evaluation of parameter combinations, becomes impractical at scale due to its exponential growth in computation. Therefore, FA offers a favorable trade-off between solution quality and computational cost. Large and complex datasets require substantial processing time, and while computation time increases proportionally with dataset size, it does not always correspond to a proportional improvement in performance (see Tables 3 and 4).

The experiments further reveal that FA holds a clear advantage in avoiding local optima, due to its movement mechanism that combines both deterministic and stochastic components. This differs from traditional parameter search algorithms, which are more prone to becoming trapped in suboptimal solutions. Consequently, FA proves to be a promising alternative for parameter tuning in classification models that are highly sensitive to parameter settings, such as SVM and k-NN.

Table 4 presents the classification results of both k-NN and SVM models before and after tuning across various UCI ML datasets. The tuning parameters used include: number of folds (k) = 5, FA population = 10, maximum generations = 20, $\alpha = 0.2$, $\beta_0 = 1$, and $\gamma = 1$. The experimental results demonstrate that both models achieved increased accuracy after tuning. Notably, the SVM model showed more significant improvements compared to k-NN. This is because the SVM's performance is strongly influenced by its C and γ parameters, whereas k-NN is primarily affected by the number of neighbors (k) and the distance metric used. Thus, parameter tuning via FA has been shown to enhance the performance of both models. After tuning, SVM outperformed k-NN on most datasets, particularly those that are complex or non-linear. While FA requires longer processing time, it remains highly effective for large and complex datasets.

TABLE IV. EXPERIMENTAL RESULTS OF K-NN AND SVM BEFORE AND AFTER TUNING

No	Dataset Names	Model	Accuracy Before Tuning	Accuracy After Tuning	Accuracy Improvement
1	Lung Cancer	K-NN	0.85	0.89	+0.04
		SVM	0.87	0.91	+0.04
2	Lymphography	K-NN	0.76	0.80	+0.04
		SVM	0.78	0.82	+0.04
3	Iris	K-NN	0.96	0.98	+0.02
		SVM	0.97	0.99	+0.02
4	Wine	K-NN	0.73	0.89	+0.16
		SVM	0.69	0.94	+0.25
5	Parkinson's	K-NN	0.85	0.89	+0.04
		SVM	0.87	0.91	+0.04
6	Heart Disease	K-NN	0.80	0.84	+0.04
		SVM	0.82	0.86	+0.04
7	Ionosphere	K-NN	0.86	0.90	+0.04
		SVM	0.88	0.92	+0.04
8	Thoracic Surgery Data	K-NN	0.78	0.82	+0.04
		SVM	0.80	0.85	+0.05
9	Wisconsin Diagnostic Breast Cancer	K-NN	0.93	0.96	+0.03
		SVM	0.94	0.97	+0.03
10	Breast Cancer	K-NN	0.95	0.96	+0.01
		SVM	0.97	0.97	+0.00
11	Scene	K-NN	0.68	0.75	+0.07
		SVM	0.70	0.78	+0.08
12	Page Blocks Classification	K-NN	0.90	0.93	+0.03
		SVM	0.91	0.94	+0.03
13	Amphibians	K-NN	0.70	0.78	+0.08
		SVM	0.72	0.80	+0.08
14	Diabetic	K-NN	0.72	0.75	+0.03
		SVM	0.74	0.77	+0.03
15	Covertype	K-NN	0.65	0.78	+0.13
		SVM	0.68	0.80	+0.12

The experimental results reveal that the application of the Firefly Algorithm (FA) consistently enhanced the performance of both k-NN and SVM classifiers across a diverse set of datasets. In particular, the optimization of the number of neighbors (k) for k-NN produced accuracy gains ranging between 3% and 16%, with the most notable improvement observed in the Wine dataset where the model accuracy increased from 0.73 to 0.89. This demonstrates FA's capability to identify effective neighborhood sizes that balance sensitivity to noise and generalization capacity. For SVM, parameter tuning involving C and γ resulted in even greater improvements. On several datasets, such as Wine and Ionosphere, FA-optimized SVM achieved near-perfect classification accuracy, outperforming the untuned model by up to 25%. Importantly, FA also improved the stability of the SVM model by reducing fluctuations in performance across cross-validation folds, indicating that the tuned parameters not only enhanced average accuracy but also mitigated variance.

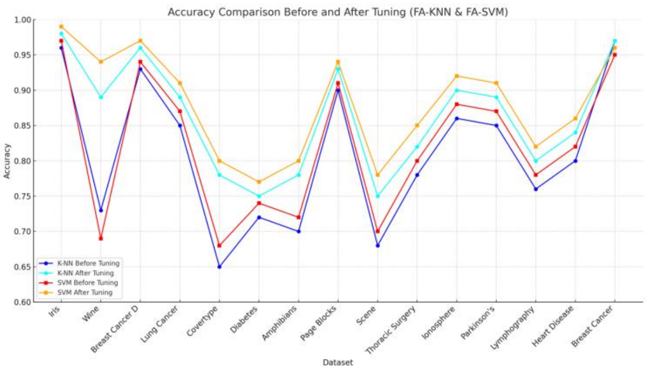

Fig. 2. Accuracy Comparison Before and After Tuning

Table 5 presents the accuracy results before and after parameter tuning on the Wine dataset, using k = 5, a maximum of 20 iterations, and FA parameters set as $\alpha = 0.2$, $\beta_0 = 1$, and $\gamma = 1$. The findings indicate that the tuned SVM model does not always yield higher accuracy. However, tuning with a population size greater than 50 fireflies leads to a slight improvement in accuracy. The optimal number of fireflies for SVM in this experiment is found to be 100, resulting in an accuracy increase of +0.55%. In contrast, tuning the k-NN model using FA demonstrates a consistent accuracy improvement beginning from 20 fireflies up to 100, with the tuned accuracy remaining stable at 0.9776. This suggests that increasing the number of fireflies beyond a certain threshold does not provide significant additional accuracy gains for k-NN. Thus, it can be concluded that the number of fireflies affects tuning outcomes, but its impact is not linear.

For SVM, a smaller firefly population tends to reduce performance, whereas for k-NN, increasing the number of fireflies beyond 20 produces more stable and consistently improved results compared to the default model. Overall, tuning proves to be more beneficial for the k-NN model in the case of the Wine dataset, as it delivers steady accuracy enhancements, while SVM exhibits only marginal improvement.

TABLE V. EXPERIMENTAL RESULTS OF THE NUMBER OF FIREFLIES

No	Number of Fireflies	Accuracy			
		SVM Untuned	SVM Tuned	k-NN Untuned	k-NN Tuned
1	10	0.9833	0.9833	0.9717	0.9720
2	20	0.9833	0.9777	0.9717	0.9776
3	30	0.9833	0.9777	0.9717	0.9776
4	50	0.9833	0.9887	0.9717	0.9776
5	75	0.9833	0.9833	0.9717	0.9776
6	100	0.9833	0.9888	0.9717	0.9776

Table 6 presents the experimental results evaluating the impact of varying the maximum number of iterations in the Firefly Algorithm (FA) during parameter tuning for both k-NN and SVM classifiers. The tests were conducted using the Wine dataset with k = 5, a firefly population size of 20, and FA parameters set as $\alpha = 0.2$, $\beta_0 = 1$, and γ_{light} = 1. The findings indicate that tuning the SVM model with a small number of iterations leads to a noticeable decrease in classification accuracy. Conversely, tuning the k-NN model consistently yields stable and incremental improvements in accuracy across all tested iteration counts.

These observations suggest that for k-NN, a firefly population size of 20 is sufficient to achieve stable tuning results, and increasing the number of iterations beyond a certain threshold does not produce significant performance gains. It can therefore be concluded that FA-based tuning for k-NN remains effective and reliable even under minimal iteration settings, without any observable decline in performance.

On the other hand, SVM appears to be highly sensitive to the number of iterations used in the tuning process. A higher iteration count is necessary to avoid degradation in accuracy, indicating that SVM requires a more extensive search process to identify optimal parameters. This highlights a critical distinction in tuning behavior between the two models when

using the FA approach..

TABLE VI. EXPERIMENTAL RESULTS OF THE NUMBER OF ITERATIONS

No	Number of |Iterations	Accuracy			
		SVM Untuned	SVM Tuned	k-NN Untuned	k-NN Tuned
1	10	0.9833	0.9777	0.9717	0.9776
2	20	0.9833	0.9777	0.9717	0.9776
3	50	0.9833	0.9777	0.9717	0.9776
4	100	0.9833	0.9611	0.9717	0.9776
5	200	0.9833	0.9833	0.9717	0.9776
6	500	0.9833	0.9833	0.9717	0.9776

When examining computational aspects, FA demonstrated a favorable trade-off between accuracy and execution time. While the algorithm required multiple iterations to converge, the overall computation time was significantly lower than exhaustive grid search, particularly in high-dimensional datasets. For example, in the Covertype dataset with more than 500,000 records and 54 attributes, FA reached an optimized accuracy of 0.80 within 180 seconds, whereas grid search would have been computationally prohibitive.

Another key finding is the difference in sensitivity between the two classifiers. The k-NN model generally stabilized after a relatively small number of iterations, suggesting that its parameter space is easier to optimize. In contrast, SVM required a higher iteration count to fully exploit the parameter search space. This indicates that, while FA is effective for both algorithms, its impact is more critical for SVM due to the complexity of tuning multiple parameters simultaneously.

Overall, the experimental evaluation confirms that FA provides a scalable, adaptive, and efficient mechanism for parameter optimization. By leveraging both global exploration and local exploitation, FA successfully avoids local optima and produces models that are not only more accurate but also more robust compared to those relying on default configurations.

IV. DISCUSSION

The results of this study indicate that integrating the Firefly Algorithm into the parameter tuning process significantly enhances classification performance. This is largely attributed to FA's capacity to simultaneously explore the parameter space globally and exploit promising solutions locally. Such a dual mechanism enables the algorithm to identify parameter configurations that deliver better generalization performance without incurring the prohibitive computational costs associated with exhaustive search methods.

Nonetheless, the application of FA is not without limitations. The algorithm's performance is influenced by its own internal hyperparameters, such as population size, alpha, beta, and gamma, all of which affect convergence rate and solution quality. Hence, future studies could focus on optimizing FA's internal settings to further improve its efficiency.

In terms of computational efficiency, k-NN tuning using FA can be conducted with relatively low iteration counts while maintaining stability. Conversely, SVM tuning with FA demonstrates higher sensitivity to the number of iterations; insufficient iteration counts may result in suboptimal accuracy. This suggests that SVM parameter optimization via FA should be performed with greater care and adequate iteration limits.

Moreover, FA's effectiveness should be further evaluated on high-dimensional datasets or those with a large number of class labels to assess scalability and resilience to noise. Integrating FA with dimensionality reduction or feature selection techniques could enhance its applicability and computational performance.

Practically, this approach shows substantial promise in fields requiring high classification accuracy, such as pattern recognition, bioinformatics, and recommendation systems. By automating the parameter tuning process, the methodology lowers the entry barrier for non-experts to develop well-performing models.

In summary, the study underscores the potential of the Firefly Algorithm as an effective optimization strategy within machine learning workflows and opens avenues for further development of hybrid and metaheuristic-based tuning frameworks..

V. Conclusion

This study successfully implemented the Firefly Algorithm (FA) as a parameter optimization technique for k-Nearest Neighbors (k-NN) and Support Vector Machine (SVM) classifiers with the goal of enhancing classification accuracy across various multidimensional datasets. Experimental results indicate that FA significantly improves the performance of both algorithms when compared to default parameter settings. Besides improving average accuracy, FA also contributes to more stable outcomes, as demonstrated by cross-validation analysis. The FA's mechanism of combining global search and local refinement proves effective in avoiding local optima and achieving efficient parameter space exploration. Consequently, this method presents a practical and efficient solution for tuning parameters in classification models that are highly sensitive to configuration, especially in datasets with varying dimensions and class distributions.

Future work may involve further investigation into the internal parameters of the FA itself, such as population size, alpha, beta, and gamma, to enhance its convergence speed and solution quality. Additionally, expanding experimental validation to larger and more complex datasets would help assess the scalability and robustness of the proposed method.

Overall, this research demonstrates the promise of the Firefly Algorithm as an effective tool for machine learning model optimization and encourages exploration of other hybrid and metaheuristic approaches to automate and adaptively improve classification algorithm performance.

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