A Firefly Optimization Algorithm for Hyperparameter Tuning of the Support Vector Classifier to Predict Water Potability

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ABSTRACT

Clean water is essential for human health and life, and assessing its potability is critical for safeguarding public well-being. Machine Learning (ML) algorithms have been widely used for water potability classification based on various water quality parameters. However, the performance of these models

strongly depends on effective hyperparameter tuning, which remains both challenging and resource-intensive. This study addresses this issue by proposing the Firefly Optimization Algorithm (FOA) to optimize the Support Vector Classifier (SVC) for water potability classification. Traditional hyperparameter tuning methods, such as GridSearchCV and RandomizedSearchCV, often lack the efficiency and effectiveness needed for achieving optimal model performance. In contrast, the proposed FOA-based approach provides a robust solution, demonstrating superior results compared with traditional methods. Model performance was evaluated using accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). The FOA-tuned SVC achieved an accuracy of 0.6773 and an AUC of 0.7065, outperforming models tuned with conventional methods. These findings highlight the potential of nature-inspired optimization techniques, such as the Firefly algorithm, to enhance ML model performance and offer a promising approach to water potability classification.

Keywords-nature inspired optimization; classification; hyper paramter tuning; firefly optimization; machine learning

I. INTRODUCTION

Safe drinking water is a fundamental human right, yet billions of people still lack safely managed drinking water and sanitation services, resulting in severe health consequences and economic losses [1]. Contaminated water sources are attributed mostly to waterborne diseases, especially in developing countries [2, 3], while conventional water quality monitoring relies on chemical and microbiological analyses, which, despite their accuracy, are time-consuming, labor-intensive, and often unavailable in remote regions [4]. These limitations underscore the need for automated and efficient methods capable of reliably predicting water potability, thereby reducing dependence on costly laboratory testing.

Machine Learning (ML) offers a promising alternative by enabling prediction from easily measurable water properties. Such models support the prioritization and allocation of resources, improving efficiency in water quality monitoring [5-7], and have already demonstrated strong potential in water quality prediction [8]. By leveraging large datasets, ML models can detect patterns in parameters such as pH, turbidity, dissolved oxygen, and microbial content, classifying water as potable or non-potable with high accuracy [9]. Among these models, Support Vector Classifiers (SVCs) are notable for their ability to handle high-dimensional and complex data [10]. However, SVC performance is highly dependent on hyperparameters such as kernel choice, regularization parameter (C), and gamma (γ), which strongly affect decision boundaries and generalization capacity [11]. Manual hyperparameter tuning is typically inefficient and suboptimal, making advanced optimization strategies essential.

Conventional hyperparameter optimization methods, such as GridSearchCV and RandomSearchCV, are computationally expensive and lack adaptability. In contrast, biologically inspired metaheuristic algorithms, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and the Firefly Optimization Algorithm (FOA), have attracted significant attention for their ability to efficiently explore high-dimensional search spaces while avoiding local minima [12]. Inspired by the bioluminescent communication of fireflies, FOA has demonstrated strong performance in solving complex optimization problems by balancing exploration and exploitation [13], making it a promising candidate for ML hyperparameter tuning.

Despite this progress, challenges remain in applying ML models to water potability prediction. Models are often prone to overfitting, especially with small or imbalanced datasets, limiting generalizability. Furthermore, the black-box nature of most ML approaches restricts interpretability and reduces trust in decision-making.

Recent research has shown the effectiveness of metaheuristic optimization. Authors in [14] applied GA to optimize ML models for coronary heart disease prediction, improving classification accuracy in complex parameter spaces. Similarly, authors in [15] emphasized the need for automated hyperparameter tuning, highlighting the promise of bio-inspired algorithms like FOA in reducing computational costs while maintaining accuracy. Authors in [16] demonstrated the applicability of metaheuristic optimization in enhancing Convolutional Neural Networks (CNNs), while authors in [17] showed that swarm intelligence techniques significantly improve deep learning model performance. These findings suggest that FOA can likewise enhance SVC-based water potability classification.

Besides hyperparameter optimization, ML performance optimization is also a persistent challenge. In breast cancer classification, achieving high sensitivity and specificity remains challenging [18], while evolutionary algorithms have been applied successfully in other domains [19]. Such issues are equally critical in water quality prediction, where misclassifications carry serious real-world implications. Trade-offs between computational cost and accuracy have been reported [20], while well-optimized hyperparameters have been shown to substantially improve ensemble learning outcomes [21]. Moreover, recently developed bio-inspired algorithms, including the Hippopotamus Optimization (HO) Algorithm [22], Beagle-Inspired Optimization Algorithm (BIOA) [23], and Artificial Eagle-Inspired Optimization (AEIO) Algorithm [24], offer further opportunities to improve optimization in high-dimensional tasks. Nevertheless, metaheuristic algorithms still face challenges such as high computational cost, slow convergence, and risks of overfitting. However, hybrid optimization frameworks, combining multiple algorithms, have shown promise in mitigating these limitations [25].

The present study applies FOA to optimize SVC hyperparameters for water quality assessment, aiming to improve classification accuracy at minimal computational cost.

II. PROPOSED METHODOLOGY

A. Dataset Description

The dataset employed in this study consists of water quality measurements structured for a supervised learning task [26]. The input feature set, denoted as $X = \{x_1, x_2, \ldots, x_n\}$, comprises nine numerical attributes: pH, hardness, solids, chloramines, sulfate, conductivity, organic carbon, trihalomethanes, and turbidity. These attributes are fundamental indicators of water quality, impacting its potability. The corresponding target variable y represents a binary classification problem, where $y = 1$ denotes potable water and $y = 0$ signifies non-potable water. The water potability dataset originally contained 3,276 datapoints, and after removing null values, 2,011 samples remain, with 811 potable water samples and 1,200 non-potable water samples. The class imbalance, with potable water constituting about 40% of the data, is moderate and does not necessitate strict balancing.

Feature relevance analysis using mutual information and random forest (Figure 1) demonstrates that all attributes provide valuable contributions to classification performance. While turbidity exhibits relatively low importance, its inclusion or exclusion has a negligible effect on overall model accuracy. This confirms that the dataset serves as a suitable benchmark for evaluating hyperparameter optimization techniques in supervised ML models.

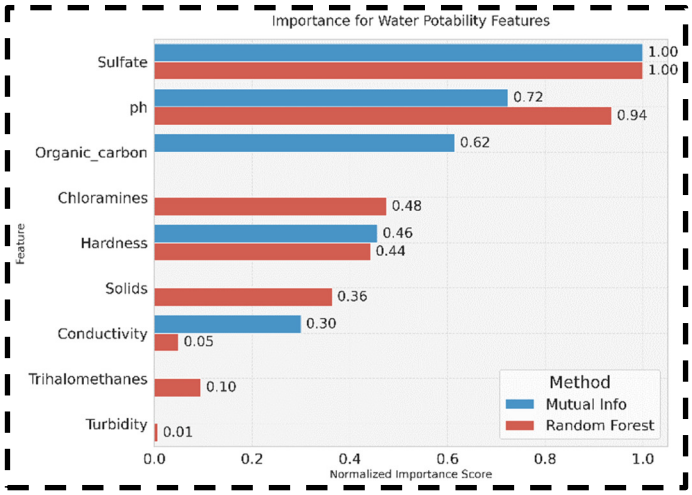

Fig. 1. Feature importance plot.

B. Architecture of the Proposed Work

This study proposes a comprehensive pipeline for water potability classification that systematically compares three hyperparameter optimization approaches while maintaining identical evaluation protocols. The overall architecture is illustrated in Figure 2.

The process begins with raw water quality measurements $X = (x_1, \ldots, x_n)$ comprising n water quality parameters. Data are normalized and cleaned using standard preprocessing techniques to ensure comparability across features. For scaling the continuous variable features, z-score normalization (scikit-learn StandardScaler) was used. A three-fold stratified splitting mechanism preserves the original distribution of potable ($y = 1$) and non-potable ($y = 0$) samples in both training and test sets, a critical step for reliable evaluation given the dataset's inherent imbalance. In each fold, approximately 66.7% of the data were used for training and 33.3% for validation; consequently, each sample served as validation exactly once and as training twice. The modular design of the pipeline also allows flexible substitution of preprocessing components while maintaining consistency throughout subsequent stages.

Given the variability in feature distributions and the presence of nonlinear dependencies in the dataset, hyperparameter tuning is critical to improving classification accuracy by refining decision boundaries. Mathematically, let Θ represent the set of hyperparameters governing a model $f(X; \Theta)$, where X denotes the input feature matrix. An optimal configuration Θ^* is determined by maximizing an objective function $J(\Theta)$ as shown in (1), where:

$$\Theta^* = \arg\max_{\Theta} J(\Theta) \quad (1)$$

The hyperparameters optimized were:

- Regularization parameter C: Controls the trade-off between maximizing the margin and minimizing classification error.
- Kernel coefficient γ: Defines the influence of training samples on model decision boundaries.
- Kernel type: Determines the transformation of the input space for better separation of classes.

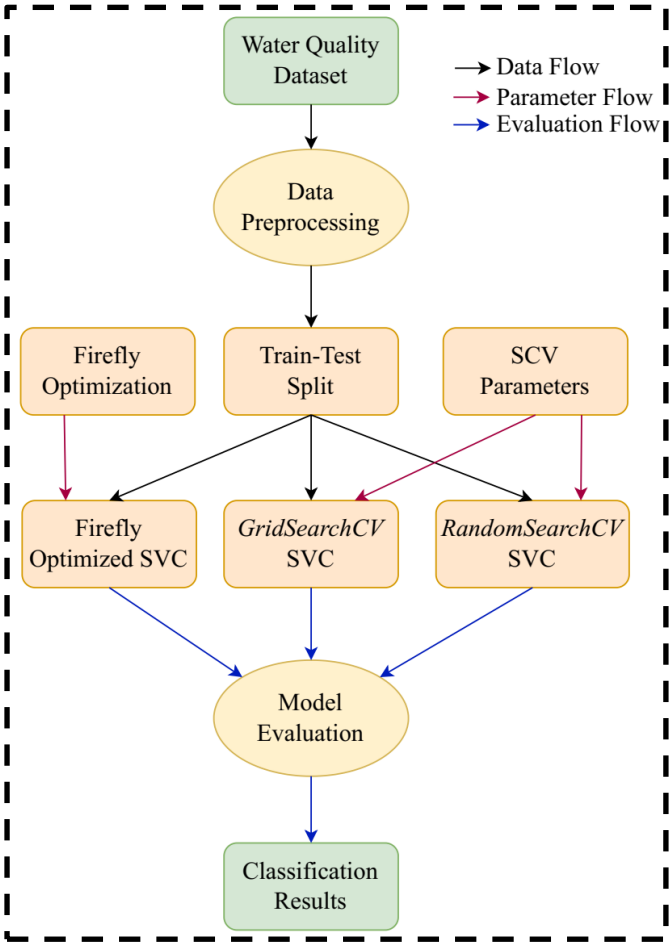

Fig. 2. Architecture showing different hyperparameter tuning methods.

Three parallel optimization methods are employed to tune the SVC's hyperparameters: the proposed FOA, and for comparison GridSearchCV, and RandomSearchCV. GridSearchCV exhaustively evaluates all parameter combinations within predefined ranges, whereas RandomSearchCV samples the parameter space stochastically. In contrast, the bio-inspired FOA branch dynamically adjusts these parameters by simulating firefly attraction behaviour, where solutions with higher accuracy emit stronger "light" I to guide the search process. The movement of a firefly i towards firefly j is governed by (2):

$$x_i = x_i + \beta e^{-\gamma r_{ij}^2}(x_j - x_i) + \alpha\varepsilon \quad (2)$$

where:

- β is the attractiveness at distance $r = 0$,
- γ is the light absorption coefficient,
- r_{ij} is the Euclidean distance between fireflies i and j,
- α is a randomization parameter,
- ε is a random number drawn from a Gaussian distribution.

The randomization term $\alpha\varepsilon$ prevents premature convergence by introducing exploratory behavior. The brightness of a firefly is calculated using the classification accuracy:

$$F = \frac{1}{1+\text{Classification Error}} \quad (3)$$

where:

$$\text{Classification Error} = 1 - \text{Accuracy}$$

Thus, F inversely relates classification error to fitness, ensuring that models with lower error yield higher fitness values. This relationship helps guide the algorithm toward better-performing solutions by naturally favoring them during the optimization process. The proposed FOA algorithm used is presented below.

```
Algorithm 1: FOA for Hyperparameter Tuning
Input: Initialize fireflies with random
hyperparameter values within defined
ranges;
Output: Evaluate fitness of each firefly
using classification accuracy on
validation set;
1. for t ← 1 to T do
2.  for each firefly i do
3.   for each firefly j ≠ i do
4.   if F_i < F_j (Firefly j is brighter) then
5.   Move firefly i towards firefly j using
     attraction formula;
6.   Introduce a small randomization
     component to enhance exploration;
7.   End if
8.   End for
9.  End for
10. Re-evaluate fitness of all fireflies;
11. Update best-found solution;
12. end
13. return best hyperparameter combination
    (C, γ, kernel*);
```

The details of the hyperparameter search space and convergence criteria are summarized in Table I. For the SVC, the regularization parameter C was searched within the range [0.1, 100], and the kernel coefficient γ within [0.0001, 1], with the kernel type fixed as Radial Basis Function (RBF) based on its strong performance in preliminary testing. The FOA was configured with 20 fireflies and executed for 10 iterations, with the best solution updated whenever an improvement was identified. To ensure robust performance estimation, stratified 5-fold cross-validation was employed. Convergence was determined by a fixed number of iterations rather than a tolerance-based stopping rule, thereby ensuring consistency across experiments.

TABLE I. HYPERPARAMETER SEARCH SPACE BOUNDARIES AND CONVERGENCE CRITERIA

Parameter/Resource	Value/Description
C	Lower Bound: 0.1 Upper Bound: 100
γ	Lower Bound: 0.0001

	Upper Bound: 1
kernel	RBF
Number of fireflies	20
Number of iterations	10
Cross-validation	StratifiedKFold, 5 splits, shuffle=True, random_state=42
Convergence Criteria	Fixed number of iterations (10); best solution updated if improved
Hardware	Intel Core i7 CPU, 16GB RAM.
Average Runtime	2 to 3 minutes per run (Google Colab environment)
Software Environment	Python 3.x, scikit-learn, numpy

All experiments were conducted on a system equipped with an Intel Core i7 Central Processing Unit (CPU) and 16GB Random Access Memory (RAM), with an average runtime of approximately two to three minutes per optimization run. The implementation utilized Python 3.x with the scikit-learn and numpy libraries.

C. Evaluation Metrics

During evaluation, all three optimized classifiers are tested on previously unseen data using complementary performance metrics. Standard classification measures, including accuracy, precision, recall, and F1-score, are computed alongside Receiver Operating Characteristic (ROC) curve analysis to assess robustness across decision thresholds. Accuracy, defined as the proportion of correctly classified instances to the total number of instances, is given in (4):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

where TP represents true positives, TN true negatives, FP false positives, and FN false negatives. Precision, defined in (5), measures the fraction of correctly identified positive instances:

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

Recall, which represents the model's ability to identify all relevant instances, is expressed in (6):

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

The F1-score, the harmonic mean of precision and recall, is given in (7):

$$F1 = 2\frac{Precision*Recall}{Precision+Recall} \quad (7)$$

Additionally, the ROC Area Under the Curve (AUC) quantifies the model's capacity to distinguish between classes.

III. RESULTS AND DISCUSSION

The primary objective of this study is to optimize the performance of the SVC using the FOA and to compare its results with traditional hyperparameter tuning techniques, namely GridSearchCV and RandomizedSearchCV. The performance metrics of the three approaches are summarized in Table II.

TABLE II. PERFORMANCE METRICS OF HYPERPARAMETER OPTIMIZATION TECHNIQUES

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
GridSearchCV	59.32	48.84	18.13	26.44
RandomizedSearchCV	67.38	70.98	33.79	45.78
FOA	67.73	69.62	33.91	45.61

The GridSearchCV method achieved an accuracy of 0.5932, with a precision of 0.4884, a recall of 0.1813, and an F1-score of 0.2644. The best hyperparameters determined by this method were $C = 100$ and $\gamma = 0$. RandomizedSearchCV improved these results, achieving an accuracy of 0.6738, a precision of 0.7098, a recall of 0.3379, and an F1-score of 0.4578, with optimal hyperparameters at $C = 56.1034$ and $\gamma = 1.0$. The proposed FOA achieved a comparable accuracy of 0.6773, with a precision of 0.6962, a recall of 0.3391, and an F1-score of 0.4561. The best hyperparameters discovered were $C = 1$ and $\gamma = 0.1$ FOA outperforms GridSearchCV with a 14.18% increase in accuracy, 42.55% higher precision, an 87.04% improvement in recall, and a 72.50% improvement in F1-score, demonstrating substantially enhanced robustness. These results suggest that while RandomizedSearchCV and FOA perform similarly in recall and F1-score, FOA provides a more structured and deterministic optimization process, ensuring stability in hyperparameter selection.

An ROC-AUC-based comparative analysis further demonstrates FOA's efficiency. The AUC achieved with FOA was 0.7065, slightly exceeding that of GridSearchCV (0.7061), whereas RandomizedSearchCV yielded a lower AUC of 0.6068. The proximity of FOA and GridSearchCV in terms of AUC indicates that both techniques produce well-calibrated classification models, while the lower AUC of RandomizedSearchCV highlights weaker class separation. Figure 3 shows the ROC curves of all methods, revealing that FOA achieves the strongest discriminative power.

The confusion matrix in Figure 4 for the FOA-tuned SVC shows that 1,088 non-potable samples were correctly classified as unsafe, while 112 potable samples were incorrectly classified as safe. Additionally, 274 potable samples were correctly identified as safe, but 537 potable samples were misclassified as unsafe. These results indicate that the model operates at a safety-first decision point, prioritizing a very low false-positive rate. This substantially reduces the risk of misclassifying unsafe water as safe, which is critical for public-health protection. The trade-off is a higher false-negative rate, where some potable samples are conservatively withheld. Such an operating point is well-suited for screening applications where minimizing false assurance is paramount, and strong specificity for non-potable detection provides the most practical outcome for deployment.

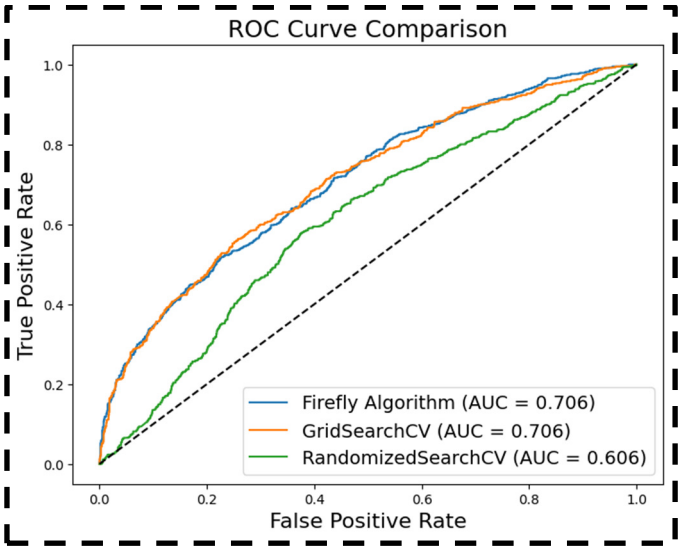

Fig. 3. ROC curves for different hyperparameter tuning methods.

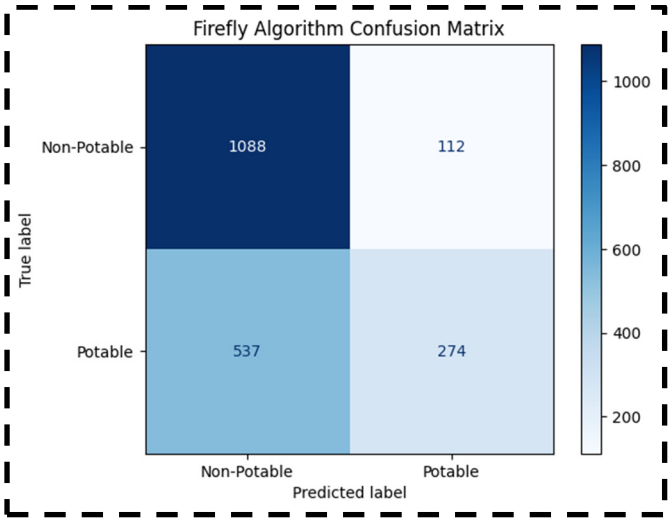

Fig. 4. Confusion matrix of SVC hyperparameter tuned with FOA.

Overall, FOA proves to be an effective hyperparameter tuning procedure by delivering competitive classification performance across all metrics. It provides deterministic optimization without compromising generalization and serves as an efficient alternative to conventional approaches such as GridSearchCV and RandomizedSearchCV. Its capability to optimize SVC for the binary water potability classification task demonstrates improved predictive accuracy and robustness.

A. Integration with Emerging Metaheuristics

Recent advancements in nature-inspired metaheuristic optimization techniques, such as HO [22], BIOA [23], and AEIO [24], offer promising avenues to further enhance hyperparameter search. These methods are designed to balance exploration and exploitation in high-dimensional spaces and can be integrated as drop-in optimizers to yield improved configurations of C, γ, kernel type, class weights, and decision functions. Their enhanced search capabilities may result in higher accuracy, improved F1-score and balanced accuracy, faster convergence, and increased robustness to noisy or imbalanced data.

The limitations of FOA can be addressed by extending its application to multiclass classification problems using one-versus-rest or one-versus-one strategies, as well as by exploring kernel–regularization interactions. Extending the presented binary pipeline to multiclass SVC requires only replacing the classifier wrapper while maintaining the optimizer interface, thereby enabling joint hyperparameter tuning and calibration. Future work will benchmark FOA against HO, BIOA, and AEIO under identical search spaces and computational budgets.

IV. CONCLUSION

This study proposes a novel hyperparameter optimization technique for Support Vector Classifier (SVC) using the Firefly Optimization Algorithm (FOA). Experimental results demonstrate that FOA outperforms conventional methods such as GridSearchCV and RandomizedSearchCV, identifying optimal hyperparameters that improve classification accuracy, precision, recall, and F1-score. FOA also achieves the highest Area Under the Curve (AUC), indicating superior discriminative power. By effectively balancing exploration and exploitation, FOA provides an efficient and organized search process for Machine Learning (ML) hyperparameter tuning.

Future research may explore hybrid approaches, combining FOA with other metaheuristics such as Genetic Algorithms (GA) or Particle Swarm Optimization (PSO), to further enhance performance. Extending FOA to deep learning models and more complex classification problems will provide deeper insight into its capabilities. Given its adaptability, robustness, and ability to avoid local optima, FOA and similar nature-inspired optimization algorithms are highly suitable for broader adoption across domains, including bioinformatics, financial modeling, image and signal processing, cybersecurity, and industrial process optimization. Embracing these biologically inspired techniques can enable the development of more accurate, scalable, and intelligent systems. Future work should also focus on adaptive optimization strategies tailored to problem-specific characteristics, facilitating the creation of efficient and generalizable models for real-world applications.

REFERENCES

[1] Q. Liu, M. Liu, and J. Liu, "Global associations between the use of basic drinking water and sanitation services with diarrhoeal disease incidence in 200 countries and territories from 2000 to 2019," *Public Health*, vol. 235, pp. 202–210, Oct. 2024, https://doi.org/10.1016/j.puhe.2024.07.004.

[2] N. Forstinus, N. Ikechukwu, M. Emenike, and A. Christiana, "Water and Waterborne Diseases: A Review," *International Journal of TROPICAL DISEASE & Health*, vol. 12, no. 4, pp. 1–14, Jan. 2016, https://doi.org/10.9734/IJTDH/2016/21895.

[3] N. U. H. Shar, G. Q. Shar, A. R. Shar, S. M. Wassan, Z. Q. Bhatti, and A. Ali, "Health Risk Assessment of Arsenic in the Drinking Water of Upper Sindh, Pakistan," *Engineering, Technology & Applied Science Research*, vol. 11, no. 5, pp. 7558–7563, Oct. 2021, https://doi.org/10.48084/etasr.4336.

[4] S. A. Sani, "Drawbacks of Traditional Environmental Monitoring Systems," *TMP Universal Journal of Research and Review Archives*, vol. 2, no. 2, Jul. 2023, https://doi.org/10.69557/ujrra.v2i2.47.

[5] F. Feng *et al.*, "Machine learning to assess and support safe drinking water supply: a systematic review," *Journal of Environmental Chemical Engineering*, vol. 13, no. 1, Feb. 2025, Art. no. 114481, https://doi.org/10.1016/j.jece.2024.114481.

[6] E.-B. Rachid, S. Abderrahim, A. Hafid, and R. Souad, "Predicting water potability using a machine learning approach," *Environmental Challenges*, vol. 19, Jun. 2025, Art. no. 101131, https://doi.org/10.1016/j.envc.2025.101131.

[7] K. M. K. Raghunath, S. B. Khan, P. Govindarajan, T. R. Mahesh, M. Alojail, and T. R. Gadekallu, "Machine learning-driven intelligent water quality assessment for enhanced drinking safety and real-time consumer awareness," *Hydrology Research*, vol. 56, no. 2, pp. 136–152, Feb. 2025, https://doi.org/10.2166/nh.2025.097.

[8] P. B. Kamath, G. Sharma, A. Bongale, D. Dharrao, and M. Seitshiro, "Exploratory Data Analysis and Water Potability Classification using Supervised Machine Learning Algorithms," *Engineering, Technology & Applied Science Research*, vol. 15, no. 2, pp. 20898–20903, Apr. 2025, https://doi.org/10.48084/etasr.8904.

[9] G. Bwire *et al.*, "The quality of drinking and domestic water from the surface water sources (lakes, rivers, irrigation canals and ponds) and springs in cholera prone communities of Uganda: an analysis of vital physicochemical parameters," *BMC Public Health*, vol. 20, no. 1, Dec. 2020, Art. no. 1128, https://doi.org/10.1186/s12889-020-09186-3.

[10] G. Masferrer, R. Carreras, M. Font-i-Furnols, M. Gispert, M. Serra, and P. Marti-Puig, "Automatic ham classification method based on support vector machine model increases accuracy and benefits compared to manual classification," *Meat Science*, vol. 155, pp. 1–7, Sep. 2019, https://doi.org/10.1016/j.meatsci.2019.04.018.

[11] R. Guido, M. C. Groccia, and D. Conforti, "A hyper-parameter tuning approach for cost-sensitive support vector machine classifiers," *Soft Computing*, vol. 27, no. 18, pp. 12863–12881, Sep. 2023, https://doi.org/10.1007/s00500-022-06768-8.

[12] X.-S. Yang, *Nature-inspired optimization algorithms*, 1st. edition. Amsterdam Waltham, MA: Elsevier, 2014.

[13] A. M. Bongale and C. R. Nirmala, "Firefly algorithm inspired energy aware clustering protocol for wireless sensor network," *International Journal of Communication Networks and Distributed Systems*, vol. 23, no. 3, 2019, Art. no. 380, https://doi.org/10.1504/IJCNDS.2019.101916.

[14] E. Y. Hidayat *et al.*, "Genetic Algorithm-based Convolutional Neural Network Feature Engineering for Optimizing Coronary Heart Disease Prediction Performance," *Healthcare Informatics Research*, vol. 30, no. 3, pp. 234–243, Jul. 2024, https://doi.org/10.4258/hir.2024.30.3.234.

[15] A. Mehdary, A. Chehri, A. Jakimi, and R. Saadane, "Hyperparameter Optimization with Genetic Algorithms and XGBoost: A Step Forward in Smart Grid Fraud Detection," *Sensors*, vol. 24, no. 4, Feb. 2024, Art. no. 1230, https://doi.org/10.3390/s24041230.

[16] D. N. Quoc and N. T. Tran, "Enhancing Accuracy for Classification Using the CNN Model and Hyperparameter Optimization Algorithm," *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, vol. 12, no. 3, pp. 575–582, Sep. 2024, https://doi.org/10.52549/ijeei.v12i3.5545.

[17] A. Bahrami, M. Rakhshaninejad, R. Ghousi, and A. Atashi, "Enhancing machine learning performance in cardiac surgery ICU: Hyperparameter optimization with metaheuristic algorithm," *PLOS ONE*, vol. 20, no. 2, Feb. 2025, Art. no. e0311250, https://doi.org/10.1371/journal.pone.0311250.

[18] R. H. Hridoy, A. D. Arni, S. K. Ghosh, N. R. Chakraborty, and I. Mahmud, "Performance enhancement of machine learning algorithm for breast cancer diagnosis using hyperparameter optimization," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, no. 2, Apr. 2024, Art. no. 2181, https://doi.org/10.11591/ijece.v14i2.pp2181-2190.

[19] R. Sorano, K. S. N. Ripon, and L. V. Magnusson, "Evolutionary Multi-objective Optimization of Hyperparameters for Decision Support in Healthcare," in *Handbook of Formal Optimization*, A. J. Kulkarni and A. H. Gandomi, Eds. Singapore: Springer Nature Singapore, 2024, pp. 155–180.

[20] E. C. Blessie, B. Sundaravadivazhagan, V. Kumutha, and V. Sumesh, "Predictive modeling of household power consumption using machine learning and meta-heuristic optimization technique," in *Machine Learning for Radio Resource Management and Optimization in 5G and Beyond*, 1st ed., Boca Raton: CRC Press, 2025, pp. 140–155.

[21] T.-Y. Hong and C.-C. Chen, "Hyperparameter optimization for convolutional neural network by opposite-based particle swarm optimization and an empirical study of photomask defect classification," *Applied Soft Computing*, vol. 148, Nov. 2023, Art. no. 110904, https://doi.org/10.1016/j.asoc.2023.110904.

[22] M. H. Amiri, N. Mehrabi Hashjin, M. Montazeri, S. Mirjalili, and N. Khodadadi, "Hippopotamus optimization algorithm: a novel nature-inspired optimization algorithm," *Scientific Reports*, vol. 14, no. 1, Feb. 2024, Art. no. 5032, https://doi.org/10.1038/s41598-024-54910-3.

[23] S. Vibhute, and C. Arage "A Novel Beagle Inspired Optimization Algorithm: Comprehensive Evaluation on Benchmarking Functions," *Journal of Information Systems Engineering and Management*, vol. 10, no. 35s, pp. 612–639, Apr. 2025, https://doi.org/10.52783/jisem.v10i35s.6042.

[24] H. Zhang, H. San, J. Chen, H. Sun, L. Ding, and X. Wu, "Black eagle optimizer: a metaheuristic optimization method for solving engineering optimization problems," *Cluster Computing*, vol. 27, no. 9, pp. 12361–12393, Dec. 2024, https://doi.org/10.1007/s10586-024-04586-1.

[25] J. Singh, J. K. Sandhu, and Y. Kumar, "Metaheuristic-based hyperparameter optimization for multi-disease detection and diagnosis in machine learning," *Service Oriented Computing and Applications*, vol. 18, no. 2, pp. 163–182, Jun. 2024, https://doi.org/10.1007/s11761-023-00382-8.

[26] *Water Quality and Potability.* (2023), L. Tharmalingam. [Online]. Available: https://www.kaggle.com/datasets/uom190346a/water-quality-and-potability.