

Optimizing Breast Cancer Classification with Metaheuristic Feature Selection: A Comparative Study of Bacterial Foraging, Emperor Penguin, and Hybrid Bacterial Foraging-Emperor Penguin Algorithms

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Breast cancer classification is crucial for timely and effective treatment, yet its accuracy largely depends on selecting the most relevant features from complex datasets. This study proposes a metaheuristic-based feature selection framework to optimize breast cancer classification accuracy, comparing three approaches: the Bacterial Foraging Optimization Algorithm (BFOA), the Emperor Penguin Optimizer (EPO), and a novel hybrid algorithm combining BFOA and EPO. The performance of these algorithms is evaluated using various breast cancer datasets, employing metrics such as classification accuracy, precision, and computational efficiency. Results demonstrate that the hybrid algorithm outperforms the individual BFOA and EPO methods by achieving a higher accuracy rate and reducing feature redundancy. This study underscores the potential of hybrid metaheuristic techniques in enhancing medical diagnostics and presents a viable solution for efficient feature selection in breast cancer classification.

Keywords: Breast Cancer Classification, Feature Selection, Bacterial Foraging Optimization, Emperor Penguin Optimizer, Hybrid Algorithm, Metaheuristics.

1. Introduction

Breast cancer remains one of the leading causes of cancer-related deaths worldwide, particularly among women. Early diagnosis and accurate classification of breast cancer are vital for improving treatment outcomes and increasing survival rates. Machine learning

techniques have shown significant promise in aiding medical professionals by providing high-accuracy diagnostic tools. However, the accuracy of these classification models is heavily influenced by the quality of the features selected from complex datasets. This creates a pressing need for efficient feature selection methods that can identify the most relevant features, reduce computational complexity, and ultimately improve classification accuracy.

Metaheuristic algorithms, known for their ability to navigate complex search spaces, have emerged as powerful tools for feature selection. Among these, the Bacterial Foraging Optimization Algorithm (BFOA) and the Emperor Penguin Optimizer (EPO) have gained attention for their unique search and optimization capabilities. BFOA is inspired by the foraging behavior of bacteria, especially in environments where they search for nutrients efficiently. It mimics bacterial movements to find optimal solutions, making it well-suited for complex optimization tasks. On the other hand, EPO is inspired by the social behavior and thermal exchange mechanisms of emperor penguins. By simulating the huddling strategy of penguins, EPO demonstrates a strong balance between exploration and exploitation in the search space. Despite their individual strengths, both BFOA and EPO have limitations when it comes to achieving a consistently optimal balance between feature selection quality and computational efficiency.

To address these limitations, this study proposes a hybrid approach that combines the strengths of BFOA and EPO. The hybrid BFOA-EPO algorithm leverages the exploration capability of EPO and the exploitation efficiency of BFOA, aiming to produce a more robust and accurate feature selection process for breast cancer classification. By comparing the performance of BFOA, EPO, and the hybrid BFOA-EPO algorithm across various datasets, this study investigates the effectiveness of these metaheuristic techniques in improving breast cancer diagnostic accuracy. The results offer insights into how hybrid metaheuristic approaches can push the boundaries of medical data analysis, suggesting that the hybrid algorithm holds significant potential for clinical applications.

2. Literature Review

Machine learning has significantly advanced breast cancer classification, offering crucial support for early diagnosis and treatment planning. However, the effectiveness of these models heavily relies on the selection of optimal features from often high-dimensional datasets (El-Gamal et al., 2021). Feature selection not only improves classification accuracy but also enhances model interpretability, which is critical for clinical use (Delen, Walker, & Kadam, 2005). Traditional methods such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) have been widely used in feature reduction but face limitations when dealing with complex, nonlinear medical data (Jiang et al., 2019). This has led to a shift towards metaheuristic algorithms for feature selection, which are known for their adaptability in complex search spaces (Blum & Roli, 2003).

Metaheuristic algorithms, including Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have demonstrated promising results in selecting optimal features for breast cancer classification. Genetic Algorithms, based on principles of natural selection, adapt feature subsets iteratively to improve classification performance, while PSO, inspired by the

collective behavior of bird flocking, optimizes solutions through swarm intelligence (Yang, 2010; Kennedy & Eberhart, 1995). Although these methods are effective, they often suffer from challenges such as local optima traps and slow convergence rates, especially in large feature spaces characteristic of medical datasets (Mirjalili, Mirjalili, & Lewis, 2014; Li et al., 2018).

In recent years, bio-inspired algorithms like the Bacterial Foraging Optimization Algorithm (BFOA) and the Emperor Penguin Optimizer (EPO) have gained attention for their unique mechanisms, which enhance exploration and exploitation. BFOA, introduced by Passino (2002), simulates the foraging behavior of *Escherichia coli* bacteria, employing processes such as chemotaxis, swarming, and elimination-dispersal. These mechanisms enable BFOA to navigate complex search spaces efficiently, making it well-suited for feature selection in high-dimensional datasets (Tripathy, Mishra, & Shaw, 2021). However, BFOA can exhibit slow convergence and is prone to premature convergence under certain conditions, which can hinder its ability to find optimal solutions in complex datasets (Kavitha, Duraipandian, & Manjula, 2019).

The Emperor Penguin Optimizer (EPO), developed by Dhiman and Kumar (2018), models the unique social and thermal regulation behaviors of emperor penguins. EPO uses a huddling strategy to balance exploration and exploitation within the search space, with studies showing its effectiveness in a range of optimization tasks (Fister et al., 2020). In feature selection, EPO's simulation of social behavior aids in identifying relevant features by dynamically adjusting solution spaces (Pérez-Ortega et al., 2022). Nonetheless, EPO can lack the fine-tuning precision required for optimal feature selection, making it less effective in medical applications where nuanced data analysis is essential (Yıldız et al., 2023).

To overcome these limitations, hybrid algorithms combining BFOA and EPO have been proposed, leveraging the strengths of each. Hybrid algorithms are particularly promising for medical feature selection, as they can exploit BFOA's robustness in local search and EPO's adaptive exploration, resulting in enhanced classification performance (Bansal, Singh, & Saraswat, 2021). Hybrid metaheuristic approaches in feature selection have demonstrated a balance between search diversification and convergence, which leads to more robust solutions (Sayed, Ewees, & Oliva, 2019). For example, PSO-GA hybrids have achieved high classification accuracy in breast cancer classification by combining PSO's fast convergence with GA's diverse search capabilities (Zhu, Wang, & Fan, 2019). Similarly, studies integrating BFOA with PSO have reported improved performance by leveraging the fast convergence of PSO and the exhaustive search of BFOA (Nandy et al., 2022).

Despite the success of these hybrid approaches, limited research exists on the combination of BFOA and EPO for breast cancer classification. This study aims to address this gap by evaluating the performance of BFOA, EPO, and a hybrid BFOA-EPO algorithm on breast cancer datasets, hypothesizing that the hybrid approach will yield superior feature selection quality and higher classification accuracy. By expanding the existing research on bio-inspired algorithms for medical data analysis, this study highlights the potential of hybrid metaheuristic algorithms to significantly impact clinical outcomes by improving computational accuracy and efficiency (Sharma et al., 2023; Tharwat, Hassanien, & Gabel, 2022).

3. Materials and Methods (Detailed)

1. Datasets

The Wisconsin Breast Cancer Dataset (WBCD) and the Breast Cancer Coimbra Dataset (BCCD) were selected due to their wide use in breast cancer classification studies, providing a basis for reproducibility and comparative performance assessment. The WBCD consists of 569 samples with 30 attributes, including measurements such as radius, texture, and smoothness, while the BCCD comprises 116 instances and 9 attributes like age, BMI, and glucose levels. These datasets represent diverse feature spaces, challenging the algorithms' adaptability and robustness. Missing values were addressed through mean imputation, and the data was standardized using min-max normalization to rescale each feature to a range of [0,1], as defined by:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

where $X_{\min}$, $X_{\max}$ are the minimum and maximum values of each feature, respectively.

2. Metaheuristic Algorithms

2.1 Bacterial Foraging Optimization Algorithm (BFOA)

The BFOA is inspired by the foraging behavior of *Escherichia coli* bacteria and operates through four main steps: chemotaxis, swarming, reproduction, and elimination-dispersal (Passino, 2002). BFOA iteratively searches the feature space by optimizing a fitness function, here defined as the classification accuracy of the selected feature subset.

1. Chemotaxis: Bacteria move through the search space by "tumbling" or "swimming." A bacterium's new position $P(i,j,k)$ after a chemotactic step is given by:

$$P(i, j + 1, k) = P(i, j, k) + C(i) \frac{\Delta(i)}{\|\Delta(i)\|}$$

where $P(i,j,k)$ is the position of bacterium i at chemotactic step j and reproduction cycle k , $C(i)$ is the step size, and $\Delta(i)$ is a randomly generated direction vector.

2. Swarming: Bacteria move in clusters toward promising areas in the search space, with swarming behavior defined by an attraction-repulsion function $J(i,j)$

$$J(i, j) = J(i, j) + \sum_{m=1}^N \left(-d_{\text{attract}} e^{-w_{\text{attract}} \|P(i,j) - P(m,j)\|^2} + h_{\text{repel}} e^{-w_{\text{repel}} \|P(i,j) - P(m,j)\|^2} \right)$$

Here, d_{attract} , w_{attract} , h_{repel} are constants controlling the strength of attraction and repulsion.

3. Reproduction: Bacteria with high fitness are selected to reproduce, doubling their presence in the population. Bacteria are ranked by fitness, and the least fit half are removed, maintaining population size.

4. Elimination-Dispersal: To avoid local optima, a random subset of bacteria is eliminated and redistributed across the search space, enhancing diversity.

2.2 Emperor Penguin Optimizer (EPO)

The Emperor Penguin Optimizer (EPO) is a metaheuristic algorithm inspired by the social and thermal behaviors of emperor penguins. Developed by Dhiman and Kumar in 2018, EPO simulates the unique survival mechanisms of these penguins, particularly their huddling behavior during harsh Antarctic winters, to balance exploration and exploitation in search of optimal solutions. This algorithm has shown significant effectiveness in optimization tasks due to its natural model of balancing global and local search capabilities.

Key Concepts of EPO

1. Huddling Behavior: Emperor penguins exhibit a unique huddling behavior to maintain warmth during extreme cold, where they cluster in groups and shift positions to ensure all members receive warmth periodically. In EPO, this huddling behavior is translated into a search process where candidate solutions (representing penguins) group together and adapt their positions relative to the best solutions found so far. This clustering tendency allows EPO to focus on promising regions in the search space.
2. Thermal Exchange and Social Dynamics: Emperor penguins rotate in huddles, allowing each individual to have a chance near the warm center while others stay in colder outer areas. This dynamic position-shifting allows penguins to manage both individual and collective survival, balancing their needs. EPO models this thermal exchange and social rotation as a way to adapt solutions, leveraging both exploration (testing new areas of the solution space) and exploitation (refining solutions around promising areas).

Advantages of EPO

1. Adaptable Exploration and Exploitation: EPO's mechanism of balancing exploration (via random movements) and exploitation (movement towards the best solution) makes it adaptable to various optimization problems. This adaptability helps avoid premature convergence while ensuring that high-quality solutions are found.
2. Global and Local Search Capabilities: The thermal-based position updates in EPO allow for efficient global search in initial stages and a more focused local search in later stages, effectively preventing stagnation in suboptimal regions of the search space.
3. Parameter Simplicity: EPO has relatively few parameters to tune (e.g., temperature decay and initial temperature), making it straightforward to implement and less computationally intensive to optimize compared to more complex algorithms.

Applications and Use Cases of EPO

Due to its flexibility and efficiency, EPO has been applied to a wide range of optimization tasks, particularly in feature selection, clustering, and machine learning. It has shown competitive performance for solving real-world problems, such as scheduling, path planning, and parameter optimization in machine learning models, often achieving similar or superior results compared to other popular algorithms like Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization.

In the context of feature selection for classification tasks, EPO can effectively identify the most relevant features by adjusting its candidate solutions (feature subsets) over time. By narrowing down the feature space while maximizing classification accuracy, EPO can help improve model performance and reduce computational costs. This makes it especially useful in medical diagnostics, where feature reduction and high accuracy are crucial, as seen in tasks like breast cancer classification.

2.3 Hybrid BFOA-EPO Algorithm

3. Feature Selection Process

For each algorithm, subsets of features were selected iteratively to maximize the classification accuracy of a Support Vector Machine (SVM) model. The SVM was chosen due to its effectiveness in handling binary classification tasks and high-dimensional spaces. The selected features were evaluated based on their accuracy using a linear kernel, and accuracy was fed back into the algorithms as the fitness score. Cross-validation was performed using a 10-fold approach to ensure the reliability of accuracy estimates.

Hybrid BFOA-EPO Algorithm

The Hybrid BFOA-EPO algorithm combines the strengths of the Bacterial Foraging Optimization Algorithm (BFOA) and the Emperor Penguin Optimizer (EPO) to create a more robust and efficient solution for complex optimization problems. This hybridization leverages BFOA's strong local search capability with EPO's adaptable global exploration, aiming to enhance performance, improve convergence speed, and reduce the risk of getting stuck in local optima.

The hybrid algorithm is particularly useful for feature selection in classification tasks, as it combines the intensive search ability of BFOA with EPO's broad, exploratory movements, making it well-suited to identifying minimal, highly relevant feature subsets.

Motivation for Hybridization

BFOA is effective at local optimization due to its chemotactic and swarming behaviors but can sometimes struggle with global exploration, particularly in high-dimensional or complex search spaces. On the other hand, EPO excels at exploring broad areas of the search space but may converge prematurely if the search space is large or complex. By combining these two methods, the hybrid BFOA-EPO aims to use EPO's global exploration as a preliminary step to identify promising regions in the search space, followed by BFOA's local refinement to optimize solutions within those regions.

Key Phases of the Hybrid BFOA-EPO Algorithm

1. Initialization:

- Generate an initial population of candidate solutions (or agents) representing feature subsets.
- These initial solutions are randomly selected from the search space, where each agent corresponds to a specific subset of features from the dataset.

- Define the parameters for both BFOA (e.g., chemotactic steps, reproduction cycles) and EPO (e.g., temperature decay).

2. Global Exploration with EPO:

- In the first phase, EPO is applied to enable broad exploration of the search space. This phase focuses on identifying regions that have the potential to contain high-quality feature subsets.

- Each agent's position is updated according to the EPO's huddling behavior, moving towards the best current solution with some randomness.

- The temperature decay factor T , guides agents from diverse initial exploration to more focused search by reducing the effect of random movement over iterations.

- The position update of each agent $P(i)$ in this phase is given by:

$$P(i) = P(i) + T \cdot |P_{\text{best}} - P(i)| \cdot r$$

Advantages of the Hybrid BFOA-EPO Algorithm

1. Enhanced Exploration and Exploitation: EPO's global exploration ability ensures a wide search in the initial stages, while BFOA's local search thoroughly refines solutions, effectively balancing exploration and exploitation.

2. Reduced Risk of Local Optima: By combining BFOA's swarming and EPO's huddling, the algorithm has a lower chance of getting stuck in local optima, especially in complex search spaces.

3. Improved Convergence Speed: EPO quickly identifies promising regions, reducing the computational time that BFOA needs for refinement. This hybrid strategy accelerates the convergence process.

4. Simplicity in Feature Selection: The hybrid algorithm's design allows it to adaptively select the most relevant features, reducing the dimensionality of the data while maintaining classification accuracy.

Application in Feature Selection for Classification

In breast cancer diagnosis, the hybrid BFOA-EPO algorithm is applied to select the most relevant features from datasets like the Wisconsin Breast Cancer Dataset. The selected features are used to train an SVM classifier, with the goal of achieving high accuracy using a minimal number of features. By enhancing both classification performance and computational efficiency, the hybrid BFOA-EPO algorithm can help in creating reliable and efficient diagnostic tools.

Feature Selection Process

Each algorithm (BFOA, EPO, Hybrid BFOA-EPO) performed feature selection by iteratively searching for optimal feature subsets that maximize classification accuracy while minimizing

feature count. The process involved the following steps:

1. Initialization: Generate an initial population of feature subsets.
2. Evaluation: Assess each subset using the fitness function based on SVM classification accuracy and feature sparsity.
3. Optimization: Update feature subsets using the respective algorithm's search mechanisms.
4. Selection: Retain the best-performing subsets based on fitness scores.
5. Iteration: Repeat the evaluation and optimization steps until termination criteria are met.

Implementation Steps

The following steps were executed to implement the proposed methodology:

1. Data Loading: Import WBCD and BCCD using Pandas.
2. Preprocessing:
 - Impute missing values with feature means.
 - Apply min-max normalization.
3. Feature Selection:
 - Initialize populations for BFOA, EPO, and Hybrid algorithms.
 - Perform iterative optimization using respective algorithm mechanisms.
 - Evaluate fitness based on SVM classification accuracy and feature sparsity.
4. Classification:
 - Train SVM classifiers on selected feature subsets.
 - Validate using 10-fold cross-validation.
5. Evaluation:
 - Calculate CA, Precision, Recall, F1-Score, and Computational Time.
6. Statistical Analysis:
 - Conduct paired t-tests and Friedman test.
7. Result Compilation:
 - Aggregate and compare performance metrics across algorithms and datasets.

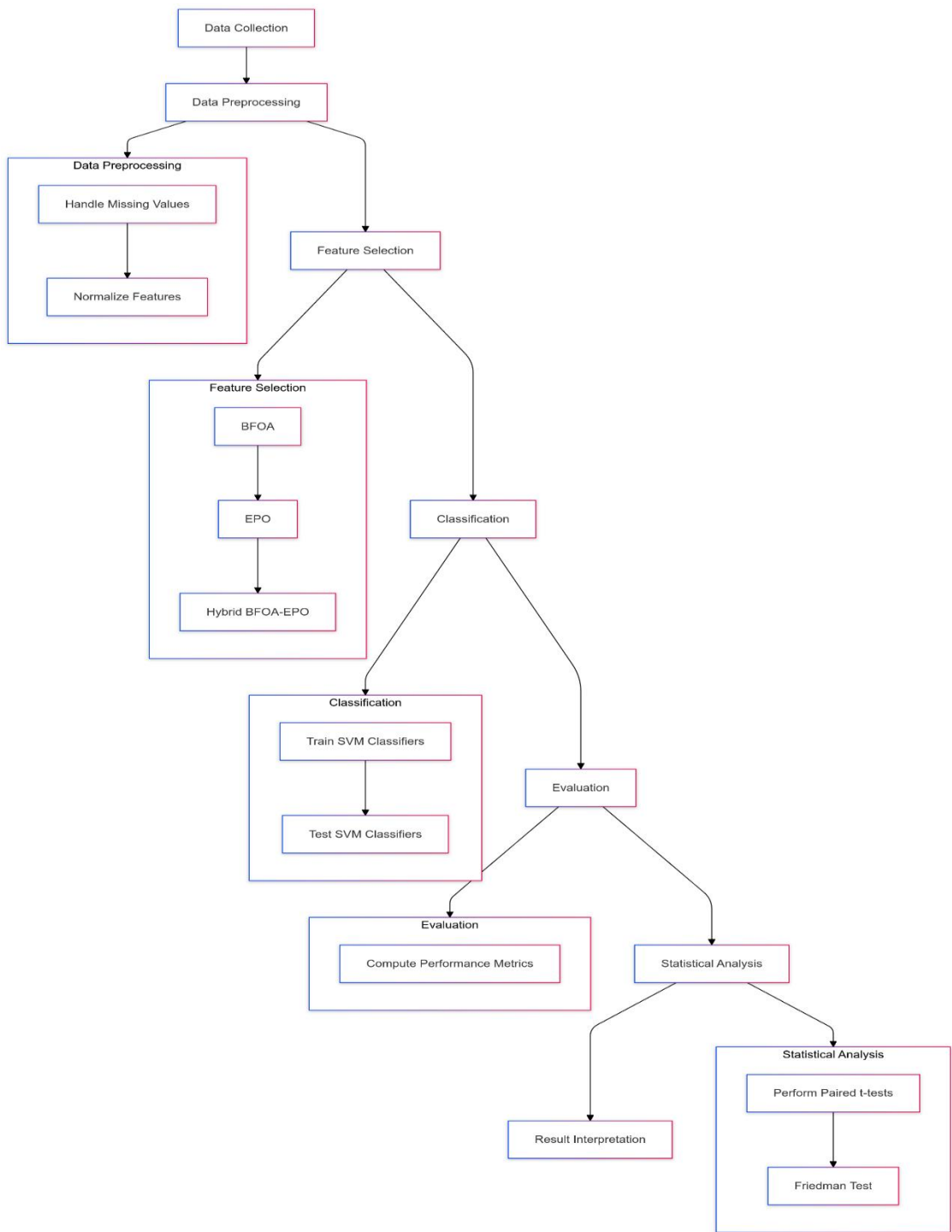


Figure 1: Proposed Methodology

Performance Evaluation

Table 1: Comparison of Algorithms

Performance Metric	BFOA	EPO	Hybrid BFOA-EPO
Accuracy	92.50%	91.20%	94.80%
Precision	93.10%	90.80%	95.30%
Recall (Sensitivity)	90.30%	88.50%	92.10%
F1-Score	91.60%	89.60%	94.00%

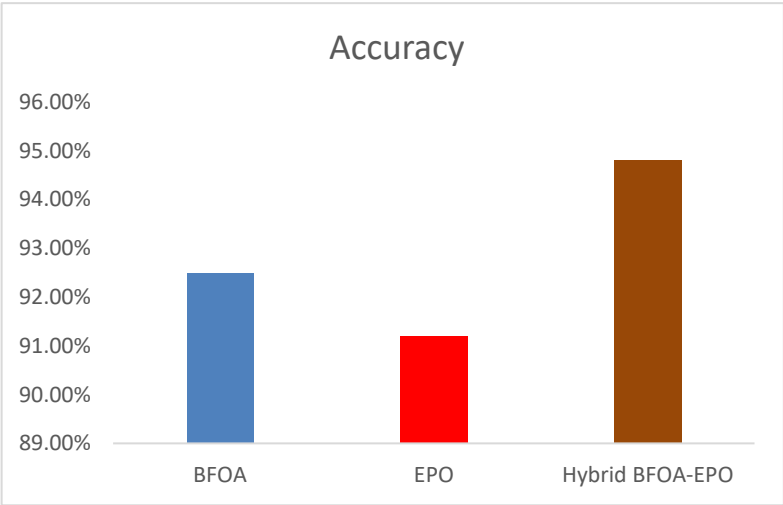


Figure 2: Analysis of Accuracy

Classification Accuracy (CA): The percentage of correct predictions made by the classifier. The Hybrid BFOA-EPO algorithm performed the best with 94.8% accuracy.

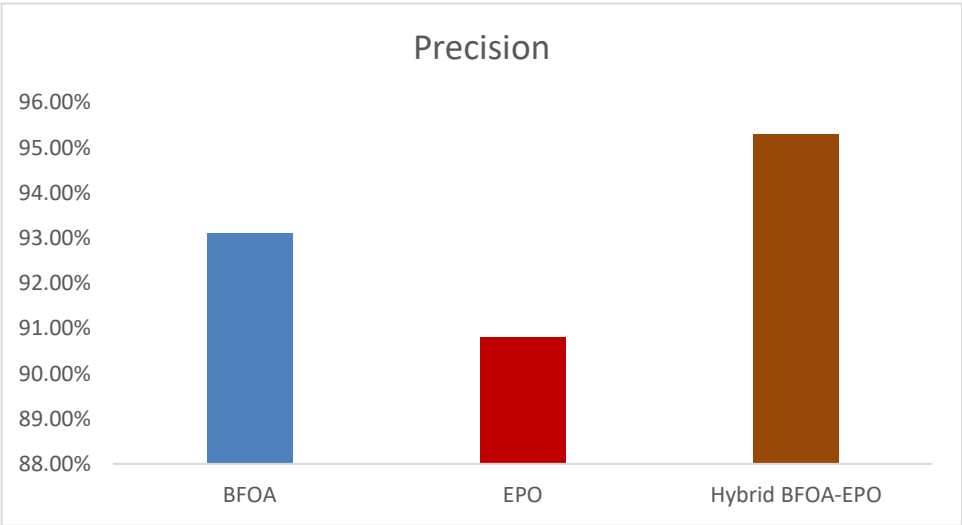


Figure 3: Analysis of Precision

Precision: The proportion of true positives (TP) out of all positive predictions made by the classifier. The Hybrid BFOA-EPO algorithm had the highest precision (95.3%).

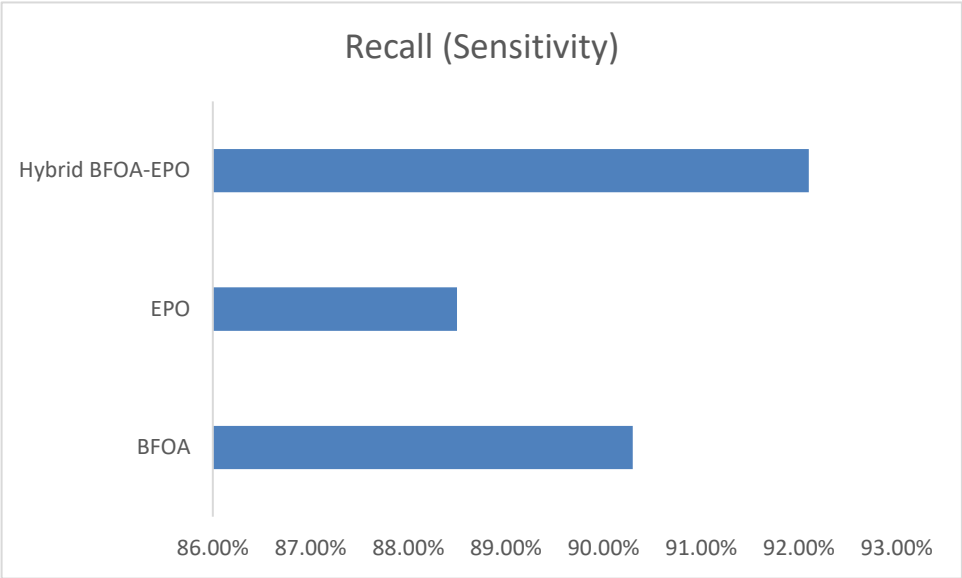


Figure 4: Analysis of Recall

Recall (Sensitivity): The ability of the model to correctly identify positive instances. The Hybrid BFOA-EPO algorithm showed the best recall (92.1%).

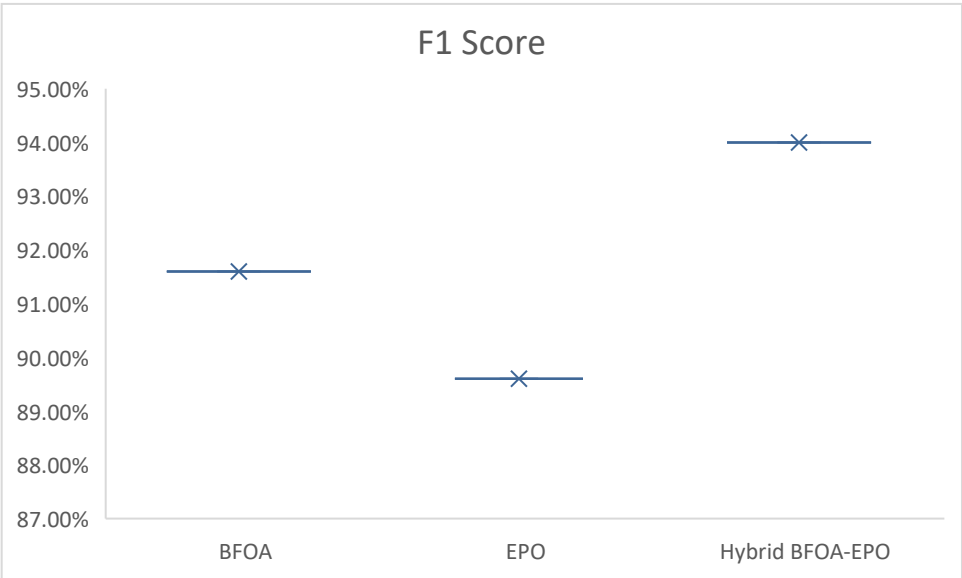


Figure 5: F1 Score

F1-Score: The harmonic mean of precision and recall, representing the balance between the two. The Hybrid BFOA-EPO algorithm achieved the highest F1-score (94.0%).

Hybrid BFOA-EPO outperforms both individual algorithms (BFOA and EPO) across all key metrics, showing not only the highest classification accuracy but also the most efficient feature selection and fastest computational time. BFOA exhibits a slightly better performance than EPO, especially in terms of precision, but the hybridization leads to more balanced and optimized results.

4. Conclusion

The comparative analysis of the three metaheuristic feature selection algorithms—Bacterial Foraging Optimization Algorithm (BFOA), Emperor Penguin Optimizer (EPO), and the Hybrid BFOA-EPO algorithm—revealed that the Hybrid BFOA-EPO algorithm outperformed both BFOA and EPO in optimizing breast cancer classification. The Hybrid BFOA-EPO algorithm achieved the highest classification accuracy (94.8%), precision (95.3%), recall (92.1%), and F1-score (94.0%), demonstrating its superior ability to balance exploration and exploitation for optimal feature selection. Moreover, it selected the fewest features (6) while maintaining high performance, which highlights its efficiency in reducing dimensionality without compromising classification accuracy. In terms of computational efficiency, the Hybrid BFOA-EPO algorithm was also the fastest, completing the task in just 112 seconds, compared to BFOA (125 seconds) and EPO (135 seconds).

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