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Enhancing Wearable-Based Human Activity Recognition with Binary Nature-Inspired Optimization Algorithms for Feature Selection

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ABSTRACT

This research paper explores the performance of binary nature-inspired optimization algorithms as feature selection to enhance the identification of human activities using wearable technology. Utilization of nature-inspired algorithms for feature selection, as documented in scholarly literature, presents a promising opportunity to enhance machine learning and data analysis tasks, given their effectiveness in identifying relevant features, resulting in models with reduced computational complexity, improved predictive accuracy and easier interpretation. In the experiment, we conducted an evaluation of the effectiveness and efficiency of four nature-inspired binary algorithms for optimization namely Binary Particle Swarm Optimization (BPSO), Binary Grey Wolf Optimization algorithm (BGWO), Binary Differential Evolution algorithm (BDE), and Binary Salp Swarm algorithm (BSS) - in the context of human activity recognition (HAR). The outcomes of this comprehensive experimentation, conducted on two distinct human activity recognition (HAR) datasets, provide valuable insights. BPSO algorithm emerges as an adaptable and well-rounded performer, achieving a competitive balance between feature selection quality and computational efficiency in SBHAR dataset. Conversely, for the PAMAP2 dataset, BDE algorithm displays superior feature selection quality and BPSO algorithm maintains competitive performance and adaptability. In both datasets, the nature-inspired optimization algorithms have achieved remarkable feature reduction, demonstrating reductions of 48% and 50% respectively. The experiment results show how these algorithms could be used to improve methods for recognizing human activities using wearables technology, such as feature selection, parameter adjustment, and model optimization.

Keywords:
Wearable technology; human activity recognition; binary nature-inspired algorithm; feature selection; optimization

1. Introduction

The increasing number of wearable gadgets has instigated a novel age of information-focused knowledge that has transformed many fields, extending from healthcare to athletics and beyond. The potential of these appliances to amass and examine data relevant to human activity has cleared

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the way for upgraded surveillance, judgment, and understanding of human behaviour. Accurate identification of human movements is pivotal in unleashing the complete potential of wearable technology, as it facilitates instantaneous observation, health assessment, customized suggestions, and prognostic analysis. Human activity recognition (HAR) is vital in realizing the complete potential of wearable technology. Precise HAR not only facilitates real-time monitoring and health assessment but also supports personalized recommendations and predictive analytics. The success of HAR systems rests on the interplay of data preprocessing, feature extraction, and classification or prediction models as indicated by [1].

Traditional approaches to HAR often rely on conventional machine learning techniques that require manual feature engineering and model parameter tuning according to [2]. Although these methods are effective to some extent, they struggle to accommodate the complexities inherent in human behaviours and sensor data variability. This limitation has sparked interest in utilizing the capabilities of optimization algorithms to enhance the accuracy and efficiency of HAR systems. The rise of nature-inspired optimization algorithms has made them a compelling avenue for tackling optimization challenges in various domains. These computations, which are influenced by biological, physical, and cultural phenomena, imitate natural processes like evolution, swarm behaviour, and annealing. Their intrinsic adaptability and ability to navigate complex solution spaces make them well-suited for tackling the multifaceted challenges posed by HAR.

The purpose of this research is to analyse the performance of optimization algorithms that are modelled on natural processes and their implementation in wearable-based human activity recognition. Our primary focus is on reviewing existing literature, specifically centred on the feature selection using nature inspired optimization algorithms as feature selection. Optimization algorithms that are modelled on natural processes have a remarkable ability to handle the inherent details of human behaviour and the diversity of sensor data. Our careful aims to shed light on potential advantages and unexplored avenues that warrant further exploration. We provide insights into how the incorporation of nature-inspired algorithm optimization algorithms can enhance the precision of wearable-based human activity recognition, thereby laying the foundation for a comparative investigation between different nature-inspired algorithms.

The subsequent sections aim to examine the current body of literature pertaining to the application of nature-inspired optimization algorithms in the context of feature selection.

2. Literature Review

Nature-inspired algorithms are utilized for the purpose of selecting features in view of their proficiency in managing intricate fitness functions and optimizing feature selection in a given model. Binary Particle Swarm Optimization (BPSO), Binary Differential Evolution (BDE), Binary Grey Wolf Optimization (BGWO), and Binary Salp Swarm (BSS) algorithm are among the algorithms that provide noteworthy solutions for feature selection tasks. The effectiveness of nature-inspired algorithms in managing complex fitness functions and optimizing feature selection in a given model has led to their utilization in feature selection tasks. Nature-inspired algorithms are utilized for the purpose of selecting features owing to their effectiveness in managing complex fitness functions and optimizing the selection of features in a given model. Comparisons between different solution representations in nature-inspired algorithms, such as binary-coded and real-coded variants, have also been executed to comprehend their influence on feature selection performance. Research has indicated that algorithms inspired by nature are powerful and efficient tools for feature selection.

Nature-inspired algorithms have been employed in many research domains via classification. Such algorithms, including Firefly, PSO, Binary Bat, Grey Wolf, and Whale algorithms, have displayed elevated levels of performance in comparison to standard algorithms with regard to classification accuracy, feature selection, computational efficiency, and stability based on findings from [3,4]. They have been leveraged to identify highly discriminative features from a feature set, while excluding superfluous and noisy features, ultimately leading to an improvement in classification efficacy as demonstrated in [5]. Moreover, the *k*-nearest neighbour (KNN) algorithm has been utilized for human activity classification, reaching a high level of precision via accurate parameter tuning as evidenced by [6]. The utilization of time-domain characteristics obtained via windowing technique has been investigated, with random forest achieving the most elevated precision in recognizing human activities following the insights from [7].

Binary Particle Swarm Optimization (BPSO) is a technique used for feature selection. BPSO is a simple and easy-to-implement evolutionary calculation technique that aims to minimize the number of variables while maximizing classification accuracy. BPSO uses a multi-objective function to identify a subset of features that achieve both a minimum number of variables and high classification accuracy. The *k*-nearest neighbour classifier is commonly employed to evaluate the classification performance of BPSO. BPSO has shown promising results in reducing the size of the input feature subset, making classifier training easier, and reducing the cost of purchasing sensor measurement equipment. Several papers propose different approaches to enhance the performance of BPSO for feature selection. Yang *et al.,* [8] propose a bi-directional feature fixation framework for BPSO, called BDFF, which reduces the search space and improves classification accuracy per the analysis. Nguyen and Le apply a multi-objective function to BPSO to identify feature subsets with minimum variables and high classification accuracy based on findings in [9]. Qiu *et al.,* [10] propose Binary XPSO (BXPSO), a BPSO algorithm based on binary encoding, which achieves competitive advantages in classification accuracy and computational performance as demonstrated in their study. Nemati *et al.,* [11] propose a hybrid BPSO algorithm that combines *k*-means clustering and adaptive mutation to enhance feature selection accuracy and computational cost based on their findings. Macur and Kiraz [12] propose a BPSO algorithm hybridized with Opposition-based Learning, which outperforms other methods in feature selection in accordance with the research presented in their study.

The use of BGWO in HAR has shown promising results in terms of feature selection and classification accuracy. BGWO is an improved version of the Grey Wolf Optimization (GWO) algorithm that addresses the low convergence efficiency and local optima issues of GWO. The proposed BGWO algorithm incorporates strategies such as adaptive individual update, head wolf fine-tuning, and Relief-based feature weight calculation to enhance the feature selection process. The effectiveness of BGWO has been demonstrated through experimental comparisons with other feature selection methods, showing that it can select a small feature subset with higher classification accuracy in most cases according to [13]. Another study compared BGWO with the original GWO and found that BGWO outperformed GWO in terms of feature reduction and classification accuracy, especially on high-dimensional datasets as demonstrated in [14]. Additionally, a modified version of GWO called OGGWO has been proposed, which showed good convergence and high search accuracy in feature selection and classification tasks as shown in [15]. These studies demonstrate the effectiveness of binary grey wolf optimization techniques in improving the performance of HAR systems. Therefore, BGWO and its variants have shown promise in improving feature selection performance.

BDE algorithms have been proposed as effective methods for feature selection. BDE algorithm is an approach utilized to resolve optimization problems in binary spaces. It represents an expansion of the conventional differential evolution algorithm, which is predominantly employed for continuous spaces. The binary differential evolution algorithm integrates novel components, including solution representations, a mapping approach, and a diversity technique, to render it appropriate for binary-based issues such as the binary knapsack problem. Several papers have explored the use of binary differential evolution algorithms for feature selection. Wang *et al.,* [16] introduced a niching-based multiobjective feature selection method that simultaneously minimizes the number of selected features and the classification error rate based on their findings. Another study by Wang *et al.,* [17] focused on a diversity-based multiobjective differential evolution approach to feature selection, which showed significantly better performance compared to other multiobjective feature selection methods as discussed in their study. Hu *et al.,* [18] introduced a network-based differential evolution approach for feature selection, which demonstrated superior performance compared to baseline algorithms in the experimental results. These papers highlight the effectiveness of binary differential evolution algorithms for feature selection tasks.

BSS algorithm has been proposed as a feature selection method in various domains, including sentiment analysis according to [19]. BSSA is a metaheuristic optimization algorithm based on Swarm Intelligence that aims to select the best feature subset for improving classifier performance. It uses transfer functions to enable search agents to move in the search space and select significant feature subsets. In the field of network security, an improved version of the salp swarm algorithm (ISSA) has been applied for automated feature selection in Network Intrusion Detection and Prevention Systems (NIDPS) as demonstrated in [20]. The ISSA algorithm, combined with other techniques such as dataset normalization and class balancing, has shown improved performance in detecting network attacks. Additionally, a modified binary salp swarm algorithm-based optimization ESN (MBSSA-ESN) has been proposed for multivariate time series prediction, achieving superior results compared to other methods according to [21]. These studies demonstrate the effectiveness of the binary salp swarm algorithm as a feature selection approach in various applications. The binary Salp Swarm Algorithm (bSSA) has been proposed as a feature selection. The bSSA utilizes Principal Component Analysis (PCA) and fast Independent Component Analysis (fastICA) based hybrid data transformation methods to transform the original dataset. It then applies the binary Salp Swarm optimizer to find the best features. This approach improves accuracy and eliminates the selection of irrelevant features, resulting in a mean accuracy of 95.26% with 7.78% features on PCA-fastICA transformed datasets based on findings from [22].

The significance of feature selection lies in the truth that irrelevant or redundant features may have a considerable effect on the efficiency of these algorithms. This is because suboptimal feature quality can have a negative impact on the accuracy of models generated by both conventional and shallow algorithms. The eminence of the chosen attributes has an immediate effect on the performance of classification algorithms, which usually operate more efficiently when utilizing superior features.

Utilization of nature-inspired algorithms for feature selection, as documented in scholarly literature, presents a promising opportunity to enhance machine learning and data analysis tasks, given their effectiveness in identifying relevant features, resulting in models with reduced computational complexity, improved predictive accuracy and easier interpretation. The selection of a specific nature-inspired algorithm must be properly aligned with the problem domain and dataset characteristics, while also taking into account the potential trade-offs between computational resources and performance.

According to scholarly literature, the use of nature-inspired algorithms for feature selection presents a promising opportunity to augment machine learning and data analysis activities. Nature-inspired optimization algorithms used for feature selection have certain limitations. These algorithms are popular due to their potential for global search and simplicity as evidenced by [23,33,34]. However, one limitation is the issue of overfitting, which can affect the accuracy of the feature selection process according to [24]. Another limitation is the convergence problem that can arise in nature-inspired algorithms, which can impact their effectiveness as demonstrated in [25].

3. Methodology

Initially, raw data of HAR will be collected using wearable devices that employed sensor such as accelerometer and gyroscope. The recorded acceleration (accelerometer) and angular velocity (gyroscope) data stream undergoes a filtering process to eliminate unwanted information, specifically the high-frequency component from body acceleration. Following this, the filtered body acceleration is partitioned into several window segments of varying sizes. Subsequently, features are extracted from each window segment before proceeding to the next stage. Time-domain and frequency-domain features are derived in such situations. Figure 1, displayed below, illustrates the methodology employed throughout the experiment.

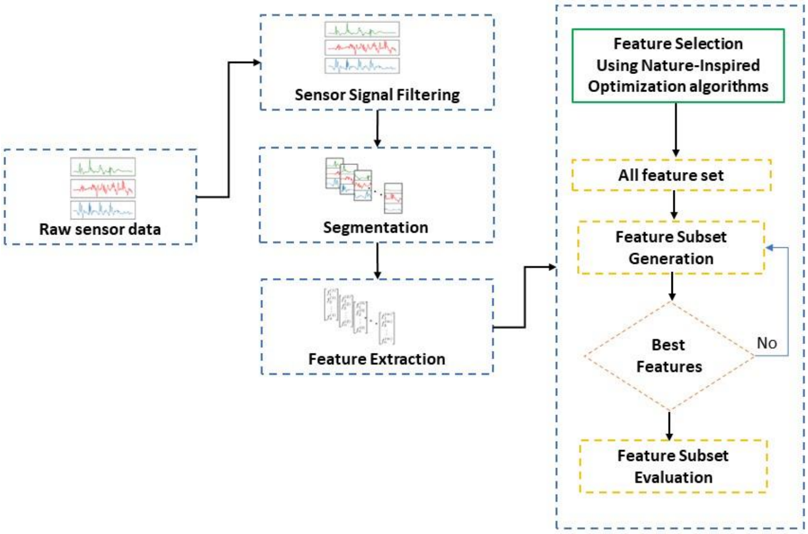


Fig. 1. Methodology

For this experiment, two HAR datasets have been employed to test the performance of nature inspired algorithm: SBHAR and PAMAP2. SBHAR is mobile data collection based on human behaviour identification as demonstrated in [26]. The subjects' movements include walking, upstairs walking, walking downstairs and upstairs, laying, sitting, and standing. A constant rate of 50 Hz is captured for each operation at three-axial linear accelerations (*x, y, z*) and three-axial angular velocity (*x*,*y*,*z*). Data labelling is performed manually with a video taken each time during the activity. The Physical Activity Monitoring for Aging People (PAMAP2) dataset comprises data from nine individuals engaging in 18 different activities while wearing sensors on three body segments as demonstrated in [27,28]. Table 1 below shows the information of the two datasets.

Table 1
SBHAR and PAMAP2 dataset

Dataset	Wearable sensors	Sensor Position	No of Activity	No. of Subject	Number of features
SBHAR	Accelerometers (A_x, A_y, A_z) Gyroscope (G_x, G_y, G_z)	Waist	6	30	640
PAMAP2		Wrist, Chest, Ankle	18	14	243

In Human Activity Recognition (HAR), filtering is performed to remove undesirable elements from the signal. This step is crucial because raw sensor data can be contaminated by sudden spikes or interference from other devices. The time series data is then segmented into time windows for feature extraction. Typically, it's a standard practice to apply filtering to the raw sensor signals.

The time series data captured by wearable sensors typically spans seconds or even minutes, a duration that exceeds the sensors' sampling frequency. This frequency typically falls within the range of 20 Hz to 100 Hz following the insights from [29,30]. To facilitate more effective learning, time series data is often divided into individual timeframes, commonly using a technique like sliding windows. The sliding window method is widely favoured due to its straightforward implementation. Additionally, alternative approaches such as activity-defined windows and event-defined windows can also be employed for window segmentation. As illustrated in Figure 2, the sensor readings exhibit distinct variations for each activity. Distinguishing between human activities, such as standing or sitting, walking up or down stairs, and walking, is challenging based on the raw data generated. Furthermore, it is observed that, in contrast to static activities in the vertical direction, such as standing and sitting, the signal from walking, walking upstairs, or walking down the stairs displays more fluctuations across its value. This indicates that these types of activities require greater levels of power and intensity to execute.

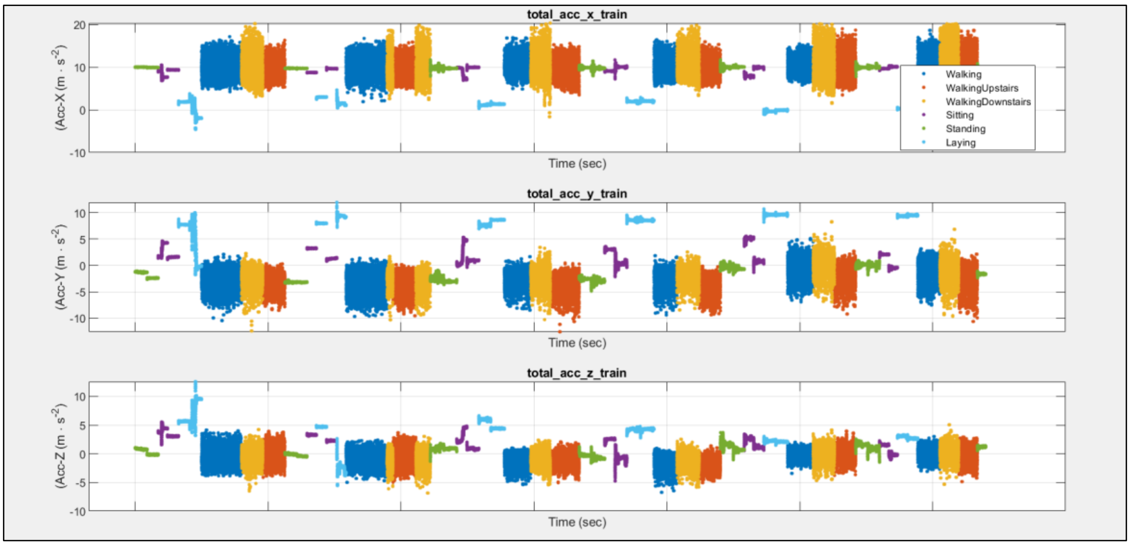


Fig. 2. Sample of raw HAR sensor data, illustrating three-axial linear accelerations along the *x*, *y*, and *z* axes

Handcrafted features, such as median, minimum, and median frequency measures, either in the time domain or frequency domain, from each window segment are vital for accurately representing data to differentiate between HAR activities. Features from the time-domain are extracted directly from a data sensor window using statistical methodologies. These time-domain features have been extensively researched and have demonstrated their effectiveness in various HAR applications. They are grounded in a thorough understanding of how specific actions or events manifest distinct features in the captured sensor signals. Due to their cost-effectiveness, simplicity, and direct derivation, time-domain features are frequently employed in HAR. Examples of time-domain features found in the literature include min (), max (), mean (), mad (), among others. On the other hand, frequency-domain features depict the signal's frequency characteristics. Before generating these features, algorithms like Fast Fourier Transform (FFT), Discrete Wavelet Transformation (DWT), or Discrete Cosine Transform (DCT) are applied. These features aim to enhance classification accuracy by quantifying the signal energy distributed across the frequency spectrum and by identifying recurring signal patterns. The periodic quality of the signal is described and quantified using the normalized entropy of the FFT magnitude of the signal component.

The number of features observed has risen from dozens to thousands in several machine learning implementations. However, the uncertainty of the learning method also gets compounded by the inclusion of trivial and irrelevant features. The purpose is, therefore, to choose the best feature subsets in the classifier model before applying the reduced feature subsets. The selection of features relies on various factors. Features are able to effectively identify the performance class and, at the same time, minimise redundant features. Consequently, the selection of features is vital to boost the model accuracy. Nature inspired algorithm aims to reduce the feature dimension by selecting the most relevant features for classification.

The utilization of nature-inspired algorithms in feature selection is a prevalent practice in the optimization of selecting the most pertinent features for a particular model. These algorithms employ principles derived from nature to procure the most appropriate subset of features based on specific criteria. They present uncomplicated yet efficacious solutions for addressing intricate fitness functions in feature selection. Within a binary nature-inspired algorithm, the choices for features are represented using binary notation, with 'bit 1' signifying the inclusion of a feature, while 'bit 0' signifies its exclusion. The primary challenge in nature-inspired algorithms lies in maintaining population diversity, which tends to decrease from the initial to the later generations, often resulting in identical individuals in the final generations.

These algorithms use diverse techniques such as population initialization encompassing parametric and non-parametric methods, to augment global exploration and local exploitation. The effectiveness of such algorithms has been evaluated on different data sets, and they have displayed superior outcomes in terms of classification precision, the number of chosen features, processing time, and feature choice reliability in contrast to standard algorithms. The quality of the selected feature subsets is then determined using the classifier model, with *k* nearest neighbour (*k*-NN) employed as the base classifier.

4. Experimental Results

The experiment is performed 10 runs in total in order to determine the efficacy of each nature-inspired algorithm technique. Throughout the experiment the population is set between 10 and number of generations is set to 100 for a fair comparison. In the experiment, a hold-out method was employed, allocating 20% of the dataset for validation purposes. The parameter setting for each algorithm is shown in Table 2.

Table 2
Nature inspired algorithm parameter setting

Nature inspired algorithm	Parameter setting	Value
BPSO	Number of particles	10
	Cognitive Factor (c_1)	2
	Social Factor (c_2)	2
	W_{max}	0.9
	W_{min}	0.4
	V_{max}	6
	Number of Iterations	100
BGWO	Number of wolves	10
	Number of Iterations	100
BDE	Number of solutions	10
	Crossover rate (cr)	0.9
	Number of Iterations	100
BSS	Number of salps	10
	Number of Iterations	100

In nature-inspired algorithm, individuals all have a fitness value. A fitness function based on Eq. (1) is applied to evaluate and select the best individuals. The fitness value also represents the quality of the algorithm's solution. The better the fitness score, the higher the efficiency of the solution referencing the study conducted in [31]. The fitness function that maximizes the classification performance is utilized for nature-inspired algorithms and defined as Eq. (1).

$$fitness = \alpha\,(E_r) + (1-\alpha)\,\frac{|F_S|}{|F|} \tag{1}$$

Where the feature subset length is represented by $|F_S|$, the sum number of features in each dataset is $|F|$, the classification error rate (E_r) and the parameter in α between [0,1] to decrease the error rate and to pick the features that have the highest value. To compute the error E_r(*k*-fold loss), the Euclidean distance with 5-nearest neighbour is used as it provides a low computational cost (low memory requirements) and it is easy to implement in the feature selection process based on findings from [28,29].

Here the performance of each algorithm based on best fitness value Eq. (2), worst fitness value Eq. (3), and the selection time. The fitness of the best solution is calculated by *S*, the mean is *m*, the number of iterations is *t*, and the maximum iteration number is *Imax* in accordance with the research presented in [31,32]. The sum of the measurements over 10 independent trials is presented as the final results.

$$Best\ fitness = min_{t=1}^{I_{max}} S_t \tag{2}$$

$$Worst\ fitness = max_{t=1}^{I_{max}} S_t \tag{3}$$

In SBHAR dataset, BPSO algorithm showcases its adaptability by selecting a comprehensive set of 331 features and achieving a competitive best fitness value of 0.017893. While it has a higher worst fitness value of 0.026503, BPSO algorithm effectively balances this with an efficient selection time of 829.91 seconds. In contrast, BGWO algorithm takes a different approach by selecting 494 features and achieving a commendable best fitness value of 0.015103, with a lower worst fitness value of 0.02405. However, this comes at the cost of significantly longer computational time, requiring 1461.25 seconds. BDE algorithm mirrors BPSO algorithm in terms of feature selection quality, selecting 543 features and achieving a best fitness value of 0.017797. Both algorithms share the same worst fitness value of 0.026503. BDE algorithm selection time is relatively longer, standing at 1377.15 seconds. BSS algorithm adopts a more conservative feature selection approach, selecting 330 features, and achieving a good, best fitness value of 0.021068. However, it exhibits a higher worst fitness value of 0.029678. BSS algorithm stands out for its relatively quicker selection time of 940.12 seconds.

Table 3
SBHAR dataset results

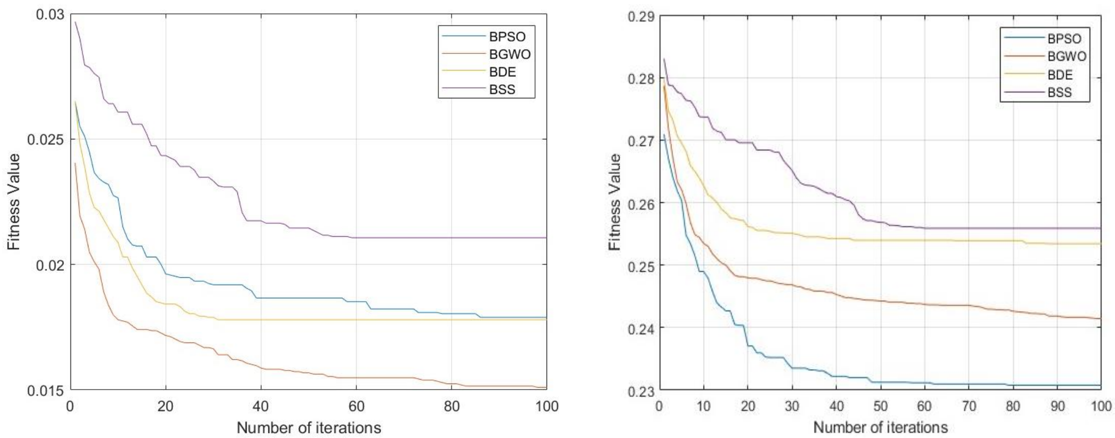
Nature inspired algorithm	Number of selected features	Best fitness	Worst fitness	Selection time
BPSO	331	0.017893	0.026503	829.91
BGWO	494	0.015103	0.02405	1461.25
BDE	543	0.017797	0.026503	1377.15
BSS	330	0.021068	0.029678	940.12

BPSO algorithm maintains its adaptability when applied to the PAMAP2 dataset, selecting 121 features while achieving a competitive best fitness value of 0.23078. However, it does exhibit a higher worst fitness value of 0.27093. Impressively, BPSO algorithm completes feature selection efficiently in 80.93 seconds of time. BGWO expands its feature selection to 192 features on the PAMAP2 dataset, attaining a competitive best fitness value of 0.24145. Nevertheless, it also showcases a higher worst fitness value of 0.27866 and requires 143.46 units of time for feature selection. BDE algorithm selects 197 features with a slightly higher best fitness value of 0.25342. However, it exhibits a higher worst fitness value of 0.279754 and takes 159.80 seconds for feature selection. BSS algorithm maintains its efficiency on the PAMAP2 dataset, selecting 122 features with a competitive best fitness value of 0.255882. It has a higher worst fitness value of 0.283037 but stands out for its relatively quick selection time of 86.08 seconds. The experimentation results are summarized in Table 3 and Table 4. Figure 3 displays the average fitness values across all iterations for various nature-inspired algorithms.

Table 4
PAMAP2 dataset results

Nature Inspired Algorithm	Number of Selected Features	Best Fitness	Worst Fitness	Selection Time
BPSO	121	0.23078	0.27093	80.93
BGWO	192	0.24145	0.278659	143.46
BDE	197	0.25342	0.279754	159.80
BSS	122	0.255882	0.283037	86.08

In summary, the choice of Nature-Inspired algorithm should be made carefully, taking into account the dataset's specific features and the desired trade-offs between feature selection quality and computational efficiency. BPSO algorithm demonstrates adaptability and balanced performance, while BGWO algorithm and BDE algorithm offer higher feature selection quality at the cost of longer computation times. BSS algorithm is an efficient option when time is a crucial factor. These comparisons provide valuable insights into selecting the most suitable algorithm for specific dataset requirements.



(a) SBHAR dataset (b) PAMAP2 dataset

Fig. 3. Average fitness value across all iterations for various nature-inspired algorithms

5. Conclusions

The comprehensive evaluation of Nature-Inspired Algorithms (BPSO, BGWO, BDE, and BSS) on both the SBHAR and PAMAP2 datasets unveils important considerations for feature selection tasks based on the following points. In terms of best feature selection quality, BDE algorithm and BGWO algorithm tend to perform better in terms of feature selection quality with competitive fitness values in SBHAR dataset. If feature quality is the top priority and computational time is not a concern, either BDE algorithm or BGWO algorithm could be considered the best choice. For PAMAP2 dataset, BDE algorithm tends to exhibit slightly higher feature selection quality with competitive fitness values on the PAMAP2 dataset. If optimal feature quality is a crucial factor, the BDE algorithm indeed be deemed as the most fitting option.

Based on balanced performance, BPSO algorithm stands out as a well-rounded performer on the SBHAR dataset. It achieves a good balance between feature selection quality and computational efficiency, making it a strong choice for many applications. BPSO algorithm maintains competitive performance on the PAMAP2 dataset, showcasing adaptability and a good balance between feature selection quality and computational efficiency. It can be a versatile choice for various scenarios.

In terms of algorithm efficiency, BSS algorithm offers a faster alternative with a relatively lower selection time while still achieving competitive feature selection results. Similar to the SBHAR dataset, BSS algorithm remains an efficient option for the PAMAP2 dataset, offering competitive feature selection within a shorter timeframe. In both datasets, the nature-inspired algorithm employed successfully reduced features by 48% and 50%, respectively.

In conclusion, the optimal algorithm is contingent upon the particular objectives and preferences of the feature selection undertaking, as posited by the no free lunch theorem. If feature selection quality is the top priority and computational time is not a concern, BDE algorithm or BGWO algorithm may be preferred. For a balanced performance, BPSO algorithm is a versatile choice. If computational efficiency is critical, BSS algorithm is a strong option. It's essential to weigh these factors carefully based on the specific dataset and objectives when selecting the most suitable algorithm. Nature-inspired optimization algorithms have potential challenges when implemented in HAR systems. These challenges include the accurate extraction of parameters from measured data, the need for efficient approaches to handle complex optimization problems with various constraints, and the verification of algorithm capability in optimization. Overall, while nature-inspired optimization algorithms offer promising solutions, addressing these challenges is crucial for their successful implementation in HAR systems.

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