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A REVIEW ON HYBRID ARTIFICIAL BEE COLONY FOR FEATURE SELECTION

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ABSTRACT

Due to the presence of redundant and irrelevant features in the dataset, the feature space's high dimensionality has an impact on classification accuracies and computational complexity. Feature Selection gets the most relevant and valuable information and aids in classification speed. Since finding the suitable, optimal feature subset is critical, feature selection is viewed as an optimization problem. One of the efficient nature-inspired optimization techniques for handling combinatorial optimization issues is the Artificial Bee Colony algorithm. It has no sensitive control parameters and has been demonstrated to compete with other well-known algorithms. However, it has a poor local search performance, with the equation of solution search in ABC performing well for exploration but poorly for exploitation. Furthermore, it has a quick convergence rate and can thus become caught in local optima for some complex multimodal situations. Since its introduction, much research has been conducted to address these issues in order to make ABC more efficient and applicable to a wide range of applications. This paper provides an overview of ABC advances, applications, comparative performance, and future research opportunities.

Keywords: Feature selection, swarm intelligent algorithms artificial bee colony, exploration, exploitation, classification

1. INTRODUCTION

A huge number of features are generated for improved image representation, hence classification of data in large databases necessitates effective analysis algorithms. In the feature selection process, optimization approaches can be used to determine the most relevant subset of features from the data set while keeping the accuracy rate indicated by the original set of features. (Hancer *et al.*, 2017).

The process of choosing the most relevant features from a group of features that create patterns in a dataset is known as feature selection. Irrelevant and redundant data in a dataset can degrade a biometric system's performance. The subset should be capable of describing target concepts while correctly representing the original features. The goal of feature subset select ion is to lower the computational complexity of a high-dimensional dataset by limiting the number of features used to characterize it, hence improving the performance of a learning algorithm on a certain task. (Xiang *et al*., 2015).

The process of feature selection is an NP-hard problem since it requires selecting an optimal subset of features without losing classification quality. Meta-heuristics are one of the most effective methods for determining the best subset of features in the shortest period of time (Bindu and sabu 2020). For feature selection, swarm intelligent algorithms (SI), a type of meta-heuristic technique can be applied. The social behavior of insects such as ants, bees, and flocks of birds inspired the SI algorithms. They model a self-organized community working together to attain a common goal, like as food foraging, using collective intelligence (Brezocnik et al, 2018).

Ant Colony Optimization, based on ant colonies (Dorigo, 1992), Particle Swarm Optimization, based on fish schooling/bird flocking (Kennedy and Eberhart, 1995), Immune Algorithm, based on swarm of cells and molecules (Timmis et al., 2000), and Artificial Bee Colony, based on honey bee swarms (Karaboga, 2005) are SI-based feature selection. Also, Cat Swarm Optimization (Chu and Tsai, 2007), Cuckoo Search Algorithm (Yang and Deb, 2009), Firefly Algorithm (Yang, 2009) based on flashing behavior of tropical fireflies, Gravitational Search Algorithm based on newton's law of universal gravitation (Rashedi et al., 2009). The algorithms address an optimization problem and search for the best solutions across a number of iterations using primitive mechanisms and procedures (Barak *et al.*, 2015).

The algorithms begin with a population of random solutions and improve their optimality with each iteration step. Most meta-heuristic algorithms start by randomly generating a set of initial solutions, and then using a fitness function to determine the optimality of the generated population's individual solutions. A new generation of production will begin if none of the termination criteria are met. This cycle continues until one of the termination criteria has been met (Hu *et al*., 2020; Wang *et al*., 2020).

Karaboga and Akay developed the ABC method in order to solve numerical optimization problems (Karaboga, 2005). ABC is a metaheuristic algorithm inspired by honey bee swarms. ABC shares information among the bees in the population and selects possible solutions that meet the defined criteria. ABC offers a unique solution update technique (updating in two parts), which allows the results to fast converge to the best solution. It is also simple and easy to implement because it has fewer control parameters to configure and good exploration characteristics. Therefore, ABC has been used in feature selection, optimization, error detection, and neural network training and intrusion detection.

2. HYBRID ARTIFICIAL BEE COLONY ALGORITHMS

The artificial bee colony (ABC) is a powerful optimization technique that is used to tackle real-world problems. The standard ABC algorithm, on the other hand, has a fast convergence rate and a tendency to become trapped in local minima. Combining two successful algorithms to create a new approach is beneficial since the new method will have the benefits of both algorithms while compensating for their drawbacks (Gunasekaran and Subramaniam, 2016). As a result, there are opportunities to improve ABC's exploitation capacity, and numerous versions of ABC have been developed to address its shortcomings and improve performance. For these reasons, this method must be hybridized with other algorithms (Sharma *et al.,* 2020)**.**

Ozturk and Karaboga (2011) proposed a hybrid algorithm ABC - Levenberq-Marquardt (LM). The ABC algorithm is good at finding global optimistic results, while the LM algorithm is good at finding local optimistic results. The basic principle behind this hybrid algorithm is that the ABC was employed at the start of the search for the optimal. Then, LM continues training by using the best weight set of the ABC method and attempting to reduce training error. The LM algorithm interpolates between the Newton technique and the gradient descent approach, approximating network error using a second order expression. On the XOR, 3-Bit Parity, and 4-Bit Encoder-Decoder benchmark tasks, the proposed hybrid approach was employed to train feed-forward artificial neural networks. The results of the experiments showed that the hybrid ABC-LM algorithm outperforms the individual techniques.

To improve the exploitation process, Tuba and Bacanin (2014) proposed a hybrid version of the standard ABC algorithm that incorporates the local search characteristics of the fire fly algorithm. On twenty unimodal and multimodal standard benchmark test functions, the proposed hybrid method was assessed. A comparison of robustness and efficiency with the pre-existing population-based algorithms: tabu search, PSO, GA, and simulated annealing was also performed (SA).

Chun-Feng *et al.* (2014) presented a hybrid ABC algorithm based on a particle swarm searching mechanism (ABC-PS). To compensate for the ABC algorithm's poor performance, the initial food supply was generated using good point set theory. Second, the employed bee, onlookers, and scouts use the PSO process to find new candidate solutions in order to improve exploitation ability. Finally, in the best solution of the current iteration, the chaotic search operator was applied to boost the searching capabilities. The algorithm was compared to other algorithms and tested against several benchmark functions. The ABC-PS exceeds other algorithms such as ABC, GABC, COABC, and PABC in the majority of cases, according to the experimental observations.

Sharma *et al.* (2015), A Levy flight inspired search technique was proposed and integrated with ABC to strike a balance between diversity and convergence in the ABC. The proposed technique, known as Levy Flight ABC (LFABC), can do both local and global searches at the same time and can be accomplished by modifying the Levy flight parameters and thereby automatically tuning the step sizes. The LFABC generates new solutions based on the best solution, which helps to improve ABC's exploitation capabilities. Furthermore, the number of scout bees was increased to improve exploration capability. In most of the experiments, the proposed technique outperformed the basic ABC and recent versions of ABC, namely, Gbest-guided ABC, best-so-far ABC, and modified ABC, on 20 test problems of varying difficulties and five real-world engineering optimization issues.

Li *et al*. (2015), to handle high-dimensional optimization issues, a hybrid technique dubbed PS–ABC was proposed. In the algorithm process, this method makes use of the ABC's exploration ability based on PSO. The exploitation ability of PSO was employed in PS–ABC to discover the optimal solution and boost the algorithm's convergence rate, whereas the exploration ability of ABC was used to search the solution space. The proposed method's efficiency was evaluated using 13 high-dimensional benchmark functions from the IEEE-CEC 2014 competition challenges. The PS–ABC algorithm is an effective, quick converging, and robust optimization approach for addressing high-dimensional optimization problems, according to the results.

Gunasekaran and Subramaniam (2016) developed a hybrid optimization technique for optimizing multiple objective functions that uses fractional order ABC and the Genetic Algorithm (GA). Employee bee, onlooker bee, mutation, and scout bee were the four steps of the proposed algorithm. During the employee bee phase, a neighbor solution is developed using the ABC method. The probability was further utilized to pick a solution in onlooker bee, and a new solution is generated based on Fractional Calculus (FC) dependent neighbour solution. The GA mutation operation was employed in the mutation module, followed by the scout bee phase. To evaluate the algorithm's performance, unimodal benchmark functions such as De jong's, axis parallel hyper-ellipsoid, rotated hyper-ellipsoid, and rastrigin are used, as well as multi-modal functions such as Griewank and rastrigin. After that, the algorithm was compared to the current ABC, GA, and hybrid algorithms. According to the results, the proposed technique produced better outcomes by achieving a higher minimization and convergence rate.

To address premature convergence in the later search stage, Anam (2017) presented a hybridization of the elementary ABC algorithm with the Broyden–Fletcher–Goldfarb–Shanno (BFGS) method. A point was discovered within the ABC method, and the same point was used to initialize the population location for the BFGS algorithm. The simulation results show that the hybrid technique can solve practically all benchmark test functions and overcome basic ABC algorithm issues including premature and poor convergence speed.

Sharma and Kazakov (2017) developed a variation of the ABC method by hybridizing it with the evolutionary computation (EC) algorithm in three steps. First, the ABC algorithm was fine-tuned with new parameters. Second, the mutation operator was applied to solve diversity. Third, the average fitness comparison of the poorest employed bee was replaced to avoid adjusting the 'limit'parameter and discarding good alternatives. The simulation results were compared to six population-based algorithms: GA, PSO, DE, adaptive ABC, conventional ABC, and quick ABC.

Jadon *et al., (*2017) proposed combining the ABC algorithm with the differential evolution (DE) algorithm to improve convergence speed and avoid premature convergence. The onlooker bee phase updates their position dependent on DE. The employed bee phase was changed by employing the idea of the appropriate individual, and the scout bee phase also was changed for further exploration. More than twenty test problems and four real-world optimization difficulties were used to evaluate the predicted HABCDE. The effectiveness of the HABCDE controller was evaluated to the elementary variants of the ABC and DE algorithms. The simulation findings indicated that HABCDE was a reliable meta-heuristic algorithm.

Ghanem *et al., (*2018), used a hybrid of the ABC algorithm and the dragonfly algorithm (DA) to train a multi-layer perceptron. Whereas DA performs global searches, the onlooker bees were responsible for local search. The proposed approach was tested on thirty-three standard functions in order to analyze performance in terms of three static parameters: mean, standard deviation, and median.

For continuous optimization issues, Panniem and Puphasuk (2018) proposed a modified artificial bee colony algorithm with firefly algorithm (MABC) approach. The approach was designed to address the issues of slow convergence, premature convergence, and being stuck within the local solutions that may arise during the ABC search process. In the employed bee phase, a new search equation was utilized, which boosted the chances for onlooker bees to locate better places and replaced some of the worst positions with the new ones in the onlooker bee phase. In addition, the Firefly algorithm technique was employed to construct a new position in the scout bee phase, replacing an unupdated position. Its performance was measured using a set of benchmark functions. The findings of the experiments reveal that MABC is more successful than ABC and certain other ABC variations.

Jarrah *et al.,* (2020) merged an ABC algorithm with a -hill climbing algorithm to build a high-performing local search system. The primary purpose of this hybridization is to increase the exploitation potential of the ABC algorithm. The procedure begins with an ABC initialization phase to establish a random beginning population in the hybrid ABC–βHC. Then, instead of the employed bee phase, the βHC phase is used for exploration and exploitation procedures. Following that, the onlooker bee phase changes the solutions in accordance with the roulette wheel selection technique. The proposed algorithm was experimentally tested and validated using selected benchmark functions with diverse properties, as well as evaluated and compared to well-known population-based algorithms. The results demonstrated that ABC– βHC exhibited high-performance exploitation and exploration operations, resulting in faster convergence in most benchmark functions and outperforming eight algorithms, including the original ABC, across all measurement variables.

3. HYBRID ABC-BASED FEATURE SELECTION METHODS

Suguna and Thanushkodi (2011) proposed an improved Rough Set-based Attribute Reduction (RSAR) approach by combining RSAR with the Artificial Bee Colony (ABC) algorithm, which first discovers the subset of attributes independently based on decision attributes (classes) and then finds the final reduct. The cases are initially categorized based on decision attributes. The Quick Reduct technique was then used to determine the reduced feature set for each class. The ABC method is performed to this collection of reducts to select a random number of characteristics from each set, based on the RSAR model, to obtain the final subset of attributes. The performance was compared to six other reduct algorithms using five different medical datasets: Dermatology, Cleveland Heart, HIV, Lung Cancer, and Wisconsin. The proposed approach achieves higher accuracy of 92.36, 86.54, 86.29, 83.03, and 88.70%, respectively. According to the results of the studies, the proposed approach minimizes computational cost while improving classification accuracy when compared to some conventional techniques.

Yusoff *et al.* (2014) developed a hybrid ABC-DE algorithm for feature selection by applying the mutation and crossover operators of DE to the four food sources that can be abandoned in the ABC algorithm's scout bee process. Instead of moving at random, the search mechanism is aided by the use of an existing solution in the search space. Using an SVM classifier, the proposed hybrid method is compared to other types of nature-inspired algorithms such as ACO and PSO, and it is discovered that the proposed hybrid method achieves 100% and 98.44% accuracy in the training and testing phases, respectively, for the ovarian cancer dataset; and 100% and 94.44% accuracy for the TOX dataset.

The hybrid method which consists of ABC and DE for feature selection belongs to Shanthi and Bhaskaran (2014). In this study, the neighborhood generation operator of ABC is included to the DE/current-to-rand/1 mutation operator to discover feature subset solutions. Self-adaptive Resource Allocation Network (SRAN) is used for classification process with 10-folds cross-validation. The method is experimented on Mammography Image Classification dataset, and performance of new hybrid method is compared with ABC, ACO, and GA. The hybrid method selected 42, 45, 56, 50 features from 84 attributes and achieve 96.89%, 96.27%, 96.27% and 95.96% of accuracy respectively.

Hancer *et al*. (2015) proposed a binary ABC algorithm for feature selection that is based on an advanced similarity scheme. In the study, DE operators such as mutation and recombination are used instead of the ABC neighborhood search technique. Then, for the DE algorithm, a new mutation mechanism based on the dissimilarity Jaccard coefficient was proposed. According to the DE algorithm, the similarity measure was utilized to determine the difference vector of features. The best solution (that is, the feature vector) in the swarm was used to generate a mutant vector. The proposed algorithm's performance was proved by comparing it to standard binary PSO, velocity-based binary PSO, angle modulated ABC, and genetic algorithms on ten benchmark datasets using accuracy values. The findings showed that the proposed algorithm outperforms the previous approaches in terms of classification performance in training and test sets, as well as the elimination of irrelevant and redundant features.

Zorarpac and Ozel (2016) developed a hybrid feature selection method for classification tasks that combined the ABC optimization strategy with the differential evolution algorithm. The hybrid feature selection technique combines a binary neighborhood search mechanism, a modified onlooker bee process of the ABC algorithm, and the DE algorithm with a binary mutation phase to identify optimal feature subsets. The hybrid approach developed was evaluated on fifteen datasets from the UCI Repository that are commonly used in image classification. Experiment results demonstrated that the proposed hybrid technique was capable of selecting outstanding features for classification tasks in order to improve the classifier's run-time performance and accuracy.

Shunmugapriya and Kanmani (2017) proposed an Ant Colony-Artificial Bee Colony (AC-ABC) hybrid algorithm based on swarm intelligence. Ants employed Bee exploitation to find the best Ant and feature subset. This method combines the features of the Ant Colony and ABC algorithms to optimize feature selection and classification. By hybridizing, the ants' stagnation behavior was abolished, as was the employed bees' time-consuming global search for initial solutions. As food sources, bees adapt ant-created feature subsets. Thirteen UCI (University of California, Irvine) benchmark datasets were utilized to evaluate the proposed technique. According to the findings of the trials, the proposed strategy has the ability to improve classification accuracies and choose the best features. In contrast, the swarm-based hybrid technique was not tested on a dataset with a large number of dimensions.

Hancer *et al*. 2017 presented a multi-objective feature selection method based on a multi-objective artificial bee colony algorithm combined with a non-dominated sorting mechanism and genetic operators for classification. The proposed approach was implemented in two ways: ABC with binary representation and ABC with continuous representation. On 12 benchmark datasets, their performance was measured and compared to that of linear forward selection, greedy stepwise backward selection, two single objective

ABC algorithms, and three well-known multi-objective evolutionary computation techniques. The results showed that the proposed binary representation strategy outperformed the other strategies in terms of both dimensionality reduction and classification accuracy. However, despite their high performance, the suggested methods have several limitations. For example, they are computationally expensive, and their scalability to datasets with thousands of features is uncertain.

Alshamlan (2018) proposed the Co-ABC algorithm, a novel hybrid feature selection method. As a preprocessing step to the ABC method, the proposed technique uses a Correlation-based feature Selection (CFS) filter to increase search time and classification performance by deleting unnecessary genes and filtering noisy genes. In the tests and comparisons, six binary and multi-class microarray cancer gene expression profiles were used. According to the findings, the provided Co-ABC method outperforms comparable algorithms.

In 2018, Hajisalem and Babaie proposed a hybrid classification system based on the Artificial Bee Colony (ABC) and Artificial Fish Swarm (AFS) algorithms. To partition the training dataset and remove the unnecessary features, the Fuzzy C-Means Clustering (FCM) and Correlation-based Feature Selection (CFS) approaches are used. Furthermore, If-Then rules are produced using the CART technique based on the selected attributes in order to differentiate between normal and abnormality records. Similarly, the generated rules are used to train the proposed hybrid technique. The simulation results on the NSL-KDD and UNSW-NB15 datasets show that the proposed method outperforms in terms of performance metrics, with a detection rate of 99% and a false positive rate of 0.01%. Furthermore, an examination of computational complexity and time cost reveals that the proposed method's overhead is comparable to that of comparable alternatives.

Djellali *et al.* (2018) proposed feature selection method using two hybrid approaches based on ABC with PSO algorithm and ABC with Genetic Algorithm (ABC-GA). An improvement was made to the ABC algorithm to achieve a balance between exploration and exploitation. PSO was found to contribute to ABC in employed bees, and GA mutation operators were used in the Onlooker and Scout phases of the study. It was discovered that the proposed hybrid ABC-GA method outperforms existing methods (GA, PSO, ABC) in terms of finding a small number of features and classifying the WDBC, colon, hepatitis, DLBCL, lung cancer dataset. The results of the experiments were performed on the UCI data repository and demonstrated the effectiveness of mutation operators in terms of accuracy and particle swarm for smaller features. ABCPSO, on the other hand, had a low level of accuracy.

Khellat-kihel and Benyettou (2018) presented a methodology for feature selection using the Genetic Algorithm with the Firefly, Ant colony optimization and ABC Algorithms to select the most relevant features in a synthetic datasets. Instead of random initialization, the Genetic Algorithm established a new population of chromosomes utilizing the populations formed by the three algorithms (ACO, ABC, and FA) as the initial population. The key objective of this selection was to reduce the amount of features by removing redundant and irrelevant features while also enhancing the performance of the classifier using the neural network method. In order to evaluate the results comparable to the results in feature selection evaluations, datasets from the UCI machine learning repository was used. Simulation results showed that the new approach outperformed the traditional algorithms. Rich assessment measures, on the other hand, received less attention.

Bindu and Sabu (2020) proposed a hybrid feature selection approach using Artificial Bee Colony and Genetic Algorithm. The proposed approach combines two algorithms, ABC and GA, with the aim that hybridization can further increase their performance. The proposed approach suggested exchanging the populations from ABC and GA to each other after every iteration. By receiving a diverse population generated from GA after every iteration, the proposed method avoided ABC's local optima stagnation. The hybrid approach's results showed that GA compensates for ABC's limitations. For the experiment, a Random Forest classifier was utilized on UCI repository dataset. The classification accuracy after 10 fold cross-validation was used to evaluate the learning model's performance. Superior results of the proposed approach proved that hybridisation have improved the performance of the ABC algorithm for feature selection. It selected a better subset of relevant features resulting in improved classification accuracy. At the same time, it selected a lesser number of features than the existing feature selection algorithm using ABC. On high-dimensional datasets, however, improving the hybrid technique was not considered.

Vani and Shashi, 2020 used a hybrid algorithm of Artificial Bee Colony and Linear Vector Quantization (ABC-LVQ) to investigate the classification accuracy of DDoS attacks. The bio-inspired algorithm, Artificial Bee Colony (ABC), was modified to reduce the number of features in order to create a dataset on which a supervised classification algorithm, LVQ, was applied. The ABC technique was applied to the KDD dataset to provide the optimized dataset that was trained by LVQ for model structure. Again, 40% of the KDD dataset is used as a test dataset, and the model is used to classify the accurate DDoS attack. The effectiveness of classification methods in grading the NSL-KDD dataset was evaluated. The testing findings show that the improved ABC-LVQ is the best choice for classifying DDoS attacks. It has a true classification rate of 96%, which is greater than kNN and LVQ. To summarize, it is anticipated that optimum classification may be reached by preferring the optimized LVQ over other existing techniques.

Lin *et al.* (2021) presented a binary ABC approach for identifying features (molecular descriptors) in Quantitative Structure–Activity Relationships (QSAR). To increase the prediction accuracy and interpretability of QSAR modeling, two ABC variants for feature selection are proposed: ABC-Partial Least Squares (ABC-PLS) and ABC-PLS-1. In the ABC-PLS variation, a threshold was used to convert continuous space to discrete space, which was then used to pick features in QSAR. Crossover and mutation operators are introduced in the ABC-PLS-1 variant to employed bee and onlooker bee phase to modify various dimensions of each solution, which not only saves the process of transforming continuous values into discrete values, but also minimizes processing resources. In addition, a greedy selection technique was used, which selects feature subsets with higher accuracy and fewer features, allowing the algorithm to converge quickly. The suggested technique was evaluated using three QSAR datasets. In terms of accuracy, root mean square error, and number of selected features, ABC-PLS-1 surpasses PSO-PLS, WS-PSO-PLS, and BFDE-PLS. Different Limit values for the scout bee phase were investigated, and it was determined that the scout bee phase is unnecessary when dealing with feature selection in low-dimensional and medium-dimensional regression situations. However, no multi-object ABC approach for QSAR was investigated in order to maximize prediction accuracy while minimizing the number of selected features.

4. EVALUATION RESULTS

Table I: shows the performance of feature selection techniques. The techniques' results demonstrated that hybridization increased the performance of the ABC algorithm for feature selection and other optimization problems. It selects a more relevant collection of characteristics, resulting in enhanced classification accuracy. At the same time, it chooses fewer features than the previous feature selection algorithm based on ABC.

Author	**Hybridization technique**	**DataSet**	**Accuracy**	**Limitation**
Suguna and Thanushkodi, 2011	RSAR- ABC	medical datasets	92%	Different normalization rules
Yusoff et al. (2014)	ABC-DE	Drug-Induced Toxicity dataset ovarian cancer dataset	94% 98%	Not applied for other domain of problems in feature selection purposes.
Shanthi and Bhaskaran (2014)	ABCDE	Mammography Image dataset	96.89%	Not tested on large dimensional datasets
Hancer et al 2015	ABCDE	ten benchmark datasets	22.17% error rate	Not tested on large dimensional datasets
Zorarpac and Ozel (2016)	ABCDE	fifteen datasets from the UCI Repository		Not tested on large dimensional datasets
Hancer *et al*. 2017	ABC and non-dominated sorting procedure and genetic operators	12 benchmark datasets	91%	Not tested on large dimensional datasets
Shunmugapriya and Kanmani (2017)	AC-ABC	Cancer Dataset	99.43%	hybrid algorithm was not evaluated on high dimension dataset.
Hajisalem and Babaie, 2018	(ABC) and Artificial Fish Swarm (AFS)	NSL-KDD and UNSW-NB15 datasets	99% detection rate and 0.01% false positive rate	
Djellali *et al.* (2018)	ABCPSO ABCGA	Hepatitis Dataset	87.50% 91.67%	mutate scheme was not used on ABCPSO
Khellat-kihel and Benyettou (2018)	ACO, ABC and FA	datasets from the UCI machine learning repository	0.02 ERR	Sensitivity measure was not carried out
ALSHAMLAN (2018)	CORRELATION-BASED ABC	MICROARRAY CANCER GENE DATASET	96.77%	CFS FILTERS SELECTS ONLY THE HIGHLY CORRELATED GENES AND THIS AFFECT THE ACCURACY.

Bindu and Sabu (2020)	GA-ABC	UCI repository dataset	97.2%	Not tested on large dimensional datasets
Vani and Shashi, 2020	ABC-LVQ	NSL-KDD dataset	96%	high dimensional feature space was not considered
Lin et al. 2021	ABC and Quantitative Structure–Activity Relationship (QSAR)	Artemisinin, Selwood and BZR dataset	0.1906 root mean square error	multi-object ABC algorithm for QSAR was not considered

5. CONCLUSION

This paper presents a review of prior research on ABC hybridization with other SIs and feature selection applications. ABC is a potent optimization technique that has been widely applied in the solution of combinatorial optimization issues. ABC algorithms were successfully deployed for feature selection and produced excellent results, resulting in improved classification performance. The proposed algorithm has resulted in reduced feature size of the feature subset, increased classification accuracies, and low computing complexity, as demonstrated by experimental findings. While ABC has immense potential, it was clear to the research group that several adjustments to the existing structure were still needed to improve its efficiency. A new probability selection technique for dispersing onlookers to select food sources can be proposed in order to improve the population variety of the ABC algorithm. New scout generation algorithms are required for the development and distribution of good solutions, as well as faster convergence, which makes ABC perfect for handling complicated real-world issues. It is believe that this survey will be extremely useful to researchers working in the field of ABC and feature selection.

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