DOI: https://doi.org/10.52756/10.52756/ijerr.2023.v31spl.006 *Int. J. Exp. Res. Rev.*, Special Vol. 31: 51- 60 (2023)

Original Article | Peer Reviewed | Open Access

International Journal of Experimental Research and Review (IJERR)
© Copyright by International Academic Publishing House (IAPH)
ISSN: 2455-4855 (Online)
www.iaph.in

Analysis of Meta-Heuristic Feature Selection Techniques on classifier performance with specific reference to psychiatric disorder

Chandrabhan Singh[1], Mohit Gangwar[2*] and Upendra Kumar[3]

[1]Computer Science & Engineering, Dr. A.P.J. Abdul Kalam Technical University, Lucknow, UP, India;
[2]Department of AI & ML, SIRT, Bhopal, MP, India; [3]Department of Computer Science & Engineering, IET, Lucknow, UP, India

E-mail/Orcid Id:

CS, chandrabhan98@gmail.com; *MG*, mohitgangwar@gmail.com, https://orcid.org/0000-0001-5654-2317;
UK, upendra.ietlko@gmail.com, https://orcid.org/0000-0003-3792-7945

Article History:

Received: 24th Apr., 2023
Accepted: 20th Jun., 2023
Published: 30thJul., 2023

Keywords:
Feature selection, Meta-Heuristic techniques, optimization, classification

Abstract: Optimization plays an important role in solving complex computational problems. Meta-Heuristic approaches work as an optimization technique. In any search space, these approaches play an excellent role in local as well as global search. Nature-inspired approaches, especially population-based ones, play a role in solving the problem. In the past decade, many nature-inspired population-based methods have been explored by researchers to facilitate computational intelligence. These methods are based on insects, birds, animals, sea creatures, etc. This research focuses on the use of Meta-Heuristic methods for the feature selection. A better optimization approach must be introduced to reduce the computational load, depending on the problem size and complexity. The correct feature set must be chosen for the diagnostic system to operate effectively. Here, population-based Meta-Heuristic optimization strategies have been used to pick the features. By choosing the best feature set, the Butterfly Optimization Algorithm (BOA) with the Enhanced Lion Optimization Algorithm (ELOA) approach would reduce classifier overhead. The results clearly demonstrate that the combined strategy has higher performance outcomes when compared to other optimization strategies.

Introduction

In any learning technique, feature selection plays an important role. Any learning system can be trained using all its features. Data processed in a learning system consists of many dimensions. Learning any system with all its features will take a lot of computational time and cost. This computational overhead plays a role in introducing intelligent approaches for feature selection. A training system with fewer features, i.e., features with high weightage, will reduce the computational overhead and help in efficient prediction. Classification is an important approach in any learning system. Artificial neural networks (ANN), due to their high accuracy and performance, are the most preferred approach for classification (Schmidhuber, 2015; Galeshchuk, 2016). Due to a lack of explanation, a neural network is combined with fuzzy logic, giving birth to the Neuro-fuzzy concept. The concepts of Neural networks and fuzzy logic are combined to meet human-like decision capability and learning ability. Learning with this type of system provides the optimal, or, say, most reliable, result. Feature selection is the process of finding the subset of the most reliable features from the overall set of features. Selecting optimal features will not only avoid the curve of dimensionality but also simplify the model by reducing its training cost and time (Gangwar et al., 2012; Singh et al., 2020). It will enhance the generalization of the model by reducing overfitting.

Figure 1 mentioned below, shows the working of the learning system. Here after normalization, feature

***Corresponding Author:** mohitgangwar@gmail.com

selection process will be used to find the finest subgroup of features from the dataset. Feature selection using a meta-Heuristic approach plays an important role in various problems in different domains. Disease diagnosis, education, robotics, finance, and agriculture are the leading domains where Meta-Heuristics methods are introduced by researchers (Sharma and Kaur, 2020). Especially in disease diagnosis domain research, the last five years have shown a huge increase in the use of these nature-inspired methods (Sharma and Kaur, 2020; Gangwar et al., 2014). Medical data is not simple in nature (Gangwar et al., 2020a). The dimensionality, complexity, and vastness of data require the use of intelligent approaches for feature selection (Gangwar et al., 2020b).

(Arora and Singh, 2019), etc. The Butterfly Optimization Algorithm (Arora and Singh, 2019) is a recent Meta-Heuristic Algorithm based on the mating and foraging behavior of butterflies. This algorithm uses the sense of smell and behavior of butterflies to determine the direction and location. Wang et al. (2019) introduce the Monarch Butterfly Optimization (MBO), a unique kind of metaheuristic algorithm inspired by nature that idealizes and simplifies the flight of monarch butterflies. Meta-Heuristic algorithms based on the nature of animals are also popular and play an important role in optimization. Lion Optimization Algorithm (LOA) (Yazdani and Jolai, 2016), Elephant Herding Optimization (Wang et al., 2015), and Spotted Hyena Optimizer (Dhiman and Kumar, 2019) are some popular animal-based

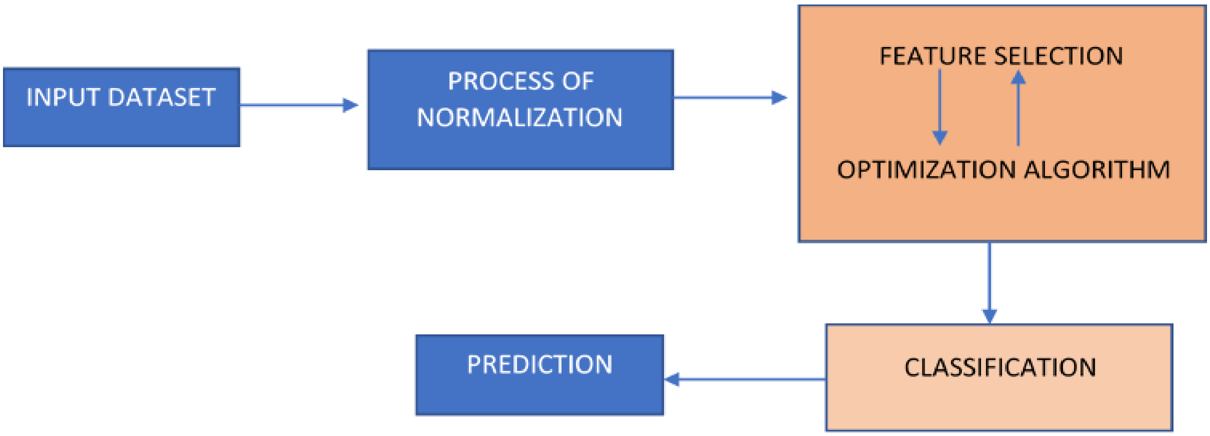

Figure 1. Overall Working Model of Learning System for Classification

In 1995, Particle Swarm Optimization (PSO) was introduced to optimize the problem (Kennedy and Eberhart, 1995). PSO has slow convergence, which means the local search ability of PSO-based methods is weak. In 1999, another insect-based Meta-Heuristic algorithm called Ant Colony Optimization was introduced based on the activities of ants (Dorigo and Di Caro, 1999). The foraging behavior of ant colonies served as the basis for this algorithm. ACO has demonstrated good performance, but it falls short when dealing with massive volumes of data in terms of the learning system's accuracy and convergence speed. Later, several other algorithms that model insect behavior are presented, including the Artificial Bee Colony (Karaboga and Basturk, 2007), the Firefly Algorithm (Yang, 2009), the Bat Algorithm (Yang, 2010), the Fruit Fly Optimization (FFO) (Pan, 2012), the Moth-Flame Optimization (Mirjalili, 2015), the Butterfly Optimization Algorithm (BOA) Meta-Heuristic algorithms. The Lion Optimization Algorithm (LOA) is inspired by the social behavior of lions. Roaming, mating, migration, etc. are the behaviors that are used for the algorithm. Verma et al. (2022) employed an ensemble data mining strategy to improve a specific and trustworthy illness prediction model. To anticipate patient illnesses from the symptoms of a study, a novel neurofuzzy-based optimization technique called Generalized Fuzzy Intelligence-based Ant Lion Optimization (GFIbALO) is introduced in this work. LOA shows a fast rate of convergence. Unlike BOA, LOA shows global optima achievement (Yazdani and Jolai, 2016). Using Deep learning, Dubey (2021) offers a ground-breaking method for multi-disease prediction. In this instance, optimal feature selection is applied to the collection of available features. Two Meta-Heuristic Algorithms, such as the Butterfly Optimization Algorithm (BOA) and the Lion

DOI: https://doi.org/10.52756/10.52756/ijerr.2023.v31spl.006

Algorithm (LA), are combined to accomplish this. These prediction algorithms adjust or optimize the hidden neuron count of NN and DBN using the same hybrid Lion-based BOA (L-BOA). Convolutional neural networks were used by Nandhini & Ashok Kumar (2021) to produce an improved crossover-based Monarch Butterfly Optimization for the classification of tomato leaf diseases. In this study, the four forms of leaf diseases that affect tomato plants-bacterial spot, Septoria leaf spot, late blight, and tomato mosaic virus are classified automatically without the need for any manual labor. A binary solution encoding strategy is offered utilizing the Improved Crossover-Based Monarch Butterfly Optimization (ICRMBO) approach to reduce this complexity and improve the parameters identified in the CNN. Meta-Heuristic algorithms based on the nature and behavior of birds are also popular for optimization of problem domains in any search space. Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995) was first introduced in 1995 as a nature-inspired Meta-Heuristic Algorithm based on the behavior of birds. Recently, the Crow Search Algorithm (CSA) (Askarzadeh, 2016), Artificial Feeding Birds (AFB) (Lamy, 2019), Harris Hawks optimizer (HHO) (Heidari et al., 2019), and Emperor Penguin Colony (EPC) (Harifi et al., 2019) have been introduced as bird-inspired Meta-Heuristic approaches. A Multi-Objective Grasshopper Optimization Algorithm (MOGOA) for Alzheimer's disease identification is presented by Ismail et al. (2023). A new swarm intelligence system-based Meta-Heuristic Algorithm called CSA was just created, and it mimics how crows store extra food and get it back when they need it (Askarzadeh, 2016). According to optimization theory, the crow is the searcher, the immediate area serves as the search space, and storing the position of food at random is a workable approach. To solve numerous optimization issues, CSA simulates the cognitive behavior of crows. Since it has benefits like easy implementation, few parameters, adaptability, etc., it has attracted a lot of interest throughout the globe (Hussien et al., 2020).

Each optimization algorithm works on the nature and behavior of its inspiration. Thus, these algorithms have some advantages and disadvantages. The integrated Meta-Heuristic Algorithm has recently become popular to overcome each other's short comings. Some optimization algorithms show better local search ability, and some show excellent global search ability. To improve the convergence rate, research should focus on the combination of two or more Meta-Heuristic Algorithms. Dealing with huge amounts of data, these combinations play an excellent role in achieving accuracy and convergence rates (Singh et al., 2021). The most common problem with the Meta-Heuristic Algorithm is falling into local optima. Due to this problem, a global optimal solution cannot be discovered. The next selection will be able to explore an algorithm's convergence rate as an individual or a combination of any two. This research especially deals with BOA, LOA, ACO, and BOA-ELOA (Enhanced Lion Optimization Algorithm). By introducing opposition-based learning in LOA, the enhanced LOA approach is used. Various other enhancements by mixing two different approaches have been discussed earlier, like Ant-Lion Optimization (Tarle and Jena, 2021), etc. Because of their effectiveness, Meta-Heuristic Algorithms are currently employed in healthcare data to identify illnesses more effectively than conventional techniques. Kaur et al. (2023) conducted a study on research papers influenced using metaheuristic approaches to diagnose disorders. Thus, this research focused on analyzing Meta-Heuristic Optimization approaches' performance as feature selection techniques. Furthermore, various popular population-based Meta-Heuristic approaches have been compared.

Methodology

Recent research shows that the use of Meta-Heuristic approaches for optimization increases in disease diagnosis. Psychiatric is an important medical Domain. Decision-making in mental illness is complex work. To help the practitioner to improve the decision-making process needs robust system. Intelligent computing will play an important role in this process. Parkinson's Disease (PD) and Autism Spectrum Disorder (ASD) are the most popular psychiatric diseases. Here, the study of Meta-Heuristic Algorithm is done on PD and ASD detection and diagnosis. Dataset of PD and ASD has

DOI: https://doi.org/10.52756/10.52756/ijerr.2023.v31spl.006

been taken from benchmark repositories. After Normalization the input data of the PD and ASD dataset is provided to this intelligent feature selection optimization method. ACO, BOA, ELOA and PSO are the individual population-based approaches that are compared with BOA-ELOA algorithm. The convergence rate indicates that the integrated BOA-ELOA algorithm shows better result. This will further improve the computational overhead also.

fewer characteristics, as shown in Table 1 below. This will cut down on computing overhead and classifier learning costs.

Population-based Meta-Heuristic Methods work in two basic search spaces: local and global. Here, enhanced LOA, which has the capability of opposition learning, is coupled with the Butterfly Optimization Algorithm as BOA has issues, including decreased variety in the population and a

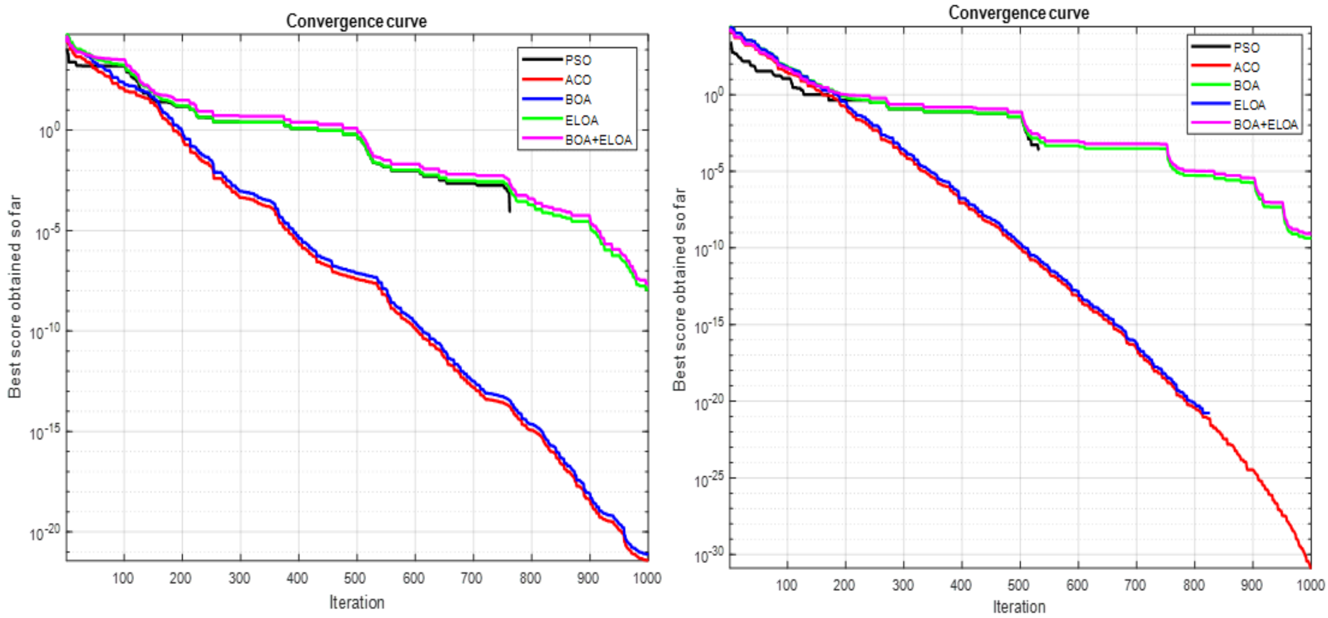

Figure 2.Convergence Curve of various Optimization Methods for ASD and PD dataset respectively

Figure 2 clearly indicates that with reference to these two datasets, ASD and PD, the rate of convergence based on the score obtained after specific iterations, the combined optimization shows the best result. Although the rate of convergence of ELOA is better in comparison to BOA, PSO and ACO. The above graph clearly shows that BOA and ACO have slow convergence rates due to falling in local optima. From the machine learning data repository at UCI, benchmark datasets for PD and ASD have been collected. ASD includes 292 data occurrences, compared to 240 in the Parkinson data set. There are about 46 characteristics in the PD dataset compared to 21 in the ASD dataset. In both data sets, the number of features selected using integrated BOA+ELOA is less compared to other algorithms like PSO, ACO, BOA, ELOA, etc. Table 1 shows number of features selected for Autism dataset using various Meta-Heuristic Algorithms. The integrated technique offers a superior convergence rate and trains the learning system with propensity to become stuck in local optimums (Zhou et al., 2021). The table above shows that the number of features selected by the combined method is less than that selected by the individual approaches.

Table 1. Feature selection using Meta-Heuristic Algorithms on Autism dataset

Optimization Algorithm	Feature Selected
PSO	19
ACO	17
BOA	15
ELOA	16
BOA+ELOA	13

Results and Discussion

The decision tree (DT) is one of the most useful techniques for classification and prediction. A decision tree is a tree structure that mimics a flowchart, in which each leaf node (terminal node) has a class or value label, each branch displays the outcome of the test, and each decision node (interior node) denotes a test on an attribute. A tree can be "learned" by breaking the source set up into groups based on an attribute value test. This process of

DOI: https://doi.org/10.52756/10.52756/ijerr.2023.v31spl.006

repeating for each derived subgroup is referred to as recursive partitioning. In the KNN (K-Nearest Neighbors) classification technique, learning is based on "how similar" data (a vector) is to data from other objects. In data mining and machine learning, it is one of several supervised learning methods that are employed. KNN classifies a data point by looking at the nearby annotated data point, also known as the nearest neighbor. Artificial Neural Networks (ANN) are inspired by the biological neural networks that form the human brain's architecture. Artificial neural networks include several layers like how neurons are connected to one another in the biological brain. Node is the name for these neurons. Neural network is also used to learn systems to predict the pattern from datasets. The most well-known supervised learning techniques are Support Vector Machines (SVM), which are applied to classification and regression issues. However, Machine learning classification difficulties are primarily handled by it. The well-known machine learning algorithm Random Forest (RF) is part of the supervised learning strategy. Regression- and classification-based issues can be resolved. To tackle a difficult problem and improve the performance of the model, Random Forest uses the technique of combining several classifiers. To increase the input dataset's projected accuracy, a Random Forest classifier employs many decision trees on various subsets of the input dataset and averages the results. The Random Forest predicts the outcome depending on whatever guesses received the most votes, rather than using predictions from only one tree.

In any prediction model feature's role is important. The goal of feature selection is to select a subgroup of features without degrading the accuracy of the classifier. This section compares the accuracy of the classifier using different meta-heuristic methods. The neuro-fuzzy system combines fuzzy logic's knowledge representation with neural networks' capacity for learning. This combination addresses the shortcomings of each component. To increase prediction accuracy, Khan and Algarni (2020) developed a healthcare nursing structure for the detection of heart illness in an Internet of medical things (IoMT) cloud atmosphere. They used Modified Salp Swarm Optimization (MSSO) and an Adaptive Neuro-Fuzzy Inference System (ANFIS). Li et al. (2023) presented a mixed feature selection method for the diagnosis of diabetes. That study used K-means to explore various groupings of the Harmony Search Algorithm, the Genetic Algorithm, and the Particle Swarm Optimization method. The diabetes dataset is classified using K-nearest neighbors.

Here, ANFIS based classification is done. Heuristic-based ANFIS training algorithms are becoming more popular because of their improved performance (Karaboga and Kaya, 2019). The feature selection is performed using combined Meta-Heuristic Methods BOA-ELOA. Here, FCM is also imposed before applying classification. The accuracy of ANFIS-based classification on PD dataset with BOA-ELOA is 92.85% approximate, while on ASD dataset the accuracy is near about 92.47%. This improved method shows better accuracy in comparison with other methods like DT, RF, SVM, KNN, etc. While compared with KNN and SVM the RF gives better accuracy.

Table 2. Comparison of Performance measures using Meta-Heuristic algorithms on Autism Dataset

Measure/Method	PSO	ACO	BOA	ELOA	BOA+ELOA
Accuracy	73.65	74.37	84.39	89.07	92.47
Precision	74.68	77.63	84.11	87.85	91.66
Recall	71.27	80.25	87.26	91.71	92.28
F-measure	77.83	78.92	85.66	89.74	91.97
Error	26.35	25.63	15.60	10.92	7.53

The above table shows that the accuracy of the combined approach is approximately 92.47% for the Autism dataset, which is higher than the accuracy of the individual approach. Also, the recall value of the combined method is approximately 92.28% for the Autism dataset.

Table 3. Comparison of performance measures using Meta-Heuristic Algorithms on Parkinson's dataset

Measure/Method	PSO	ACO	BOA	ELOA	BOA+ELOA
Accuracy	53.04	64.11	86.44	87.19	92.85
Precision	54.09	70.38	86.03	88.73	92.99
Recall	52.03	75.17	86.30	90.43	92.83
F-measure	78.27	79.94	81.42	90.77	92.08
Error	46.95	35.88	13.55	12.80	7.14

The above table shows that the accuracy of the combined approach is approximately 92.85% for the Parkinson's dataset, which is higher than the accuracy of the individual approach. Also, the

DOI: https://doi.org/10.52756/10.52756/ijerr.2023.v31spl.006

combined method's recall value is approximately 92.83% for Parkinson's dataset.

The above-mentioned comparisons were carried out using ANFIS. The objective is to evaluate the

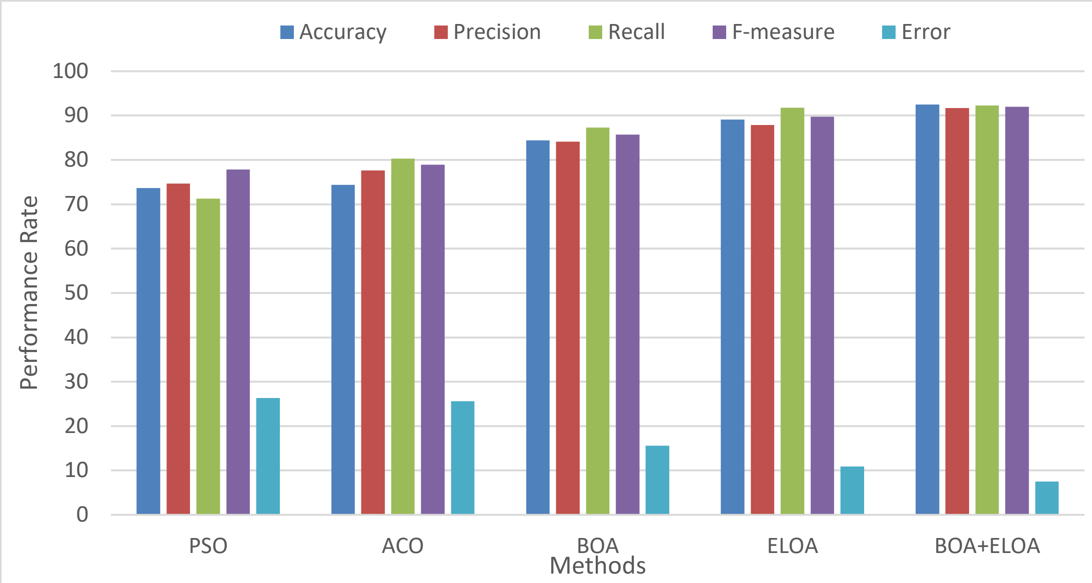

Figure 3. Comparison of performance measures on the Autism dataset using Meta-Heuristic Algorithms

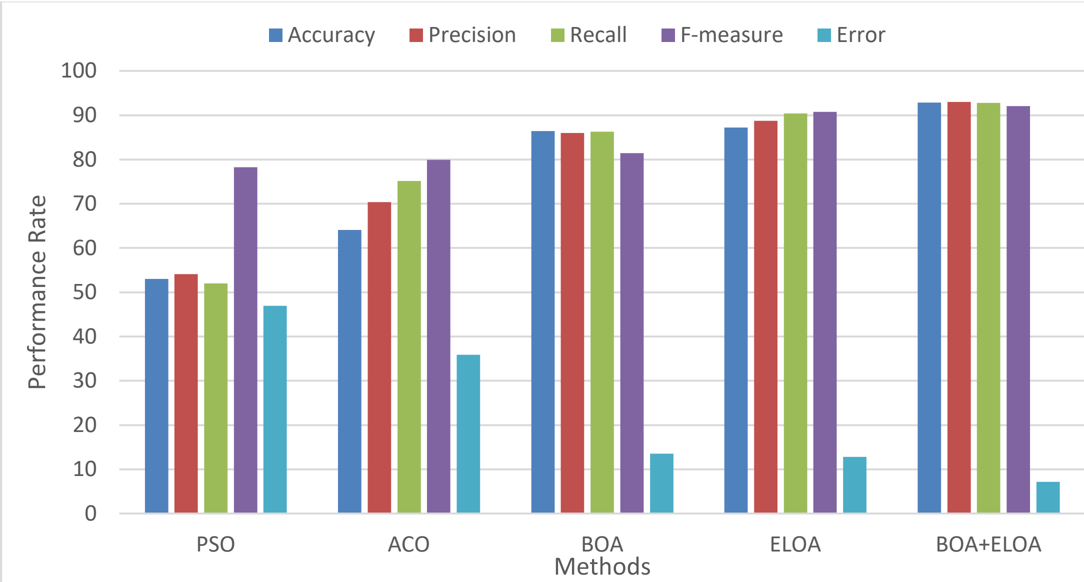

Figure 4. Comparison of performance measures on the Parkinson's dataset using Meta-Heuristic Algorithms

Figures 3 and 4 display the classification's accuracy, precision, recall, F-measure, and error rate when different meta-heuristic optimization algorithms are applied to datasets for autism and Parkinson's disease. In comparison to PSO and ACO, BOA performs better; however, it falls short of ELOA. As opposed to this, the integrated technique (BOA-ELOA) displays high-performance rates across the board. The accuracy of the integrated technique for the Parkinson's dataset provides better results when compared to others, as demonstrated in Figures 3 and 4. For both datasets, PSO and ACO have poor performance rates.

performance of the KNN, SVM, and ANFIS classifiers. If the data or database is limited, ANFIS appears to be more successful than SVM. Because the ANFIS can handle fuzzy logic, which reduces the uncertainty of ambiguous or incomplete data, it should be favored for adjusting weights and approximating data to create the desired result. This approach is suitable for problems with relatively few input variables since the size of the fundamental rules is important for the computational cost. On the autism dataset and the Parkinson's dataset, respectively, Tables 4 and 5 mentioned below illustrate the performance rate utilizing SVM, KNN,

DOI: https://doi.org/10.52756/10.52756/ijerr.2023.v31spl.006

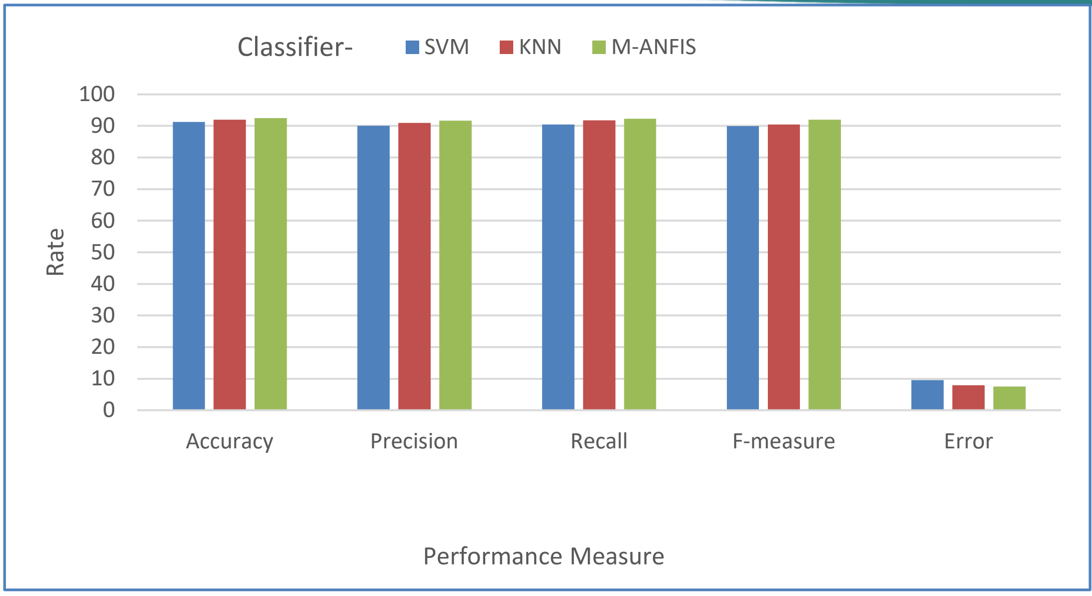

Figure 5. Comparison of performance using various classifiers on Autism dataset

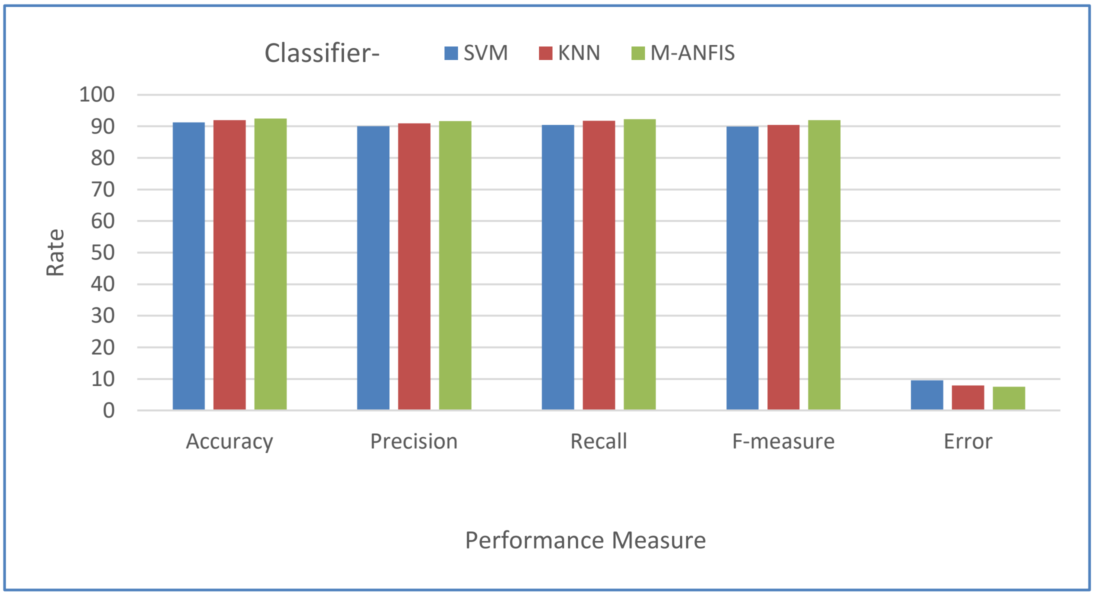

Figure 6. Comparison of performance using various classifiers on Parkinson's dataset

and modified ANFIS-based classifiers. Fuzzy C-mean (FCM) Clustering is employed in modified ANFIS to create data classes prior to presentation into ANFIS. Here, the combined BOA-ELOA technique is employed to pick features.

Table 4. Comparison of performance using various classifiers on Autism dataset

Measure/Classifier	SVM	KNN	M-ANFIS
Accuracy	91.27	91.97	92.47
Precision	90.04	90.98	91.66
Recall	90.43	91.78	92.28
F-measure	89.97	90.45	91.97
Error	9.54	7.94	7.53

The accuracy of the M-ANFIS classifier for the Autism dataset is around 92.47%, which is greater than the accuracy of SVM and KNN, as seen in the above table. The M-ANFIS classifier's precision value for the Autism dataset is around 91.66%.

Table 5. Comparison of performance using various classifiers on Parkinson's dataset

Measure/Classifier	SVM	KNN	M-ANFIS
Accuracy	90.45	91.67	92.85
Precision	90.63	91.43	92.99
Recall	90.05	91.26	92.83
F-measure	89.85	91.34	92.08
Error	9.13	8.37	7.14

DOI: https://doi.org/10.52756/10.52756/ijerr.2023.v31spl.006

The accuracy of the M-ANFIS classifier for the Parkinson's dataset is roughly 92.85%, which is greater than the accuracy of SVM and KNN, according to the table above. The M-ANFIS classifier's precision value for the Parkinson's dataset is around 92.99%.

Figures 5 and 6 provide the performance rate chart for several metrics for a number of classifiers. The results clearly showed that when the combined BOA-ELOA feature selection strategy was applied, M-ANFIS surpassed SVM and KNN in terms of performance.

Conclusion

Feature selection is an important stage of any prediction system. One can train or say learn a system will all feature set. Learning will all features will take a lot of computational cost and time. Learning with an optimal feature set will not only avoid the curve of dimensionality but also reduce computational costs. This research shows the use of Meta-Heuristic methods for optimization of search space. The outcomes clearly indicate that the accuracy of the combined approach using M-ANFIS is improved than the individual approach. The accuracy of the combined Meta-Heuristic approach using M-ANFIS for the Autism dataset is approximately 92.47%, which is higher than the accuracy of the individual approach. The accuracy of the combined approach is approximately 92.85% for Parkinson’s dataset, which is higher than the accuracy of the individual approach. In comparison to PSO and ACO, BOA performs better; however, it falls short of ELOA. As opposed to this, the integrated technique (BOA-ELOA) displays high-performance rates across the board. The outcome demonstrates that, compared to other methods, the accuracy of the integrated strategy for the Parkinson's dataset has better results. While BOA and ELOA have accuracy rates of 86.44% and 87.19%, respectively, the integrated strategy has a rating of 92.85%. The integrated feature selection method also demonstrates a low error rate for classifier performance. Classification followed by an intelligent feature selection method based on nature-inspired optimization methods has a high convergence rate. This will also improve the classifier accuracy and reduce computation time. Learning overhead can also be reduced by training time with fewer features. Results clearly indicate that the convergence rate of the combined optimization approach for PD is better for classifying the healthy and unhealthy classes. We know that selecting the right feature set improves the diagnostic system's performance. Here, feature selection is accomplished using population-based Meta-Heuristic Optimization techniques. The combined BOA-ELOA technique will lessen classifier overhead by selecting fewer features. The integrated approach to feature selection that has been recommended has been put up against other optimization techniques, and the results clearly demonstrate that utilizing the suggested approach to learning with fewer feature sets has resulted in superior performance rates. ANFIS appears to be better suited after employing Fuzzy C-Mean (FCM) Clustering for small data volumes, according to comparative findings of ANFIS-based classification with SVM and KNN utilizing the BOA-ELOA method for feature selection.

Conflict of Interest

No conflict of interest.

Acknowledgement

We are grateful to Dr. A.P.J. Abdul Kalam Technical University, Lucknow, for providing the opportunity and resources to conduct the research.

References

Arora, S., & Singh, S. (2019). Butterfly optimization algorithm: a novel approach for global optimization. *Soft Computing*, *23*(3), 715–734. https://doi.org/10.1007/s00500-018-3102-4

Askarzadeh, A. (2016). A novel metaheuristic method for solving constrained engineering optimization problems: Crow search algorithm. *Computers & Structures*, *169*, 1–12. https://doi.org/10.1016/j.compstruc.2016.03.001

Dhiman, G., & Kumar, V. (2019). Spotted hyena optimizer for solving complex and non-linear constrained engineering problems. In Harmony Search and Nature Inspired Optimization Algorithms: Theory and Applications, ICHSA 2018, Springer Singapore, pp. 857-867.

Dorigo, M., & Di Caro, G. (1999). Ant colony optimization: A new meta-heuristic. *In: Proceedings of the 1999 Congress on Evolutionary Computation-CEC99*, *2*, 1477.

https://doi.org/10.1109/CEC.1999.782657

Dubey, D.A. (2021). Optimized hybrid learning for multi disease prediction enabled by lion with butterfly optimization algorithm. *Sadhana*, *46*, 63. https://doi.org/10.1007/s12046-021-01574-8

Galeshchuk, S. (2016). Neural networks performance in exchange rate prediction. *Neurocomputing*, *172*, 446–452. https://doi.org/10.1016/j.neucom.2015.03.100

Gangwar, M., Mishra, R. B., & Yadav, R. S. (2014). Application of decision tree method in the diagnosis of neuropsychiatric diseases. *IEEE, In Asia-Pacific World Congress on Computer Science and Engineering*, pp. 1-8. https://doi.org/10.1109/APWCCSE.2014.7053880

Gangwar, M., Singh, A.P., Ojha, B. K., Shukla, H. K., Srivastava, R., & Goyal, N. (2020a). Intelligent Computing Model For Psychiatric Disorder. *Journal of Critical Reviews*, *7*(7), 600-603. https://doi.org/10.31838/jcr.07.07.108

Gangwar, M., Singh, A.P., Ojha, B. K., Srivastava, R., & Singh, S. (2020b). Machine learning techniques in the detection and classification of psychiatric diseases. *Journal of Advanced Research in Dynamical and Control Systems*, *12*(5), 639-646. https://doi.org/10.5373/JARDCS/V12SP5/20201799

Gangwar, M., Yadav, R. S., & Mishra, R. B. (2012). Semantic Web Services for medical health planning. IEEE, In 2012, *1st International Conference on Recent Advances in Information Technology* (RAIT), pp. 614-618. https://doi.org/10.1109/RAIT.2012.6194599

Harifi, S., Khalilian, M., Mohammadzadeh, J., & Ebrahimnejad, S. (2019). Emperor Penguins Colony: a new metaheuristic algorithm for optimization. *Evolutionary Intelligence*, *12*(2), 211–226. https://doi.org/10.1007/s12065-019-00212-x

Heidari, A. A., Mirjalili, S., Faris, H., Aljarah, I., Mafarja, M., & Chen, H. (2019). Harris hawks optimization: Algorithm and applications. *Future Generation Computer Systems*, *97*, 849–872. https://doi.org/10.1016/j.future.2019.02.028

Hussien, A. G., Amin, M., Wang, M., Liang, G., Alsanad, A., Gumaei, A., & Chen, H. (2020). Crow Search Algorithm: Theory, Recent Advances, and Applications. *IEEE Access*, *8*, 173548–173565. https://doi.org/10.1109/ACCESS.2020.3024108

Ismail, W.N., Fathimathul Rajeena, P.P., & Mona A.S. Ali. (2023). A Meta-Heuristic Multi-Objective Optimization Method for Alzheimer's Disease Detection Based on Multi-Modal Data. *Mathematics*, *11*(4), 957. https://doi.org/10.3390/math11040957

Karaboga, D., & Basturk, B. (2007). A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. *Journal of Global Optimization*, *39*(3), 459–471. https://doi.org/10.1007/s10898-007-9149-x

Karaboga, D., & Kaya, E. (2019). Adaptive network based fuzzy inference system (ANFIS) training approaches: a comprehensive survey. *Artificial Intelligence Review*, *52*(4), 2263–2293. https://doi.org/10.1007/s10462-017-9610-2

Kaur, S., Kumar, Y., Koul, A., & Kumar Kamboj, S. (2023). A systematic review on metaheuristic optimization techniques for feature selections in disease diagnosis: Open issues and challenges. Archives of Computational Methods in Engineering. *State of the Art Reviews*, *30*(3), 1863–1895. https://doi.org/10.1007/s11831-022-09853-1

Kennedy, J. and Eberhart, R. (1995). Particle Swarm Optimization. *Proceedings of the IEEE International Conference on Neural Networks*, *4*, 1942-1948. https://doi.org/10.1109/ICNN.1995.488968

Khan, M.A., & Algarni, F. (2020). A Healthcare Monitoring System for the Diagnosis of Heart Disease in the IoMT Cloud Environment Using MSSO-ANFIS. *IEEE Access*, *8*, 122259–122269. https://doi.org/10.1109/ACCESS.2020.3006424

Lamy, J.B. (2019). Artificial feeding birds (AFB): a new metaheuristic inspired by the behaviour of pigeons. Advances in nature-inspired computing and applications, Cham: Springer. pp. 43–60. https://doi.org/10.1007/978-3-319-96451-5_3

Li, X., Zhang, J., & Safara, F. (2023). Improving the Accuracy of Diabetes Diagnosis Applications through a Hybrid Feature Selection Algorithm. *Neural Processing Letters*, *55*(1), 153–169. https://doi.org/10.1007/s11063-021-10491-0

Mirjalili, S. (2015). Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm. *Knowledge-Based Systems*, *89*, 228–249. https://doi.org/10.1016/j.knosys.2015.07.006

Nandhini, S., & Ashokkumar, K. (2021). Improved crossover based monarch butterfly optimization for tomato leaf disease classification using convolutional neural network. *Multimedia Tools* *and Applications*, *80*(12), 18583–18610. https://doi.org/10.1007/s11042-021-10599-4

Pan, W.T. (2012). A new Fruit Fly Optimization Algorithm: Taking the financial distress model as an example. *Knowledge-Based Systems*, *26*, 69–74. https://doi.org/10.1016/j.knosys.2011.07.001

Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, *61*, 85–117. https://doi.org/10.1016/j.neunet.2014.09.003

Sharma, M., & Kaur, P. (2020). A Comprehensive Analysis of Nature-Inspired Meta-Heuristic Techniques for Feature Selection Problem. *Archives of Computational Methods in Engineering*, *28*(3), 1103–1127. https://doi.org/10.1007/s11831-020-09412-6

Singh, C., Gangwar, M., & Kumar, U. (2021). A Review on Neuro-Fuzzy System in the Diagnosis of Psychiatric Disorder. *Webology*, *18*(SI01), 164-182.https://doi.org/10.14704/WEB/V18SI01/WEB18052

Singh, S., Gupta, P., Ojha, B.K., Kumar, R., Shukla, H.K., Srivastava, R., Singh, C., & Gangwar, M. (2020). A supply chain management based patient forecasting model for dental hospital. *Journal of Critical Reviews*, *7*(3), 600-603. https://doi.org/10.31838/jcr.07.03.76

Tarle, B., & Jena, S. (2021). Ant lion optimization based medical data classification using modified neuro fuzzy classifier. *Wireless Personal Communications*, *117*(2), 1223–1242. https://doi.org/10.1007/s11277-020-07919-6

Verma, A., Agarwal, G., & Gupta, A. (2022). A novel generalized fuzzy intelligence-based ant lion optimization for internet of things based disease prediction and diagnosis. *Cluster Computing*, *25*(5), 3283-3298. https://doi.org/10.1007/s10586-022-03565-8

Wang, G.G., Deb, S., & Coelho, L. (2015). Elephant Herding Optimization. In: 2015 3rd international symposium on computational and business intelligence (ISCBI), Bali, Indonesia. https://doi.org/10.1109/ISCBI.2015.8

Wang, G.G., Deb, S., & Cui, Z. (2019). Monarch butterfly optimization. *Neural Computing and Applications*, *31*(7), 1995–2014. https://doi.org/10.1007/s00521-015-1923-y

Yang, X.S. (2009). Firefly Algorithms for Multimodal Optimization. In O. Watanabe & T. Zeugmann (Eds.), Stochastic Algorithms: Foundations and Applications, Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 169–178.

Yang, X.S. (2010). A New Metaheuristic Bat-Inspired Algorithm. In J. R. González, D. A. Pelta, C. Cruz, G. Terrazas, & N. Krasnogor (Eds.), Nature Inspired Cooperative Strategies for Optimization (NICSO 2010), pp. 65–74. https://doi.org/10.1007/978-3-642-12538-6_6

Yazdani, M., & Jolai, F. (2016). Lion Optimization Algorithm (LOA): A nature-inspired metaheuristic algorithm. *Journal of Computational Design and Engineering*, *3*(1), 24–36. https://doi.org/10.1016/j.jcde.2015.06.003

Zhou, H., Cheng, H., Wei, Z., Zhao, X., Tang, A., & Xie, L. (2021). A Hybrid Butterfly Optimization Algorithm for Numerical Optimization Problems. *Computational Intelligence and Neuroscience*, *2021*, 1–14. https://doi.org/10.1155/2021/7981670

How to cite this Article:

Chandrabhan Singh, Mohit Gangwar and Upendra Kumar (2023). Analysis of Meta-Heuristic Feature Selection Techniques on classifier performance with specific reference to psychiatric disorder. *International Journal of Experimental Research and Review*, *31*, 51-60.

DOI：https://doi.org/10.52756/10.52756/ijerr.2023.v31spl.006