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Enhancing Brain Tumor Classification through Feature Selection with Beetle-Swarm Optimization

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ABSTRACT- The selection of features is a crucial part of machine learning and data mining. The feature sets that are used for classification are always prone to having redundant and correlated features that can affect the performance. The goal of this study is to remove redundant and irrelevant features from the system and retain only relevant ones. This study presents Beetle-Swarm optimization process which involves selecting the features from a segmented image with a Random Forest classifier. The process is performed through a series of steps such as pre-processing, feature extraction, and feature classification. Two objective functions are used to perform the process: image entropy and accuracy function. The proposed method is evaluated on publicly available Kaggle brain tumor dataset. The results of the study revealed that the BSO+RF approach performed well compared to other techniques such as the PSO, ABC, and MVO. The proposed BSO+RF outperforms other similar algorithms in terms of accuracy. It has a performance of 0.8% compared to PSO, while it is slightly better than ABC, and slightly better than MVO. The performance of the proposed BSO+RF algorithm is also higher than that of the comparative techniques, with a learning percentage of 80. It has a low FDR value of less than PSO, ABC, and MVO, which suggests that it has better performance The proposed BSO-RF technique is more accurate than the existing algorithms when it comes to training and testing. In addition, it requires less features to achieve better accuracy. This results in faster computing time and more accuracy. This study presents a new approach to predict cancer using the combination of Beetle Swarm Optimization (BSO) and Random Forest. Beetle-swarm optimization is used to find threshold. This is used to segment the tumor from MR images resulting in better accuracy.

Keywords: Image segmentation, Optimization techniques, Feature selection, PSO.

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1. INTRODUCTION

The selection of features is a crucial part of machine learning and data mining, especially in brain tumor classification [1] [2]. They help improve the efficiency of both the development and analysis of models. They also make it easier for developers to find patterns that are not readily observable [3]. The selection of features is also important to improve the accuracy of models and predict their classification. This process involves identifying the most appropriate feature subset. Usually, the selection of features is carried out based on the quality of the solutions generated by the researchers. In most cases, the selection of features is performed with the lowest number of features. This allows for fast and accurate classification of brain tumor.

The process of creating a predictive model is known as feature selection. It involves reducing the number of variables in the model. Doing so can help reduce the computational cost of the model and improve its performance. A statistical-based method is used to perform feature selection. This method involves analysing the relationship between the target variable and the input variable. Although there are various statistical measures that can be used to perform feature selection, choosing the right one can be challenging due to the data type and the complexity of the process.

The two most common feature selection methods are the filter and the Wrapper. The former focuses on identifying the most desirable features by scoring and ranking them according to certain statistical criteria [4][5]. The latter method, on the other hand, considers the various constraints that affect the selection process and produces the best possible subset of features [6].

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The Wrapper method aims to identify the optimal feature set for a given target, employing a learning algorithm to assess the predictive accuracy of its predictions. The objective of a Greedy algorithm is to discover the most effective combination of features for optimal performance within a given model. To address large-scale problems, a suite of stochastic algorithms is devised [7]. These can capture the interaction between features and their redundancy. The main advantage of the Greedy algorithm is that it does not have to follow the monotonicity assumption. It can also produce the best function subset. Unfortunately, the hybrid methods used for finding optimal features are not reliable since they can only find small subsets of features.

2. RELATED WORKS

According to Gupta et al., in the case of medical data, the potential of machine learning lies in its ability to analyse and improve the quality of information. This technology can be found in algorithms that do not require the development of complicated hand-making features. The rapid emergence and evolution of image diagnosis and electronic medical records has also contributed to the increasing number of people using machine learning [18].

A study was conducted on the use of the multi-verse optimization (MVO) tool to classify a tumor part from an image taken with an MRI machine. The researchers were able to select the appropriate characterization techniques and classification technique for the part [19]. Another research [20] presents an improved version of the beetle swarm optimization algorithm that combines the concepts of particle swarm optimization and BSO. It is designed to provide effective representation of various multi-objective functions, such as power consumption and resource wastage. But feature selection was not considered in this research work.

According to Pradipta Kumar Mishra et.al.[21], before implementing a segmentation procedure in a DCNN model, it is important that the weights are considered. This can help improve the accuracy of the model. They proposed a framework that includes the use of various intelligent algorithms such as the Genetic Algorithm, the PSO, the Gray Wolf Optimization, and the Whale Optimization. These models are the PSO-DCNN, GA-DCNN, and GWO-DCNN. D. Bhanu Prakash. et.al [22] proposed plant leaf classification model based on feature selection method. In this, feature selection is done by Electric fish optimization method. The proposed method is 4.8% better than the conventional model, while it is 3.5% better than VGG16 and 3.7% better than LSTM. Moreover, the outcomes of the experimental studies demonstrate the viability and efficacy of the proposed method in comparison to alternative models.

To categories the malignancies from the MR images, Salem et al. [23] have suggested a CAD system. Using the chaos theory, this model has calculated the complexity metrics Lyapunov Exponent (LE), Approximate Entropy (ApEn), and Fractal Dimension (FD). Additionally, the Discrete Wavelet Transform (DWT) and GLCM techniques were used for feature extraction to separate benign from malignant tumours. Three machine learning methods, including pattern net, K-Nearest Neighbours (KNN), and SVM, were given the extracted features. In the validation phase, many experiments were run by mixing the features. The proposed model has a higher accuracy rate than the designed model, which can be used to specify its efficacy.

A study was conducted by V. Agrawal et.al. [24] to determine if the data provided as input is malignant or not, a meta-heuristic algorithm called Artificial Bee Colony (ABC) was utilised for feature selection in CT scan images of cervical cancer. But this method was not applicable to MRI images.

By analysing the existing literature, it was concluded that many researchers have already started to develop new methodologies to address the various challenges related to optimization. However, some of these problems remain. For instance, the high computational time and the small size of the algorithm are still some of the issues that prevent the development of effective optimization methods.

3. MATERIALS AND METHODS

Numerous complex optimization challenges, including feature selection, have been addressed using Metaheuristic optimization techniques. Feature selection problems have been solved using a variety of metaheuristic techniques in the literature, including Particle swarm optimization (PSO) [25], Artificial Bee Colony (ABC) [24], and Multi-verse Optimization (MVO) [17]. The ABC technique struggles from poor exploitation while tackling challenging issues and whereas MVO has low classification accuracy. To overcome these issues, we propose a new feature selection BSO+RF method.

Figure 1 illustrates the proposed method. In this stage, an analysis of the input MRI image is conducted to eliminate noise. The threshold is then calculated using the Beetle-swarm Optimization method. This method segments the tumour part in the image. Initially, features are extracted through the utilization of LBP and GLCM methods in the first step. These extracted features are subsequently forwarded to the succeeding phase, where feature selection takes place. The Beetle-Swarm Optimization algorithm is employed to execute this selection process. Following the feature selection, a classification algorithm is applied to categorize the various types of tumours.

3.1 Extraction of Features Utilizing GLCM

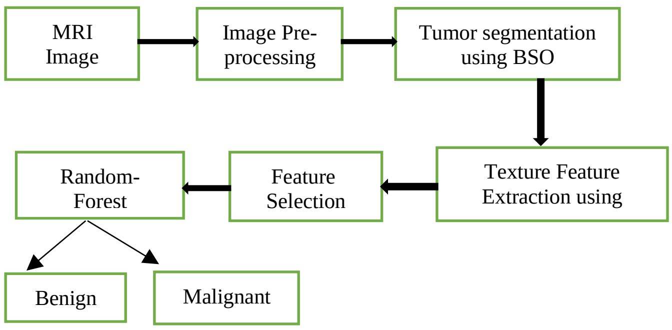

Figure 1. Proposed Method Architecture

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The texture feature extraction tool is widely used for various image processing tasks, such as segmentation, image classification, and pattern recognition [8][9][10][11]. It can also be used to generate multi-scale texture features from various images.

It's a 2D matrix where each entry corresponds to the co-occurrence of two pixels in an image, divided by a specific vector. This matrix is commonly known as the Gray-Level Co-occurrence Matrix.

$$G_{jk}(\triangle w, \triangle x) = KS(j,k \mid \triangle w, \triangle x) \quad (1)$$

where $$K = \frac{1}{(D-\triangle w)(H-\triangle x)} \quad (2)$$

$$S(j,k \mid \triangle w, \triangle x) = \sum_{h=1}^{H-\triangle x} \sum_{d}^{D-\triangle w} B \quad (3)$$

where $$B = \begin{cases} 1, & \text{if } f(d,h) = j \text{ and } f(d+\triangle w, h+\triangle x) = k \\ 0, & \text{otherwise.} \end{cases} \quad (4)$$

It is a square matrix of size M * M, where both rows and columns represent the range of possible pixel values in the image.

The matrix comprises two parameters: 'theta' and 'dis.' 'Theta' represents the relative distance between pixel pairs, while 'dis' indicates the relative orientation of the pair. The rotational angle of the two is illustrated in *figure 1*.

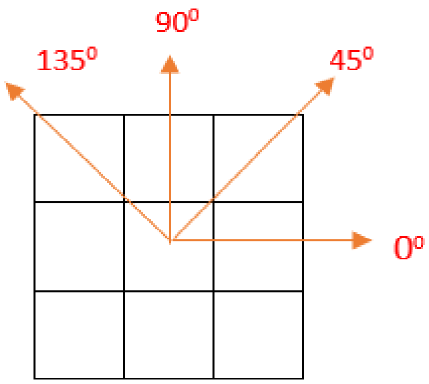

Figure 2. Adjacency directions

Image texture directionality refers to the pixel shifts within a region, reflecting the regularity and similarity of gray values in various directions. This function, as described in [13], illustrates the directionality of textured images. The path calculation function considers both statistical and structural characteristics of an image, aiming to capture the inherent properties of its pixels. The direction measurement involves dividing the image into different directions, and the grayscale values are quantitatively assessed in each direction to highlight variations among the image pixels.

The texture measure is derived from statistical parameters that depend on the second-order values of the GLCM. *Table 1* enumerates the various categories of statistics that have been discussed.

Table 1. Extracted Features Utilizing GLCM Matrix

Parameter	Mathematical formula
ASM- Angular Second Moment	$f1 = \sum_{j}\sum_{k} g2_{jk}$
Contrast	$f2 = \sum_{r=0}^{M-1} r^2 [\sum_{j}\sum_{k} g_{jk}]$
Correlation	$f3 = \frac{\sum_j \sum_k (jk) g_{jk} - \mu_w \mu_x}{\sigma_w \sigma_x}$ where μ_w and μ_x are means, σ_w and σ_x are standard deviations
Variance	$f4 = \sum_{j}\sum_{k} (j-\mu)^2 g_{jk}$
IDM- Inverse Difference Moment	$f5 = \sum_{j}\sum_{k} \frac{g_{jk}}{1+(j-k)^2}$
Sum average	$f6 = \sum_{r=0}^{2M-2} r g_{j+k}(r)$
Sum variance	$f7 = \sum_{r=0}^{2M-2} (r - f6)^2 g_{j+k}(r)$
Sum entropy	$f8 = -\sum_{r=0}^{2M-2} g_{w+x}(r) \log(g_{w+x}(r))$
Entropy	$f9 = -\sum_{j}\sum_{k} g_{jk} \log(g_{jk})$
IMC-1	$f10 = \frac{f9 - H_{wx1}}{\max\{Hw, Hx\}}$ Where $H_{wx1} = -\sum_j \sum_k g_{jk} \log(g_w(j) g_x(k))$
IMC-2	$f11 = \sqrt{1 - \exp(-2(H_{wx2} - f9}$ Where $H_{wx2} = -\sum_{j}\sum_{k} g_w(j) g_x(k) \log(g_w(j) g_x(k))$

3.2 Extraction of Features through Local Binary Patterns

LBP looks at the pixels in a decimal image and marks them with a series of LBP codes that are enclosed around each individual pixel [14]. These codes are labeled with either "0," or "1." The resulting negative values are then divided by the center value of the pixel. Each of the 8 pixels in the 3*3 neighborhood is equivalent to its 8 neighbors. A binary is achieved by separating the values of the various binary values into a single number.

One of the main constraints that LBP operators have when it comes to catching up with the larger architecture features in the 3 * 3 neighborhood is that they cannot catch up with the dominant features of these architectures.[15] To tackle diverse texture challenges across different scales, the LBP operator was expanded to encompass neighborhoods of varying sizes. A local area is a collection of sample points that are spaced uniformly around a circle and are then combined with bilinear interpolation to produce a total of sampling points that are not flowing in the pixels.

The sampling around the central pixel is normal in the clockwise direction, and the radius value is defined by the scattering point's spatial resolution. If the R grows, LBP needs more neighbors to learn more about the texture pattern. This paper shows that the number of neighbors is set to 8 to ensure that the re-sampling does not lead to extreme artifacts.

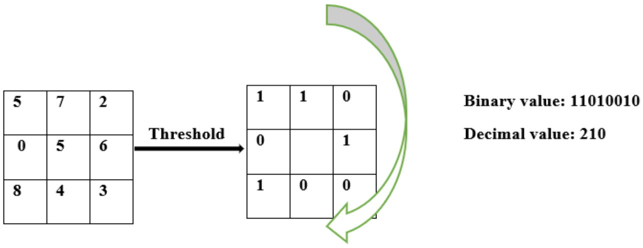

Figure 3. Example of LBP operator

3.3 Beetle-Swarm Optimization

The first two steps in this series introduce the concepts of beetle search and beetle swarm optimization. The former is a single-entity algorithm, while the latter is a combination of multiple individuals.

The BAS algorithm [16] for searching for beetle antennae was inspired by the behavior of the insects, which involved searching and detecting behavior. It is also noted that the beetles are very likely to search randomly for an unknown environment. The BAS algorithm primarily aims to assess the influence of individuals on a single particle, whereas the PSO concentrates on the interactions within groups. This paper suggests introducing the concept of BSO, aiming to integrate these two models. The entities in the PSO are commonly denoted as beetles. The BSO, as proposed in [17], can address diverse issues associated with the PSO algorithm, including the tendency to converge to local optima. The movement and position of the beetles are the same as those in the standard PSO. In addition, the BSO proposed by this method can also update the position of the beetle cluster by considering the various factors that affect its movement. For instance, the fitness function values of the individuals in the BSO will be compared with those of the right and left sides of the beetle. This approach can also be employed to discover the optimal solution for clustering. The revised formula for the position of the beetle swarm is articulated as follows.

$$vbi = -\,\delta^t \cdot \boldsymbol{b} \cdot \text{sign}\,(f\,(x^{rt}) - f\,(x^{lt})) \tag{5}$$

$$vik + 1 = vik + 1 + c1 \cdot \text{rand} \cdot (Pbik - xik) + c2 \cdot \text{rand} \cdot (Pgik - xik) + c3 \cdot \text{rand} \cdot vb1 \tag{6}$$

$$xik + 1 = xik + vik + 1 \tag{7}$$

The BSO's update rate is also represented by the vbi.

#Algorithm

1. The size N of the PSO, as well as the learning factors (c1, c2, c3) for each beetle, are determined by the following parameters. These parameters encompass the distance (d0) between the two antennae and the inertia weight 'w' of the object.

2. To obtain the optimal global solution (Gbest), initiate the process by calculating the position (x) and velocity (v) for each position. Subsequently, employ the current position as the optimal solution.

3. Enter the iteration:
• For assessing the fitness of the beetles, randomize the heads of everyone. Next, evaluate the left and right positions of the beetles, and calculate their fitness based on their respective positions. This approach enables the creation of a speed update rule for each population.

$$\text{vbi} = \delta\text{t} \cdot \mathbf{b} \cdot \text{sign (f (xrt)} - \text{f (xlt))} \tag{8}$$

The objective of the speed update rule is to compare the current fitness of different beetles with the optimal solution.

• Combine the two speed update rules to formulate the current update rules for the speed of each antenna.

$$\text{vik} + 1 = \text{vik} + 1 + \text{c1} \cdot \text{rand} \cdot (\text{Pbik} - \text{xik}) + \text{c2} \cdot \text{rand} \cdot (\text{Pgik} - \text{xik}) + \text{c3} \cdot \text{rand} \cdot \text{vb1} \tag{9}$$

Rules for updating the current location.

$$xik + 1 = xik + vik + 1 \tag{10}$$

The learning factors c1, c2, and c3, along with the updated weight w, are now accessible. Additionally, new global optimal solutions have been identified.

4. Following the iteration process, the optimal solution *f(Gbest)* and Gbest are achieved, with the optimal solution position being determined.

4. RESULTS

We have examined multiple slices of the human brain and scrutinized MRI images for the detection of brain tumors. These images were sourced from diverse datasets, specifically from the Kaggle dataset.

In total, 240 datasets are considered for the proposed algorithm. Out of these, 130 are related to benign and the rest related to malignant tumors. The simulations were performed to validate the proposed algorithm's significance. Magnetic resonance imaging images are known to be useful in diagnosing various types of cancer. The proposed algorithm was first performed to pre-process the input MRI image. It then uses the BSO algorithm to segment the tumor from the image. For every 30 images, the threshold is applied.

The BSO parameters are set as follows:
The optimization process was conducted with a population size of 30 individuals, and a maximum of 30 iterations were allowed. The inertia weight 'w' was set to 0.7, while the learning factors

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were configured as follows: c1=0.5, c2=2, and c3=3. These parameter values were chosen to influence the exploration and exploitation aspects of the algorithm, striking a balance between global and local search intensities.

Like other metaheuristic algorithms, the BSO algorithm can be sensitive to the settings of its parameters. For our tests, the tuning parameters were the population size, learning factors, and inertia weight. These were chosen using references to previous optimization studies.

(1) Parameter Sensitivity Analysis: To ensure the BSO algorithm's robustness, we performed a sensitivity analysis to examine how different key parameters influence its performance. We varied each of them within a reasonable range, ensuring that the other parameters remained constant. The results of the analysis revealed that the BSO algorithm performed well with small variations in its parameters. It maintained stable FDR values and accuracy within these ranges.

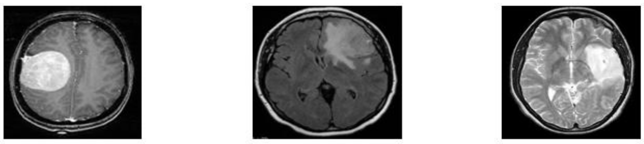
(2) The inertia weight: It is a measure of the trade-off between exploitation and exploration. We tested the values of 0.9, 0.5, and 0.7. We found that the moderate 0.7 level provided a good compromise between the solution quality and convergence speed. On the other hand, when the w value was increased to over 0.9, the algorithm would tend to overshoot the optimal result, which resulted in a reduced accuracy.

(3) The learning factors, namely c1, c2, and c3, play an important role in the evolution of beetles toward personal best solutions and global excellence. We tested the values of these factors from 0.5 to 3 to determine their accuracy and convergence speed. We discovered that increasing or decreasing the number of learning factors significantly increased the likelihood of premature convergence.

(4) Population Size: The computational efficiency of the population was selected by selecting a size of 30. The smaller the population, the more accurate the solution. On the other hand, the increase in the population size above 30 did not improve the accuracy and increased computation time.

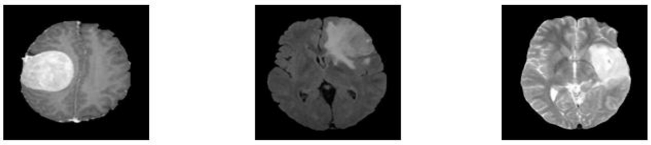
(5) Iteration Limit: The computation count was set to 30 to ensure that the algorithm's improvement gradually decreased as it became stable.

Three MRI images are considered for processing in *figure 4*. After skull stripping and median filter, the outputs are shown in *figure 5*. BSO was then used to set a threshold value.



(a) (b) (c)

Figure 4. Input MR Images



(a) (b) (c)

Figure 5. Pre-processed MR Images

(a) (b) (c)

Figure 6. Tumor segmentation using Particle-swam optimization

(a) (b) (c)

Figure 7. Tumor segmentation using Artificial-Bee Colony optimization

(a) (b) (c)

Figure 8. Tumor segmentation using multi-verse optimization

(a) (b) (c)

Figure 9. Tumor segmentation using Beetle-swam optimization

The results of the BSO algorithm's segmentation are presented in *figure 9*. It is a powerful tool for solving the most common parameter optimization problems. It is very easy to implement and ensures that the global and local searches are always balanced. The BSO outperforms other similar algorithms. The threshold values of various algorithms are shown in below *table 2*. These threshold values are divided by 255 to separate background from foreground.

To ensure that the results of our analysis are representative of the actual performance of the different algorithms, we conducted several statistical significance tests. These tests were designed to analyse the differences between the various metrics, such as FDR, accuracy, and MVO.

Paired t-test: Since the experiments were carried out on the same dataset, we used a paired test to analyse the differences

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between the different performance metrics, such as accuracy and FDR, between the proposed BSO-RF and the other algorithms, namely ABC, MVO, and PSO. The paired t-test can help us determine if the differences are statistically significant or random. We used a significance level of $p < 0.05$.

BSO+RF vs PSO:

- t-statistic = 270.10, $p = 6.65 \times 10^{-19}$
- The very small *p*-value indicates a statistically significant difference in performance between BSO+RF and PSO.

BSO+RF vs ABC:

- t-statistic = 99.00, $p = 5.55 \times 10^{-15}$
- The extremely small *p*-value confirms a statistically significant improvement of BSO+RF over ABC.

BSO+RF vs MVO:

- t-statistic = 103.76, $p = 3.64 \times 10^{-15}$
- This also shows a statistically significant improvement of BSO+RF over MVO.

ANOVA testing was used to analyze the variations in the performance of the four different algorithms: PSO, BSO+RF, ABC, and MVO. By carrying out this test, we can determine if the differences in the performance metrics of the algorithms are statistically significant in multiple comparisons.

F-statistic = 1924.84, $p = 8.82 \times 10^{-40}$

The *p*-value is extremely small, indicating that there is a statistically significant difference in the performance among all four algorithms (BSO+RF, PSO, ABC, MVO).

The BSO algorithm's algorithmic analysis is performed against the various heuristics used in the classification of brain tumours using the data collected from the Kaggle tumor database. The results of the analysis are shown in Figure 10. The main objective of this study is to compare the proposed BSO algorithm with the existing PSO, ABC, and MVO heuristics. The proposed BSO+RF method achieved an accuracy improvement of 0.8% compared to PSO and marginal improvements over ABC and MVO, with statistically significant results confirmed through paired t-tests ($p < 0.05$). The performance of the proposed BSO+RF algorithm is also higher than that of the comparative techniques, with a learning percentage of 80.

The *paired t-test* between BSO+RF and PSO yielded a t-statistic of 270.10 and a *p*-value of 6.65×10^{-19}, indicating a statistically significant difference. Comparisons between BSO+RF and ABC ($t = 99.00$, $p = 5.55 \times 10^{-15}$) and between BSO+RF and MVO ($t = 103.76$, $p = 3.64 \times 10^{-15}$) also showed statistically significant improvements.

ANOVA further confirmed a significant difference in performance across all algorithms (F-statistic = 1924.84, $p = 8.82 \times 10^{-40}$).

The proposed BSO+RF outperforms the existing PSO, ABC, and MVO heuristics when it comes to the performance of the FNR measure. It has a low FDR value of less than PSO, ABC, and MVO, which suggests that it has better performance. On the other hand, when compared to the MCC values, the proposed BSO algorithm has a significant advantage over the other algorithms. The proposed BSO algorithm has a high sensitivity measure, which shows that it outperforms the existing PSO, ABC, and MVO heuristics when it comes to the performance of the FNR measure. It also has better accuracy compared to the other algorithms.

Table 2. Threshold values utilized in different meta-heuristic algorithms for tumor segmentation

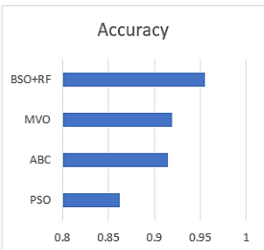
Optimization Technique	Image 1	Image 2	Image 3
PSO	111	88	129
ABC	85	85	135
MVO	89	77	116
BSO	105	95	125

Feature extraction is conducted utilizing the Local Binary Pattern (LBP) and Gray-Level Co-occurrence Matrix (GLCM) techniques. A total of 42 features were extracted using these methods. They were then selected using the BSO technique and the Random-Forest classifier. The performance of these techniques was evaluated by running 25 experiments. The following *table 3* shows the various parameters that were observed during the process. Three optimization techniques are also considered: PSO, ABC, MVO and BSO.

Table 3. Evaluation of the performance of four optimization techniques

Meta-heuristic technique	PSO [25]	ABC [26]	MVO [17]	BSO + RF
Time (Sec.)	3.98	4.59	4.88	3.75
Accuracy (%)	85.22	90.23	91.9	96.12
Selected features	27	29	25	23

The proposed BSO+RF technique is generally considered to be more accurate than the existing PSO, ABC, and MVO algorithms when it comes to training and testing. In addition, it requires less features to achieve better accuracy. This results in faster computing time and more accuracy.



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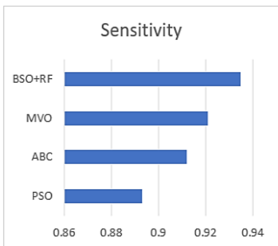

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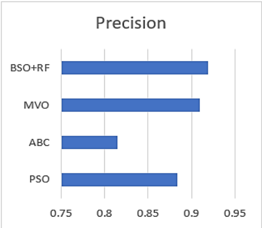

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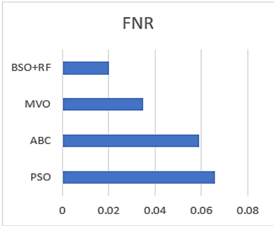

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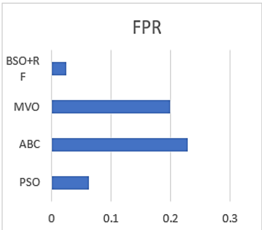

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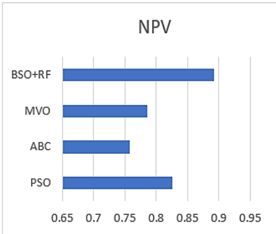
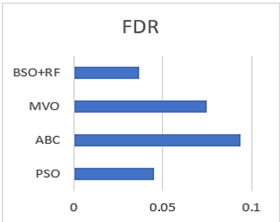
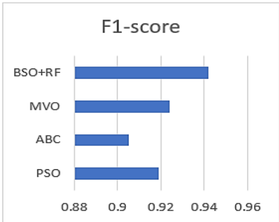


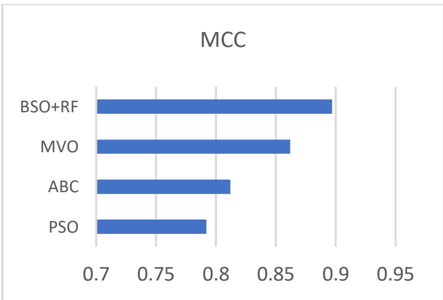
(vi)



(vii)



(viii)



(ix)

Figure 10. Investigation of optimization techniques for tumor segmentation and classification- performance metrics- (i) accuracy (ii) Sensitivity (iii) precision (iv) FNR (v) FPR (vi) NPV (vii) FDR (viii) F1-score (ix) MCC

5. CONCLUSIONS

The proposed BSO-RF combination has demonstrated a significant improvement in the classification of brain tumors using Random Forest. It is compared to other methods such as the Particle Swarm Optimization, Multi-Verse Optimization, and Artificial Bee Colony. The key findings of this study include improved accuracy, where the BSO+RF method achieved a higher accuracy of 96.12% compared to PSO (85.22%), ABC (90.23%), and MVO (91.9%). The method also selected fewer features, reducing computational time while maintaining superior classification performance. The BSO+RF technique performed better than the other algorithms in terms of its False Discovery Rate. This shows that it is more accurate when it comes to identifying tumors. In addition, it performed better on various metrics, such as precision and sensitivity.

In the future, there are numerous areas of research that can be pursued to improve the BSO+RF algorithm's capabilities. One of these involves parameter optimization. BSO+RF's flexibility and robustness can be further improved by studying adaptive or automatic tuning methods. One promising area of research is the development of hybrid models. Although the BSO+RF algorithm has been widely used in the field of cancer detection, combining it with other optimization techniques such as CNNs can lead to significant performance gains. In addition, studies that explore the utilization of the BSO+RF technique in other medical imaging applications can help improve its effectiveness and generalizability. For instance, it could be utilized in detecting breast cancer and other lung diseases. The proposed method should be tested on large datasets to check its robustness and scalability in real-world conditions. Although the Kaggle tumour dataset's results were encouraging, validating the method in clinical settings is crucial.

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