

A Hybrid Framework for Brain Tumor Classification using Grey Wolf Optimization and Multi-Class Support Vector Machine



Arun Kumar, M.A.Ansari, Alaknanda Ashok

Abstract: Medical image processing has a vital role in the detection of diseases in human beings. The accuracy for disease detection using any medical image is highly dependent on the image processing methods. Features extraction and reduction are the two key steps during the medical image processing for disease classification. To develop an effective and efficient mechanism with high accuracy for classification of malignant brain tumor from Magnetic Resonance Imaging (MRI) is the objective of the present research. To achieve this, a nature inspired algorithm; namely, Grey Wolf Optimization (GWO) along with a classification method, multiclass Support Vector Machine (MSVM) is used. Further, Results for the classification accuracy obtained from GWO are compared with other two well-known optimization algorithms such as Particle Swarm Optimization (PSO) and Firefly Algorithm (FA).

Keywords : Brain tumor, Feature extraction and reduction, Grey Wolf Optimization, SVM, MRI images.

I. INTRODUCTION

Brain tumor is a disease which occurs due to the undesirable and uncontrollable growth of tissue in the brain[1,2]. The number of cases of brain tumor has been increasing day by day due to many reasons like stress due to our lifestyle, some environmental changes like increase of pollution and many more like that. Although brain tumor is a life threatening disease, yet its impact can be minimized, with timely and proper diagnosis. Brain tumors can be broadly classified into two types such as a benign tumor with is non-cancerous and malignant tumor, which is cancerous[3].Some MRI images of brain 'without tumor and with tumor' are shown in figure 1. The various activities of the human body like thought, muscles, action and feelings are affected by the electrochemical impulses produced by the neurons that may provide some indication for something

unusual happening in the brain. Now a days, Physicians use MRI images that provide more precise and relevant information related to the brain by using Computer Aided Diagnosis (CAD) system because MRI images are the high-resolution images with low radiation as compare to the X-rays images that seems enough helpful for the easy detection of the brain tumor [4,5].But in many cases, accurate tumor detection with its type is still a very tedious task for the physicians because the every tumor type has a different impact on the patients, hence required different treatment.Medical image processing has provided many techniques that deal to computerize this task as almost equivalent to physician work with less time and with extra accuracy. Features extraction and selection are the key steps in medical image processing [6]. Out of these two, feature selection is even more important than feature extraction because optimal features are highly desirable to improve the performance of image classifier, and to decrease the computation time [7].

The present research aims on the malignant brain tumor classification using a GWO algorithm for feature reduction along with an SVM classification method that is well established and used by many authors in the past for classification purpose. The rest of the study is organized as follows: section 2 contains the description of existing research; Section 3 describes the proposed method for the tumor classification followed by an experimental set-up in section 4. The results, which prove the study, are discussed in section 5 whereas conclusion and future scope is provided in section 6.

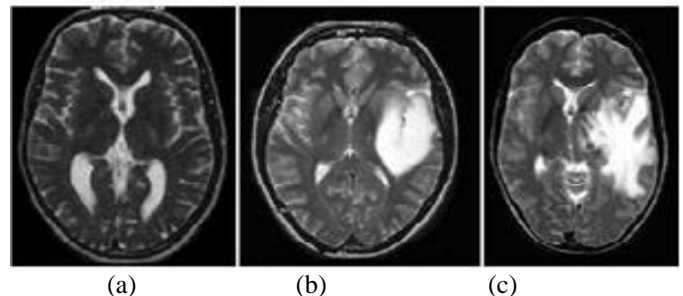


Fig. 1. MRI images: (a) without tumor (b) with benign tumor (c) with malignant tumor[7]

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II. LITERATURE REVIEW

This section of the present research highlights the various existing researches carried out by many authors in the field of brain tumor detection and classification-using nature inspired algorithms. Unfortunately, the traditional methods of feature reduction such as Principal Component Analysis (PCA), Independent Component Analysis (ICA) etc. are not much enough in the case of hyper spectral images [8,9]. Later, in 1990's, the concept of evolutionary computation (EC) algorithms attracted the authors to get the most precise and optimal results. Mirjalili et al. developed nature inspired algorithm known as Grey wolf optimization (GWO) for feature reduction that become a benchmark in this area[10]. Ahmad et al. in year 2014 implemented a genetic algorithm (GA) to search the principal space for the feature subset selection and further enhanced the performance of SVM for intrusion detection using optimal feature subset selection based on genetic principal components [11].

Rymer et al. proved that the GA is capable to produce more optimal results in comparison to PCA[12]. Sonar and Bhosle in year 2016 suggested many nature inspired algorithms such as Ant Colony Optimization (ACO) algorithm, Cuckoo Search (CS), Firefly Algorithm (FA) and Particle Swarm Optimization (PSO) for the classification of brain tumor from any MRI image [13]. In the similar work related to brain tumor classification, Taie and Ghonaim applied CS for the feature reduction [14]. Karnan and Logheshwari (2010) implemented ACO with Fuzzy Logic to segment brain tumor from MRI[15]. In the contemporary work, PSO was implemented with OTSU's thresholding algorithm to detect a tumor in the brain [16]. Gopal and Karnan (2010) compared the classification accuracy level of two methods, namely, PSO and GA along with fuzzy C-mean

to detect the brain tumor[17]. Akhil et al. extended the artificial bee colony (ABC) algorithm with a binary input mechanism to get results that are more precise[18]. In long-established approaches, as principal component analysis (PCA) and linear discriminant analysis (LDA) for linear, and Kernel-PCA have been used for non-linear features. On the other hand, the use of Evolutionary computation (EC) techniques is found more suitable as compared to these traditional approaches. Although, different authors implement many EC techniques, still, there is a need to achieve high accuracy for the disease classification in medical field.

The comprehensive study of the available literature reveals the existence of many techniques for the tumor classification implemented by the various authors. All authors conclude that Feature selection has a main role in term of classification accuracy.

III. RESEARCH METHODOLOGY

In the present study, a framework is developed for the classification of malignant brain tumor using GWO and MSVM as shown in figure 2. This framework contains mainly 3 steps as (i) Input, (ii) Processing and (iii) Output as described below in figure 2.

- 1). Input: An MRI image with malignant brain tumor is provided as the input to this developed framework.
- 2). Processing: The processing of the input MRI image is done in 4 sub-steps as Pre-processing, image segmentation, feature extraction and reduction using GWO and Tumor classification of the input image.
- 3).Output: Malignant Tumor with its class will be the output from the framework.

The detailed description of these steps is given further.

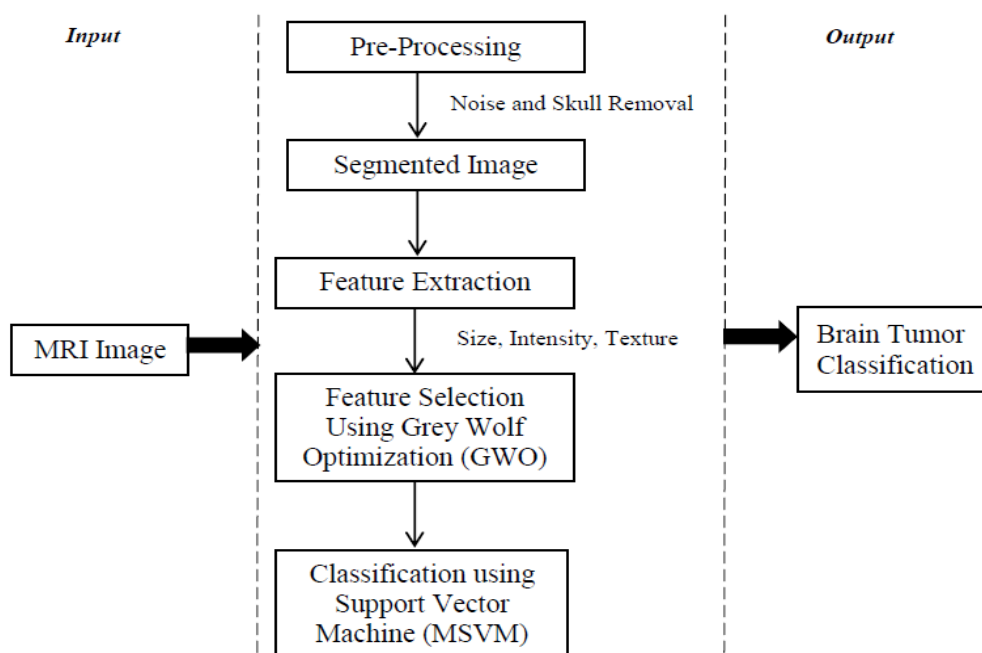


Fig. 2. GWO-MSVM framework for tumor classification

(a) Pre-processing:

In the image pre-processing, the input MRI image is converted into a grey scale image after noise and skull removal. Noise removal is very significant in extracting features which will lead to increase the accuracy.

(b) Image segmentation:

Dividing any image into different homogenous parts is known as Image segmentation [19],[20]. In this paper, the portion which contain brain tumor will be segmented from the given MRI. This area of the image which contain tumor is known as Region of Interest (ROI).

(c) Feature extraction and reduction using GWO:

Feature Extraction is a technique in which we take the original data and afterward represents pertinent information in terms of important factors known as feature vectors with the intention that these feature vectors can be utilized as a substitute of whole data for further processing. On the other hand, feature selection or reduction is referred as a method by which certain features which are affecting the final decision of classification are selected out of features vector. Once the features are finalized, GWO is implemented to optimize them. The working concept of the GWO is explained below.

GWO Working Concept: The basic principle of the GWO is hunting behavior of grey wolves. The wolf, which is in the best position with respect to prey, will be at the top level of the hierarchy which will give command to others [10].

The wolves encircle the prey and mathematically it can be written as;

$$D = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \quad (1)$$

$$\vec{X}(t + 1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (2)$$

Here t represents the present iteration, \vec{A} and \vec{C} are coefficient vector, \vec{X}_p specify a position vector of prey and \vec{X} shows position vector of grey wolf.

\vec{A} and \vec{C} are computed as:-

$$\vec{A} = 2 \vec{a} \cdot \vec{r}_1 - \vec{a} \quad (3)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (4)$$

In eq. 3.3 and eq. 3.4, elements of \vec{a} are linearly decreasing from 2 to 0 for iterations and r_1, r_2 both are random vectors in $[0, 1]$.

In the hunting process, the β and δ follows the guidance given from α for getting the best optimal position with respect to the prey. The updations for all wolves are made accordingly.

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|; \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|; \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \quad (5)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha); \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta); \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \quad (6)$$

$$\vec{X}_p(t) = \vec{X}_1 + \vec{X}_2 + \vec{X}_3 \quad (7)$$

When prey is encircled by equations. 1 and 2 then the $\vec{a} \cdot \vec{A}$ is reduced from $-2a$ to $2a$ to get near to prey where \vec{a} reduces from 1 to 0 as shown in figure 3.

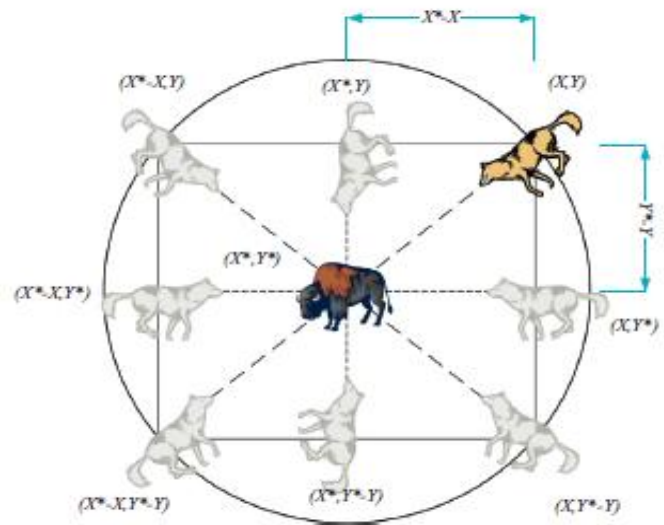


Fig. 3. 2-D position vectors and their possible next locations[10]

(d) Image classification: Classification is referred as the process of pixel's categorization in a particular class. In this study, multi-class SVM is applied for this purpose. SVM is a machine-learning model, which works on supervised learning models associated with an adaptive learning algorithm to analyze data which is used for classification and regression analysis.

The integrated implementation procedure of GWO with multi class SVM method is further provided in figure 4 as given below:

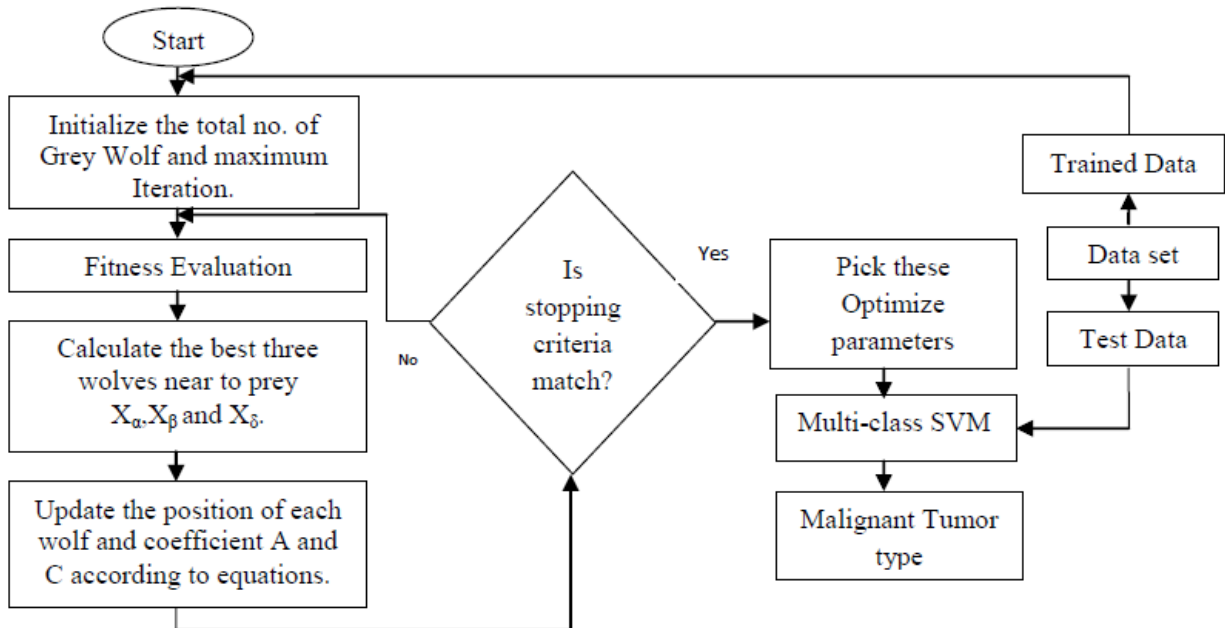


Fig. 4. GWO-MSVM integrated implementation procedure

IV. EXPERIMENTAL SET-UP

To demonstrate the applicability of GWO-MSVM, a data set containing 3064 MRI images of T1 type with weighted contrast. The implementation steps of developed framework in this study on this dataset using MATLAB 2016 a are given below.

Total 315 images are selected after pre-processing that contain 248, 12 and 55 slices of three types of malignant tumor as 'Type-1: Meningioma tumor', 'Type-2: Glioma tumor' and 'Type-3: Pituitary tumor' respectively.

Total 14 features area, perimeter, circularity, mean, standard deviation, variance, skewness, kurtosis, entropy, contrast, correlation, energy, Inverse difference moment (IDM) are extracted from above 315 segmented images of the tumor using Grey level co-occurrence matrix (GLCM) method[21,22]. These 14 features are related to three main categories such as size, intensity and texture.

Now, the above extracted features are optimized using eqs. 1 to 6 of the GWO working concept as described earlier in section research methodology. Finally 03 features, namely perimeter, Standard deviation and variance are taken into consideration for classification. The consistency of this feature optimization using GWO is compared with two more nature inspired algorithms such as FA and PSO. Results of all the three optimization algorithms have been implemented on the same set of the images taken from the same dataset. The feature selection comparison statistics of all the three algorithms, namely, GWO, FA and PSO are provided in Table-I

The next step is to train MSVM with these three optimum features to classify the tumor type. Some of the input MRI images along-with classification results using all the steps are shown in figure 5.

Table- I: Feature selection comparison statistics of GWO, FA and PSO

Features	GWO	FA	PSO	Features	GWO	F A	PSO
Area	0	1	1	Kurtosis	0	0	1
Perimeter	1	1	0	Entropy	0	0	1
Circularity	0	0	1	Contrast	0	0	0
Mean	0	1	0	Correlation	0	1	0
Standard Deviation	1	0	0	Energy	0	1	1
Variance	1	1	1	Homogeneity	0	0	0
Skewness	0	1	1	IDM	0	0	0

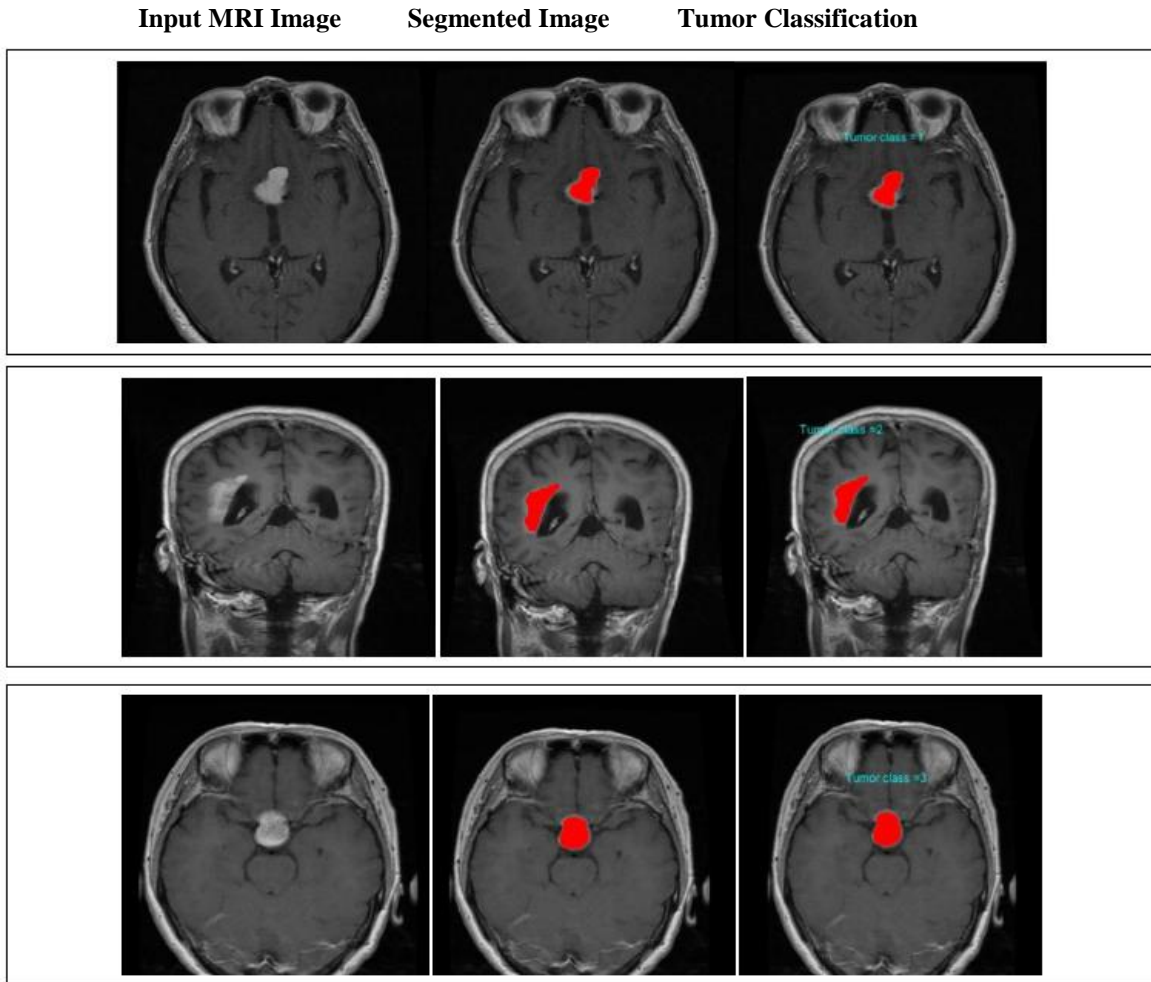


Fig. 5. MRI images along-with tumor classification

V. RESULTS AND DISCUSSION

The major objective of the present study is the classification of the malignant brain tumor using GWO-MSVM. The major findings of the present research are given below.

A novel attempt is also made for consistency check of the GWO by using two more optimization algorithms such as FA and PSO. The comparison statistics provided in Table-I depicts that the GWO selects minimum number of features as 03 features in this case as compare to FA and PSO which selects 07 features each respectively. The extensive study of the literature related to the image classification reveals that the accuracy of the classification is inversely proportional to the number of features. Further, the number of features selected by any of the optimization algorithm is also dependent on the input MRI image.

The accuracy of the classification results using GWO-MSVM is estimated as 95.238% as compared to accuracy, using FA and PSO as 85.714 and 77.777 respectively. The accuracy comparison statistics using GWO, FA, PSO and all 14 features are given in figure 6. Accuracy will vary with the type of tumor present in the image as it can be observed from the Table-II that accuracy for GWO Type-1 tumor image is 96.82% ,while Type-2 and Type-3 tumor

image have 93.65% each for some given image. Features selected by different optimization algorithm will not be fixed for every image; they will vary with the type of tumor in the MRI image. As shown in Table 2, total 4 features are selected by GWO in Type 1 tumor, in Type-2 tumor image total 3 features are selected while in Type 3 tumor image 05 features are selected to achieve better accuracy in comparing to other optimization algorithms.

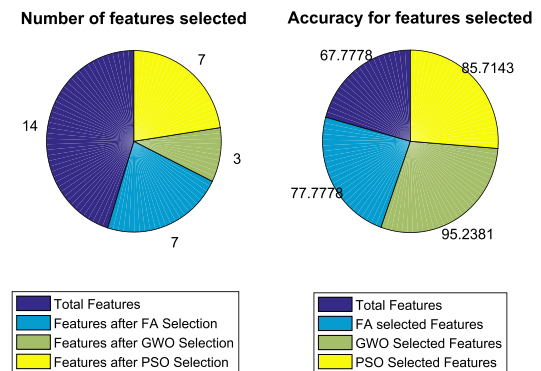



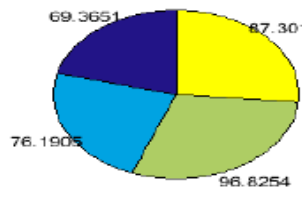
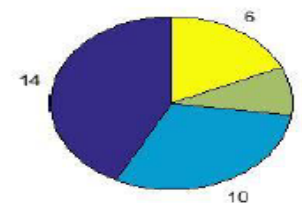
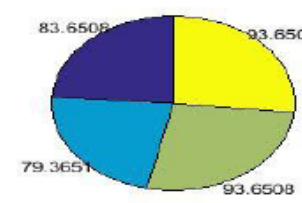
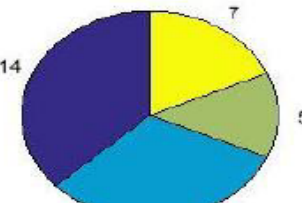
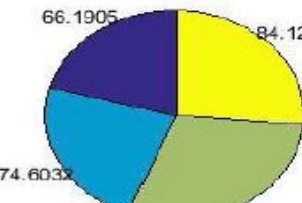
Fig. 6. Accuracy comparison statistics

VI. CONCLUSION AND FUTURE SCOPE

In this study, a framework based on GWO-MVSM is developed for the malignant tumor classification in MRI images. The GWO, nature inspired algorithm used for the feature optimization works better as compared to other algorithms such as PSO and FA when MSVM is used for the classification of tumor images into their different types.

Another major contribution of this research is the high accuracy i.e. 95.238% during the classification that recommend its usage to medical practitioners. The present work can be enhanced in various aspects such as consideration of more malignant tumor types, implementation of other nature inspired algorithms and use of other machine learning methods for classification.

Table- II: Features Selected by Different optimization algorithm

Type of Tumor	Accuracy and Numbers of Features opted by different optimization algorithms	
Type-1	<p style="text-align: center;">Number of features selected</p>  <p style="text-align: center;"> ■ Total Features ■ Features after FA Selection ■ Features after GWO Selection ■ Features after PSO Selection </p>	<p style="text-align: center;">Accuracy for features selected</p>  <p style="text-align: center;"> ■ Total Features ■ FA selected Features ■ GWO Selected Features ■ PSO Selected Features </p>
Type-2	<p style="text-align: center;">Number of features selected</p>  <p style="text-align: center;"> ■ Total Features ■ Features after FA Selection ■ Features after GWO Selection ■ Features after PSO Selection </p>	<p style="text-align: center;">Accuracy for features selected</p>  <p style="text-align: center;"> ■ Total Features ■ FA selected Features ■ GWO Selected Features ■ PSO Selected Features </p>
Type-3	<p style="text-align: center;">Number of features selected</p>  <p style="text-align: center;"> ■ Total Features ■ Features after FA Selection ■ Features after GWO Selection ■ Features after PSO Selection </p>	<p style="text-align: center;">Accuracy for features selected</p>  <p style="text-align: center;"> ■ Total Features ■ FA selected Features ■ GWO Selected Features ■ PSO Selected Features </p>

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