Artificial Bee Colony Algorithm for Adaptive Glioblastoma Detection

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Abstract

Glioblastoma is a most dangerous and aggressive high-grade brain tumour. The high-grade tumors necessitate early detection and treatment due to the rapid growth rate, and early diagnosis may improve the chance of survival. The glioblastoma detection is currently done by a radiologist, however it is time-consuming, invasive, and prone to errors due to the enormous volume of cases. Thus, in this study, the Artificial Bee Colony (ABC) algorithm was employed to provide a non-invasive approach of adaptive glioblastoma detection. The feature properties of the glioblastoma were studied using the basic feature analysis of Minimum, Maximum, and Mean of grey level values. Four different types of T1-weighted, T2-weighted, Fluid Attenuated Inversion Recovery (FLAIR), and T1-contrast MRI images were used to assess the ABC's performance for adaptive glioblastoma detection. A total of 120 MRI glioblastoma images were evaluated, with 30 images per imaging category. The overall mean percentage of accuracy for glioblastoma detection was 93.67%, indicating that the suggested adaptive ABC algorithm has a high capability for glioblastoma brain tumor detection. Other feature extraction strategies, however, could be introduced in the future to improve the feature extraction performance.

Keywords: Adaptive, Glioblastoma, Artificial Bee Colony, Evolutionary Algorithm, Detection and Segmentation

I. INTRODUCTION

The brain tumor is characterized by anomalies that affect brain cells (Bahadure et al., 2018). The brain tumor can be divided into two categories which are benign and malignant (Hamid & Khan., 2020). A benign brain tumor is a mass of cells that is non-cancerous and develops slowly in the brain. A malignant brain tumor, on the other hand, is a cancerous growth in the brain. A simple grading system is used to classify the brain tumor types (Tustison et al., 2015). Grade I and II are low-grade tumors such as gliomas and meningiomas while grade III and IV are high-grade tumors such as astrocytoma and glioblastoma.

Early detection of brain tumor is important to prevent serious damage to the brain and determine the treatment needed by the patient (Jyoti, 2017). High-grade tumors such as glioblastoma required an early diagnosis and treatment due to the fast growth of tumors. Immediate diagnosis can facilitate to increase in the rate of survival (Naser & Deen, 2020). Detection of brain tumor can be done by several tests such as imaging tests, tissue sampling, and cerebral arteriogram, and it depends on the size or location of the tumor (Tiwari et al., 2020).

Yet, in order to get treatment or therapy, a complete disease diagnosis must be finalized. Early detection of brain tumor including the type and grade will assist in enlarging the chances of survival rate of the patient (Bahadure et al., 2018). The expansion of cell growth will bother the brain functionality that will lead to serious problems for the whole body if the tumor is left untreated for a long time (Naser & Deen, 2020). The time taken in brain tumor detection needs to be minimized so that all patients which tend to have a serious brain tumor can be immediately treated.

A radiologist is needed to manually interpret and elaborate the medical images of a brain tumor before it will be reported or delivered to regular doctors, which is may susceptible to errors Mohan & Subashini, 2018). Due to a large number of patients as well as brain tumor images generated, radiologists and other staff will take too much time in segmentation and classification of the images to diagnose the disease (Mustafa & Hassan, 2018). The changes in the health environment become challenging to radiologists therefore any improvement with the technology can assist in increasing the accuracy of radiologist diagnosis (Aslam et al., 2015).

The different types of MRI brain images which are T1-weighted, T2-weighted, FLAIR, and T1-contrast reflect different meanings and representations (Gao et al., 2020). To segregate tumors from these images, it requires different knowledge and understanding due to its various image representation. Thus, a mechanism that could differentiate these images could assist in better tumor segregation. On another note, an adaptive learning refers to a system that can understand and keep track of the user's activities. It adapts training to the needs of the user by using an algorithm and it will change to match the user requirements (Sfenrianto et al., 2018). The adaptive learning processes the information obtained from the training data to automatically analyse data and make the decision, recommendation or classification. In brief, it modifies a certain decision in response to a certain condition.

The Evolutionary Algorithm (EA) is based on nature evolution and the behaviour of living things. It focuses on a population of possible solutions, constructing better approximations to a solution using the survival of the proper principle (Samantha et al., 2017). The EA is also claimed to be able to find the optimal solution within the least amount of time [13]. There are a few techniques of EA such as Artificial Bee Colony (ABC) (Bian et al., 2020), Particle Swarm Optimization (PSO) (Amiri & Dehkordi, 2018). Ant Colony Optimization (ACO) (Wang et al., 2018), Cuckoo Search (CS) (Asghari & Navimipour, 2018) and Firefly Algorithm (FA) (Zhang et al., 2018). Karaboga (2005) invented a new intelligent algorithm named ABC in 2005, which was inspired by the intelligent behaviors of bees. ABC, like ACO and PSO, has become one of the most common optimization algorithms over time (Wang et al., 2020). The ABC algorithm is based on the foraging behaviour of honey bees. It is much better because of the structure, simplicity, and stability higher than other algorithms, and the application of ABC has succeeded extended into several applications (Xu et al., 2015).

Therefore, this paper proposes an adaptive glioblastoma detection using the ABC algorithm. The venture of adaptive learning in the ABC algorithm is hoped to enhance the efficiency and produce a better result in glioblastoma detection. The remainder of this paper is organized as follows: Section 2 describes our research method, as well as the MRI brain image data and the ABC structure. Our findings and discussions are presented in Section 3. Finally, in Section 4, we present our conclusions.

II. METHODOLOGY

The aim of this study is to employ the ABC to detect glioblastoma and to evaluate the accuracy of glioblastoma detection. The proposed glioblastoma detection process flow is shown in Figure 1.

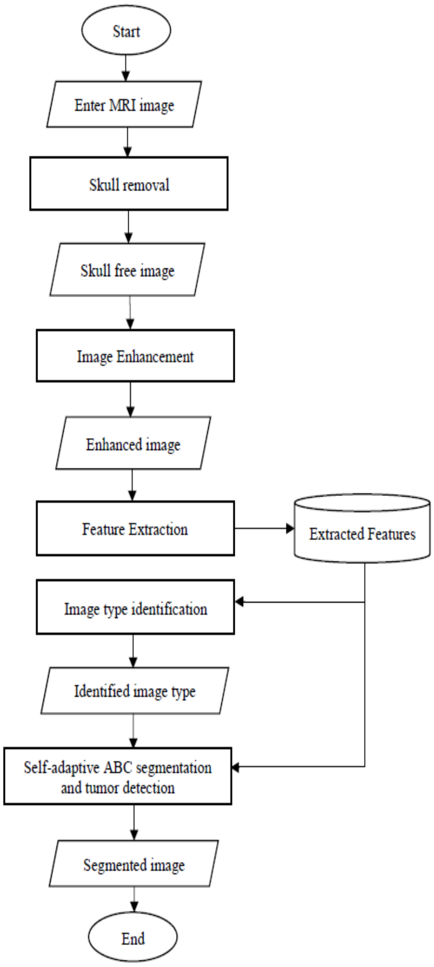
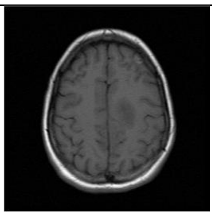
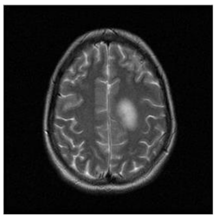
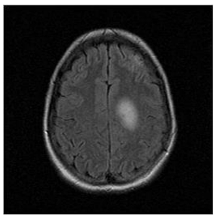
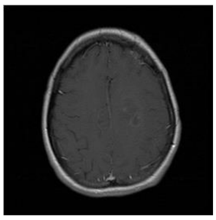


Figure 1. Proposed process flow

A. MRI Images

The glioblastoma images were collected from The Cancer Imaging Archive (TCIA) Public Access. Thirty selected patients with four different types of MRI images which are T1-weighted, T2-weighted, FLAIR, and T1-contrast images were gathered. Table 1 tabulates some samples of four types of MRI images obtained.

Table 1 Samples of MRI Images

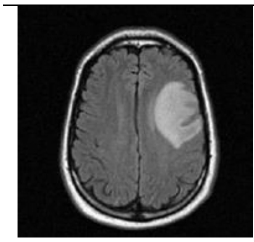
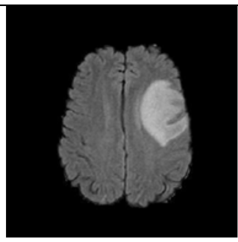
Image Type	**Image**
T1	
T2	
FLAIR	
T1-contrast	

III. B. SKULL REMOVAL

Skull removal has recently gained popularity due to an increased demand for an efficient, reliable, and general algorithm for a variety of brain datasets. Accurate skull removal is a crucial process for neuroimaging diagnostic systems as the outcomes could lead to an unfixed error in the subsequent analysis (Rehman et al., 2020). It is the process of removing the skull to increase the accuracy of segmentation and reduce the disturbing pixel that might affect the tumor segmentation.

The skull removal process was applied using the Thresholding technique. An adaptive threshold was implemented where it established the threshold value accordingly, depending on the image variations. The process involved the changing of a grey level image to a binary image to remove the skull. The image is then converted into a grey level image afterward. Table 2 shows the sample of MRI images before skull removal and skull-free image.

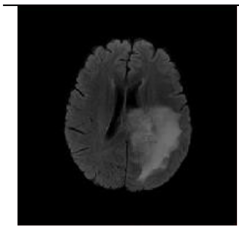
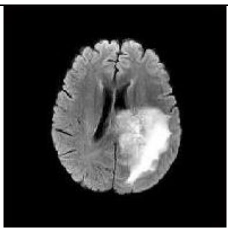
Table 2 Skull Removal

Original Image	Skull Free Image
	

C. Image Enhancement

Medical images, in general, have poor contrast and are distorted by noise. Image enhancement enhances the visual quality of an image so that the information could be easily extracted (Ullah et al., 2020). The image enhancement was applied by increasing the image contrast using the Contrast Enhancement technique which is a spatial domain enhancement. Table 3 tabulates the sample of the enhanced image.

Table 3 Image Enhancement

Before Enhancement	Enhanced Image
	

D. Feature Extraction

The features extraction is one of the crucial step in pattern recognition as it can predict an object based on its characteristics such as texture, shape, color, and to name a few (Khan et al., 2020). The implementation of feature extraction was using statistical feature extraction which is the intensities extraction of the Minimum, Maximum, and Mean pixel value of the image. The feature extraction process is divided into two categories which are image type identification and glioblastoma detection.

The image type identification is used to facilitate the adaptive segmentation process that belongs to the correct image type. Whereas, the extraction of Minimum, Maximum, and Mean values of glioblastomas is essential in detecting the different features of glioblastoma for every image type. These range values were then used as the fitness function in the adaptive ABC segmentation and tumor detection process afterward. Table 4 and 5 tabulate the summary table for the range value of extracted statistical features for image types and glioblastoma respectively.

Table 4 Summary of Range Values for Extracted Statistical Features - Image Type Identification

Image Type	Mean Pixel Value	Minimum Pixel Value	Maximum Pixel Value
FLAIR	27-56	10-42	255-255
T2-weighted	22-60	24-52	255-255
T1-weighted	43-92	53-61	255-255
T1-contrast	36-79	41-66	255-255

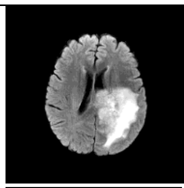
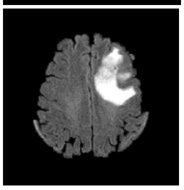
Table 5 Summary of Range Values for Extracted Statistical Features - Glioblastoma Detection

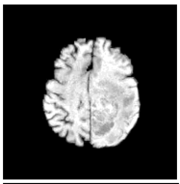
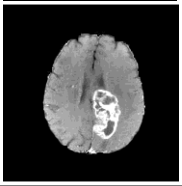
Image Type	Mean pixel value	Minimum Pixel Value	Maximum Pixel Value
FLAIR	226-251	100-166	255-255
T2-weighted	234-254	165-200	255-255
T1-weighted	122-199	86-120	173-200
T1-contrast	135-236	89-230	234-255

E. Image Type Identification

The image type identification is a process to identify the four different types of MRI images which are T1-weighted, T2-weighted, FLAIR, and T1-contrast. Table 6 depicts some samples of image identification.

Table 6 Samples of Image Identification

No	MRI Image	Expected Image Type	Actual Image Type	Accuracy
1		FLAIR	FLAIR	TRUE
2		FLAIR	T2-Weighted	FALSE

3		T1-weighted	T1-weighted	TRUE
4		T1-contrast	FLAIR	FALSE

F. Adaptive ABC Segmentation and Tumor Detection

The ABC algorithm is a simple algorithm that easy to implement and consists of a few parameters to adjust. It was inspired by honey bee's foraging behaviour and being applied in detecting patterns within sequences. Figure 2 portrays the flowchart diagram of the ABC algorithm by (Randazzo, 2012).

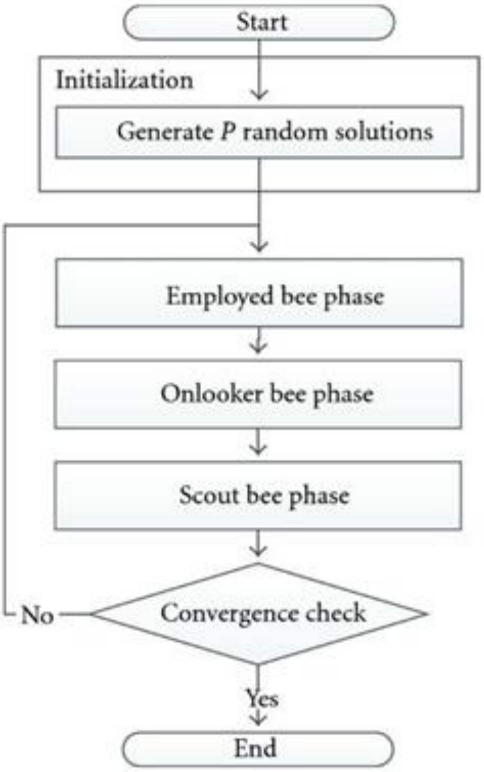


Figure 2. Flowchart diagram of ABC algorithm

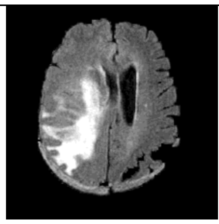
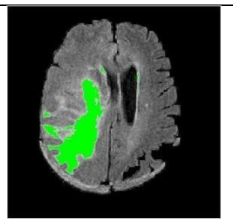
The ABC algorithm begins by searching 100 random pixel points that fit the range of Minimum, Maximum, and Mean values of tumor pixels. Next, the employed bee phase involved the surrounded neighbouring pixels search that fit the similar range of Minimum, Maximum, and Mean value of tumor pixels. The concept of 4-neighbourhood pixel searching was used it was implemented to increase the number of fitted pixels. The onlooker bee phase consequently repeats the same procedure to the other surrounded neighbouring of the new centre pixel points. Figure 3 shows the 4-neighbourhood pixel concept.

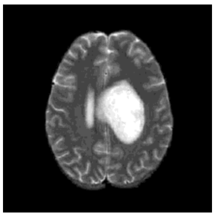
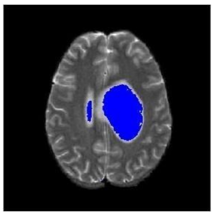
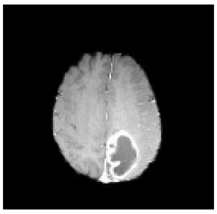
	(x, y+1)	
(x-1, y)	(x, y)	(x+1, y)
	(x, y-1)	

Figure *3*. 4-neighbourhood pixel

The scout bee phase was then used to find a new random solution which means, in this case, the new random pixels were generated when neighbouring pixels from the previous phase were not fit to the tumor range values. The unfit pixels indicate that the pixels were not located in the tumor area. The steps continued and repeated until they converged. The convergence halted when the termination condition appears in which no more pixels that fit the tumor criteria were found. The final segmentation outcome of the tumor-segmented image was then produced. Table 7 portrays the samples of ABC tumor segmentation and detection.

Table 7 Samples of ABC tumor segmentation and detection

Image Type	**MRI Image**	**ABC Segmentation**
FLAIR		
T1-weighted		

T2-weighted		
T1-contrast		

G. Performance Evaluation

The performance of adaptive ABC glioblastomas segmentation and detection was evaluated using a confusion matrix. The confusion matrix involves the calculation of True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) values. It works by comparing the segmented images with the ground truth images. Based on the confusion matrix obtained, the accuracy of glioblastoma detection for each image is then calculated using (1):

$$\%\ of\ Accuracy = \frac{TP+TN}{TP+TN+FP+FN}\ x\ 100\% \quad (1)$$

IV. RESULTS

A total of 120 MRI glioblastoma images, in which 30 images for each image type were tested. Table 8, Table 9, Table 10, and Table 11 tabulate the samples of glioblastoma detection accuracy results for FLAIR, T1-weighted, T2-weighted, and T1-contrast accordingly.

Table 8 Samples of Glioblastoma Detection Accuracy results – FLAIR Images

No.	TP	FP	TN	FN	% of Accuracy
1	3626	2442	96110	1127	96.55
2	2142	978	96044	581	98.44
3	716	8792	92659	0	91.39
4	4167	1948	97800	1322	96.89
5	708	2226	97998	1819	96.06

Table 9 Samples of Glioblastoma Detection Accuracy results –T2-weighted images

No.	TP	FP	TN	FN	% of Accuracy
1	919	4109	93467	3905	92.17
2	1507	0	98388	2505	97.55
3	1224	5815	95126	235	94.09
4	2193	1358	96547	2302	96.43
5	1330	773	97568	2729	96.58

Table 10
Samples of Glioblastoma Detection Accuracy results – T1-weighted images

No.	TP	FP	TN	FN	% of Accuracy
1	1235	5578	91998	3589	91.05
2	1525	8198	90190	2487	89.57
3	592	10924	90017	867	88.49
4	3837	10411	87494	658	89.19
5	3284	14357	83984	775	85.22

Table 11
Samples of Glioblastoma Detection Accuracy results – T1-contrast images

No.	TP	FP	TN	FN	% of Accuracy
1	2547	182	97394	2277	97.60
2	1507	0	98388	2505	97.55
3	801	4174	96767	658	95.28
4	3023	5507	92398	1472	93.18
5	2708	2221	96120	1351	96.51

Subsequently, the overall performance of the glioblastoma detection is demonstrated in Table 12.

Table 12
Overall Performance of Adaptive ABC Glioblastoma Detection

Image Type	% of Accuracy
FLAIR	96.61
T2-weighted	94.94
T1-weighted	89.79
T1-contrast	93.34
OVERALL MEAN	**93.67**

Based on Table XII, the FLAIR image has the highest overall percentage of accuracy with 96.61%. It is followed by the T2-weighted and T1-contrast images with an overall detection accuracy of 94.94% and 93.34% respectively. Meanwhile, the T1-weighted image has the lowest overall accuracy with 89.79%. It might have caused by the confusion in differentiating the T1 and T1-contrast images.

The overall mean percentage of accuracy produced 93.67% of glioblastoma detection which signifies that the proposed adaptive ABC algorithm seems to have a great capability in detecting the glioblastoma brain tumor in various types of MRI image sequences.

V. DISCUSSION AND CONCLUSION

This paper presented a study on adaptive glioblastoma brain tumor detection using Artificial Bee Colony (ABC) algorithm. The intensity-based features of the Minimum, Maximum, and Mean pixel value of the image were extracted in analyzing the characteristics of the glioblastomas and four different types of images which are T1-weighted, T2-weighted, FLAIR, and T1-contrast. The application of the adaptive ABC algorithm to a variety of testing images has been successful. A confusion matrix was used to evaluate the performance of glioblastoma detection. The overall mean percentage of accuracy was 93.67% which indicating solid detection accuracy. It can be concluded that the proposed implementation of the ABC algorithm for adaptive glioblastoma detection is found to be successful. Nevertheless, other feature extraction techniques could be incorporated to improve feature extraction performance in the future.

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