Substantial adaptive artificial bee colony algorithm implementation for glioblastoma detection

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ABSTRACT

Glioblastoma multiforme (GBM) is a high-grade brain tumor that is extremely dangerous and aggressive. Due to its rapid development rate, high-grade cancers require early detection and treatment, and early detection may possibly increase the chances of survival. The current practice of GBM detection is performed by a radiologist; due to the enormous number of cases, it is nevertheless tedious, intrusive, and error-prone. Thus, this study attempted a substantial adaptive artificial bee colony (a-ABC) algorithm implementation in providing a non-invasive approach for GBM detection. The basic statistical intensity-based analysis of minimum (minGL), maximum (maxGL), and mean (meanGL) of grey level data was employed to investigate the GBM's feature properties. The a-ABC's performance for adaptive GBM detection identification was evaluated using T1-weighted (T1), T2-weighted (T2), fluid attenuated inversion recovery (FLAIR), and T1-contrast (T1C) which are four different magnetic resonance imaging (MRI) imaging sequences. Hundred and twenty MRI of GBM images were assessed in total, with 30 images per imaging sequence. The overall mean of GBM detection accuracy percentage was 93.67%, implying that the proposed a-ABC algorithm is capable of detecting GBM brain tumors. Other feature extraction strategies, on the other hand, may be added in the future to enhancee the performance of feature extraction.

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1. INTRODUCTION

The brain tumor is characterized by a mass of abnormal cells in the brain [1]. Benign and malignant brain tumours are the two types of tumours that can occur in the brain [2]. A benign brain tumour is a collection of non-cancerous cells that grows slowly inside the brain. On the other hand, a malignant brain tumour is a cancerous growth in the brain. Brain tumour types are classified using a simple grading system [3] such that the gliomas and meningiomas are low-grade tumours, while astrocytoma and glioblastoma (GBM) are high-grade tumours.

Early detection of brain tumor is critical in preventing catastrophic brain damage and determining the patient's treatment options [4]. An initial detection and treatment were essential due to the quick growth of high-grade malignancies such as GBM. The increase in the rate of survival can be aided by prompt diagnosis [5]. Several techniques including imaging tests, tissue sample, and cerebral arteriogram can be used to detect a brain tumor, depending on the the tumor's size and location [6].

However, a comprehensive disease diagnosis is required before treatment or therapy may begin. A timely diagnosis of a brain tumor by determining its form and grade could increase the patient's chances of survival [1]. If the tumour is left untreated for a long period of time, the development of cells will have an impact on brain functionality which resulting in major complications for the body [5]. The time required to detect a brain tumor should be as minimal as possible so that all patients with a serious brain tumor can be treated immediately.

The medical images are manually analysed and interpreted by the radiologists, which might lead to human errors [7]. The image segmentation and classification process in disease detection would consume a significant amount of time due to the enormous number of patients and brain tumor images created [8]. Changes in the health care environment present a challenge for radiologists, thus any advancement in technology could significantly assist to improve the accuracy of radiologist diagnosis [9].

The evolutionary algorithm (EA) is inspired by natural evolution and live organism behaviour. It focuses on a population of possible solutions, using the survival of the appropriate principle to develop improved approximations to a solution [10]. The EA has been said to be capable of selecting the best solution in the shortest possible time [11]. There are a number of different EA approaches for instance artificial bee colony (ABC) [12], particle swarm optimization (PSO) [13], ant colony optimization (ACO) [14], cuckoo search (CS) [15] and firefly algorithm (FA) [16]. In 2005, Karaboga [17] devised a new intuitive algorithm named ABC, which was inspired by bee intelligence. ABC, like PSO and ACO, has evolved into one of the most widely used optimization techniques [18]. The ABC is established on honey bee foraging behaviour. It is outstanding to other algorithms in terms of structure, simplicity, and stability, and ABC has been successfully extended into a variety of applications [19].

The T1-weighted (T1), T2-weighted (T2), T1-contrast (T1C), and fluid attenuated inversion recovery (FLAIR) sequences of magnetic resonance imaging (MRI) brain images reflect diverse interpretations and representations [20]. Due to the diverse visual representations, segregating tumours from these images necessitates different knowledge and understanding. Thus, a technique that can distinguish these images could aid in tumour segregation. A system which understands and keeps track of the user's activities is referred to as adaptive learning. It uses an algorithm to adapt training to the demands of the user, and it will modify to meet the user's requirements [21]. Adaptive learning analyses data automatically and makes a decision, recommendation, or classification based on the information collected from the training data. In a nutshell, it alters a decision in reaction to a certain circumstance.

Therefore, this paper proposes an adaptive ABC (a-ABC) algorithm to offer a non-invasive approach for GBM detection. The implementation of adaptive learning into the ABC algorithm is expected to improve efficiency and yield improved GBM detection results. These are the remaining sections of the paper: section 2 presents on research technique, together with the MRI brain image data and the ABC design. Section 3 elaborates our results and discussion of findings. Lastly, we describe the conclusions in section 4.

2. METHOD

The goal of this research is to craft the a-ABC algorithm for GBM detection and to assess the accuracy of the detection. Figure 1 in appendix portrays the suggested GBM detection process flowchart. The process starts with the input image, which is the MRI brain image. The skull will be removed from the image throughout the skull removal pocess. It proceeds to the image enhancement process which is used to enhance an image's visual quality so that features data could be extracted efficiently. The subsequent process is feature extraction. The features extraction is a vital step in pattern recognition as it is used to study the characteristics of an object established on its feature's representations for instance texture, shape, and color. In this study, the two categories of the feature extraction technique are GBM detection and image type identificatiom. The extracted features are significant to be fed in image type identification of T1, T2, T1C, and FLAIR, as well as to be the objective function in the subsequent process. The final step is ABC segmentation and tumor detection which produced the final detection and segmented image of GBM.

2.1. MRI images

The images of GBM were obtained from the cancer imaging archive (TCIA) public access. Four types of MRI images were collected which are T1, T2, T1C, and FLAIR. A total of 120 images, comprising 30 images for each imaging type were selected.

2.2. Skull removal

Skull removal has lately acquired popularity as a result of escalated demand for a fast, reliable, and consistent algorithm for different variations of brain datasets. For neuroimaging diagnostic systems, precise skull removal is critical since the results could lead to an unnoticed inaccuracy in the upcoming processing [22].

It refers to a process of eliminating the skull from the image to escalate segmentation accuracy, and lessen the number of distracting pixels that could interfere with tumour segmentation.

The Thresholding approach was applied in the skull removal process. Based on the image variations, an adaptive threshold was executed in which it adjusted the threshold value correspondingly. The process transformed the grey level image to a binary image and converted it back to a grey level image to eliminate the skull.

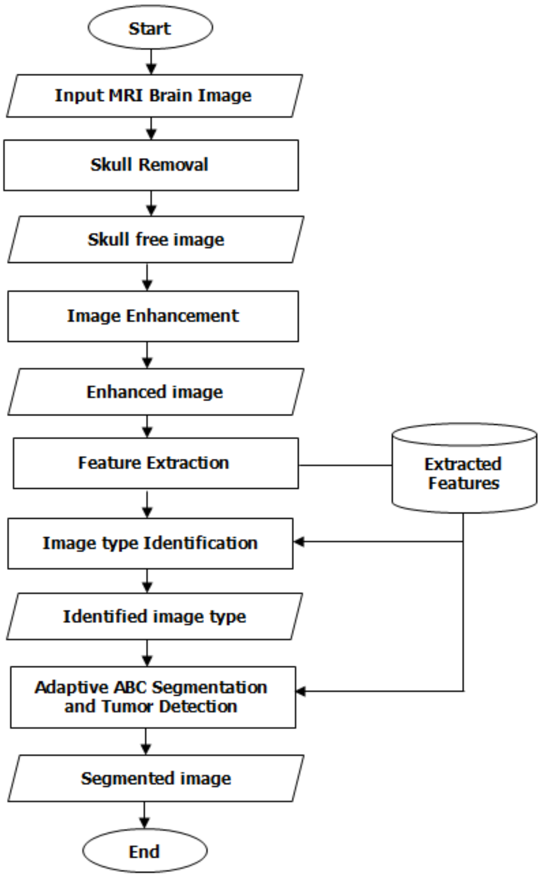


Figure 1. Process flowchart

2.3. Image enhancement

Generally, medical images have low contrast and are affected by noise. Image enhancement improves an image's visual quality such that information may be extracted more effectively [23]. The image was enhanced by employing the spatial domain enhancement techniques which is contrast enhancement, which increase the visual contrast.

2.4. Feature extraction

Among the most important steps in pattern recognition is features extraction, which may anticipate an object based on its properties such as texture, shape, colour, and many more [24]. Statistical feature extraction, which is the retrieval of intensities of the image's minimum (minGL), maximum (maxGL), and mean (meanGL) of grey level was utilized to perform feature extraction. The image type identification and GBM detection processes are categorized into two parts in the feature extraction process.

The adaptive segmentation process is aided by the image type identification in identifying which image type it belongs to. On the other hand, detecting the different features of GBM in each of the four image types requires the extraction of minGL, maxGL and meanGL values of GBM. The a-ABC segmentation and tumour identification technique then utilized these range values as the objective function. Table 1 presents the composite table of statistical features’ range values for image type identification and GBM detection.

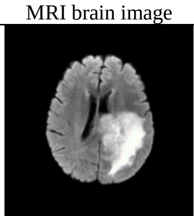
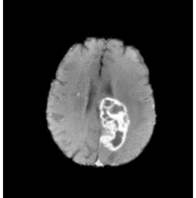
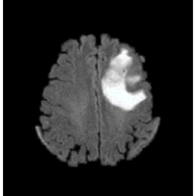
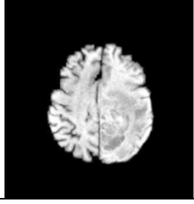
Table 1. Range values summary of statistical features extraction

Feature Extraction	Image type	meanGL	minGL	maxGL
Image type identification	FLAIR	27-56	10-42	255-255
	T1	43-92	53-61	255-255
	T1C	36-79	41-66	255-255
	T2	22-60	24-52	255-255
GBM detection	FLAIR	226-251	100-166	255-255
	T1	122-199	86-120	173-200
	T1C	135-236	89-230	234-255
	T2	234-254	165-200	255-255

2.5. Image type identification

Subsequently, the derived data during the feature extraction process is used for image type identification of four types of MRI images T1, T2, T1C, and FLAIR. A comparative experiment was designed in which the expected image types were compared with the actual image type. Table 2 shows a few illustrations for image identification.

Table 2. Image identification – samples

No.	MRI brain image	Expected image type	Actual image type	Accuracy
1.		FLAIR	FLAIR	TRUE
2.		T1C	FLAIR	FALSE
3.		T1C	T1	TRUE
4.		FLAIR	T2	FALSE

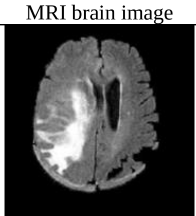
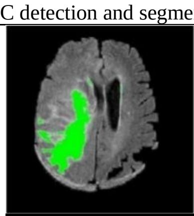
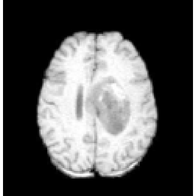
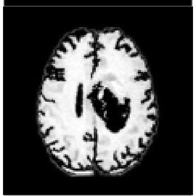
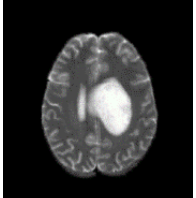
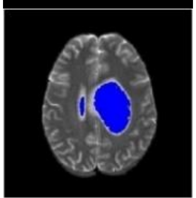
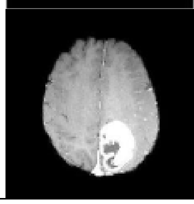
2.6. A-ABC segmentation and tumor detection

The T1, T2, T1C, and FLAIR sequences of MRI brain images reflect diverse interpretations and representations. Due to the diverse visual representations, segregating tumours from these images necessitates different knowledge and understanding. Thus, a technique that can distinguish these images could aid in tumour segregation. Adaptive learning analyses data automatically and makes a decision, recommendation, or classification based on the information collected from the training data. It alters a decision in reaction to a particular circumstance.

The ABC algorithm is a straightforward, easy-to-use algorithm with only little parameters to modify. It was motivated by honey bee foraging behavior and is used to detect patterns within sequences [25]. Thus, the implementation of a-ABC algorithm is expected to improve efficiency and yield improved GBM detection results. In this study, the searching for 100 random pixel locations that fit the range of tumour pixels' minGL, maxGL and meanGL values is implemented to begin the a-ABC algorithm. The employed bee phase then concerned the surrounded neighbouring pixels that adaptively fit the same range of tumour pixel minGL, maxGL and meanGL values, guided by the extracted features (T1, T2, T1C, and FLAIR) in feature extraction process which acted as the objective function. The 4-neighbourhood pixel searching concept was applied to increase the number of fitted pixels; (x, y+1), (x–1, y), (x+1, y), (x, y–1). During the onlooker bee phase, the same process is repeated in the surrounding pixels of the new centre pixel locations.

Random pixels were generated through the scout bee phase if neighbouring pixels from the prior phases did not match the tumour range values. The pixels that did not fit indicated that they were not in the tumour area. The stages were pursued and repeated until they reached a point of convergence. The convergence came to a halt when the termination condition appeared, indicating that there were no more pixels that met the tumour requirements. The tumor-segmented image's final segmentation result was then generated. Table 3 illustrates a-ABC tumour detection and segmentation samples.

Table 3. Samples of a-ABC tumor detection and segmentation

Image type	MRI brain image	A-ABC detection and segmentation
FLAIR		
T1		
T2		
T1C		

2.7. Performance evaluation

The a-ABC GBM segmentation and detection performance was assessed using confusion matrix. The confusion matrix calculates the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) values. It is done by matching the ground truth with the segmented images. The GBM detection accuracy for each image is then calculated utilising the confusion matrix acquired using (1),

$$\%\ of\ Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}\ x\ 100\% \quad (1)$$

3. RESULTS AND DISCUSSION

This section presents the perfornance analysis of GBM detection. There were 120 MRI of GBM images evaluated in total, comprising 30 images for each imaging type. Table 4 summarises the T1, T2, T1C, and FLAIR of GBM detection accuracy results. Next, Table 5 shows the overall performance of GBM detection. Table 5 indicates that the FLAIR image has the best overall accuracy of 96.61%. The T2 and T1C images are the next, with overall detection accuracy of 94.94% and 93.34% accordingly, respectively. Meanwhile, with an overall accuracy of 89.79%, the T1 image has the least overall performance. It could have been led by some uncertainty in distinguishing both T1 and T1C images. A 93.67% overall accuracy rate was recorded for GBM detection, demonstrating that the a-ABC algorithm has a great ability to detect GBM brain tumours in diverse types of MRI image sequences.

Table 4 Accuracy results for GBM detection - samples

Image Type	Image No.	TP	TN	FP	FN	% of Accuracy
FLAIR	1	3626	96110	2442	1127	96.55
	2	2142	96044	978	581	98.44
	3	716	92659	8792	0	91.39
	4	4167	97800	1948	1322	96.89
	5	708	97998	2226	1819	96.06
T1	1	1235	91998	5578	3589	91.05
	2	1525	90190	8198	2487	89.57
	3	592	90017	10924	867	88.49
	4	3837	87494	10411	658	89.19
	5	3284	83984	14357	775	85.22
T1C	1	2547	97394	182	2277	97.60
	2	1507	98388	0	2505	97.55
	3	801	96767	4174	658	95.28
	4	3023	92398	5507	1472	93.18
	5	2708	96120	2221	1351	96.51
T2	1	919	93467	4109	3905	92.17
	2	1507	98388	0	2505	97.55
	3	1224	95126	5815	235	94.09
	4	2193	96547	1358	2302	96.43
	5	1330	97568	773	2729	96.58

Table 5. Overall GBM detection using a-ABC

MRI Image Type	Percentage of Accuracy
FLAIR	96.61
T2	94.94
T1C	93.34
T1	89.79
OVERALL MEAN	93.67

4. CONCLUSION

A study on GBM brain tumour detection using the a-ABC algorithm was presented in this paper. The basic statistical features of minGL, maxGL and meanGL values of the image were extracted to analyse the characteristics of GBM and four image types of T1, T2, T1C, and FLAIR images. The a-ABC algorithm has been successfully applied to various testing images. The detection performance of GBM was evaluated using a confusion matrix. The overall mean accuracy percentage was 93.67% which signifying solid detection accuracy. It is reasonable to conclude that the proposed a-ABC algorithm implementation for GBM detection is successful. Other feature extraction methodologies, on the other hand, may be added in the future to increase the performance of feature extraction.

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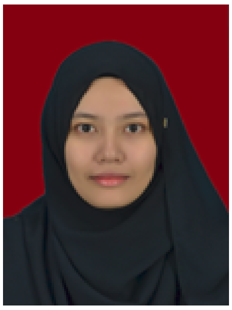

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