

BIR-CAT Optimization Technique for Automatic Segmentation and Classification of Brain Tumours on Pre- and Post-Operative MRI

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ABSTRACT

The main goal of this research is to find brain tumours by use MRI scan. After that, to find all the abnormalities in the brain and put them into groups. It is a challenging task to detect and segment the tumour tissues and other tissues from the brain. The MRI is initially fed into the preprocessing system and is then segmented using the Region Growing segmentation algorithm. This will produce the segmented area and is then forwarded for classification. In the classification step, the Bir-Cat optimization algorithm is used. This is a deep learning idea that trains the neural network using a Deep Belief Network. The Bird-Swarm algorithm and the Cat-Swarm algorithm are both parts of the Bir-Cat algorithm. This will give the classified tumour tissues and also classify the different types of tissues or abnormalities in a brain tumour. The extended idea is the segmentation and classification of a brain tumour after surgery. This includes all of the image processing steps that were done for the MRI before surgery. Finally, the segmented results of the pre-operative MRI and the post-operative MRI were compared to see if any pixels had changed. These both identify the post-surgery new tumour that has developed and demonstrates how well the procedure was performed.

Keywords***:*** *Brain Tumor Segmentation, Post-Operative MRI, Segmentation, Neural Network, Region Growing*

INTRODUCTION

Most of the time, an image is an intensity function that is defined by its spatial coordinates and its amplitude. This is written as f (x, y). Here, x and y are the coordinates of space, and the amplitude is the image's intensity at a certain point. Brightness or the grayscale values are other names for intensity. So, an image is said to be a function of light in two dimensions. A digital image includes numerous elements called pixels. Picture or image

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elements are another name for these pixels. Digital image processing is the process of using a computer to run an algorithm on a digital image. Because of this, the internal structures of an image, even if they are hidden by things like skin and bones, become clear. This helps doctors figure out what's wrong and give the right treatment.

Medical image processing is the process of turning pictures of the inside of the body into pictures that can be used in medicine or for other purposes. These medical images are also used in digital image processing. Digital image processing has many advantages over analogue image processing because algorithms can be used in more situations and noise and distortion problems are solved.

Medical imaging is the process of making pictures of the insides of the body or of how some organs or tissues work on the inside. This is used in clinics and hospitals for medical purposes. Also, medical studies are done to look at how some tissues or organs work on the inside. So, the problem of finding and dealing with disorders is solved. In order for medical image processing to move forward, a data bank must be created that stores the regular structure and functions of the organs. This information is very helpful for figuring out what's different. Also used a lot are organic and radiological images that use the electromagnetic force, such as gamma images, sonography, and isotope images.

Also, different ways to figure out where the body is and what it does were suggested. But these techniques are limited in many ways compared to the ones that are already used. Each year, billions of images are looked at to help make diagnoses. Brain tumours have led to a lot of growth in the medical field over the past few decades. This sudden increase in medical cases is a threat to people and has been found to be the 10th most common type of tumour in the history of the world. So, scientists are working on new ways to find tumour tissue inside the human body. People have also noticed that these brain tumours are easy to treat if they are found early. When looking for tumour tissue, the shape and stage of the tumour are also important. Most of the time, people use Magnetic Resonance Imaging (MRI) and Computer Tomography (CT) to find these tissues. The resectioning and examining process, on the other hand, shows any problems with the size, shape, or position of the brain tissue. Even though both MRI and CT scans are used a lot, doctors prefer MRI because it has more benefits and can be used in more ways. Since an MRI scan doesn't hurt the patient, finding and cutting out a tumour from an MRI picture of the brain has been found to be one of the most difficult tasks in the medical field.

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First, a simple input image is used to start the segmentation process. However, this method results in an image that is too segmented. So, the merging algorithm and the region-growing algorithm are combined to handle the complex images. In order to find, find, and confirm the edges of a region, boundary information is added to the algorithm for growing and dividing regions. Here, an automated seed segmentation algorithm based on texture is used. It has been seen that this method is more accurate and works well for dividing up MRI brain images.

The multi-grade classification technique in [1] is used to look at the MRI pictures and find the brain tumours. Deep learning is used in conjunction with neural networks to separate the tumour areas in MRI scans. By using the multi-grade tumour classification technique, the problem of adding more data is solved and high performance is reached. Optimization techniques were used with neural networks to cut down on noise and smooth out the process of segmentation [2]. Here, the brain tumour is found and categorised automatically, so there is no need to find it by hand. The sine-cosine algorithm is used to find the best weights for the proposed model. This method is more accurate than others.

Brain tumours are often hard to tell apart, but deep learning techniques help a lot. People were talking about Brain MR Net [3], which uses both augmentation and deep learning to diagnose and treat the disease. Using the hyper column technique and attention modules, the proposed network is built. This lets the best MRI images be chosen to find the brain tumour [4]. Here, a lot of people are put in the right group. In recent years, fuzzy c-means clustering algorithms have been used a lot in the process of sorting things into groups. In fuzzy c-means and the genetic algorithm are used together to improve the clustering and categorizing process [5]. So, the performance of clustering has improved, and the problems with the fuzzy c-means algorithm are gone.

Combining the wavelet transform and the image denoising process made it possible to use the genetic algorithm to find breast cancer in mammograms [6]. Also, the wiener filter is used to find the masses in the mammogram images and separate them into groups. Using the genetic algorithm to look at the different views of mammogram images improves how well this method works. Brain tumour classification involves a number of steps. First, the noise is taken out, and then the data is processed in the stripping procedure. When the Bayesian classifier and fuzzy neural networks are used together, a genetic algorithm and a technique called "grey wolf optimization" [7] are used. Here, the proposed method is better than other

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methods because it picks out the hidden neurons from the neural networks. It has been seen that this method works better than other methods. The neural networks and the classification algorithm are used to separate the white blood cells [8]. For training and testing, the proposed method uses the feature extraction process and the learning network. This method has been shown to be very accurate. An encoder-decoder neural network [9] is used to pull retinal features out of an image so that the strategy for reusing features can be improved. The network is also made better by adding data to it. A careful and sensitive evaluation of the proposed network is done to figure out how well the approach works.

This paper contributes an optimization-driven classifier has been made for finding tumour tissues in the brain. It is suggested to use the BirCat optimization algorithm to train the Deep Belief Network (DBN) to find the brain tumour. Furthermore, the BirCat algorithm uses the Bird Swarm Algorithm (BSA) and the Cat Swarm Optimization (CSO) method to tune the weights of the DBN classifier.

LITERATURE REVIEW

In the state of the art, different ways of separating the brain's tissues were suggested. By combining deep learning with classification techniques, it is possible to tell the difference between tumour tissues and other tissues. The Magnetic Resonance (MR) images of the brain can also be broken up using the region-growing and edge detection techniques.

Feature extraction methods, neural networks, and K-NN algorithms [10] were used to put brain tumours into groups. The proposed method improves the classification process with a high rate of success. An improved feature selection method is used to improve the accuracy of brain tumour classification. Neural networks with cosine transformation [11] are proposed to deal with the huge amount of data and cut down on the noise in the process of classifying brain tumours. The method gets a high rate of recognition and a lot of processing power. It is suggested to use the greedy algorithm and the wake-sleep algorithm [12] to get rid of the noise and improve the accuracy of classification. A cosine transform is used with a neural network to support this method [13]. It has been seen that the proposed method achieves high accuracy with low computational complexity. A model is made with a learning process and a greedy algorithm for fine-tuning, as well as several hidden layers. The proposed model does a better job of separating things. The time series data from the sensors is used to classify activities in the neural networks. Different layers were added to improve the performance of

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the whole network. Also, the number of feature maps was increased to keep the information secret [14]. Information is gathered from the sensors, and the different architectures are analysed based on how many layers they have. To solve the optimization problems, the bird-swarm [15] and CAT behaviours were taken into account [16]. Their performances were judged based on the different benchmark values and many test functions, and it was found that the proposed method is a big step up. Brain tumours are found in MRI images and then put into different subclasses using the region-growing algorithm and wavelet features [17]. Using an algorithm called "region growing," the tumours are separated and put into different groups. Experiments were carried out, and the proposed method was found to be effective. Tensors and agents were used to break up the white fibres [18]. This led to an improved T1wMRI image that is more likely to be real. We used automatic segmentation of tumour tissues with a kernel size of 3x3 and gave neural networks the least amount of weight possible [19]. Techniques for normalising data and adding to it were used, and this method was tested with the segmentation challenge 2013 database. Fuzzy inference with contour let transform [20] was used to tell the difference between the normal image and the image of the glioma. The dilation and erosion functions are used to separate the abnormal images, and an open access segmentation dataset was used to test the method.

MRI BEFORE AND AFTER SURGERY WITH THE BIR-CAT OPTIMIZATION ALGORITHM

Segmentation is an important part of figuring out if a brain tumour or other abnormality is in normal brain tissue or not. In the "state of the art" section, different approaches have been suggested and explained. It is planned to use the Bir-Cat algorithm to automatically divide MRI images from before and after surgery.

Figure 1 show that brain tumour segmentation is made up of five steps: preprocessing, segmentation, feature extraction, tumour classification, and change detection. In the next section, the steps for segmenting a brain tumour are described in detail, along with the proposed algorithm and a dataflow diagram.

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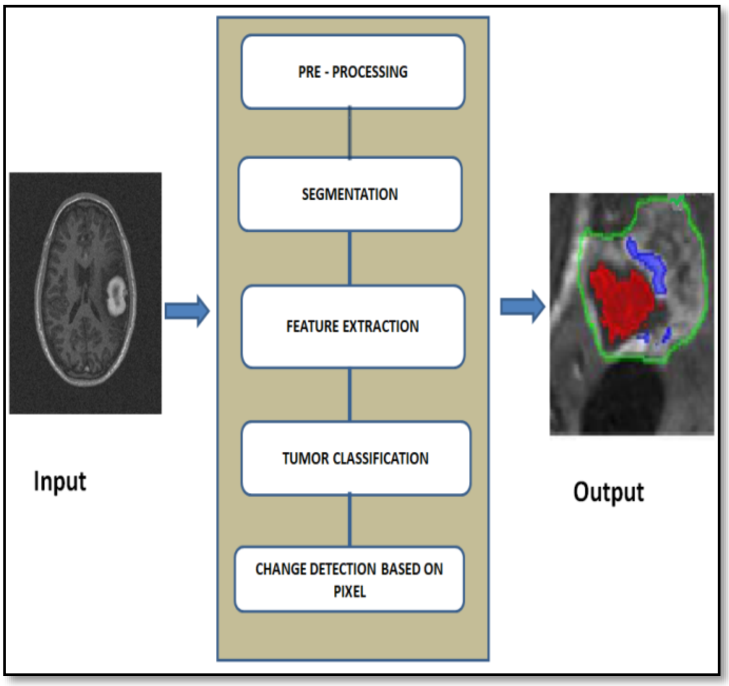

Figure 1. A Block Diagram of Divide Up a Brain Tumor

Preprocessing

The first step in the process of segmentation is preprocessing. The intensity images are used to start the process of segmentation. The original images that the sensors took are like the intensity images, but the intensity images are usually shown as a function of brightness.

Preprocessing is used to increase the image's details and remove any distortions and the MRI being prepared for use as shown in Figure 2. The picture that was submitted is utilised in the preprocessing step. In this case, filters are used to get rid of the image's high-frequency parts, smooth out the image, and find its edges. After the image has been filtered, the area of interest is taken from it.

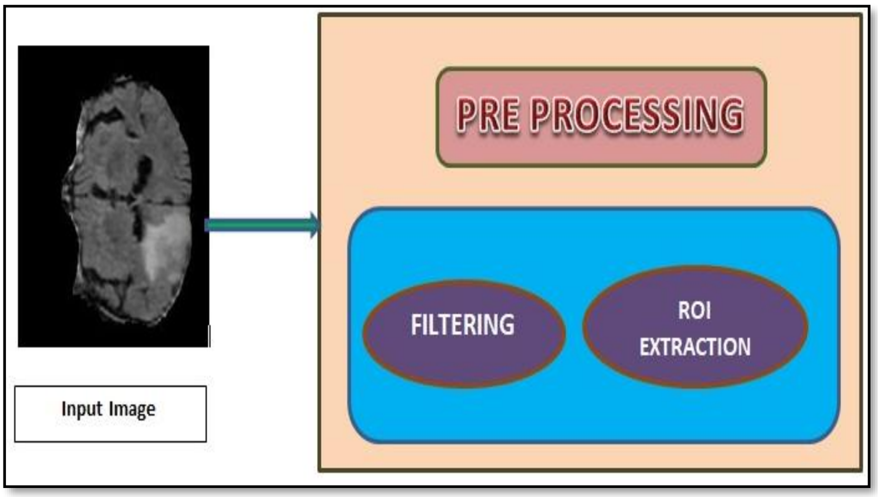

Figure 2. Preprocessing for an MRI

Segmenting an image

Here, the digital image is broken up into many small squares called pixels. Image objects are what these pixels are called. By separating them, the image's complexity is greatly reduced, and it's easier to figure out what it's all about. Different segmentation algorithms were used. These segmentation algorithms were made to put images into groups based on the values of their pixels. So, pictures with a certain number of pixels make a category or label, and so on. With the help of these pixels, you can make borders or lines, and you can separate the important parts of an image.

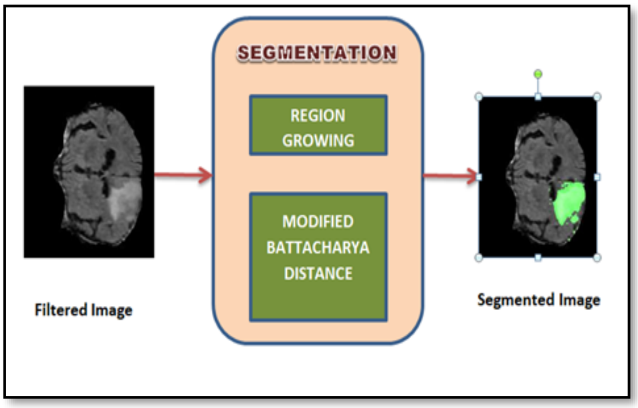

Figure 3. Breaking up a Brain Tumour on an MRI Scan

MRI is used to divide up brain tumours as shows in Figure 3. The image that has been cleaned up is fed into the process of segmentation. In this case, the region-growing algorithm is used. A lot of things are done, such as dividing, sorting, and labeling information. This labeled information is then used to train many machine learning models that solve different medical problems.

Identifying and finding objects are two of the most important steps in image segmentation. These are used to find and group pixels that are the same and get rid of pixels that are different. In our work, we use the Modified Battacharya Distance and the region growing algorithm to split up the images. Several algorithms for growing regions were suggested. All of these algorithms, though, tend to break the image up into separate parts called pixels. At first, region-based segmentation looks for seed points that can be small or large. There were different ways to add more pixels, reduce the number of pixels, or combine the pixels.

Region Growing is an approach that works from the bottom up. The process starts with smaller pixels, and elements with smaller pixels are combined or added together based on how similar they are. The algorithm starts by picking an image with a random seed pixel and comparing it to the pixels around it. During the comparison, if a similarity is found between a pixel and its neighbors, the value of that pixel is added to the value of the initial seed pixel, and the region grows. If there is no similarity, the value of that pixel is ignored. When the saturation value is reached, the algorithm stops, and a new seed value is chosen. This new seed value is chosen so that it does not belong to any current region, and the algorithm repeats.

Algorithms that make regions grow are used to get better segmentation, which makes it easier to see and find the edges. But sometimes, the region-growing algorithm lets a region grow without trying any of the other pixel seeds. This is because the regions that are segmented first are given more weight in the process. So, to get around this, the inputs with the most similar pixels are allowed to grow first, and this lets more than one region grow at the same time.

The thresholding is related to the algorithms for growing regions. In thresholding, a region is taken out based on how similar the pixels are, but in the region growing approach, only the pixels that are next to each other are taken out. Most of the time, region-growing algorithms are good for noisy images, but it's hard to see the edges.

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Feature Extraction

In feature extraction, the image's size is cut down a lot. Here, the raw data that comes in is broken up into different groups to make it easier to work with. Large datasets need a lot of variables and a lot of computing power, so the best features can be pulled out. By combining a large number of variables into features, which are then used to find the best features, the size of the data is greatly reduced. The original data set is described with high accuracy using the extracted features.

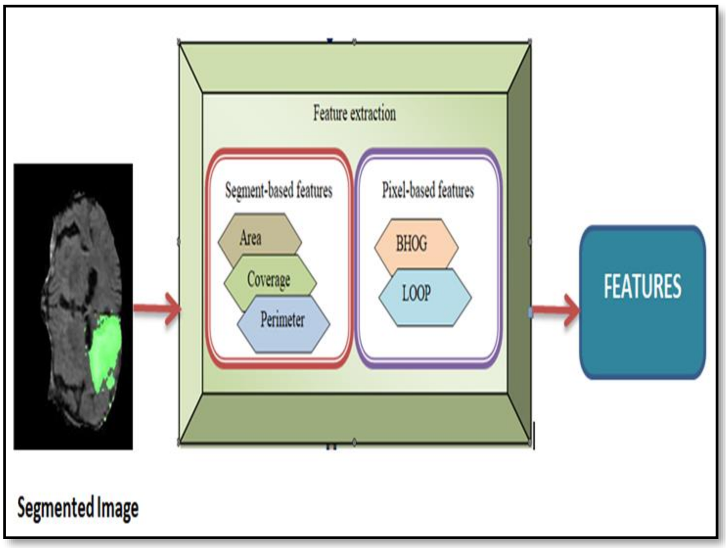

Figure 4. Taking out the Features

The process of extracting features as shown in figure 4. The image that has been cut into pieces is given to the process of extracting features. The segments and pixels are used to figure out what the features are. The best features from these datasets are taken out. Here, an increment method is used to figure out the Bhattacharyya distance between two histograms. Most of the time, incremental algorithms are used to get rid of the histograms. We use histograms and differences in space to figure out this distance in our work. For the reference image, histograms are used, and the differences between the reference image and the current image are called "spatial differences."

Image Classification

Most of the time, neural networks and image classification techniques are used together to look at medical images. Classifications of image are usually used to sort the pictures that come in and see if the pictures that come out are normal or not.

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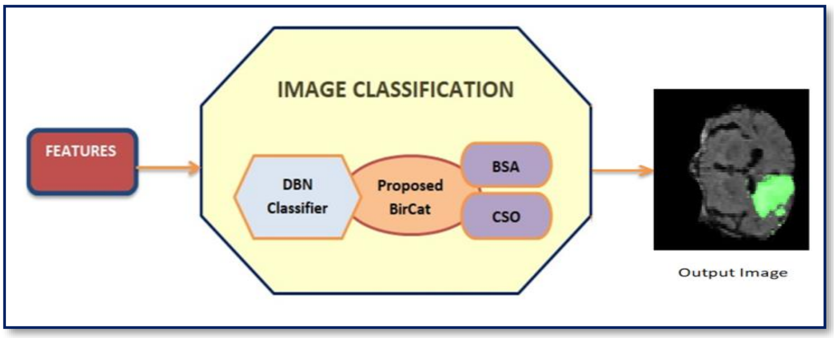

Figure 5. MRIs Classify Brain Tumours

As shown in Figure 5, the image classification process is done on the extracted features and DBN classifier is used. The BirCat optimization algorithm, which is a mix of the Bird and Cat algorithms, is used. When these are used, the output image is made.

Change Detection

Using the pixel mapping technique, the change is found by comparing the segmented and classified MRIs from before and after surgery as shown in figure 6. The amount of tumour in the postoperative image will be shown by the changes in the pixels of the image.

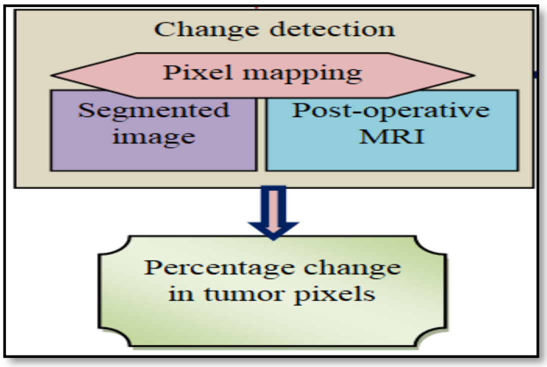

Figure 6. Pixel Mapping is used to find changes in an MRI

PROPOSED AUTOMATIC SEGMENTATION FLOW DIAGRAM USING BIRCAT ALGORITHM

The proposed automatic segmentation of MRI images using the BirCat algorithm as indicated in Figure 7. The pre-operative MRI image is let into the preprocessing phase, where the region of interest is defined and the image is filtered. The image is filtered to get rid of any distortions, and then the region of interest is taken from the filtered image. The image

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that has already been processed and filtered is fed into the process of segmentation. In segmentation, the Bhattarcharya distance is used to find the edges, and the region-growing algorithm is used to find them.

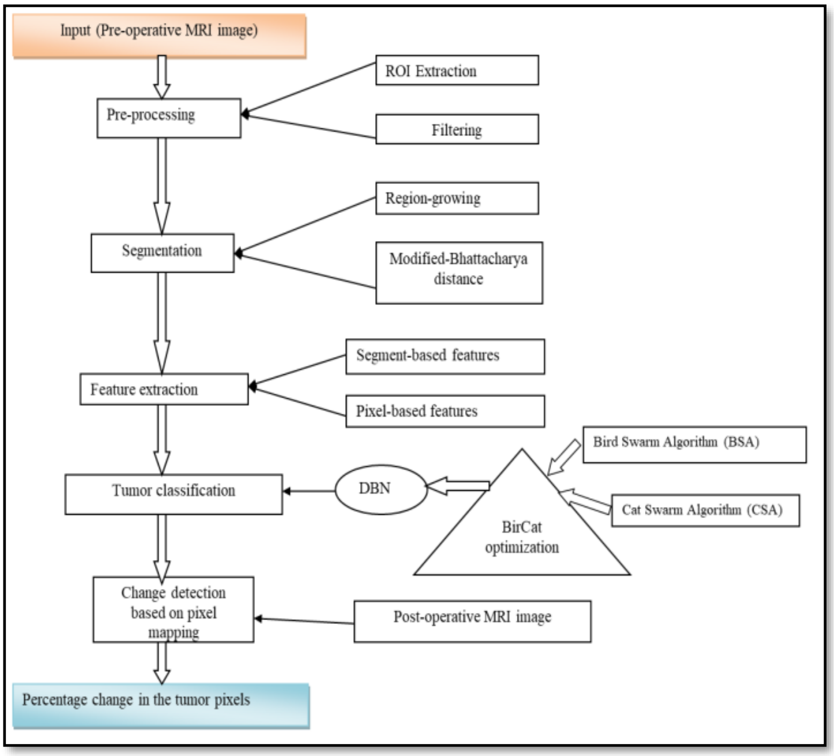

Figure 7. A Flowchart of Grouped Brain Tumours

During the feature extraction phase, the features are put into two groups: those based on segments and those based on pixels. Here, the best parts are picked out. A DBN classifier and the BirCat optimization algorithm are used to sort tumours into groups. The Bircat optimization method takes the best parts of the Bird optimization and Cat optimization algorithms and puts them together. Pixel mapping and post-surgery MRI images are used to find the changes and figure out what percentage of the pixels in the tumour have changed.

Features in BIRCAT

This method makes use of the following:

- Features based on segments.
- Features based on pixels.

- Using a pixel mapping strategy, the post-surgery MRI image and the segmented image are looked at to see how well the change detection works.

- Pixel mapping is done to figure out how much tumour pixels have changed.

COMPARATIVE ANALYSIS

Matlab was used to make the proposed automatic segmentation using the Bircat algorithm work. Existing methods like convolutional neural networks, active contour with random forest, and DBN with bird swarm are compared to the new DBN and Bircat algorithm. Performance metrics like specificity, accuracy, and sensitivity for two datasets are used to compare them.

Table 1. Comparative Analysis

Dataset	Metrics	CNN	Active contour+random forest	ANFIS	DBN-birdswarm	Proposed DBN-BirCat
Using dataset 1	Specificity	0.864	0.890	0.629	0.849	**0.92**
	Accuracy	0.909	0.906	0.863	0.906	**0.920**
	Sensitivity	0.915	0.915	0.878	0.907	**0.916**
Using dataset 2	Specificity	0.842	0.702	0.6	0.714	**0.9**
	Accuracy	0.870	0.820	0.787	0.822	**0.927**
	Sensitivity	0.914	0.932	0.897	0.919	**0.938**

The proposed DBN+Bircat algorithm is much better than the existing approaches in terms of specificity, accuracy, and sensitivity as indicated in Table 1.

RESULTS AND DISCUSSION

The differences between the pre-operative and post-operative MRI segmented images were looked for, and the percentage of differences was found and shown. These show how much the MRI brain tumour changed from before surgery to after surgery in terms of pixels. The experiment was done with two different samples.

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Results of Sample 1

The pixel difference and the pre-operative and the post-operative MRI images for sample 1 as shown in figure 8.

Figure 8. Different Percentages of Pixel Variations in Tumor

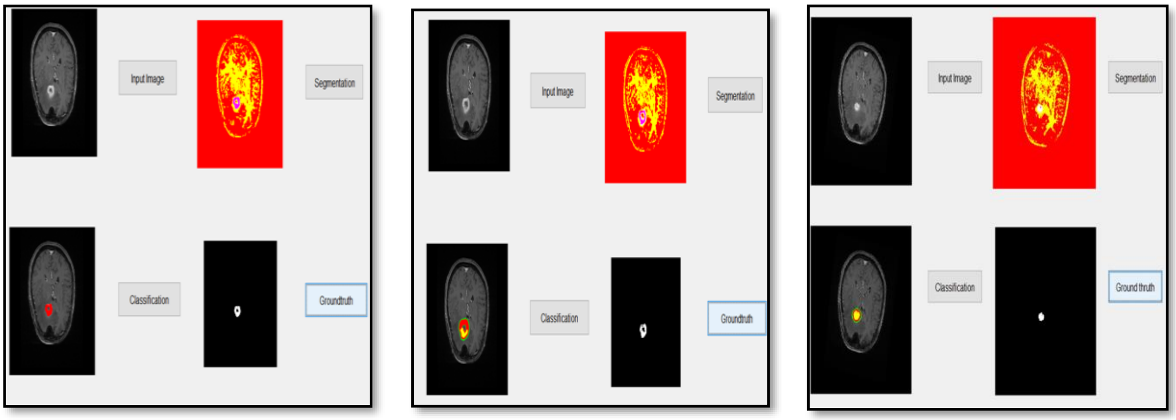

Figure 9. Conditions of Brain Tumor (a) Pre-operative Brain Tumor MRI (b) Identifying the Necrotic Cells (c) Post-operative Brain Tumor MRI

Figure 9 (a) & (b) shows the MRI of the brain tumour before surgery and how to find the dead cells. It also stands for the part about the cells getting bigger and the swelling. Fig. 9 (c) shows the results of MRI scans taken after surgery.

Results of Sample 2

The pixel difference and the pre-operative and the post-operative MRI images for sample 2 are shown below. The results of the second experiment are indicated in Figure 10 (a), (b) & (c). The tumour part is again divided into three groups: necrotic cells, cells that are getting bigger, and edoema. Figure 11 shows the results of the segmentation and classification of MRI images of brain tumours after surgery.

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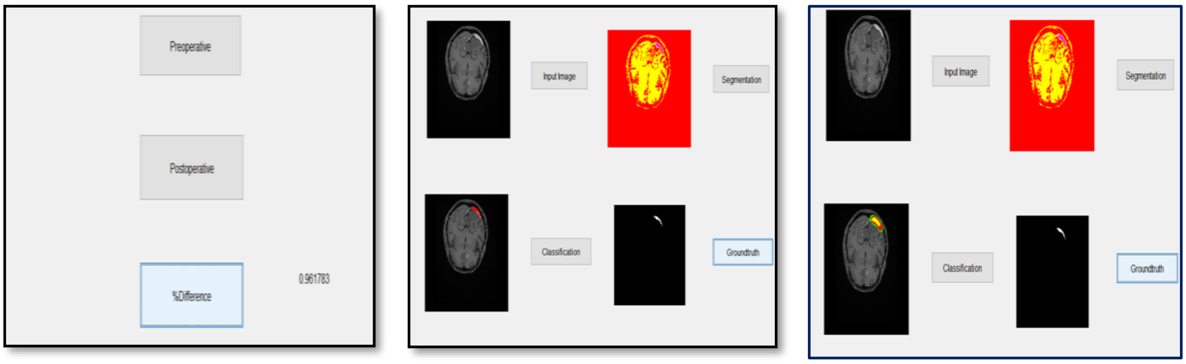

Figure 10. (a) Percentage of Pixel Difference in Tumor (b) Pre-operative Brain Tumor MRI (c) Identifying the Necrotic Cells

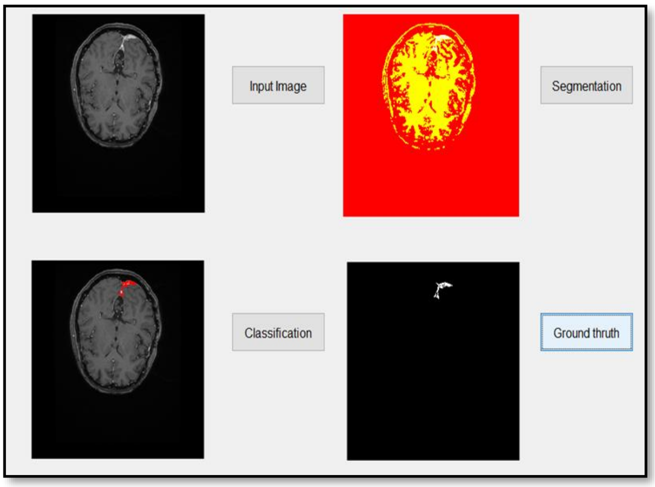

Figure11. Segmentation and Classification Results of Post-operative Brain Tumor in MRI

CONCLUSION

The proposed method solves the problem of necrotic and enhancing cells in brain tumours that overlap on MR images. This makes the segmentation process more accurate, specific, and sensitive. Also, this method compares the results of both the MRI done before surgery and the MRI done after surgery. This method predicts the change detection based on pixel mapping in segmented MRIs taken before and after surgery. The advantage of the proposed method is getting a good look at the edges of the tumour. Since there is no need to go through an iteration process, this method is not as hard to understand as the current method. This method makes it possible to automatically separate solid tumours in MR images of the brain based on their textures. It finds the shortest route, users don't have to do much and the amount of time needed to do the computation is the smallest.

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