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Brain Tumor Image Analysis Using FCM with Enhanced BFA Algorithm

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Abstract

In this particular piece of research, we will be integrating the clustering technique with the segmentation algorithm. The fuzzy c means algorithm was utilized for the clustering, while the bacterial foraging algorithm was employed for the segmentation. An algorithm for optimizing bacterial foraging that takes into account the dynamics of infections as shown in medical imaging. The objective function was optimized by the use of bacterial foraging. Cluster validation indexes were applied in order to get the numerical results and best solution discovered by BF-FCM. This was done so that the validation of the composite algorithm could be examined. The newly developed algorithm BF-FCM was able to segment the images of the brain tumor and locate the various components of the tumor. The findings of the trial indicate that the BF-FCM has superior performance.

Keywords: Bacterial Foraging Algorithm (BFA), Classification, Brain Tumor, Image Segmentation, Clustering.

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Introduction

The process of picture segmentation involves breaking an image into multiple segments and assigning labels to each pixel. Pixels with the same label share visual properties to a similar degree. The purpose of segmentation is to transform the representation of an image into something that is easier to evaluate and more relevant to the viewer. The process of picture segmentation produces a collection of individual segments that make up the whole image as a whole. If any two pixels in the segmented region share the same color, intensity, or other attributes, this indicates that the segmented images share some similarities. These characteristics include computed properties such as color and color intensity [1-9].

The segments that are adjacent to one another are distinct from one another in regard to the same quality or characteristics. The term "clustering approaches" refers to an unsupervised procedure in which a pattern categorization is present in groups. When looking at the photos, you'll notice that each cluster in the image has its own distinct significance. Different approaches to data analysis via clustering and unsupervised image segmentation include Nearest Neighbor Clustering, Fuzzy C-Means (FCM) clustering, and Artificial Neural Networks. Each of these approaches is described in more detail below. The bio- and socially-inspired methodologies are approaches that, in an effort to address the issues at hand, look to the manner in which nature addresses similar challenges for guidance. In socially inspired techniques, this can help the entire population identify a better answer in comparison to the initial and already established inadequate solution. The tumor segmentation is performed by qualified medical professionals using MRI data. Even if it requires more time, it is a very important activity. Because of the tumor tissue's high level of morphological variation and its striking similarities to normal tissue, it is a challenging undertaking to automate this procedure [10-20].

There are a variety of methods that may be used to segment brain images into tumors; the BF-FCM approach is the one that we are going to focus on here.

Literature Survey

The major goal of medical image analysis in general, and brain Magnetic Resonance Image (MRI) analysis in particular, is the extraction of clinical data, which would help in improving the diagnosis and treatment of disease. This can be said to be a general objective of medical image analysis. In addition to that, these techniques ought to have a quick rate of convergence, which is what will make it possible to use them in real-time applications. In the body of published research, one may find a number of different research papers that employ a wide variety of approaches to picture classification and segmentation. This section provides an extensive review of the various methods that can be utilized for the identification of abnormalities in brain pictures.

As a preprocessing step for brain MRI, Corso et. al. suggested using fuzzy connectedness, which is based on the intensity non uniformity correction [21]. The approach that was taken was a sequential one, and it included fuzzy connectedness, atlas registration, and bias field correction. The proposed system suffers most from the drawback of having a restricted range of possible intensity value variations.

Devkota et.al. developed a wavelet-based bilateral filtering system in order to cut down on the amount of noise that was present in MR images [22]. Undecimated Wavelet Transform is the noise coefficient that is utilized in the process of noise removal (UWT). Bilateral filtering of the approximated coefficients can improve the effectiveness of the noise removal process known as denoising. This particular denoising methodology has seen widespread application in the removal of Rician noise. In addition, the visibility as well as the diagnostic quality of the image that has been denoised are improved thanks to the utilization of this filtering technique. This technique has a larger capacity for reducing the amount of noise that is present in the image.

Fogel developed an automatic method for detecting tumors in brain MR images utilizing region growth [23]. In this piece of technical work, the segmentation of the brain tumor core is accomplished with the help of the traditional region growth algorithm. The process of seed selection is influenced by problems that arise from the use of automated seed generation. The fuzzy c means algorithm is utilized in order to carry out the process of automatically selecting seed points. This section provides an explanation of the Region expanding algorithm as well as the fuzzy c means algorithm, as well as the approach that was designed. [24] Greif et al. described a fully automated system for segmenting images of the brain using a thresholding method. This method is predicated on the assumption that contiguous pixels whose value (gray level, color, value, texture, etc.) is within a given range are members of the same class. As a result, it is possible to gain a better segmentation of images that have only two contrasting components.

[25] A thresholding and edge detection method was published by Ghazal et al. This method is one of the most significant concepts of brain image segmentation prior to feature extraction and image recognition system. This strategy assists in the extraction of the core shape of a picture, while at the same time overloading the image with unimportant minor details. In this piece of technical work, a range of geosatellite photos, medical images, and architectural images are reviewed using image segmentation (thresholding and edge detection) approaches. These methods are utilized to analyze the photographs. The error measure is utilized in order to fulfill the objective of providing a quantitative assessment of the reliability of the results.

[26] Hamamci et al. (2017) developed an AdaBoost SVM for picture segmentation of brain tumors. The detecting and classifying of images in this approach is accomplished through the use of three distinct processing processes. These processes include the elimination and classification of noise, the creation of textures, and segmentation based on multifractal characteristics. For segmentation, an AdaBoost SVM algorithm is utilized, which incorporates registered atlas information. On the other hand, a Fisher SVM technique is better appropriate for segmenting the complex tumors.

[27] Using Fully Convolutional Neural Networks (FCNN) and a hierarchical dice loss, Han X et al. developed a novel method for the segmentation of brain tumors. This method is based on the findings of previous research. In this study, the FCNN algorithm is used to analyze the brain image, and segmentation is carried out by modifying the network designs in order to reach higher levels of accuracy. A precision analysis, a recall analysis, a mean of intersection of union (mIoU) analysis, and a dice score coefficient analysis are all performed on the experimental data (DSC).

[28] Ibrahim et. al. developed a brand new texture-dependent feature extraction technique in order to extract pertinent and informative features from MR images of the brain that were damaged by the tumor. The success of the recommended technique is dependent on being able to obtain a representation of the texture using nine distinct types of texture objects. After that, a high pass and a low pass spiral filter are utilized to generate an intermediate texture index matrix, which is then filled with texture objects. The two index matrix that was produced as a consequence is what is used for the production of the texture co-occurrence matrix (TOM).

Image Processing

A technique known as image processing is a method that can be used to improve the overall quality of an image. A single approach can encompass a large number of different image processing procedures. These include image representation, image preprocessing, image enhancement, image restoration, image analysis, image reconstruction, and image data compression. Other terms include image enhancement, image analysis, and image reconstruction. A great number of pictures have a lot of extraneous or unneeded components. Following the completion of the preprocessing step, the next step is the enhancement of the pixel intensity as well as the image quality. The elimination of noise and the reduction of distortions in the input images are two of the primary goals of image preprocessing, both of which contribute to an improvement in image quality. Therefore, preparation procedures are necessary for photographs because an image often contains a number of distracting elements. The method of picture filtering is one that is utilized by the vast majority of image processing systems. In this work, we discuss the numerous image filtering methods and filtering algorithms that are utilized for the purpose of image filtering or smoothing. Image smoothing is one of the most significant aspects of image processing, and it is utilized extensively in the application of images. In this article, we will discuss which method is the most effective at smoothing and filtering photos. Image smoothing is a technique used to minimize noise and improve the image's overall visual quality. The preprocessing techniques of median filtering, Gaussian high filtering, and Gaussian low filtering are all described by the system that has been proposed. The median filter is a method of nonlinear digital filtering that can be utilized to clean data of unwanted noise. Sharpening often involves the application of Gaussian high pass filters. Matlab 2018a was used to do simulations on the various filtering approaches. The performance of this filtering approach, known as low pass filtering, is superior to that of other filtering methods, and it requires significantly less time to process than those methods. Following the use of the preprocessing, the image quality is improved.

Segmentation

Image Segmentation is a field that has existed for a significant amount of time and continues to offer prospects for research work. In image processing and analysis, picture segmentation is responsible for the majority of the judging and analyzing functions. The technique of segmenting a picture involves dividing the image into relevant sections that are either identical to one another or similar to one another but differ from one another in some features. The outcomes of picture segmentation have an impact on image analysis as well as the higher level activities that follow on from it. Image analysis encompasses both the description and representation of objects, as well as the measurement of feature

characteristics. After classifying the object, move on to the next higher order job. Image segmentation relies heavily on characterization, the visualization of a region of interest within any given image, and demarcation. These methods of picture segmentation require comparative analysis in order to go further in their development and undergo adjustments in order to achieve continuous and consistent advancement. In light of this, the authors of this paper describe a picture segmentation method that makes heavy use of bacteria foraging and Fuzzy C Means approaches. This method necessitates a significant amount of research. Within the BF-FCM algorithm, tumor sections are partitioned with the assistance of bacterial foraging strategies. Utilize this strategy in order to account for varying magnet strengths or other circumstances. A knowledgeable person will label the pixels.

Technique for Foraging for Bacteria

An ideal algorithm that was inspired by the foraging activity of infections seen in medical pictures of the brain is called the Bacterial.

Foraging Optimization Algorithm

The BFO algorithm is broken down into four distinct phases, which are referred to as Chemotaxis, Swarming, Reproduction, and Elimination-Dispersal respectively. It repeats these four steps in a cyclical manner in order to find a global optimal solution if one is available.

Chemotaxis

E. coli has a set of flagella that allow it to move. With the help of these flagella, the bacteria may switch between rolling and running in response to the nutritional gradient, which is a phenomena known as chemotaxis that can be used in optimization procedures. The tumbling step of the bacteria is considered to be exploitative in nature because it searches within a small region in the search space. On the other hand, the alternate swimming step is considered to be exploratory because the bacteria "swims" with its flagella through significant distances in the nutrient medium. The inclination of bacteria to travel towards a high-nutrient gradient (lower values of J () for a minimization technique) or away from a noxious gradient (high values of J ()) is what guides the movement of chemotactic bacteria. Let's say we want to symbolize the tossing operation with a unit-length random direction of movement denoted by the symbol (j), which will remain constant during the entire method. Let cr represent the distance traveled by the ith bacterium after each of the jth, kth, and lth steps in the chemotactic, reproductive, and elimination dispersion processes. Let's call the size of the step that was taken C I After each chemotactic phase, the bacterium will move to a new position, and this new position can be expressed mathematically as follows:

$$\theta i(j, k, l) = \theta\, i(j, k, l) + C(i)\, \phi\, (j) \quad (1)$$

- **Swarming**

In the presence of nutritional medium, certain types of bacteria, such as E. coli, display an intricate pattern that is known as swarms. During this particular phase, it is possible to picture bacteria either releasing cell-attractants to attract other cells or cell-repellents to drive them away. Both of these possibilities are possible. One way to express this cycle of attraction and repulsion is as follows:

$$J_{cc}(\theta, P(j,k,l)) = \sum_{i=1}^{s} j_{cc}^{i}(\theta, \theta^{i}(j,k,l))$$

$$= \sum_{i=1}^{s}[-d_{attract} \exp(-w_{attract} \sum_{m=1}^{p}(\theta_m - \theta_m^i)\text{^}2)] + \sum_{i=1}^{s}[-h_{repellent} \exp(-w_{repellent} \sum_{m=1}^{p}(\theta_m - \theta_m^i)\text{^}2)] \quad (2)$$

Where J cc(,P(j,k,l)) stands for the additional cost function, S stands for the total number of bacteria, and p represents the size of the search space. The suitable coefficients are referred to as attract d, attract w, and repellent hand repellent ware, and their values need to be chosen appropriately. In order to avoid an overpopulation of bacteria on a local optimal solution, the computational process incorporates both processes of repulsion and attraction. The additional cost function has not been utilized in this paper in order to keep the computational techniques as simple as possible.

- **Reproduction**

During this phase, a percentage of the initial bacterial population S will die due to the bad health they experience as a result of being in this phase. The bacteria that are able to survive and remain healthy are the ones that have lower values of objective function. These bacteria are the ones that are able to divide themselves in half in order to continue living and producing new generations of bacteria. As a direct consequence of this, the overall bacterial population does not change as a direct result of the optimization process that took place.

- **Elimination and Dispersal**

This stage comes immediately after the reproductive phase that came before it. In order to simulate occurrences that actually take place in the world, including the spread of germs by wind, new bacteria are arbitrarily scattered around the search space. At the same time, a portion of the older bacterial population is destroyed so that the global optimal position can be attained as rapidly as possible. This is done in order to ensure that the best position is obtained. On the other hand, the overall population of S is maintained at a level that is constant at all times. You will find a detailed BFO algorithm in the section of this guide that is headed "Algorithm."

BFO Algorithm

BEGIN
Initialize the parameters S, N_{ed}, N_{re}, N_c, C(i), i=1,2,.....s,

REPEAT:
FOR l=1 to N_{ed} [elimination dispersal loop]
FOR k=1 to N_{re} [reproduction loop]
FOR j=1 to N_c [chemotactic loop]
FOR i=1 to S

Compute J(i,j,k,l) [fitness function]

Then let J(i,j,k,l)=J(i,j,k,l)+ Jcc (θ^j(j,k,l),P(j,k,l))
[simulate swarming cell to cell attractant repellent profile added. Jcc is cell to cell signaling as random number [-1,1]]
J_{last}=J(i,j,k,l) [save since better cost found via run]
Tumble: Generate a random vector Δ(i)$\in R^p$ [with each element on random number[-1,1]]

Move :θ^i(j+1,k,l)=θ^i(j,k,l)+C(i) $\frac{\Delta(i)}{\sqrt{\Delta^T\Delta(i)}}$ [result in step size in tumble direction]

Compute (J(i,j+1,k,l)=J(i,j+1,k,l)+ J_{CC}(θ^i(j+1,k,l),P(j+1,k,l))

m=0 [swim length counter]

WHILE m < N_s

m=m+1

IF J(i,j+1,k,l) <J_{last}

J_{last}=J(i,j+1,k,l)

Move
θ^i (j+1,k,l) = θ^i (j+1,k,l)+ C(i) $\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$

Use this θ^i (j+1,k,l) to compute new J(i,j+1,k,l) with Cell to cell attraction effect
ELSE
m=N_S
ENDIF
ENDWHILE
ENDFOR
FORi=1 to S

Compute$J^i{}_{health}$ =$\sum_{j=1}^{N+1} J(i,j,k,l)$ [how much nutrient got over life time and how it avoid noxious substance]

ENDFOR

Sort bacteria in order of ascending cost values of J_{health}
Destroy S_r bacteria with the highest values of J_{health}
Split each of the S_r bacteria with the lowest values of J_{health} into two and
each such pairs resides in the same original location of the parent

ENDFOR

FOR i=1 to S

Eliminate and disperse each bacterium with probabilityp_{ed}, keeping Population of bacteria constant

ENDFOR

ENDFOR

UNTIL termination criterion is satisfied

END

Clustering

A mapping of the archive photos into several clusters is performed throughout the clustering process. The full picture-set collection, in addition to the set of classes, provides the same information that can be found in the image archive. The demonstrate its ability to consistently that we are utilizing here is called Fuzzy C Means.

Fuzzy C Means

The FCM algorithm is implemented through the process of data compression.

It offers efficiency in the segmentation process. Clustering tumor components from various types of tumors is accomplished with the help of the FCM algorithm. Extracting properties such as correlation, contrast, and entropy from the photos is what this method is all about. After that, these are input into the algorithm that does the clustering. Analyses of the segmented outputs are performed with regard to the effectiveness of the segmentation and the pace of convergence. Patterns are categorized by placing samples that are comparable together in the same category. More of the information included in the original image is kept with fuzzy clustering algorithms. The fuzzy C-means technique allows for a variety of classes to be represented by individual pixels. The fact that the FCM approach takes a lot of time is the primary issue.

$$J_{FCM}=\sum_{K=1}^{n}\sum_{i=1}^{c}(\,U_{ik})\;d^2(x_{k,}v_i)\;(3)$$

J_{FCM} is the objective function, X=$\{x_1, x_2, x_n\}\subseteq R^p$ the data set in the p-dimensional vector space, U_{ik} is the degree of membership of x, v_i is the prototype of the centre of cluster of i, q is a weighting exponent on each fuzzy membership, $d^2(x_{k,}v_i)$ is a distance measure between object x_k and cluster centre v_i.

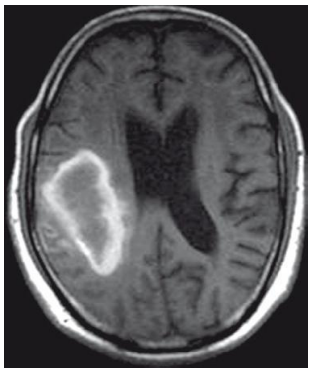


Fig. 1: Input Image

The original image of the brain can be seen in the figure to the right, which also shows the image being processed by the BF-FCM algorithm, which locates the precise tumor portions in the original image of the brain. The segmented

section of the tumor is displayed in the next image. In this approach, the Bacterial Foraging algorithm is utilized first, and only then does the clustering algorithm come into play. This is the most effective method for dividing the tumor into its component pieces.



Fig. 2: BF-FCM Output Image

Feature Extraction

In the field of image processing, the function of the feature is one that is of critical significance. Feature extraction is the process of describing the pertinent shape information that is contained in a pattern in order to facilitate a formal technique that makes the work of classifying the pattern easier. In the fields of pattern recognition and image processing, dimensionality reduction takes the form of feature extraction in its more specific form. The primary objective of extracting features from raw data is to get the information that is most pertinent to the problem at hand and to represent that information in a space with a lower dimensionality. The methods of feature extraction are utilized so that the desired features, which will assist in the categorization and recognition of images, may be obtained. In a wide variety of image processing applications, feature extraction techniques are of great assistance. Because features determine how an image behaves, they also explain where it falls in terms of the amount of storage it requires, how efficiently it can be classified, and how much time it takes. In this research, we employ approaches for feature extraction that make use of a co-occurrence matrix, and we use strategies for feature selection that make use of an optimization algorithm.

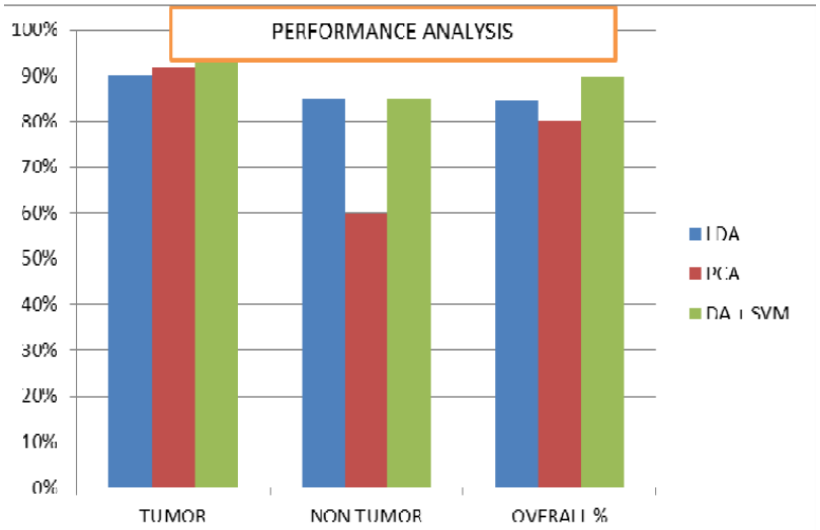
Classification

The picture categorization plays a significant role in a variety of applications, including environmental and socioeconomic analyses. Scientists have been working hard to pave the way for the development of more complex classification systems in order to improve the accuracy of classification. However, classifying remotely sensed data into a thematic map is still extremely difficult due to a number of elements, including the complexity of the environment, image sensing and processing, and classification methodologies. There are a wide variety of approaches that can be taken when classifying data. The two methods that are most frequently utilized for the processes of data categorization and dimensionality reduction are known as principal component analysis (PCA) and linear discriminant analysis (LDA). The situation in which the frequencies of items within a class are not equal can be simply handled by linear discriminant analysis, and their performance can be evaluated using test data that was created at random.

Evaluation of the Results

In the past, MRI picture of a brain tumor classification efforts have been made using the selection and extraction of various features, but with only limited success. Image collection, normalization, intensity, shape, and texture feature extraction, feature selection, and classification are the steps that are included in the methodology that is proposed in this study for the work that has been described above. In this approach, features such as shape, intensity, and texture are retrieved and put to use in the categorization process. LDA is used to choose the most important characteristics. PCA dimension reduction techniques are used to evaluate the results of this study. The number of features selected or extracted by PCA is 98.87%, while the accuracy of classification achieved by SVM is 98.87%. In this training

approach, the system is educated using data that is both continuous and not continuous. As a result, we bring the mistake rate down while simultaneously improving the classification accuracy. Therefore, the proposed strategy has superior results.



Conclusion

The FCM algorithm is a method that is both reliable and effective. The optimization-based methods of picture segmentation that are employed now are extremely widespread. The majority of them spend their attention on looking for the FCM in the right center of the cluster. Developed an FCM that was based on the algorithm used by bacteria for foraging. The proposed method was capable of effectively segmenting brain images and achieved better results than the other algorithm when it was used to the FCM that was tuned by particle swarm optimization to perform the segmentation of images. The approach of bacterial foraging is utilized to segment the brain images, and with the assistance of the FCM algorithm, the tumor sections are identified in a more effective manner.

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