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Research paper

Fuzzy Deformable Based Fusion Approach for Tumor Segmentation and Classification in Brain MRI Images

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Abstract

In recent years, the automatic identification and classification of tumor regions have gained more interest due to accuracy and reduced time complexity. One of the important strategies in tumor identification is segmenting the image as tumor and nontumor region, and this helps the researchers more significantly, as the MRI image comes in different modalities. This work introduces novel optimization based strategy for segmenting and classifying the image. Initially, the MRI images in the database are subjected to pre-processing and given to the segmentation process. For segmentation, this work utilizes the deformable model, and Fuzzy C Means (FCM) algorithm and the resultant segmented images are hybridized through proposed Dolphin based Sine Cosine Algorithm, preferred to be Dolphin-SCA. After segmentation, the tumor and non tumor-related features are extracted using the power LBP operator. The extracted features are subjected to Fuzzy Naive Bayes classifier for the classification, and finally, the classifier finds the suitable tumor class labels. Here, the entire experimentation is done by taking the MRI images from the BRATS database, and evaluated based on sensitivity, specificity, accuracy and ROC metrics. The simulation results reveal the dominance of proposed scheme over other comparative models, and the proposed scheme achieved 95.249% accuracy.

Keywords: MRI image, Tumor region, segmentation, classification, BRATS database.

1. Introduction

Automating the brain tumor classification is an emerging technology developed in recent decade and it helps in medical diagnosis. For the classification of brain tumor regions, the Magnetic Resonance Imaging (MRI) is commonly used. MRI can be considered as one of the most successful diagnostic tools for capturing the soft-tissues and visualizing the various organs in body [9]. As the MRI captures the organs in three dimensions, it helps much in analyzing effects occurring in inner organs. The MRI generates the images based on the principle of Nuclear Magnetic Resonance (NMR). Further MRI helps in capturing the heart, lungs, pelvis, abdomen and soft tissues in brain [10]. Image output made from MRI has different modalities, and hence, needs different processes in order to detect the cancer/ tumor region in the brain image. MRI is mostly applicable in diagnosing the tumor region in brain section, as it provide more visualized appearance to brain section. For adopting MRI image in tumor classification process, few of the processes, such as pre-processing, segmentation and feature extraction need to be carried out before the classification task. Image segmentation gets prime importance in brain tumor classification, as the MRI has different modality. Segmentation of MRI image makes the classification process to be more efficient, as the segmentation carries out the tasks, such as visualization of brain's internal anatomical structures, analysing changes inside a brain, extracting pathological regions, aid surgical planning, dose estimation and image-guided brain incision. Most of the image processing schemes prefer to choose the segmentation as the primary task.

In the last few decades, numerous segmentation techniques with varying degree of accuracy and level of complexity have been developed [2]. Segmentation of MRI images is a primary step in most applications of medical image processing [9]. Segmentation is a procedure to separate similar portions of images showing resemblance in different features, like shape, size, color, etc [22]. Segmentation of brain images lead to three segments preferably, White Matter (WM), Gray Matter (GM) and Cerebro-Spinal Fluid (CSF) [11] [9]. Application of the segmentation algorithm in the image results in group of segments. In some of the specified regions, it is notable to consider the factors, such as color, intensity, or texture for the segmentation [3]. As the medical field is more sensitive to results, the classification algorithms specially designed for diagnosis should be more accurate and fully automatic. In fields, such as surgical and treatment planning, compensating the accuracy is strictly not acceptable, as the results may alter the treatment provided to the patient. In brain image segmentation and classification, one of the commonly used techniques is the thresholding and edge detection [7]. Manual interpretation of classification results is mostly inaccurate along with high error rate. Improving precision in manual classification of results leads to high time consumption [23].

1. Classification of tumor from MRI imager is quite a tedious task as the image has different modalities. Literature has identified several algorithms and techniques for brain tumor classification. One of such algorithm is the region growing algo-

rithm, which provides high robustness during the identification of well-defined regions. But the algorithm fails to perform well in other condition, and hence, used along with several clustering algorithms for achieving improved classification accuracy. For the relatively simple data, most researches prefer to use the Region growing algorithms, and for larger database, clustering algorithms are preferred. One of commonly used clustering scheme is the Fuzzy C-Means (FCM) algorithm [18] [19], and it is preferred for the segmentation purpose [7]. Clustering algorithms defined in previous works mostly prefer the unsupervised learning, where the information regarding the total number of clusters to be segmented is already fed to the process. Clustering is done by gathering the similar and dissimilar pixels to their individual cluster group [20]. Clustering algorithms defined in the literature owing to image processing fall into two category, they are partitioning and grouping pixels [21]. Analysis from above stated issues reveals that using only one algorithm for the segmentation and the classification may lead to reduced results. Using combination of different set of algorithms may improve the overall tumor classification results [23]. Owing to the above mentioned challenges and issues, this paper tries to develop combination of different algorithms for both segmentation ad classifications of MRI brain images.

2. The primary intention of this research is to design and develop a technique for the segmentation and classification of brain tumor using MR image. The proposed technique of segmenting and classifying the brain tumor involves four stages, such as Pre-processing, Segmentation, Feature extraction, and Classification. The input MRI brain image is pre-processed using a Non-local Mean filter to filter the artifacts and to obtain the interesting regions of the image. The pre-processed image is segmented using newly developed fusion-based segmentation approach, where the segmentation is carried out using two techniques, such as deformable model [15], and Fuzzy C Means [7]. The resulting outcomes are fused using the proposed Dolphin-SCA, which is newly devised by incorporating Dolphin Echolocation (DE) Algorithm [13], and Sine Cosine Algorithm (SCA) [12]. Then, the segmented image is subjected to the feature extraction process, and the important features are extracted using Power LBP operator [14]. Finally, the classification is performed using the Fuzzy Naive Bayes classifier [17], to classify the image into normal or abnormal class.
3. The major contributions of this paper are
   i) Design and development of fuzzy deformable fusion scheme for segmenting the MRI images. The proposed fuzzy deformable fusion scheme uses the deformable scheme and FCM for segmentation, and the segmented results are fused together with constants optimally selected with the proposed dolphin-SCA.
   ii) Devising the optimization algorithm, namely dolphin-SCA by combining the DE and SCA algorithms.
4. The rest of this paper structure is arranged as follows: Section 2 surveys eight literary works dealing with the medical image segmentation and classification techniques. Section 3 describes the proposed fuzzy deformable fusion scheme for segmentation and FNB based classification scheme. Section 4 briefly describes the simulation results achieved through the proposed brain tumor segmentation and classification scheme, and it further discusses the comparative analysis with other existing models. Finally, the conclusion of this research is presented in section 5.

2. Motivation

2.1 Literature Survey

This section presents a brief explanation of eight literary works contributing towards the image classification and segmentation schemes, specifically towards the tumor segmentation and classification.

presented the learning-based deformable model for segmenting the brain ROI regions. The model provided improved robustness via the prior shape model. Further, it used the joint regression and classification model for tumor classification. The model achieved high prediction accuracy along with reduced implementation cost. This scheme cannot simultaneously segment the ROI images. Shoaib Amin Banday, and Ajaz Hussain Mir [2] proposed the semi-automatic technique by adopting a deformable model for tumor classification. For training the classifier, this scheme extracts the statistical texture features. From, the extracted features, a feature map are generated. Along with the deformable shape model, active contour was used for the segmentation, and hence, the segmentation process is more viable, and robust. The model failed to outline the abnormalities in each slice, and further, the computation time is high for the segmentation. **[1]**

proposed the segmentation scheme for the tumor classification, and it incorporates the Wavelet Multi-Resolution (WM), morphological pyramid fusion (M), and Fuzzy C-Means (FCM) clustering segmentation system (WMMFCM). The scheme achieved high sharpness in the segmentation process, as it includes the morphological pyramid in the segmentation. The model achieved satisfied performance even though the noise effects are present in the MRI image. Incorporating some noise resistive segmentation algorithms and different modalities may improve the classification performance. **[3]**

proposed the Dynamic Classifier Selection Markov Random Field (DCSMRF) algorithm owing to the challenges faced during the brain tumor classification. Here, several features, such as spatial, contextual and textural features used for the classification are extracted from the image and they serve as the training information for the classifier. The classification task is carried out with use of the ensemble scheme. The computational time used by the ensemble classifier is high as the complex feature space is enabled for the training purpose. **[4]**

presented the Multi-objective semi-supervised clustering technique for the brain tumor classification. The technique allowed automatic detection of the shape clusters. The technique used the multiple objective functions for the optimization and hence, the training time is significantly high. **[5]**

proposed the Convolutional Neural Networks (CNNs) based classifier for the tumor classification. Using different protocols for the classification improves the accuracy. The model needs to be retrained when different set of data inputs is given for processing. **[6]**

proposed the Improved Kernel Possibilistic C-Means (IKPCM) for segmenting the brain image. The algorithm tackled the presence of noise in the image by using the kernel function. The algorithm faces difficulty while dealing with the initial level set. Jeetashree Aparajeeta et al. [8] proposed the Bias Corrected Possibilistic Fuzzy C-Means (BCPFCM) algorithm for the classification and segmentation of brain tumor image. The model achieved small misclassification results through the clustering process. But, the scheme selected the parameters for segmentation through trial and error and hence, has increased complexity. **[7**]

2.2 Challenges

Challenges in developing the classification and segmentation algorithms for brain tumor identification are stated below:

- The deformable model used for the segmentation uses the some smoothness constraints along with the shape model for achieving improved segmentation results. While using the deformable model along with learning scheme, smoothing operation done in the shape model may be considered as the major limitation [1].
- The semi-automatic technique [2] uses the deformable model for the segmentation purpose. Here, the deformable models assume circular vessel cross sections for the segmentation

purpose. But, this assumption holds stable for the healthy patients, not for those affected by conditions, such as stenosis or an aneurysm. Also, the deformable model is computationally expensive.

- The WMMFCM system [3] achieved improved segmentation results, but the presence of noise in the image makes the segmentation task to be difficult. Even though the MRI image provides different modalities for brain tumor classification, it has failed to remove the noise present in the image completely.
- The multi-objective semi-supervised clustering technique defined in [5] requires some of the labeled data for training. Generation of supervised information for training may be difficult in certain cases, as this requires the human annotators. Using the human annotators may be time-consuming and sensitive to cost parameter.
- Incorporation of fuzzy logic in brain tumor classification yields improved results, but faces several challenges. In [8], BCPFCM algorithm faces the bottleneck issues as the parameters are selected based on trial and error method. Parameter estimation through the prototypes is not possible.
- Some of the brain tumor classification algorithms use the unsupervised training for the classification purpose. Unsupervised training requires more time. Nevertheless, the training process may fail to recognize the abnormal tissue in the image. Thus, to make the unsupervised training to be efficient, overtraining of samples should be reduced. Further providing some of the segmentation information may provide improved results.

3. Proposed Fuzzy Deformable Based Fusion Approach for Brain Tumor Segmentation and FNB Based Classification Scheme

This section explicitly describes the proposed brain tumor segmentation system. Here, segmentation is done through the proposed fuzzy deformable fusion system, while the classification is done through the FNB classifier. The entire architecture of the proposed brain tumor segmentation system is depicted in figure 1.

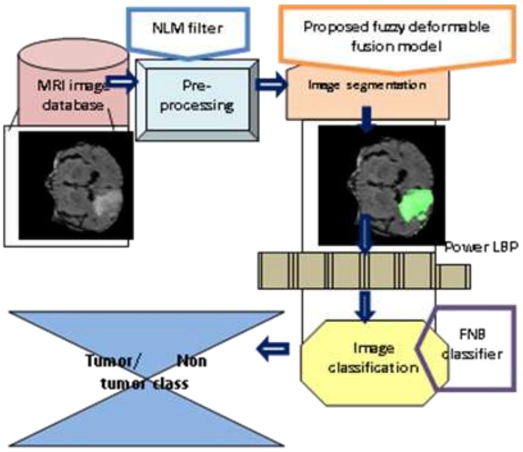

Figure 1:. Block diagram of the proposed approach of segmentation and classification of tumor in MRI brain image

As shown in above figure, the entire process has major tasks: they are 1) pre-processing, 2) Segmentation, 3) Feature extraction, and 4) Classification. The MRI image database contains MRI images of different modalities. For making the images suitable for classification, the pre-processing done through NLM filter, extracts the suitable region of interest. After that, the ROI is given to segmentation process, and here a novel method namely fuzzy deformable fusion model is used for segmenting the MRI image. The fuzzy deformable fusion model uses both the deformable scheme and FCM algorithm for the segmentation, and the results extracted from each model are integrated using the proposed dolphin-SCA algorithm. The proposed dolphin-SCA algorithm is nature-inspired algorithm owing to the characteristics of DE and SCA. Then, the power LBP model extracts the necessary features from the segmented regions, and develops the feature vector for training the classifier. The FNB classifier is adopted in this work for the classification purpose, and it identifies the tumor class label for each image.

3.1 Pre-Processing: Nonlocal Means Filtering

The initial stage in brain tumor classification is the pre-processing, where the region of interest in MRI image is identified. For the pre-processing, this research makes use of NLM filter for identifying the ROI from the MRI image. Consider the MRI image database M, having N brain images, and it is represented as,

$$M = \{B_i \ ; \quad 1 \le i \le N\} \tag{1}$$

where, B_i indicates the i^{th} brain MRI image in the database. The image is subjected to pre-processing using the NLM filter, and the required ROI is extracted from the image.

3.2 Segmentation: Fuzzy Deformable Based Fusion Approach

Here, a novel segmentation algorithm, namely fuzzy deformable fusion model is developed for segmenting the MRI images. The proposed segmentation algorithm possess the characteristics of deformable model [15], and Fuzzy C Means [7] algorithms. The entire architecture model of the proposed fuzzy deformable fusion model is given in figure 2.

Figure 2 states the block diagram of the proposed fuzzy deformable fusion scheme. As stated in the figure, the pre-processed MRI image is given to both the deformable model and the FCM model. The resulted images from both the algorithms are multiplied with the optimal segmentation constants generated by the proposed dolphin-SCA algorithm. The proposed dolphin-SCA has the integrated characteristics of DEA and SCA. The resulted image from the proposed fuzzy deformable fusion algorithm is Q segmented regions. The mathematical representation of the proposed Fuzzy deformable algorithm is given as follows.

Consider the brain image B_i is given to both the deformable model and the FCM algorithm. The resultant image from the deformable model is expressed as Q_{deform}, whereas the resultant image from FCM is represented as Q_{FCM}. Both the resultant images undergo changes as the segmentation constants from the proposed dolphin-SCA changes the output of both the images. The final segmented output of the proposed fuzzy deformable fusion approach for brain image B_i is given as,

$$Q = \alpha . Q_{deform} + \beta . Q_{FCM} \tag{2}$$

where, Q_{deform} and Q_{FCM} refer to the segmented output from deformable model and the FCM model, respectively. Also, the constant terms α and β refer to the segmentation constants selected optimally by the proposed dolphin-SCA algorithm. The proposed fuzzy deformable fusion model specifies the segmented pixels into individual groups. The image B_i after the segmentation process has k segments, and the segmented results are indicated as $Q = \{Q_1, Q_2, \ldots Q_k\}$

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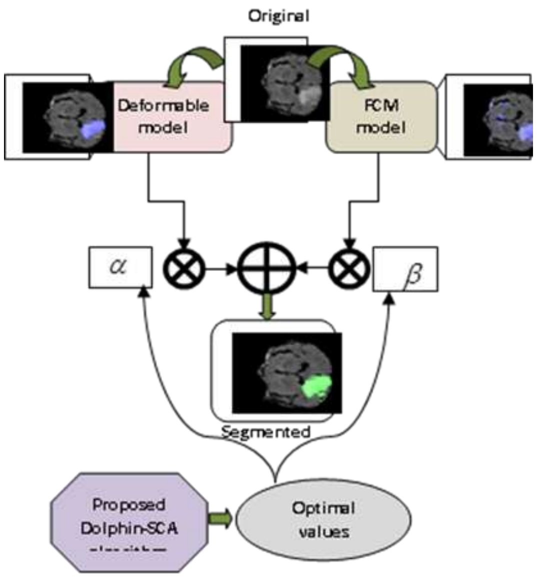

Figure 2:. Segmentation of MRI images with the proposed Dolphin-SCA algorithm

The mathematical representation of the proposed Fuzzy deformable algorithm is given as follows:

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3.2.1 Algorithmic Procedure of Deformable Scheme

Here, the algorithmic steps to segment the brain image B_i with the deformable scheme are briefed. Consider the brain image B_i subjected for the segmentation, and for the segmentation, some of the algorithmic parameters, such as patch size, dictionary size, and normalization flag are initialized for the curve C. After initializing the algorithmic parameters, the patch vectors are extracted from the image B_i. From the initialized patch vectors, the dictionary is built with the k-means clustering. Then, it is subjected for normalization by assigning each patch to the dictionary length. The dictionary length is calculated for performing the clustering process and the segmented images are represented as Q_{deform}

3.2.2 Algorithmic Procedure of FCM Algorithm

The FCM algorithm develops the fuzzy matrix, by calculating the Euclidean distance measure for the clustering process. The FCM matrix derived for the clustering process is initiated as,

$$D = \sum_{v=1}^{a} \sum_{l=1}^{b} J_{vl}^{r} d_{vl}; \quad 1 \le r \le \infty \qquad (3)$$

where, r indicates the fuzziness variable. The Euclidean distance measure d_{vl} is calculated as,

$$d_{kl} = \left\| p_k - K_l \right\| \qquad (4)$$

From this measure, the cluster centre is calculated as,

$$K_l = \frac{\sum_{v=1}^{a} J_{vl}^{r} p_x}{\sum_{v=1}^{a} J_{vl}^{r}} \qquad (5)$$

The above expression refers to the cluster centroid for the clustering. After clustering is done based on K_l, the fuzzy matrix changes as follows,

$$J_{jl} = \frac{1}{\sum_{f=1}^{j} \left(\frac{d_{vl}}{d_{fl}} \right)^{\frac{2}{r-1}}} \qquad (6)$$

The iteration continues until the FCM finds the suitable cluster centroid, and the segmented images through the FCM is expressed as Q_{FCM}.

3.2.3 Finding the Segmentation Constants Using the Proposed Dolphin-SCA Algorithm

Here, the segmentation constants α and β are optimally found using the proposed Dolphin-SCA algorithm. Dolphin-SCA is newly developed by integrating the properties of DE algorithm in SCA algorithm. The SCA algorithm finds the optimal results based on the properties of sine and cosine mathematical functions, whereas the DE algorithm is inspired by the behaviour of the dolphin. SCA algorithm employs the exploration and the exploitation phases in order to avoid the local convergence problem. The SCA provides better effectiveness in generating the optimal value in unknown search space. The DE algorithm locates the optimal solution through the echolocation behaviour of dolphins. The results of the optimization algorithms greatly depend on the tuning parameter, and hence, the integration of both the algorithms improves the overall accuracy of the optimization process. Here, the update of the SCA is modified with the update of the DE algorithm. The entire process in identifying the segmentation constants is given as follows:

i) Solution encoding

The proposed Dolphin-SCA intends to identify the segmentation constants α and β for integrating the results of FCM and deformable model. The segments resulted from both models may have some variation, and for avoiding this, both the resultant images are integrated with α and β. The Thus, the solution vector has the size of 1×2. The constants have the values ranging between 0 and 1. At the starting stage of the initialization, the solution is given random values, and at the end, optimal value is identified.

ii) Fitness evaluation

Here, the fitness is derived for finding the optimal value of the segmentation constants. The fitness depends on the centre of segmented image and the pixel surrounding the centre pixel of the segmented image. Consider the s^{th} segment in the image with Z number of pixels, and each pixel is represented as P_j. Now, the centre for the segmented image is calculated as,

$$X^{s}_{centre} = \frac{1}{Z}\sum_{j=1}^{Z} P_j \qquad \in Q_s \tag{7}$$

where, X^{s}_{centre} indicates the centre of image segment Q_s and P_j refers to the j^{th} pixel belonging to the s^{th} segment. Now, the expression for the fitness function for deriving the segmentation constants is expressed as,

$$F_{min} = \sum_{s=1}^{k}\sum_{\substack{j=1\\ j\in s}}^{Y}\left(X^{s}_{centre} - P_j\right) \tag{8}$$

where, Y refers to the size of the brain image B_i.

iii) Algorithmic steps of Dolphin-SCA algorithm

In the proposed Dolphin-SCA algorithm, the update specified by SCA gets modified with the DE algorithm. The algorithmic steps for proposed Dolphin-SCA are given as follows:

Initialization: The initial step in the proposed Dolphin-SCA algorithm is randomly initializing the solution space with the population size as 2. The proposed Dolphin-SCA is specifically designed to find the optimal value for the segmentation constants. The solution space initialized in the dolphin-SCA is expressed as follows,

$$S = \{S_1, S_2, \ldots, S_c, \ldots, S_g\} \tag{9}$$

where, S_c indicates the c^{th} solution, each of dimension 1×2, and g is the total number of solutions.

Fitness evaluation: After randomly initializing the population, the next step is to evaluate the fitness of the solution space. In this work, the fitness is derived as the minimization function to obtain better segmentation results. Here, the fitness of the solution is evaluated and the solution providing the minimal value is retained as the best solution. The fitness function for the proposed Dolphin-SCA algorithm is expressed in equation (8).

Solution update with proposed Dolphin-SCA algorithm: Generally, the SCA algorithm provides two solution update, each for the sine and cosine respectively. The proposed Dolphin-SCA algorithm modifies both the equations based on the solution update provided by DE algorithm. The solution update for the sine and cosine functions as specified by existing SCA algorithm is expressed as follows,

$$S(t+1) = S(t) + h_1 \sin(h_2)\left|h_3 P(t) - S(t)\right|; \quad h_4 \le 0.5 \tag{10}$$

$$S(t+1) = S(t) + h_1 \cos(h_2)\left|h_3 P(t) - S(t)\right| \quad h_4 > 0.5 \tag{11}$$

where, $P(t)$ refers to the solution with minimal fitness up to iteration t. The SCA algorithm offers four constants h_1, h_2, h_3 and h_4 for refining the search space and each of its value ranges between 0 and 1. Here, it is assumed that the best solution is better than the current solution i.e) $P(t) > S(t)$. Now, the above mentioned equation is modified as,

$$S(t+1) = S(t) + h_1 \sin(h_2)\left(h_3 P(t) - S(t)\right) \tag{12}$$

Rearranging the above equation,

$$S(t+1) = S(t)\left[1 - h_1 \sin(h_2)\right] + h_1 \sin(h_2) h_3 P(t) \tag{13}$$

The next major step in designing the Dolphin-SCA algorithm is considering the update equation of DE, and it is expressed as,

$$S(t+1) = S(t) + v(t) + \delta_1\left(R - S(t)\right) + \delta_2\left(G - S(t)\right) \tag{14}$$

Further, rearranging the solution in terms of $S(t)$, the following equation can be obtained,

$$S(t) = \frac{1}{1-\delta_1-\delta_2}\left[S(t+1) - v(t) - \delta_1 R - \delta_2 G\right] \tag{15}$$

Now, substituting equation (15) in equation (13), and rearranging, the following equation can be obtained,

$$S(t+1) = \frac{1-\delta_1-\delta_2}{1-\delta_1-\delta_2-1+h_1\sin(h_2)}\left[\begin{array}{l}\frac{h_1\sin(h_2)}{1-\delta_1-\delta_2}\left[v(t)+\delta_1 R+\delta_2 G\right]\\ -\frac{\delta_1 R}{1-\delta_1-\delta_2}-\frac{\delta_2 G}{1-\delta_1-\delta_2}+h_1 h_3\sin(h_2)G\end{array}\right];\ h_4 < 0.5 \tag{16}$$

The above equation is limited for the condition of $h_4 < 0.5$. For the other case, the solution update of the proposed Dolphin-SCA algorithm is specified as follows,

$$S(t+1) = \frac{1-\delta_1-\delta_2}{1-\delta_1-\delta_2-1+h_1\cos(h_2)}\left[\begin{array}{l}\frac{h_1\cos(h_2)}{1-\delta_1-\delta_2}\left[v(t)+\delta_1 R+\delta_2 G\right]\\ -\frac{\delta_1 R}{1-\delta_1-\delta_2}-\frac{\delta_2 G}{1-\delta_1-\delta_2}+h_1 h_3\cos(h_2)G\end{array}\right];\ h_4 \ge 0.5 \tag{17}$$

The above two expressions provide the solution update for the proposed Dolphin-SCA algorithm.

Evaluating the best solution based on the fitness: In this step, the fitness of the solution is evaluated and the solution providing minimal fitness replaces the best value $P(t)$.

Termination: The algorithm terminates while it reaches the maximum iteration count T. After several rounds of iteration, the optimal value for the segmentation constants is found out.

3.3 Feature extraction: Developing the feature vectors with the Power LDP model

After the segmentation, the feature extraction is carried out using the power LBP operator developed in [14]. The feature extraction generates the series of feature vectors that serve as training information to the classification stage. Here, the power LBP operator is adapted for the feature extraction, and it extracts the texture related features from the segmented image. Power LBP is the redefinition of the LBP operator, as it uniquely ranks for the pixel. The mathematical representation of the power LBP is briefed as follows:

Consider that the s^{th} segmented region Q_s of the image is subjected to feature extraction. The s^{th} segmented region has p pixels represented as $\{q_1, q_2, \ldots q_p\}$. The power LBP feature of the segmented image is represented as,

$$\mathrm{LBP}(Q_s) = \sum_{u=1}^{p} \eta\left(\nu_{q_u} - \nu_{q_o}\right) 2^{u-1} \tag{18}$$

where, ν_{q_u} refers to the cumulative distance of u^{th} pixel from neighbouring pixel, and ν_{q_o} refers to the cumulative distance from centre pixel.

3.4 Classification: FNB Classifier

Finally, the features extracted from the power LBP model are fed to the FNB classifier as the training sample. Here, FNB classifier is adopted for the classification purpose. FNB classifier was derived through the characteristics of NB model, and fuzzy theory, and hence, yields better classification results.

3.4.1 FNB Training Phase

The features obtained from the power LBP model serve as the training information to the FNB classifier defined in [17]. The features serving as the training information are represented in the probability index table represented as follows,

$$T = \begin{cases} T_{x,y}; & 1 \le x \le \rho \\ & 1 \le y \le \varsigma \end{cases} \tag{19}$$

where, $T_{x,y}$ refers to the data and its corresponding attribute. The terms x and y signify the total number of features and the attributes served for the FNB classifier. The features are represented as row, and attributes are represented in the column. From the training sample, the FNB classifier finds the class information. The class information provided by the FNB classifier is represented in vector form and is given as follows,

$$V = \{z_x \quad ; 1 \le x \le \rho\} \tag{20}$$

where, z_x indicates the class value for the corresponding data. The FNB classifier is formerly a combination of the NB with the fuzzy attributes. Hence, for the training purpose, it is necessary to clearly define the attribute information. The attributes owing to the training data sample is represented as,

$$A = \{A_y \quad ; 1 \le y \le \varsigma\}$$
(21)

where, A_y refers to the attribute of the data. The next major process in the training is defining the membership function for the FNB classifier. The membership degree function is used for obtaining the class information and thus, designed with the unique data symbols present in the attributes. Consider the attributes in the training data has unique data symbols. The unique symbols in the attribute follow, $A_y \in m^w$. The membership degree defined based on the unique symbols is expressed as follows,

$$\mu_q^s = \frac{\left|m_y^w\right|}{e} \tag{22}$$

where, $\left|m_y^w\right|$ indicates the total occurrence of the data symbol in the attribute. The next membership class derived for the FNB classifier depends on the class information. Consider the brain image belongs to any of the classes, and the membership degree derived based on the class information is expressed as follows,

$$\mu_n^R = \frac{\left|m^R\right|}{e} \tag{23}$$

where, $\left|m^R\right|$ indicates the total occurrence of R^{th} class. After deriving the membership function, the class information is derived with both the membership degree.

3.4.2 FNB Testing Phase

In the testing phase, the features of the brain image under test are given to the FNB classifier. The testing of FNB is done with the deriving the posterior probability of NB classifier. Other than this, the fuzzy membership function is also used for the testing purpose. Consider the test brain image B_{test} is given to the FNB classifier for testing. FNB classifier tends to classify the brain image into two class, i.e.) presence and absence of tumor. The output of FNB classifier is represented as follows,

$$V = \arg \underset{n=1 \text{ to } R}{\mathrm{Max}} P(z_x | B_{test}) \tag{24}$$

where, $P(z_x | B_{test})$ refers to the posterior probability for the test image, and it is expressed as,

$$P(z_x | B_{test}) = P(z_x) \prod_{x=1}^{\rho} \left[\frac{P(A_y | z_x)}{P(A_y)} * \mu_y \right] \tag{25}$$

where, $P(A_y | z_x)$ and $P(A_y)$ indicate the posterior probability for the attribute and the probability of occurrence of the attribute for the class. After identifying the class information, the FNB performs the adjustment through the Laplacian correction [25]. The Laplace correction done to the class output is expressed as,

$$P(B_{test} | z_x) = \frac{\left[\sum_{B \in e} \mu_y^B . \mu_B^n\right] + 1}{\left[\sum_{B \in e} \mu_B^n\right] + \left|\mathrm{dom}(A_y)\right|} \tag{26}$$

$$P(z_n) = \frac{\left[\sum_{X \in d} \mu_B^n\right] + 1}{e + \left|\mathrm{dom}(\mu_B^n)\right|} \tag{27}$$

where, $\mathrm{dom}(\mu_B^n)$ refers to the dominant class, and (μ_B^n) total data symbols in the attribute, respectively.

4. Results and Discussion

This section presents the results achieved by the proposed tumor segmentation and classification algorithm. The simulation results are gathered by using the BRATS and SimBRATS database and evaluated based on metrics, such as sensitivity, specificity, and accuracy.

4.1 Experimental Setup

The entire setup for the implementation of the proposed tumor classification and segmentation scheme with the proposed Dolphin-SCA algorithm is to be done in MATLAB tool. The setup requires the PC with the configuration of Windows 10 OS, 4 GB RAM, and Intel I3 processor. Here, the Dolphin-SCA algorithm is newly proposed, and for effective optimization, the following parameters need to be initialized.

Parameters: Maximum iteration T_{max} =50 and population size, $g = 25$.

4.1.1 Database Description

As this works deal with the tumor segmentation and classification, MRI image is required for the experimentation and they are taken from the standard BRATS database given in [16] and SimBRATS [24].

4.1.2 Comparative Techniques

The entire work is done with the proposed fuzzy deformable fusion, and FNB classifier is compared with several existing works for comparative analysis. Here, three existing models, such as Deformable model + Naive Bayes (NB), FCM + Support Vector Machine (SVM), and PFCM + k- Nearest Neighbor (k-NN) are considered for the comparative analysis.

4.2 Experimental Results

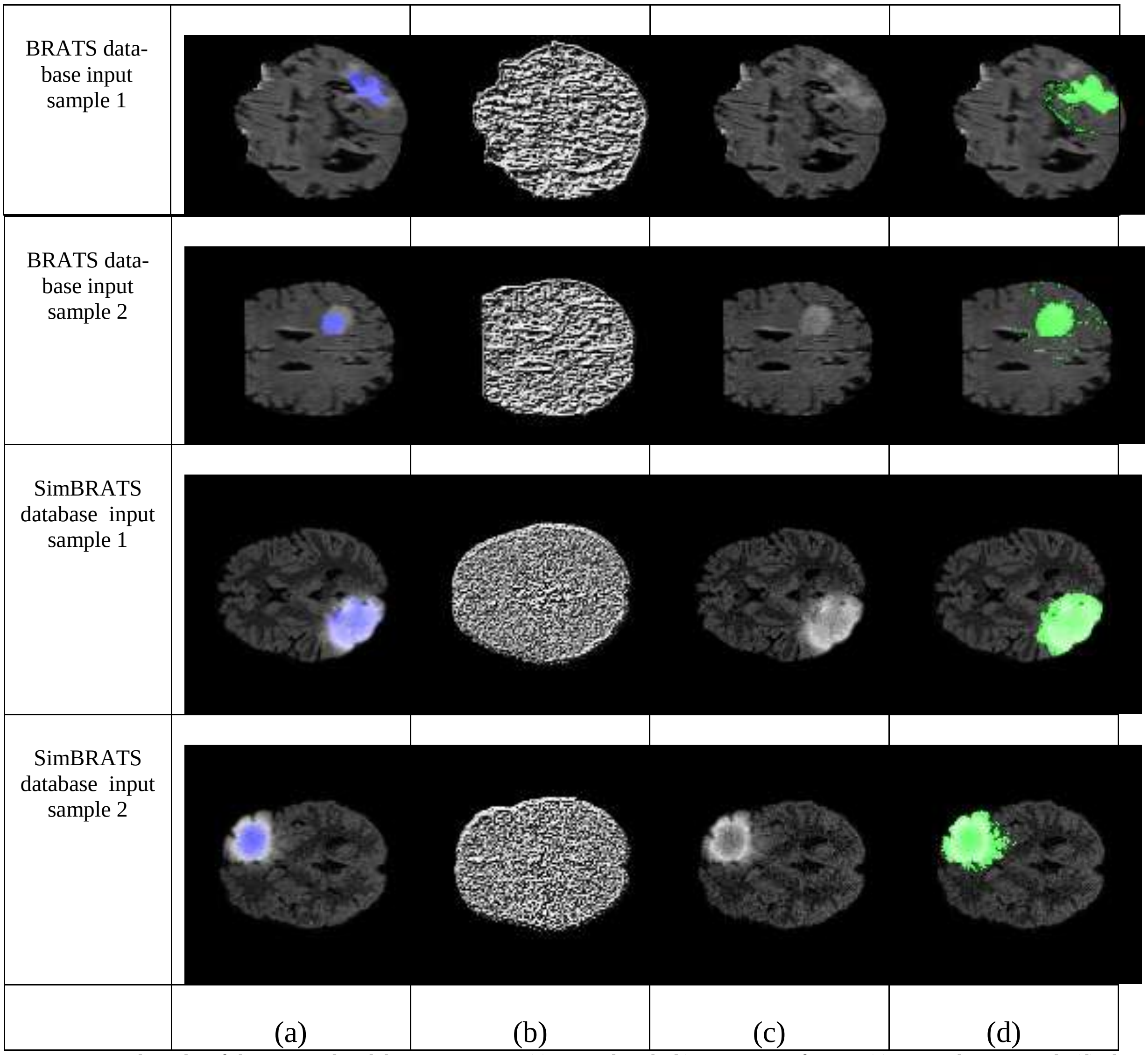

Figure 3:. Experimental results of the proposed Dolphin-SCA + FNB (a) Ground truth (b) Power LBP feature, (c) Original image, and (d) classified output.

Figure 3 states the experimental results achieved by the proposed classification scheme. Here, the results achieved by each stage of classification, and segmentation while using both the BRATS and SimBRATS database are presented. Here, the simulation results for two images taken from both the database are described. Figure 3.a presents the ground truth sample of both images from BRATS and SimBRATS database. The original image and its corresponding power LBP features are presented in figures 3.c and 3.b, respectively. The final classified result of FNB classifier is stated in figure 3.d. The output indicates that the simulation results have two colors, green and grey-white. The region indicated by green specifies the tumor region and the other indicates the non-tumor region

4.4. Comparative Discussion

Here, comparative discussion of the results achieved by Dolphin-SCA + FNB model against the other comparative models is discussed. The results reveal that the proposed Dolphin-SCA + FNB scheme achieved high performance when compared with the other comparative algorithms. Table 1 presents the best performance of comparative models, and the results are categorized based on evaluation metrics, such as sensitivity, specificity, and accuracy.

From the table 1, it is evident that the proposed Dolphin-SCA + FNB tumor segmentation and classification model has outclassed other comparative techniques with the high value of 0.837, 0.881, and 0.842, for sensitivity, specificity and accuracy, respectively, while evaluating the BRATS database. Further, from the results, it is evident the proposed scheme achieved values of 0.982, 0.8784, and 0.952, for sensitivity, specificity and accuracy, respectively, while evaluating the SIMBRATS database.

Table 1:. Comparative discussion

Database	Comparative techniques	Evaluation metrics		
		Sensitivity	Specificity	Accuracy
BRATS database	Deformable model + NB	0.968	0.5	0.762
	FCM + SVM	0.933	0.571	0.671
	PFCM + k-NN	0.819	0.547	0.749
	Proposed Dolphin-SCA + FNB	**0.837**	**0.881**	**0.842**
SimBRATS database	Deformable model + NB	0.986	0.546	0.790
	FCM + SVM	0.643	0.5	0.555
	PFCM + k-NN	0.958	0.812	0.918
	Proposed Dolphin-SCA + FNB	**0.982**	**0.874**	**0.952**

5. Conclusion

This research intends to develop a novel brain tumor segmentation and classification scheme from Brain MRI image. Here, the images are subjected to various processes, such that the tumor region in the brain image is identified. Initially, the images are given to NLM filter, and the required ROI is extracted. The pre-processed images are given to the proposed fuzzy deformable fusion scheme for segmentation, where the pixels providing different intensities are grouped together. The proposed fuzzy deformable fusion model uses the deformable shape model and FCM algorithm for the segmentation. Further, a novel optimization algorithm, namely Dolphin-SCA, is developed for finding the optimal constants for integrating the results of segmentation algorithms. From the segmented image, power LBP features are extracted and they are fed to the FNB for training. Finally, the FNB classifier generates the classification results for each MRI image. The entire work uses the BRATS and SimBRATS database for the experimentation and evaluated based on metrics, such as sensitivity, specificity, and accuracy. The simulation results reveal the dominance of proposed scheme over other comparative models, and the proposed scheme achieved the accuracy of 95.249.

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