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Segmentation of brain MRI using Multilevel Iterative Discrete PSO based SVM

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Abstract: Image Segmentation is an important part of image processing which can be used to separate objects in images, ignoring the effects of lights and textures. The higher resolution and better spatial discrimination of soft tissues make MRI an effective method among other medical diagnostic modalities. The existing Particle Swarm Optimization (PSO) technique is not much effective approach since the space for feasible solutions of min – cut partitioning problem is excessively large, particularly when the number of vertices is in the thousands. In this paper, a multilevel segregating method is combined with discrete PSO and developed Multilevel Iterative Discrete Particle Swarm Optimization algorithm (MIDPSO) for min – cut partitioning. MIDPSO works in three steps- partitioning phase, refinement phase, and recursive partition. The classifier Support Vector Machine (SVM), based on structured risk minimization is used here. By selecting the best features in the dataset; SVM increases the performance as well as reduces the computational time complexity. The proposed technique considers local as well as global to meet the requirement of precise segmentation. The proposed method aims in classifying the healthy and pathological tissues in the MRI images with high sensitivity, specificity, and accuracy in the least time.

Keywords: PSO, Partitioning, Refinement, Recursive, SVM

I. INTRODUCTION

Medical images have become essential in medical diagnosis and treatment. These images play a substantial role in medical applications because doctors exhibit interest in exploring the internal anatomy. Over the years, medical image processing has contributed a lot in medical applications; for example, the use of image segmentation, image registration, and image guided surgery is so common in medical surgery. The oldest one is X-ray which has been applied by the doctors for more than a century. In this technique, electromagnetic radiation with a short wavelength and high energy has been used. CT is another medical imaging technique which uses X-ray in imaging internal body organs and structure. It produces a number of parallel slices of each organ by passing X-ray pulses through the body. The story of MRI is one of a long courtship between Physics and Medicine. In 1950 s it was known as “Nuclear Magnetic Resonance (NMR)”.However, the turning point came after 20 years with the advent of computers in medical imaging. Later it is now known as “Magnetic Resonance Imaging (MRI).”From the initial observation that dense materials attenuate X-rays, the complex field of medical imaging has developed. [1].

Image classification from a vast collection has become one of the interesting challenges and the development of image classification approaches based on low-level descriptors, such as color, texture, and shape has drawn the attention of researchers. The main idea of image classification schemes is used to analyse image information and to set up feature vectors of an image as its index. In addition, these image classification schemes are designed to reduce the semantic gap between low-level feature and Human Visual Perception (HVP). Medical image segmentation is a difficult and very precise task. Image segmentation, do a foremost role in biomedical imaging applications such as the record of tissue volumes identification, confinement of pathology exploration of the anatomical organization, cure planning, partial volume enhancement of practical imaging data, and computer integrated surgery [Brain tumor detection from MRI images using history based segmentation and modified neural network. V Sheejakumari1, Sankara Gomathi2].The complicated structure of the brain is well known. Hence the accurate segmentation of brain is very decisive for identifying the normal and abnormal tissues in order to provide proper treatment. The normal tissues include Gray matter, white matter, cerebrospinal fluid (CSF), while the abnormal tissues include the tumors, edema, necrotic tissues etc. [3].

A brain tumor is defined as any abnormal growing of cells in the brain. Most brain tumors have a variety of shapes and sizes. It can arise at any position and in different concentrations. It can be benign and malignant. A benign tumor is not cancerous; it does not conquer adjacent healthy tissue or extend to other parts of the body. They may be observed radiologically or surgically removed and they develop again. A malignant tumor is cancerous and had varied structure. GBM is the most common and violent malignant primary brain tumor in humans. In spite of being the most dominant form of primary brain cancer, GBM incidence is only2-3 cases per 100000 people in Europe and North America [4].

Spotting the accurate boundary of the region containing an identified brain tumor is a difficult problem and must be concentrating on since it applies to many medical modalities and tumor types. The aim of this proposal is to give an effective procedure for distinguishing edges of brain tumors to help neurosurgeons recognize the area of the acute region of the tumor and discriminate the exact boundary of the tumor from the rest of the brain tissue during the surgery. In this paper, we work on MRI brain tumor images to aid surgeons. MRI image segmentation is a major step as a beginning procedure to concentrate the region of interest, which is the brain tumor region. This work proposes a new method using a particle swarm optimization technique to identify and remove the edge of a brain tumor. Using abnormal images of a variety of brain tumors, this study shows that the proposed algorithm provides a strong technique in expressions of accuracy and computation time, making it appropriate for real-time processing.

II. LITERATURE SURVEY

Riyazul Haque, Shrikant Lade, Dayashankar Pandey [5] proposed a method for tumor detection using morphological operations from MRI images, to be used as a tool in real time during surgeries. The new method uses a particle swarm optimization technique to recognize and remove the limit of a brain tumor. In this method, image is converted to grayscale and noise is removed if any. The acquired image is then exceeded through a high pass filter to detect edges. Then the acquired image is added to the original image to improve it. Later segmentation is done on basis of a threshold, due to which entire image is transformed into a binary image. Using abnormal images of a variety of brain tumors, this study shows that the proposed algorithm provides a robust technique in expressions of accuracy and computation time, making it appropriate for real-time processing. This paper presents an analysis of various proposed methods for segmenting an MRI image which relatively take lesser time than the manual process to detect and extract the brain tumor and detecting the particular boundary of the affected region.

Iman Behravan, Over Dehghantanha, Seyed Hamid Zahiri, and Nasser Mehrshad [6] suggested a multi-objective optimization algorithm to solve various optimization problems.Selecting the useful features among several features in the dataset is an important factor. Support vector machine is a classifier, based on the structured risk minimization principle. The performance of the SVM depends on different parameters such as penalty factor, C, and the kernel factor, σ. Similarly choosing an apt kernel function can improve the recognition score and lower the amount of computation. Choosing the suitable features among quite a lot of features in dataset not only enhances the performance of the SVM, but also reduces the computational time and complexity. In some cases besides the recognition score, the reliability of the classifier’s output is important. So in such cases a, multi objective optimization algorithm is needed. In this work, authors advised MOPSO algorithm to improve the parameters of the SVM, select suitable kernel function, and choose the best feature subset simultaneously in order to optimize the recognition score and the reliability of the SVM simultaneously. Nine different datasets, from UCI machine learning repository, are used to evaluate MOPSO-SVM. The results indicated that using heuristic algorithm to convert SVM from a normal classifier into an expert one was successful. Furthermore optimizing SVM in order to increase its reliability besides its accuracy by using a multi objective heuristic algorithm is a successful idea according to the obtained results.

Hussain, Savithri, Devi [7] have devised a technique for an accurate segmentation of normal and pathological tissues in the MRI brain images. Primarily the classification process has been completed using fuzzy inference system (FIS) and FFBN in which the extracted image features are the input for the classification process. Two ways are used to extract features from the MRI brain images. The FIS implement the classification method by making the fuzzy rules by means of the extracted features. Five features: two dynamic statistical features and three 2D wavelet decomposition features have been extracted from the MRI images. During segmentation, the normal tissues such as WM, GM, and CSF have been segmented from the normal MRI images and abnormal tissues such as edema and tumor have been segmented from the anomalous images. While during the preprocessing stage, the noncortical tissues in the normal images have been removed. The performance of the segmentation technique has been analysed using performance measures such as accuracy, specificity, and sensitivity.

The authors Sheejakumari and Sankara Gomathi [12] used improved particle swarm optimization (IPSO) technique along with Neural Networks (NN). The classification method works in four stages namely, tissue segmentation, feature extraction, heuristic feature selection, and tissue classification. Tissue segmentation includes the segmentation of normal and abnormal tissues; Feature extraction exploited seven features, two features are histogram based, two are statistical features, and the other three features are from wavelet. The blend of such features made the segmentation method more effective. All features are taken out from these nonzero blocks and computed the mean value for all feature values. Heuristic Feature Selection by Improved Particle Swarm Optimization (IPSO) selects only the most optimal features. Later, the selected optimal features from the IPSO technique are given to the FFBNN. The method is implemented and the results are analysed in terms of various statistical performance measures.

III. PROPOSED METHODOLOGY

Most of the prevailing partitioning algorithms are exploratory in nature and they try to find a reasonably good solution. These algorithms come under move – based category in which solution is generated recursively from an initial solution applying the move to the recent solution. Most frequently, this move – based approaches are joined with stochastic algorithms. In this paper, we have developed Multilevel Iterative Discrete Particle Swarm Optimization (MIDPSO) technique and SVM to classify the normal and abnormal tissues in the MRI brain images. The different stages of the proposed methodology are shown in Fig 1.

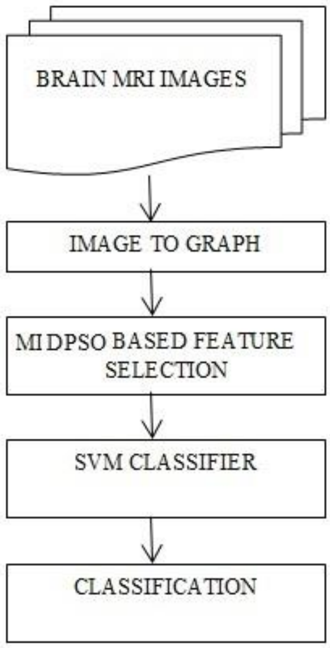

Fig 1: Image Analysis Process

3.1 Discrete Particle Swarm Optimization (DPSO)

The original PSO algorithm optimizes problems in which the elements of solution space are continuous. Since most of the real life applications are based on optimization of discrete valued space, Kennedy et al [8] developed discrete PSO (DPSO) to solve discrete optimization problems. DPSO particles works on discrete search space and paths denote differences in probability which a coordinate takes a value from rational discrete values. In this method, each particle specifies the potential solution composed of k elements. The fitness function is used to evaluate the correctness of the solution. Each particle is considered as a position in k–dimensional space and each element of the particle are restricted to '0' and '1', where '0' represents 'included' and '1' represents 'not included'. The elements can vary from 0 to 1 and vice versa. Additionally, each particle will have k – dimensional velocity between the series [-V_{max}, V_{max}]. Velocities are defined using probabilities that a bit will be in one state or the other. At the primary stage of the algorithm, the number of particles and their velocity vectors are generated arbitrarily. Then in a certain number of duplications, the algorithm aims to find the optimum or close – optimum solutions using predefined fitness functions.

Update the velocity vector using best positions best, n_{best} and then appraise the position of particles using velocity vector at iteration. Pbest and n_{best}t are k – dimensional vectors consisting of '0' and '1' which works as a memory of the algorithm. Since the initial step of algorithm, best position that the particle has visited is p_{best} and the position that the particle and its neighbor has visited isn_{best}. Depending on size of neighborhood, two different PSO algorithms can be developed. If the entire population size of the swarm is considered as the neighbor of particle, then n_{best} is called as global best (g_{best}) whereas, if for each particle smaller neighborhood are defined then $n_{best}$is called as local best (l_{best}). Star neighborhood and ring neighborhood are the topologies used by g_{best} and l_{best} correspondingly. PSO based on gbest joins faster thanl_{best} based PSO due to its larger particle connectivity, but l_{best} based PSO is less susceptible to being trapped in local minima. Stopping conditions for DPSO can either be the extreme number of iterations or formative acceptable solution or no more improvement in the number of iterations.

3.2 Support Vector Machine (SVM)

In 1992 Boser, Guyon and Vapnik introduced Support Vector Machine (SVM). SVM uses hypothesis space of linear functions in a high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias resulting from statistical learning theory. It gained popularity due to better empirical performance. The formulation uses the structural risk minimization (SRM) principle, used by the conventional neural network. SRM minimizes an upper bound on the expected risk, whereas ERM minimizes the error on the training data. It is the difference which equips SVM with a greater ability to generalize, which is the main goal in the statistical learning. SVM classifier is used to distinguish between the normal and the abnormal brain using the confusion matrix [9].

3.3 Multilevel Iterative Discrete Particle Swarm Optimization (MIDPSO)

To segment an image using swarm intelligence based approach, initially the image has to be converted to the graph in which the vertices denote the pixels and intensity difference between the pixels denote the weight of the graph. Once the weighted graph is generated the MIDPSO algorithm is implemented in three stages.

i. Coarsening using core sort heavy edge matching algorithm

Algorithm steps for coarsening using core sort heavy edge matching:
Input: Graph obtained from input image
Output: coarsened graph
Step 1: Randomly select a vertex
Step 2: Select the next vertex of maximal weight.
Step 3: Remove the above-selected vertex from the vertex set
Step 4: Add the new vertex to the coarsened vertex set.
Step 5: Repeat steps 2, 3 and 4

ii. Initial partitioning using greedy graph growing partitioning

Algorithm steps for greedy graph partitioning [10]:
Input: Set A such that w (A) =$\frac{1}{2}w(V)$
Output: coarsened graph
Step 1: Initialize A by randomly selecting a vertex, x and Set B, C is then initialized.
Step 2: Select the next vertex of maximal gain.
Step 3: For each vertex in set C which is adjacent to u is moved to the set B and calculated its gain.
Step 4: Recalculate the gain of each vertex in B that is adjacent to x.
Step 5: Repeat steps 2, 3 and 4
Step 6: Algorithm ends when w (A) =$\frac{1}{2}w(V)$

iii. Refinement using discrete particle swarm optimization to generate bisected graph and then recursively k-partitioning is generated.

Algorithm for Discrete particle swarm optimization:
Step 1: Generate the entire swarm.
Step 2: Evaluate the initial swarm using the fitness function
Step 3: Initialize the personal best particle and global best of the entire swarm.
Step 4: Update the particle velocity using the equation 1 and 2.
Step 5: Apply velocities to particle positions, evaluate new particle positions.
Step 6: Repeat the steps 4, 5 till the maximum iterations have reached. [11].

$$V_{id}(t+1) = V_{id}(t) + c_1R_1(p_{id}(t) - x_{id}(t)) + c_2R_2(p_{gd}(t) - x_{id}(t)) \quad (1)$$

$$x_{id}(t+1) = x_{id}(t) + V_{id}(t+1) \quad (2)$$

Where:

V_{id} -- Rate of position change of i^{th} particle and t denotes iteration.
x_{id} -- Position of i^{th} particle.
p_{id} -- Historically best position of particle.
p_{gd} -- Position of swarm's global best particle.
R_1 and R_2 -- two n-dimensional vectors with random numbers uniformly selected between [0,1].
c_1 and c_2 -- position constant parameters.
$p_{id} = p_i$ if $f(p_i) > f(p_{id})$
$p_{gd} = g_i$ if $f(g_i) > f(p_{gd})$
f(x) is an objective function subjective to maximization.

A recursive algorithm is applied for k-partitioning of the bisected graph generated in the first two steps of MIDPSO. The recursively generated k-partitioned graph is projected back to the segmented image.

IV. EXPERIMENTAL RESULTS

Skull image is read as the input image, Fig 2. A brain tumour is the abnormal growth of cells in the brain or the membranes surrounding the brain. When an image is resized, its pixel information is changed. A gray scale image can be of any size, only some of them are of size 256 x 256. The ranges of values are from 0 to 255, so each pixel can take one of 256 different values. A matching or independent edge set in a graph is a set of edges without common vertices. It may also be an entire graph consisting of edges without common vertices. The usual aim of the discrete particle swarm optimization (DPSO) algorithm is to solve an unconstrained continuous minimization problem. K- Partition index method is used to differentiate the region from color.

Image segmentation is the process of partitioning a digital image into multiple segments. The aim of segmentation is to simplify the representation of an image into something that is more expressive and informal to analyse, Fig 3. Finally, SVM classifier is applied to classify the output, where the tumor is detected, Fig 4 and Fig 5. Specifically, our method can achieve high classification accuracy. Accuracy measures the proportion of subjects that are correctly predicted.

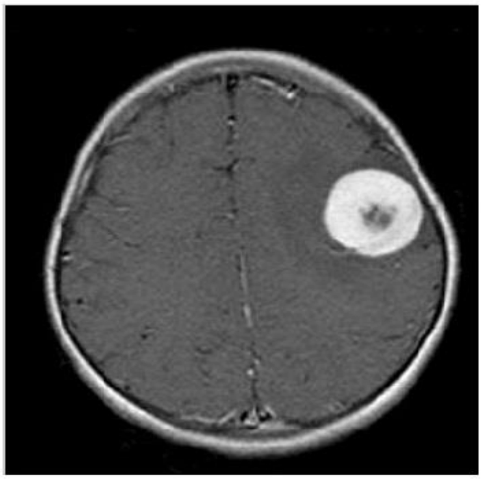

Fig 2: Input Image

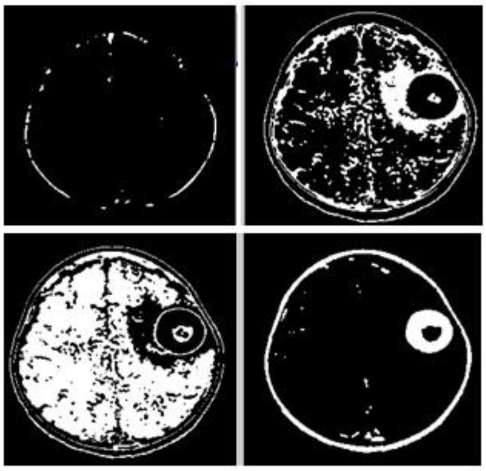

Fig 3: Multi segmented Image

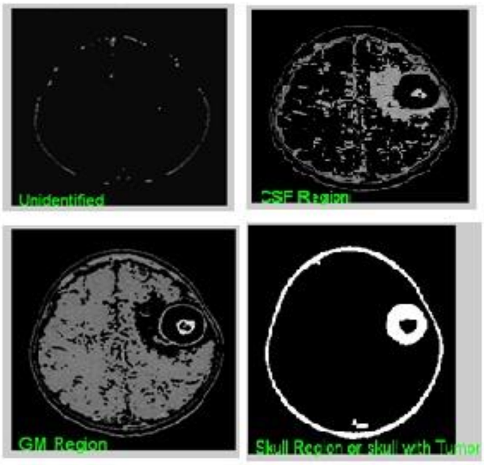

Fig 4: SVM classified output

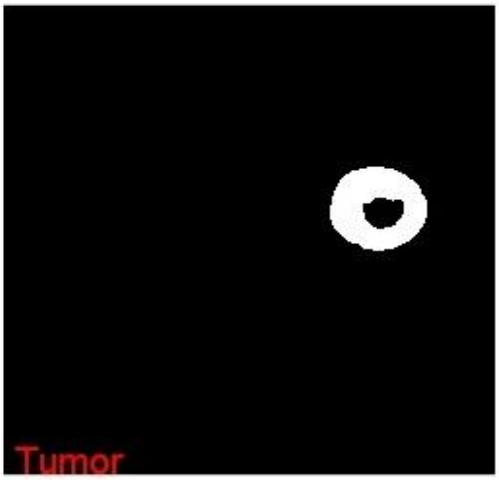

Fig 5: Tumor identified

Fig 6 shows the comparison with the existing system.

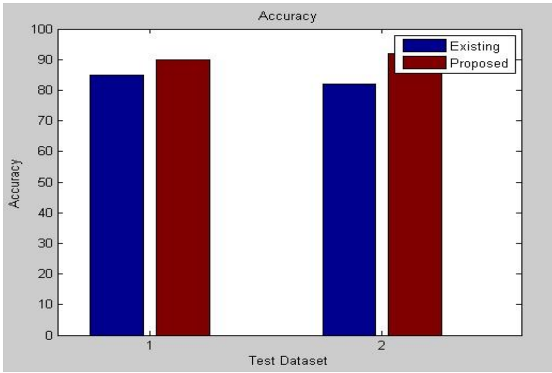

Fig 6: Comparison with the existing system

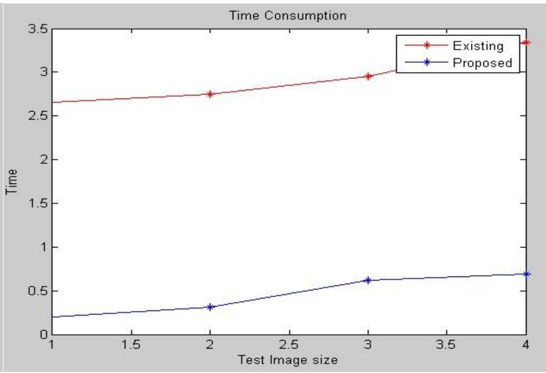

Fig 7: Image size vs. Time consumption

Compared with the existing method, the proposed system have high accuracy axis denote the image size and Y-axis denotes the time consumption. From above graph, proposed method consumes low time compared to the existing method.

CONCLUSION

A new tissue classification method is proposed in this paper to differentiate between normal and abnormal tissues in less computational time compared with the existing system.

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