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A NOVEL FUZZY CORNER APPROACH FOR BRAIN TUMOR SEGMENTATION AND CLASSIFICATION

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Abstract: Abnormal development of cells in human body contributes to the formation of cancer or tumor. The uncontrolled expansion of cells in human brain leads to the formation of brain tumors. These brain tumors are classified into two types, benign and malignant. This project presents an automatic segmentation method based on fuzzy corner metric markers and classification method using Convolutional Neural Network. The segmentation method uses a fuzzified corner metric, in view of image intensity, is proposed to recognize the component markers to be enclosed by the contour. In order to improve the accuracy level, Whale Optimization Algorithm (WOA) is used. The WOA is used to tune the hyper parameters of hybrid CNN. These parameters include the number of convolution kernels, the size of convolution kernels, activation function, batch size and learning rate. CNN models, one of the deep learning networks, are utilized for the diagnosis process. The proposed work is implemented and simulated in MATLAB. The proposed work gives exceptionally good results, when compared to recently proposed techniques and this work provide better accuracy of 98.92%, specificity of 97%, and sensitivity of 97%.

Index Terms **– Brain Tumor, Classification, Image Segmentation, GLCM.**

1. INTRODUCTION

Image Processing is a technique to improve raw images got from cameras or sensors set on satellites, space tests and airplanes or pictures required in ordinary everyday life for different applications. Different techniques have been created in Image Processing during the last four to fifty years. The majority of the techniques are created for upgrading images obtained from automated space crafts, space tests and military observation flights. Image Processing systems are becoming popular due to easy availability of powerful personal computers, large size memory devices, graphics software etc. Image Processing is utilized in different applications.

Brain is a complicated structure and also it is understood as the essential ingredient of the body. Brain tumor is unwanted growth of abnormal cell in brain in an uncoordinated fashion. Brain tumor increased the intracranial pressure within the skull which affects the region of Cerebrospinal Fluid (CSF), Gray Matter (GM) and White Matter (WM). Tumor can influence any part of brain and it seriousness depends on tumor size, type and area. Tumor cells growth in an uncontrolled manner and like the normal old cells of body, they do not die.

Brain tumor is also known as mass of abnormal cells in our brain which can be differentiated into benign tumor and malignant tumor. Benign is a type of brain tumors that does not contain cancerous cells in uncontrolled manner, it can be removed and it never grows back.

Benign tumors are non-cancerous cells, which do not invade surrounding healthy tissues. Malignant brain tumors consists of cancer cells which does not possess clear borders. This type of tumor is considered to be a dangerous life killing tumor. Tumor detection needs various processes on MRI images that comprise image preprocessing, image enhancement, feature extraction and classification.

2. RELATED WORKS

Jason et al. [8] suggested an innovative procedure to automatic segmentation of heterogeneous image data that progress in connecting the gap amidst the bottom-up affinity related segmentation techniques and top-down generative model related techniques. The key role of the article was a Bayesian formulation for integrating soft model coursework into the computation of affinities, which were traditionally model free. The proficient technique governs magnitude orders quicker than that of the modern approaches which yields enhanced outcome.

Ahmed Kharrat et al. [1] predicted a hybrid methodology to brain tissue categorization in magnetic resonance images relying upon the Genetic Algorithm (GA) and also Support Vector Machine (SVM). The optimum texture components are gleaned from the conventional and tumor regions by Spatial Gray Level Dependence Method (SGLDM). The performance of the algorithm was assessed through a sequence of brain tumor images.

Usman Akram et al. [19] presented the magnetic resonance images are a valuable device to identify the tumor development in brain however exact brain image segmentation is troublesome and tedious cycle. The frame work comprises of three phases to identify and segment a brain tumor. In the main stage, MR of brain image is gained and pre-processing is done to eliminate the noise. In the subsequent image is post handled by morphological tasks and tumor veiling to eliminate the false segmented pixels.

Ramteke and Khachane Monali [15] suggested a procedure for automatic stratification of medical images in two classes. They are normal and also abnormal regarding the image components and also automatic abnormality diagnosis. The KNN classifier was employed for classifying image. The KNN classifier performance was relating with the kernel related SVM classifier RBF and Linear. If the image was stratified like abnormal then the post processing phase as employed on the image and the abnormal region was tinted on the image.

Evangelia et al. [5] constructed a new semi-supervised system for oddity detection and also segmentation of medical images. Semi-supervised learning does not necessitate pathology modeling and therefore permits greatest degree of automation. In the abnormality diagnosis, a vector was described as anomalous when it does not fulfill the probability distribution attained form the typical data.

Jayachandran and Dhanasekaran [7] intended a tumor segmentation methodology concentrated on the structural psychiatry of the abnormal and normal tissues. They presented an effective multi-texton histogram and SVM based brain tumor detection with MRI images. The consequences for the tumor detection were authenticated through evaluation metrics like specificity, sensitivity and accuracy.

Atiq Islam et al. [3] intended a stochastic replica for distinguishing the tumor texture in the brain MR images. The efficiency of the model was verified in the patient sovereign brain tumor texture feature derivation and also tumor segmentation in the MRIs. The new patient independent tumor segmentation methodology was introduced by lengthening the renowned AdaBoost algorithm. The alteration of AdaBoost algorithm entails conveying weights to constituent classifiers relying on their capability to categorize tricky samples and assurance in such categorization.

Moumen T El-Melegy et al. [11] constructed a fresh fuzzy technique for the automatic segmentation of normal and also pathological brain MRI volumetric datasets. These datasets are classified to three main classes (WM, GM and CSF). The intended technique reformulates the trendy FCM technique to consider any obtainable data about the class center. The vagueness in that data was also modeled. That data serves to regularize the clusters created by the FCM technique thereby boosting the performance under noisy and unexpected data acquirement circumstances.

Meiyan Huang et al. [10] suggested a new automatic tumor segmentation approach for MRI images. This technique considered tumor segmentation as a classification trouble. In addition, very voxel was classified into different classes using the local independent projection based classification method. The locality was significant in the computation of local independent projections for LIPC. Besides, LIPC deliberated the data distribution of dissimilar classes by learning a softmax regression model, which additionally perked up the alternative Active Contour Model (ACM) impelled by Multi-population Cuckoo Search (CS).

Parveen et al. [14] proposed calculation is a hybrid technique for brain tumor prediction that combines SVM with fuzzy C-means. Here, the image is enhanced utilizing contrast improvement and mid-range stretch. Two fold thresholding and morphological tasks are utilized for skull striping. Grey level run length matrix is used for extraction of feature. At the point, Linear, Quadratic and Polynomial SVM technique is applied to classify the brain MRI images.

Sonu Suhag et al. [17] proposed a system highlighted approaches with image processing. Histogram equalization, enhancing image, segmenting image etc. are some of the mostly used approaches. They have developed the system user friendly by using the tool MATLAB. The most important discovery in the process is that it is unable to identify the tumor and the edges of the brain separately because the tumor tissues appear darker at the edges. This issue affects the identification of tumor at the edges.

Hai Su et al. [6] presented a sparse reconstruction and adaptive dictionary learning framework for programmed cell detection. The significant beneficence of our procedure were a sparse reconstruction related technique to rip touchup cells and an adaptive dictionary learning approach employed for disbursing with cell appearance adaptations. The computerized cell detection consequences were relating with the physically annotated ground truth and the state of the art cell detection techniques.

K. Bhima et al. [4] proposed the amazing development in image processing for discussing medical imaging is one of the arising field and the necessities for advancements in medical imaging is consistently rising and challenging. Watershed strategy is one of the typical utilized segmentation technique for brain MRI and fundamentally useful for gray scale image segmentation applied on mathematical morphology and area detection. The major recognized bottleneck of the recent research outcomes is restricted to detection of brain tumor and the general examinations of inner structure of the brain is generally disregarded being quite possibly the main factor for disorder detection.

Sergio Pereira et al. [16] devised an automatic segmentation technique regarding the Convolutional Neural Network (CNN), surveying small 3x3 kernels. The utilization of small kernels permits intending a deeper architecture and it holds a positive effect against over fitting, specified the fewer number of weights in the network. In addition, they examined the utilization of intensity regularization like a pre-processing phase that were not familiar in the CNN based segmentation techniques, confirmed collectively with the data augmentation to be very effectual for the brain tumor segmentation of MRI images.

S. Kaushal et al. [9] proposed a process to identify brain tumors using segmentation of MRI images. The optimal thresholding has been used because it assists to clearly recognize the shape and the position of tumor. This method detects the tumor tissue volume. By using these data, growth of the tumor can be measured.

Astina Minz et al. [2] proposed an effective automatic classification approach for brain MRI on the dataset of 50 MRI images is projected using the AdaBoost machine learning algorithm. Pre-processing has eliminated noise in the raw data, median filter and thresholding segmentation is applied. For classification boosting technique used (AdaBoost). The exactness of the system will be expanded by increasing training database images.

P.S. Mukambika et al. [12] proposed methodology in which image is processed through: Pre-processing, Segmentation, Feature Extraction and classification. In pre-processing, Morphology method utilizing twofold thresholding is applied to eliminate the skull out of the MRI brain images. After the segmentation is feature extraction using Discrete Wavelet Transform and Gray Level Co-occurrence Matrix and classification utilizing the SVM. SVM with level set and K-means segmentation characterize image into normal brain, benign or malignant tumor with 94.12% and 82.35% precision individually.

Tonmoy Hossain et al. [18] image segmentation plays a significant role in medical images have different diversities. Fuzzy C-means clustering is used for the tumor segmentation which can predict tumor cells accurately. The segmentation process was followed by classification using traditional classifiers and CNN. The SVM classifier gave the highest accuracy 92.42%. Further, for better results, they have implemented CNN which brought in the accuracy 97.87%.

Parasuraman Kumar et al. [13] proposed an Ensemble method called the most influential improvement in information mining and machine learning. Ensemble techniques combine the strategy of neural network, Extreme Learning Machine (ELM) and Support Vector Machine classifiers. The Ensemble classifier is at last classified the tumor and non-tumor region. The ensembles have a high accuracy and less execution time and it is very efficient when compared to all other classifier techniques. The accuracy for ensemble classifier is 91%.

Yashwant Kurmi et al. [20] proposed a multistage image segmentation strategy, the purpose regions initialization is performed utilizing low level information by the central issue descriptors. The features are extracted using the fisher vector and auto encoder. The experiments that are performed utilizing five MRI datasets confirm the predominance of proposal as that of the state of the art methods. It reports 94% and 91% average accuracy of segmentation and classification respectively.

3. METHODOLOGY

This section illustrates the procedures about the segmentation and classification of brain tumor from MRI images.

In traditional work, identify and classify the brain tumor tissue in MRI by using the image processing and neural network technique but are highly affected the image segmentation process and classification accuracy rate owing to the amount of noises. The method for segmentation of brain tumor involves pre-processing, image segmentation and the GLCM features extraction. A flow chart depicting this method is provided in the Fig.1.

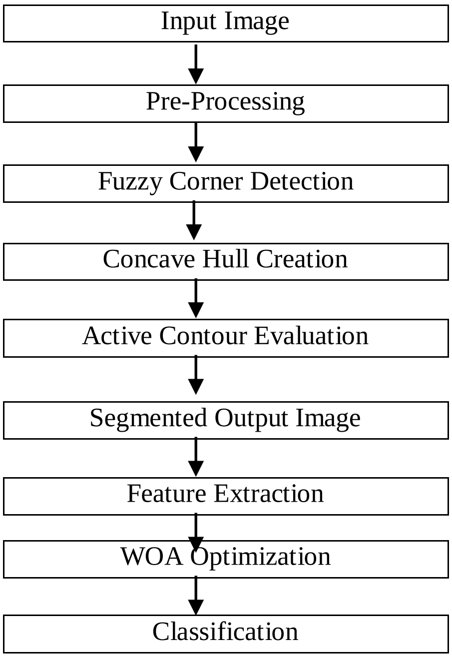

Fig.1 Flow chart of the algorithm about brain tumor segmentation and classification

3.1 MRI Scan of obtained Brain Tumor images

Magnetic Resonance Imaging is 8 bit images which have some brightness information which vary from 0 to 255 where 0 represents for black color and 255 represent for white color.

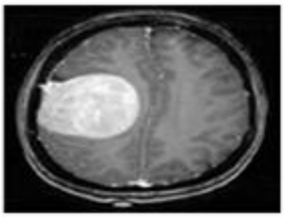

Fig.2 Input brain tumor image

3.2 Pre-processing

This is the second step of image processing where the images are used to enhance the chances of detecting the suspicious region. Clinical MRI when corrupted by noises reduces the accuracy of the images. Its goal is to improve the image data by suppressing the unwanted distortions and enhancing some image features that will be helpful in subsequent processing.

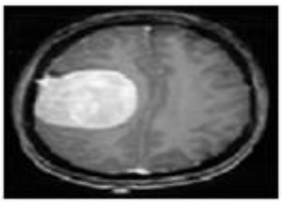

Fig.3 Result of median filtering

To read the pixel values, first obtain the images median value, and then calculate the median value by selecting the midway value for modifying the intensity level of pixels (i, j).

3.3 Image segmentation

Brain tumor segmentation has been a salient phase for diagnosis the tumor initially in the medicine field. Image segmentation plays a vital part in various biomedical imaging applications, health care experts during the diagnosis of various diseases.

3.3.1 Fuzzy method

Fuzzy level set algorithm is proposed to work with medical image segmentation which is able to directly advance from the initial segmentation of spatial induced fuzzy c-means using pixel classifications are utilizing dynamic variation boundaries for image segmentation. A fuzzified corner metric, in view of image intensity is proposed to recognize the feature markers to be encased by the contour. Corners are feature points in an image that are recognized by presence of large variation in intensity around a pixel in all directions.

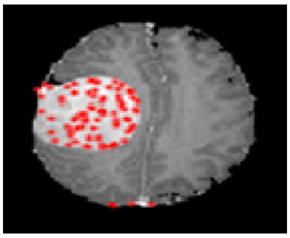

Fig.4 Fuzzy corner points

3.3.2 Active Contours

The strategy for active contours has gotten very well known for an extent of uses, essentially image segmentation and motion tracing, through the most recent decade. This technique depends on the use of deformable contours which match to various object shapes and movements.

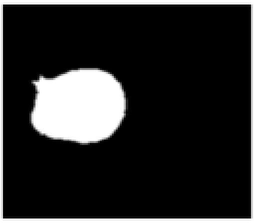

Fig.5 Active contour segmentation

3.3 Feature Extraction

Feature extraction is a crucial phase in the construction of any pattern classification because it concentrates on extracting the relevant information that defines each class. The application for extracting the features of an MRI images is Grey Level Co-occurrence Matrix (GLCM). They are different statistical method for some of the features of the images are listed below:

1. Contrast**:** The contrast in an image is defined as the distance between the darkest and brightest areas.
2. Homogeneity**:** Homogeneity is characterized as the quality or condition of being homogeneous. It is a range of values to determine the textured image and un-textured image.
3. Correlation**:** Correlation is computed into what is known as the correlation co-efficient, which range between -1 and +1. It describes the dependencies of spatial relationship between the pixels of an image.
4. Energy**:** Energy is to measure the resemblance of an image. It is otherwise called angular second moment.
5. Entropy**:** Entropy is a proportion of the uncertainty in an irregular variable.

3.3 WOA Optimization

Whale Optimization Algorithm (WOA) is a new nature inspired meta-heuristic optimization algorithm that mimics humpback whale social behavior. The humpback whale creates a trap with moving in a spiral path around preys and creating bubbles along the way. This intelligent foraging strategy is the fundamental motivation of the WOA. Another recreated conduct of humpback whales in WOA is the encircling mechanism. Humpback whales circle around preys to begin hunting them utilizing the bubble-net mechanism. The primary numerical condition proposed in this algorithm is as per the following:

$$\vec{X}(t+1) = \begin{cases} \vec{X}*(t) - \vec{A}\cdot\vec{D} & p < 0.5 \\ D^{'} e^{bl}\cos(2\pi l) + \vec{X}*(t) & p \geq 0.5 \end{cases} \qquad (1)$$

Where p is a random number in [0,1], $D^{'} = |X*(t) - X(t)|$ and indicates the distance of the i th whale the prey, b is a constant for defining the shape of the logarithmic spiral and l is a random number in [-1,1], t shows the current iteration, $\vec{D} = |\vec{C}\cdot\vec{X}*(t) - \vec{X}(t)|$, $\vec{A} = 2\vec{a}\cdot\vec{r} - \vec{a}$, $\vec{C} = 2\cdot\vec{r}$, A and C are coefficient vectors, X* is the position vector of the best solution obtained so far, X is the position vector, | | is the absolute value, and ˙is an element by element multiplication. It is worth mentioning here that X* should be updated in each iteration if there is a better solution. Components of a are linearly decreased from 2 to 0 over the course of iterations and r is random vector in [0, 1].

The first component of this equation simulates the encircling mechanism, whereas the second mimics the bubble-net technique. The variable p switches between these two components with an equal probability. The exploration and exploitation are two main phases of optimization using population based algorithms. They are both guaranteed in WOA by adaptively tuning the parameters a and c in the main equation.

The WOA algorithm starts with a set of random solutions. Each iteration, search agent update their positions with respect to either a randomly chosen search agent or the best solution obtained so far. The parameter is decreased from 2 to 0 in order to provide exploration and exploitation, respectively. A random search agent is chosen when $|A| > 1$, while the best solution is selected when $|A| < 1$ for updating the positions of the search agents. Depending on the value of p, WOA can switch either a spiral or circular development. Finally, the WOA algorithm is ended by the fulfillment of an end measure.

3.3 Classification

Classification is utilized to arrange everything in a set of information into one of predefined set of classes or groups. In other words, classification is an important technique used widely to differentiate benign and malignant tumor brain images. The objective of classification is to precisely predict the target class for each case in the data. In this proposed work the classification is done by the modified Resnet.

3.6.1 Structure of the system

The last five layers of Resnet50 have been removed from the developed model and ten new layers have been added in their place, without disturbing the CNN architecture.

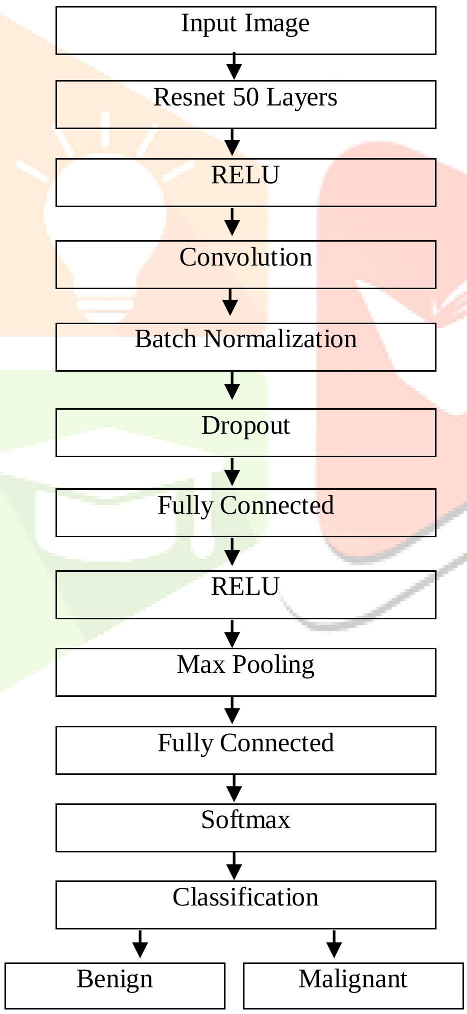

Fig.6 Structure of the Classification model

Fig.6 shows a structure of the developed model. Layer order is significant in hybrid structures and advancements to be made in CNN design used in deep learning. This expansion request depends on CNN theory knowledge. These layers are Relu, Batch Normalization, Dropout, Fully connected, Rely, Maxpooling, Fully connected, Softmax and classification layers respectively. The convolution process is a linear process that has been customised. Here, instead of matrix multiplication convolution is performed. Activation functions are used for non-linear transformation process in multi-layer artificial neural networks. There are multiple activation functions. Tan h, Sigmoid and Relu are the most commonly used. Rely was used in the developed method. Batch Normalization used to normalize the output of convolution or fully connected layers. The dropout layer gives prevention of over-learning by randomly dropping nodes and connections during the preparation of the network.

The pooling layer is typically utilized after the convolution layer. The undertaking of the pooling layer is to work on the data in the yield of the convolution layer. Softmax is used before the classification layer. It produces a value for each class by performing the probabilistic estimation made on the network. Classification layer used after the softmax layer is the last layer of the network. The output value of this layer is equivalent to the number of classes produced.

4. Result analysis

The table 1 illustrates the performance metrics comparison for our proposed method with the existing techniques in terms of Accuracy, Specificity and Sensitivity. The following Fig.7 represents the graphical representation for the performance comparison of proposed method with existing techniques. It is very clear from Table.1 and Fig.7, the performance metrics such as accuracy, specificity and sensitivity to assess the overall performance of the classifiers. The accuracy, specificity and sensitivity referred for evaluating the performance of the overall process of the system. From the overall the proposed method have high accuracy, specificity and sensitivity as 98.92%, 97%, 97% respectively.

Table 1: Comparison between various techniques with accuracy, specificity and sensitivity

Technique	Accuracy	Specificity	Sensitivity
Extreme Learning Machine	86	91	93
Support Vector Machine	89	93	94
Ensemble Classifier	91	94	94.5
Proposed Method	98.92	97	97

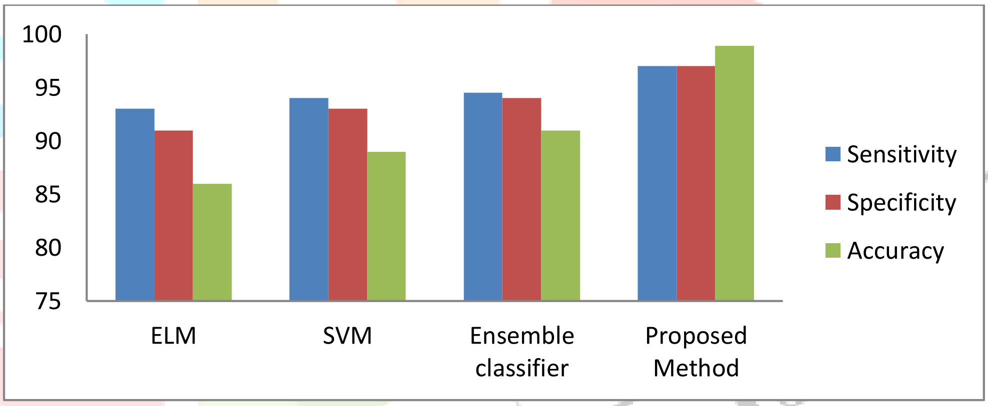

Fig.7 Graphical representation of various techniques

5. Conclusion

This proposed approach successfully does the segmentation and classification between the benign and malignant tumor images. Firstly, MRI brain image is read by the system, the pre-processing, segmentation and classification is done by using fuzzy corner metric markers and CNN networks and CNN layers. Whale Optimization Algorithm is used to tune the hyper parameters of the CNN. The features are then administered to classify the images as benign or malignant using Resnet. Classification of images incredibly relies upon the features removed from the image and thus feature extraction plays an excellent role within the correct classification of images. The scheme have been evaluating for its segmentation and classification accuracy after running the process for a large sum of data. Accurate and correct segmentation and classification of an image determines the eventually the chance of getting the failure or success of getting the failure or success of computerized analysis procedure.

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