AN AUTOMATED AND IMPROVED BRAIN TUMOR DETECTION IN MAGNETIC RESONANCE IMAGES

Sharmila Deve Venkatachalam

Ibri College of Technology, Al Aqder,Ibri, Sultanate of Oman.
E-mail: sharmiladeve.78@gmail.com

Abstract-The segmentation, identification, as well as extraction of tumor areas from magnetic resonance (MR) images is a major issue. It is a crucial as well as time-consuming process that radiologists and physicians must perform, and the precision is solely dependent on their expertise. As a result, the use of image processing approaches become increasingly important in order to resolve these constraints. In this approach, an efficient detection of brain tumor is proposed for improving performance and minimizing complexity involved in the processing of medical images. The adaptive mean filter is utilized for pre-processing and the brain tumor image segmentation depends on Fuzzy C means algorithm. Subsequently, related features are extracted from every segmented tissue by GLCM method and the optimal features are selected by fuzzy concepts. For improving the accuracy as well as quality rate, Artificial Neural Networks (ANN) are utilized for classification. The input MR brain images are attained from the database of Harvard medical school and efficient detection of brain tumor is performed.
Keywords: Artificial Neural Network, GLCM, Fuzzy C means clustering, magnetic resonance image, adaptive median filter.

1 INTRODUCTION

Brain tumors are divided into two categories: cancerous tumors as well as benign tumors. Magnetic resonance imaging (MRI) generates images of the brain with more details and is a popular method for diagnosing brain tumors [1, 2]. Figure 1 illustrates the MRI images of brain with abnormal tissue.Brain tumor detection is useful for improved identification, growth rate prediction, treatment preparation, and tracking tumor growth or shrinkage in affected humans during treatment. [3, 4]. There are two types of brain tumor detection strategies currently available: interactive approaches and automated approaches.Interactive approaches do not involve a large amount of training data. It necessitates user feedback, such as defining a point of interest or having labels denoting the labels of specific pixels to fall into a particular class. While interactive approaches produce better detection results, qualified individuals must concentrate more on detection until satisfactory results are obtained [5]. As a result, image processing-based automated brain tumor detection techniques were developed to help in the accurate diagnosis of tumors.

In image processing techniques, images have to undergo four phases given as: preprocessing, segmentation, feature extraction and classification. The elimination of speckle noise, which prevents the loss of edge information as well as essential attributes, is the first step in preprocessing. Various experiments on the reduction of speckle noise have been performed. Linear filters are widely recognized as one of the most powerful image preprocessing techniques. A linear filter's transfer function modifies a portion of the signal frequency spectrum. But they disregard the noise and image characteristics scattered around the image, which blurs the contrast as well as the edge area of the corresponding image [6]. Another type of predefined filter is the Discrete Cosine Transform (DCT) filter, which is commonly used in real-time applications to obtain input attributes with reduced reconstruction time. Yet, these filters need to be improved in terms of efficiency and quality [7]. Subsequently, for preprocessing, mean filter is used, which decreases the amount of intensity difference between one pixel and the other. The image's pixel value is substituted by the average value of neighbors, and pixels that are not similar to the neighbors are omitted. The main disadvantage of mean filters is that they can emit pseudo noise edges due to edge breakup [8]. Due to the above-mentioned disadvantages, an adaptive median filter is used in this approach for efficient image preprocessing by minimizing non-specific noise while preserving edges.

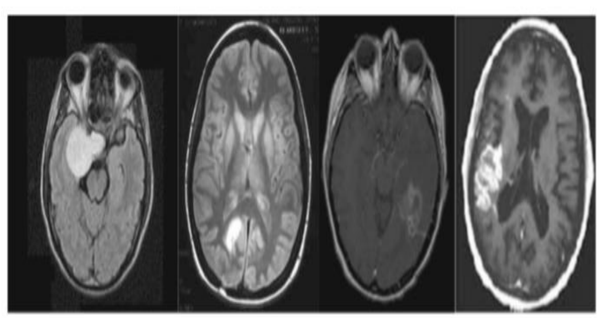


Figure 1 Images of brain with abnormal tissue

The preprocessed image is then segmented which is termed a process that separates a digital image into several segments. For image segmentation, a variety of methods were used, with region-based segmentation being one of the most common. Closed contour regions are created using this technique, but it may reject resolution and image properties [9]. The U-net algorithm, which explains the problem of minimal quality segmentations from minimal quality image data, is also used for segmentation, but it may result in feature loss [10]. OTSU image segmentation algorithm is also utilized which diminishes the occurrence of misclassification generating a perfectly segmented image. It adopts a threshold value for the segmentation process but does not provide detailed information for detected images [11]. To overcome these issues, the Fuzzy C means image segmentation algorithm is used, which produces better results and generates a perfectly segmented image.

Features must be extracted from the image after segmentation to reduce the amount of redundant data in the dataset. Local Binary Pattern (LBP) is generally adopted method for feature extraction that extracts the feature using a local neighborhood. LBP demands further enhancement to extract more complex features [12]. Linear Discriminant Analysis (LDA) is another feature extraction tool that aims to increase the gap between each class's mean as well as minimize class spread. However, it needed additional capability enhancements that provides limited side details, as well as rigidity against rotation and content loss attacks [13]. Principal Component Analysis (PCA) is an approach for the extraction of attributes that determines orthogonal transformations to increase the complete variance of predicted results. However, since spectral features of images have different properties, feature extraction using a single projection is not possible in PCA [14]. As a result, an effective Gray Level Co-occurrence Matrix (GLCM) is adopted for the extraction of features and evaluate the occurrence of various gray level combinations in an image.

Following image feature extraction, classification involves categorizing all pixels in a digital image into one of many groups. A commonly used method for image classification is the Random Forest (RF) algorithm, which employs a cascade system in which feature information is given to each layer. It takes into account the possibility of overfitting, increases accuracy, and is adaptable to both classification and regression problems. But the computing power demand and training time consumption are extremely high [15]. The Decision Tree algorithm, which uses a single polarimetric attribute in the decision tree nodes, is also used for image classification. However, when applied to nodes with identical scattering properties, the classification capacity is diminished, and the scattering properties are difficult to describe [16]. By increasing the interval between positive as well as negative samples of training set, a Support Vector Machine (SVM) classifier depending on supervised learning is used for image classification. It enhances classification and prediction capabilities, but it is unsuccessful in high-noise settings [17]. Hence, the proposed approach uses ANN to classify the inputs according to target class.

In this paper, efficient diagnosis of brain tumor is performed adopting image processing approaches. The contributions of this paper are given by:

- Adaptive median filter is utilized for the preprocessing of input image to make the image noise clear.
- Fuzzy C means algorithm is adopted for the segmentation of input image by clustering approach.
- Consequently, the feature extraction from image is done by GLCM performing texture feature extraction.
- Classification is performed by ANN representing simple linear or nonlinear connections.

The remaining paper is structured as follows: Section 2 illustrates the literature survey of the proposed system, section 3 details the proposed system, section 4 includes the discussion about obtained results as well as section 5 concludes the paper.

2 RELATED WORKS

Changhee et al [18] proposed a GAN-dependent data augmentation which generated and refined the MR images of brain possessing tumors and without tumors. Progressive Growing of GANs, many-stage noise-to-image GAN regarding increased-resolution MR image generation, initially generated diverse 256×256 images. Multimodal unsupervised Image-to-image Translation (MUNIT) which integrates GANs utilizing a DA-focused GAN loss, later refined the texture of the PGGAN-developed images equal to actual images. The CNN-dependent tumor classification outputs are investigated, and the impact of pre-training on ImageNet as well as images are considered.

Alexis et al [19] proposed an approach in which the quantitative magnetic resonance (MR) parameters is integrated with improved statistical tools which are multivariate for designing a completely automated approach performing both localization as well as characterization. The non-trivial interconnections among physiological parameters are captured providing a huge range of distributional shapes comparing to increased standard Gaussian distributions. Probabilistic mixtures of the distributions obtained before are also regarded for various tissue categories as well as potential heterogeneity of lesions.

Gottappu et al [20] described an approach of various-level extraction of features as well as progression for timely prediction of brain tumor. Utilizing two models namely Inception-v3 as well as DensNet201, two categories of detection of brain tumor were studied. Initially, the parameters from various inception approaches are obtained and progression of these features is performed. Next, pre-trained DensNet201 was utilized for extracting attributes from different DensNet blocks. Finally the parameters are progressed as well as applied to softmax classifier for classifying the brain tumor.

Eman et al [21] investigated advanced approaches for providing complete-brain coverage. It utilized K means as well as Fuzzy addressing two major problems: choosing the optimal framework for improving the quality of segmentation as well as generating improved accuracy. The evaluation concluded as the framework possessed the perfect agreement to ground truth data. In addition, comparisons were performed with state of the art algorithms.

Sergio et al [22] produced a tumor detection approach harnessing CNN by the utilization of small kernels for segmenting the tumor region. This approach investigated the utilization of normalization of intensity. The proposed approach is efficient with its high accuracy compared to other methods.

Pradeep et al [23] introduced an approach for compression of images utilizing a deep wavelet auto encoder that combines the fundamental feature reducing attribute of auto encoder with the image decomposition feature of wavelet transform. Combining both had a remarkable effect on decreasing the size of the feature set to assure remaining classification process by adopting DNN. A brain image dataset as well as DWA-DNN image classifier was considered.

Shang et al [24] proposed anobjective to improve the segmentation accuracy of brain tumor. An enhanced component for the extraction of features is presentedthereby considering the advantages of correlation between the deformation of intracranial structure and the compression which occurs due to the growth of tumor in brain.Broadly utilized algorithms for classification are deployed leading to promising results.

Munendra et al [25] proposed an approach for post processing DCE-MRI data utilizing multistable stochastic resonance method. Multi-objective ant lion optimization is used for optimizing the contrast enhancement factor as well as image anisotropy by variation of parameters linked with MSSR dynamics. The fixed regions of interest are denoted by normal and micro adenoma of pituitary attained with high accuracy level as well as confidence utilizing the introduced method.

Arunkumar et al [26] described an enhanced automated segmentation of brain tumor as well as identification method utilizing ANN from MR images in absence of human mediation with the application of perfect attributes to brain tumor case disclosure. For obtaining the appropriate brain tumor location from MR images, brain tumor segmentation method was introduced. Initially, *K*-means clustering was adopted for the principal organizing to improve the MR image which has to be positioned in regions in light of their gray scale. Further, ANN is adopted for choosing the exact object for training phase. Next, texture feature of brain tumor region will be obtained to the division process.

3 PROPOSED SYSTEM

Regardless of age, brain tumor is one of the primary causes of death. With the advent in imaging and image processing methods, physicians should be able to get more knowledge and make better healthcare decisions. Any imaging modality can be used to identify brain tumors, which can then be analyzed using image processing techniques for precise tumor classification. Numerous preprocessing concepts, feature extraction approaches, as well as classification algorithms have been proposed by many researchers. Preprocessing should be performed with a suitable filter to ensure that the image edges are not missing.

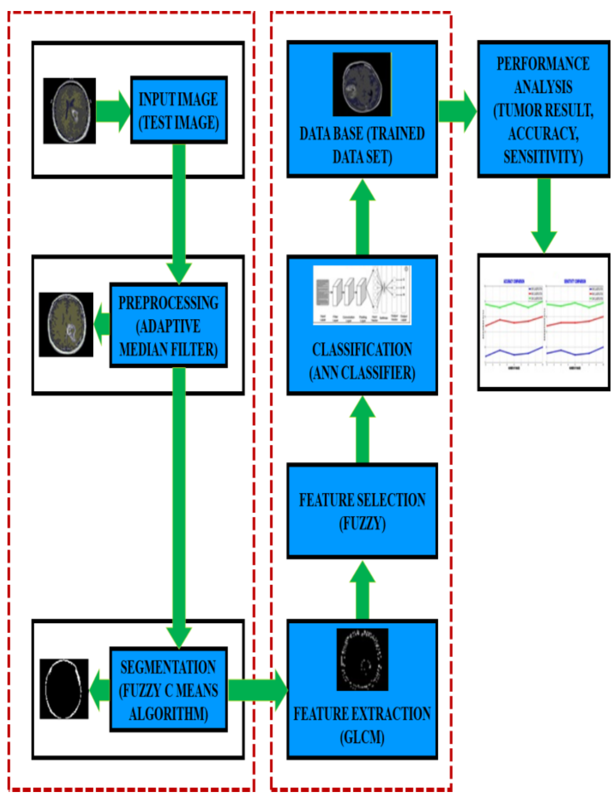


Figure 2 Block diagram of the proposed approach

3.1Image Pre-Processing

The input MR image is subjected to pre-processing by adaptive median filter for the removal of noise. Since the value of every pixel is determined the neighboring pixels' median, the median filter is minimal sensitive than outliers. The impact of adaptive median filter depends on ranking the pixels in the image area covered by the filter. Further the center pixel value is replaced with the value defined by the ranking output. It replaces the pixel value with the gray level median in its pixel neighborhood. For certain forms of random noise, median filters are common because these filters offer improved noise-minimizing abilities with substantially minimal blurring compared to linear smoothing filters of comparable scale. The center pixel in a window that slides pixel by pixel over the complete image is replaced with the median of gray levels in median filtering. Consider an $(A * B)$ image, $I(p,q)$ with $I(p,q) \in \{1,2,\dots,A\} * \{1,2,\dots..B\}$, a 2-dimensional (x*x) median filter is given by,

$$I(p,q) = median\{I(p+u, q+v)\} \quad (1)$$

Where, $u, v \in \left(-\left(\frac{x-1}{2}\right), \dots, \left(\frac{x-1}{2}\right)\right)$ and $x(i,j)$ denotes the pixel at point (i,j).

This pre-processing technique with median filters generates smoothened images while retaining the edges, which is an essential function. As a consequence, the median filter is usually employed as a denoising filter.

3.2 Image Segmentation

Fuzzy C-Means (FCM) clustering is a clustering approach that iteratively searches for a collection of fuzzy clusters and their related cluster centres that potentially represents the data structure. It permits division of existing set of points related to power n indicated by a number of fuzzy sets. The uniqueness of the approach is the utilization of fuzzy membership matrix$Y = \{y_{ik}\}$, where elements denote the degree of membership of k^{th} element of initial group of vectors to i^{th} cluster. FCM partitions data $D = \{d_1, d_2, \dots\dots, d_n\}$ into c clusters with center of the clusters $Z = (z_1, z_2, \dots\dots z_c)$ reducing the objective function,

$$F(Y,Z) = \sum_{i=1}^{c}\sum_{k=1}^{n}(y_{ik})^m \|d_k - z_i\|^2, \quad (2)$$

$$y_{ik} \in [0,1], \quad i = \overline{1,c}, \quad k = \overline{1,n}, \quad 1 \le m < \infty$$

in which m denotes fuzziness index, y_{ik} denotes degree of membership of d_k in i^{th} cluster, $z_i$is the centre of i^{th} cluster, $\|d_k - z_i\|^2$ denotes distance between the data d_k and the centre of the cluster z_i.

$$y_{ik} = \left(\sum_{j=1}^{c}\left(\frac{\|d_k - z_i\|}{\|d_k - z_j\|}\right)^{\frac{2}{m-1}}\right)^{-1}, \quad \sum_{i=1}^{c} y_{ik} = 1 \quad (3)$$

$$z_i = \frac{\sum_{k=1}^{n}(y_{ik})^m . d_k}{\sum_{k=1}^{n}(y_{ik})^m} z_i = \frac{\sum_{k=1}^{n}(y_{ik})^m . d_k}{\sum_{k=1}^{n}(y_{ik})^m} \quad (4)$$

The matrix Y is determined utilizing equation (3) and the corresponding clusters are determined by equation (4) and the square error is determined in equation (2). When the error is less than a specific tolerance value or when its performance regarding before iterations is less than specific threshold, the algorithm concludes. When $\rightarrow\infty$, objects group to clusters with same degree. The value m permits improving the impact of objects with greater values of degree of membership and minimize the impact of objects with less value of degree of membership.

3.3Feature Extraction

Gathering improved-level image details like colour, texture, shape, and contrast. In reality, texture analysis is a critical component of human visual perception as well as machine learning. By choosing prominent features, it is efficiently used to increase the precision of the diagnostic system. GLCM is an effective approach for texture feature extraction and it mainly comprises of two steps. In the initial step GLCM is evaluated and secondly, texture features depending GLCM are determined. The features extracted and employed for classification are indicated below,

a) Energy

It defines the size of the concentration of the pair with particular gray intensity in co-occurrence matrix and is expressed as,

$$Energy = \sum_{i=1}^{L}\sum_{j=1}^{L} q(i,j)^2 \quad (5)$$

b) Contrast

It indicates the size of the scattering of inertia moments or changes in image matrix and is given by,

$$Contrast = \sum_{i}^{L}\sum_{j}^{L}|i-j|^2 q(i,j) \quad (6)$$

c) Homogeneity

Homogeneity denotes the degree of homogeneity of an image on a gray scale level and is expressed as,

$$Homogeneity = \sum_{i=1}^{L}\sum_{j=1}^{L}\frac{q(i,j)^2}{1+(i-j)^2} \quad (7)$$

d) Entropy

Entropy evaluates lost information or messages from transition signal as well as determines image information and is expressed as,

$$Entropy = \sum_{i=1}^{L}\sum_{j=1}^{L} q(i,j)(-\ln q(i,j)) \quad (8)$$

e) Correlation

Correlation denotes the linear dependence estimate of gray currency matrix related to image and is given by,

$$Correlation = \sum_{i=1}^{L}\sum_{j=1}^{L}\frac{(i-\mu_i)(j-\mu_i)p(i,j)}{\sigma_i\sigma_j} \quad (9)$$

The above mentioned features are effectively extracted from the image utilizing GLCM approach and further fed to the feature selection process.

3.4 Feature Selection

A process which determines the subset of fuzzy sets is necessary when the count of fuzzy sets or the count of features is greater. The feature selection by fuzzy evaluates optimal combination of fuzzy setsμ_{ij}. When every subset of fuzzy sets are determined using criterion function $F(.)$ and all corresponding combinations of fuzzy subsets is indicated utilizing the power set P, then fuzzy feature selection denotes an evaluating fuzzy set subset $V_{optimal}$ satisfying

$$F(V_{optimal}) = E(F(V_i)), \quad \forall V_i \subseteq P, P = 2^V (10)$$

in which E is regarded as the maximum or minimum operator.

In case of conventional search or genetic algorithms one can minimize the criterion function$F(.)$. In addition, the neural networks, can also be applied by utilizing the data of the fuzzy projected set S_x as the inputs to a feed-forward neural network. The algorithm for the fuzzy feature selection is given as,

1) Perform projection of a data set which is labelled $Y\{y_i|i = 1,2,\dots,n\}$ into a fuzzy set S_x denoted by$V\{\mu_{ij}|i = 1,2,\dots,p \wedge f = 1,2,\dots\dots,|f_i|\}$. This projection can be denoted as non-linear or linear functions.
2) Identify a classifier, criterion function $F(.)$ as well as $P = 2^V$.
3) Utilize feature selection method.
4) Determine $V_{optimal}$ so that $F(V_{optimal}) = E(F(V_i)), \quad \forall V_i \subseteq P$.

3.5 Classification of Images

Artificial neural systems (ANNs) are artificial intelligence techniques that simulate the human brain's activity and can represent simple linear or non-linear connections within input as well as target data. ANN obtains data from an external source and feeds it to its internal processing units, which then transmits through methods for communicating transfer functions as well as association parameters within adjacent layers. An artificial neural network (ANN) is a network that consists of several layers, for example, a three-layer network with a large count of neurons performing the process of translating input data into necessary output. In most cases, a Multi-Layer Perceptron (MLP) feed-forward network is used, which consists of three layers: input (x), output, and a hidden layer(y) as shown in figure 3. These layers are linked to a certain number of neurons. The synaptic weights of the neurons in each layer are different. Layers are decided to move input parameters through, and the count of neurons in each layer is linked to input parameters.

The input layer data which is the obtained brain features is fed to the hidden layer. The input layer will have the same number of neurons as the count of features obtained from the input image. The resulting neurons will be predetermined and the output should coordinate the objective. The network utilizes supervised learning method, and requires a training set as (input, target) vectors.

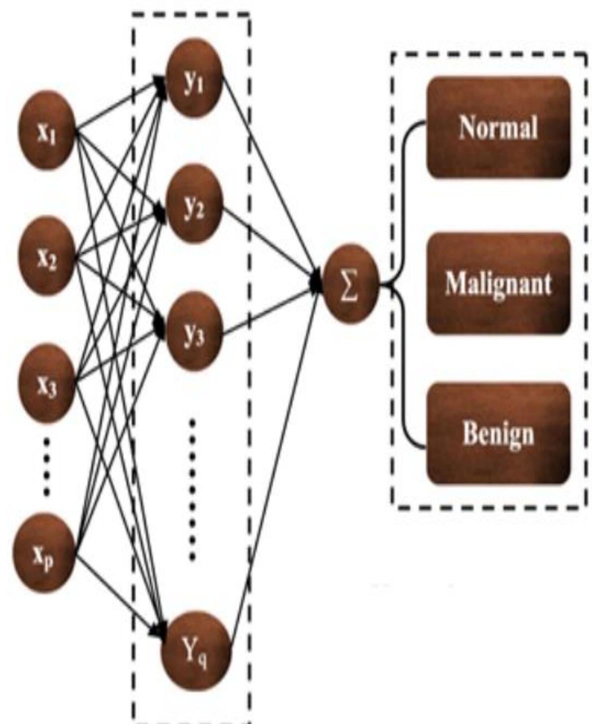


Figure 3 Proposed ANN architecture

4 RESULTS AND DISCUSSION

The MR brain images database of Harvard medical school is utilized as input data set and the corresponding images are given in figure 4. It clearly depicts the images of the malignant, benign and normal brain tumor images.

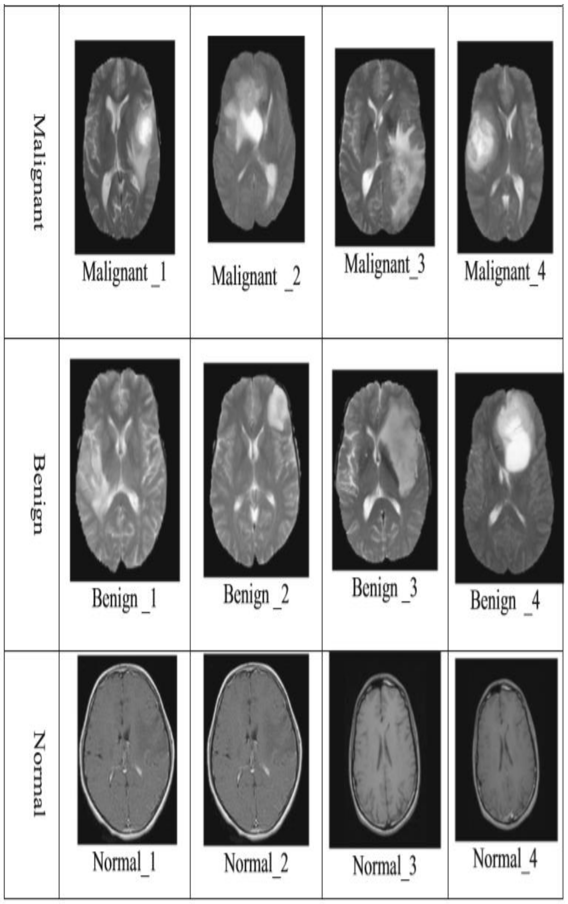
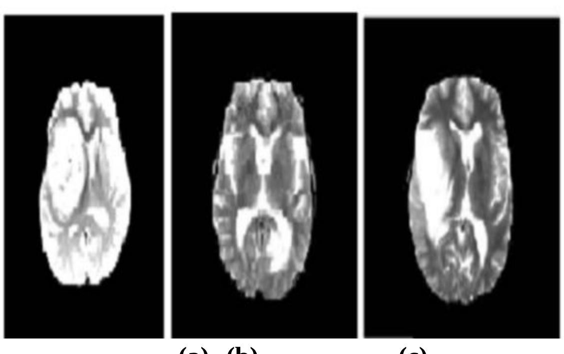


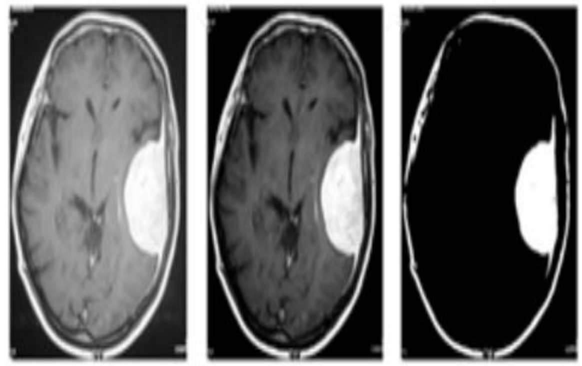
Figure 4 Images of input dataset

The pre-processing of input images are performed to eliminate the noise utilizing adaptive median filter and the pre-processed outputs are given in figure 5.



(a) (b) (c)
Figure 5 Preprocessed outputs

The pre-processed image is subjected to segmentation by FCM clustering and the corresponding enhanced as well as segmented outputs are shown in figure 6.



(a) (b)
(c)

Figure 6 FCM clustering (a) Input image (b) Enhanced image (c) Output of FCM clustering

The features extracted by GLCM approach are denoted in the table 1. Features like energy, contrast, homogeneity, entropy, correlation are extracted from the brain tumor images.

Table 1 Features extracted by GLCM approach

Images	Energy	Contrast	Homogeneity	Entropy	Correlation
Image 1	0.408	0.265	0.925	0.65	0.985
Image 2	0.382	0.473	0.863	0.94	0.945
Image 3	0.693	0.276	0.932	3.03	0.945
Image 4	0.348	0.356	0.898	0.45	0.977
Image 5	0.266	0.334	0.898	2.09	0.983
Image 6	0.384	0.304	0.903	1.12	0.980

Performance metrics

The performance metrics of the parameters like accuracy, sensitivity and specificity are evaluated.

a) Accuracy

It denotes the percentage of appropriately classified instances and is given by,

Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$

b) Sensitivity

Sensitivity expresses the proportion of positives that are exactly detected and is given by,

Sensitivity = $\frac{TP}{TP+FN}$

c) Specificity

Specificity expresses the proportion of negatives that are exactly detected and is given by,

Specificity = $\frac{TN}{TN+FP}$

Table 2 Comparison of performance metrics

Methods	Accuracy	Sensitivity	Specificity
ANFIS	90.04	96	80
Back propagation	85.57	97	75
SVM	96.51	97.5	86
KNN	87.06	95	78
ANN	97.5	98.5	95

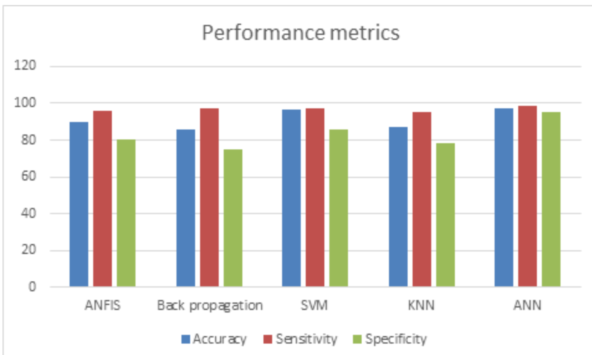


Figure 7 Performance metrics of existing methods and ANN

From the table 2 it is clear that the proposed classification method resulted in efficient outputs when compared to other classifiers like ANFIS [27], back propagation [28], SVM [29] and KNN [30]. The corresponding characteristic plot for the comparison of performance metrics is given in figure 7. From the graph it is clear that the proposed approach resulted improved values of accuracy, sensitivity and specificity. Thus the proposed approach effectively detects brain tumor in the input MR images.

5 CONCLUSION

In this paper, an efficient brain tumor detection approach is proposed which identifies the tumor affected region in input images of brain through various processing phases of images. Adaptive mean filter along with Fuzzy C means algorithm is adopted for the preprocessing and segmentation of images respectively. The features are extracted by GLCM and the optimal selection of features is performed by fuzzy concept. Finally, the classification of images is performed through ANN approach. The performance metrics including accuracy, sensitivity and specificity are analyzed. In future, the accuracy of classification can be improved by extracting more efficient features as well as utilizing increased number of training data set.

References

[1] Sultan, H. H., Salem, N. M., & Al-Atabany, W, “Multi-classification of brain tumor images using deep neural network”, IEEE Access, Vol.7, pp. 69215-69225, 2019.
[2] Shakeel, P. Mohamed, Tarek E. El Tobely, Haytham Al-Feel, GunasekaranManogaran, and S. Baskar, “Neural network based brain tumor detection using wireless infrared imaging sensor”, IEEE Access, Vol. 7, pp. 5577-5588, 2019.
[3] Ming Li, LishanKuang, Shuhua Xu, ZhanguoSha, “Brain Tumor Detection Based on Multimodal Information Fusion and Convolutional Neural Network”, IEEE Access, Vol. 7, pp. 180134 – 180146, 2019.
[4] Manogaran, G., Shakeel, P. M., Hassanein, A. S., Kumar, P. M., &Babu, G. C, “Machine learning approach-based gamma distribution for brain tumor detection and data sample imbalance analysis”, IEEE Access, Vol. 7, pp. 12-19, 2018.
[5] HimarFabelo, Samuel Ortega, Adam Szolna, DiederikBulters, “In-Vivo Hyperspectral Human Brain Image Database for Brain Cancer Detection”, IEEE Access, Vol. 7, pp. 39098 – 39116, 2019.
[6] Hyunho Choi, JechangJeong, “Despeckling Images Using a Preprocessing Filter and Discrete Wavelet Transform-Based Noise Reduction Techniques”, IEEE Sensors Journal, Vol. 18, no. 8, pp. 3131 – 3139, 2018.
[7] Lawgaly, Ashref, and FouadKhelifi, "Sensor pattern noise estimation based on improved locally adaptive DCT filtering and weighted averaging for source camera identification and verification", IEEE Transactions on Information Forensics and Security, Vol. 12, no. 2, pp. 392-404, 2016.
[8] Qiu, X., Li, M., Zhang, L., & Yuan, X., “Guided filter-based multi-focus image fusion through focus region detection”, Signal Processing: Image Communication, Vol. 72, pp. 35-46, 2019.
[9] Liyilei Su, Xianjun Fu, Xiaodong Zhang, Xiaoguang Cheng, Yimin Ma, YungenGan, Qingmao Hu, “Delineation of Carpal Bones From Hand X-Ray Images Through Prior Model, and Integration of Region-Based and Boundary-Based Segmentations”, IEEE Access, Vol. 6, pp. 19993 – 20008, 2018.
[10] Weng, Y., Zhou, T., Li, Y., &Qiu, X, “NAS-Unet: Neural architecture search for medical image segmentation”, IEEE Access, Vol.7, pp.44247-44257, 2019.
[11] Feng, Y., Zhao, H., Li, X., Zhang, X., & Li, H, “A multi-scale 3D Otsu thresholding algorithm for

medical image segmentation", Digital Signal Processing, Vol. 60, pp. 186-199, 2017.

[12]Zhikun Chen, Junjun Jiang, Chong Zhou, ShaoyuanFu;ZhihuaCai, "SuperBF: Superpixel-Based Bilateral Filtering Algorithm and Its Application in Feature Extraction of Hyperspectral Images", IEEE Access, Vol. 7, pp. 147796 – 147807, 2019.

[13]Xiang Zhang;Fei Peng, Min Long, "Robust Coverless Image Steganography Based on DCT and LDA Topic Classification", IEEE Transactions on Multimedia, Vol. 20, no. 12, pp. 3223 – 3238, 2018.

[14] Junjun Jiang, Jiayi Ma, Chen Chen, Zhongyuan Wang, ZhihuaCai, Lizhe Wang, "SuperPCA: A Superpixelwise PCA Approach for Unsupervised Feature Extraction of Hyperspectral Imagery", IEEE Transactions on Geoscience and Remote Sensing, Vol. 56, no. 8, pp. 4581 – 4593, 2018.

[15] Xia, J., Ghamisi, P., Yokoya, N., & Iwasaki, A, "Random forest ensembles and extended multiextinction profiles for hyperspectral image classification", IEEE Transactions on Geoscience and Remote Sensing, Vol. 56, no.1, pp. 202-216, 2017.

[16] Rafael Rivera-Lopez, Juana Canul-Reich, "Construction of Near-Optimal Axis-Parallel Decision Trees Using a Differential-Evolution-Based Approach", IEEE Access, Vol. 6, pp. 5548 – 5563, 2018.

[17] Chen Li, Hao Chen, Le Zhang, Ning Xu, Dan Xue, Zhijie Hu, He Ma, Hongzan Sun, "Cervical Histopathology Image Classification Using Multilayer Hidden Conditional Random Fields and Weakly Supervised Learning", IEEE Access, Vol. 7, pp. 90378 – 90397, 2019.

[18] Changhee Han, Leonardo Rundo, Ryosuke Araki, Yudai Nagano, Yujiro Furukawa, Giancarlo Mauri, Hideki Nakayama, Hideaki Hayashi, "Combining Noise-to-Image and Image-to-Image GANs: Brain MR Image Augmentation for Tumor Detection", IEEE Access, Vol. 7, pp. 156966 – 156977, 2019.

[19] Alexis Arnaud, Florence Forbes, Nicolas Coquery, Nora Collomb, Benjamin Lemasson, Emmanuel L. Barbier, "Fully Automatic Lesion Localization and Characterization: Application to Brain Tumors Using Multiparametric Quantitative MRI Data", IEEE Transactions on Medical Imaging, Vol. 37, no. 7, pp. 1678 – 1689, 2018.

[20] Gottapu, R. D., &Dagli, C. H, "DenseNet for anatomical brain segmentation", Procedia Computer Science, Vol.140, pp.179-185, 2018.

[21] Abdel-Maksoud, Eman, Mohammed Elmogy, and Rashid Al-Awadi, "Brain tumor segmentation based on a hybrid clustering technique", Egyptian Informatics Journal, Vol.16, no. 1, pp.71-81, 2015.

[22] Pereira, S., Pinto, A., Alves, V., & Silva, C. A. "Brain tumor segmentation using convolutional neural networks in MRI images", IEEE transactions on medical imaging, Vol. 35, no. 5, pp.1240-1251, 2016.

[23] Pradeep Kumar Mallick, Seuc Ho Ryu, Sandeep Kumar Satapathy, Shruti Mishra, GiaNhu Nguyen, Prayag Tiwari, "Brain MRI Image Classification for Cancer Detection Using Deep Wavelet Autoencoder-Based Deep Neural Network", IEEE Access, Vol. 7, pp. 46278 – 46287, 2019.

[24] Jui, Shang-Ling, Shichen Zhang, WeilunXiong, Fangxiaoqi Yu, Mingjian Fu, Dongmei Wang, Aboul Ella Hassanien, and Kai Xiao, "Brain MRI tumor segmentation with 3D intracranial structure deformation features", IEEE intelligent systems, Vol. 31, no. ,pp. 66-76, 2015.

[25] Munendra Singh, Ashish Verma, Neeraj Sharma, "Optimized Multistable Stochastic Resonance for the Enhancement of Pituitary Microadenoma in MRI", IEEE Journal of Biomedical and Health Informatics, Vol. 22, no. 3, pp. 862 – 873, 2018.

[26] Arunkumar, N., Mohammed, M. A., AbdGhani, M. K., Ibrahim, D. A., Abdulhay, E., Ramirez-Gonzalez, G., & de Albuquerque, V. H. C, "K-means clustering and neural network for object detecting and identifying abnormality of brain tumor", Soft Computing, Vol. 23, no. 19, pp. 9083-9096, 2019.

[27] Nguyen, S. D., Choi, S. B., &Seo, T. I, "Recurrent mechanism and impulse noise filter for establishing ANFIS", IEEE Transactions on Fuzzy Systems, Vol. 26, no. 2, pp. 985-997, 2017.

[28] Abuzneid, M. A., & Mahmood, A, "Enhanced human face recognition using LBPH descriptor, multi-KNN, and back-propagation neural network", IEEE access, Vol. 6, pp. 20641-20651, 2018.

[29] Devkota, B., Alsadoon, A., Prasad, P. W. C., Singh, A. K., &Elchouemi, A, "Image segmentation for early stage brain tumor detection using mathematical morphological reconstruction",Procedia Computer Science, Vol. 125, pp. 115-123, 2018.

[30] Tu, B., Wang, J., Kang, X., Zhang, G., Ou, X., &Guo, L, "KNN-based representation of superpixels for hyperspectral image classification", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol.11, no. 11, pp. 4032-4047, 2018.