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BrainTumor Classification Using Deep Learning

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Abstract: A brain tumor is a serious disease that takes numerous life annually. Identification and classification from magnetic resonance imaging (MRI) are valuable for a particular medical care. Identification of a brain tumor in MRI is still a decisive and complicated job for physicians. This work is seeking to produce an automated system for segmentation and classification of a tumor in theMRI image. A methodology based on the Fuzzy C-means algorithm for segmentation which, is a substantive step in medical image analysis, the Grey Level Co-occurrence Matrices (GLCM) for feature extraction, and Deep Neural Network (DNN) for classification. The proposed system has been tested with datasets and the experimental results demonstrate good performance.

Keywords: Brain tumor detection, Deep Learning,FCM, Image segmentation

I. INTRODUCTION

A brain tumor is a life threating disease that affects the human life-sustaining organ. A brain tumor is one of the common brain ailments, has influenced and ravaged numerous lives, approximately 150,000 patients diagnosed each year only in the United States [1]. For the exact diagnose of disease, physicians use medical images. Magnetic resonance imaging (MRI) inspect the brain to assert the appearance of a brain tumor and to recognize its region for chose expert treatment alternatives. Identification of a brain tumor from medical images is still a critical and complicated job for physicians. Brain tumor determination from MRI made up of several stages. Segmentation is perceived to be a fundamental step in medical image analysis. Conducting the brain MRI images segmentation by hand is an arduous task as there is respective intricacy connected with it. Doctors and medical experts spend a lengthier time for manually segmenting brain MRI images, and this is an irreversible task. In addition, a problem when performing MRI procedures images sometimes is corrupted by noise. This may lead to difficulties in identifying the tumor.

Classification of a tumor as normal or abnormal is required, which is achieved by using machine learning algorithms. Issues regarding classification of MRI images are performance, computation resources, and accuracy. Classification algorithm needs certain features to be extracted from both normal and abnormal MRI images. For the past years, various methods for extracting features from brain MRI images are developed. However, features extraction and classification brain tumors remain unwieldy task.

The proposed methodology for brain tumor detection and classification consists of four phases: the first phase, pre-processing MRI images captured may susceptible to noise. This phase performs de-noising for the MRI images by applying the median filter. The second phase, the image is segmented into various regions to locate a tumor. The segmentation performed with the aid of the Fuzzy C-means algorithm (FCM). The third phase features extraction: texture is an important characteristic used in recognizing regions of concern in the image. Grey Level Co-occurrence Matrices (GLCM) is used for feature extraction. The final phase, the deep neural network is built for classifying tumors as normal or abnormal.

The next section lists some previous related work. Section 3 describes the proposed methodology for brain tumor classification in MRI images. After that section 4 shows the experimental results with a comparative analysis of the proposed methodology. Finally, the conclusion is covered in section 5.

II. RELATED WORK

Reema Mathew A et al. [2] proposed a framework to segment and classify a brain tumor from MRI images, they used Ostu's thresholding for preprocessing. A tumor is detected with the help of K-Means clustering. Discrete wavelet transforms (DWT), Gabor wavelet and GLCM features. Extracted features fed to SVM classifier and SVM with linear kernel made the highest accuracy. Amruta hebli et al. [3] developed a methodology to distinguish between benign and malignant tumors from brain MRI's. Images segmented with morphological operations, and structural, statistical and texture features are acquired. Best classification results obtained using SVM with RBF and polynomial kernels.

Sanjeev Kumar et al. [4] suggested a Hybrid approach for classification of brain MRI tumor images. This approach is a combination of DWT applied for feature extraction, then the principal component analysis (PCA) for features selection and for the classification of images the SVM has been used. V. Anitha1 et al. [5] Proposed approach use adaptive pillar K-means for MRI segmentation and a two-tier classifier to classify tumors. The self-organizing map (SOM) is used for initial training, then K-nearest neighbor (KNN) utilized to classify images. The authors reported that the proposed two-tier classification system performance in terms of accuracy is better than SVM based classification technique.

Zhe Xiao et al. [6] proposed a deep learning approach for brain tumor segmentation and classification. The Stacked De-noising Auto-Encoder (SDAE) used to automatically learn classification features, then a network with multiple hidden layers built for classification. Results indicate that deep learning achieved better accuracy than SVM. P. Chinmayi et al. [7] designed a classification system consists of three stages first, pre-processing, second, implementing fast bounding box algorithm, finally, using Convolutional Neural Network (CNN) for classification. In terms of accuracy and the similarity index, the proposed approach considered to yield high accuracy. Kamil Dimililer et al. [9] designed a system for brain tumor detection in MRI images using a conventional 3-layer back propagation neural network for classifying the organs with tumors and without tumors on two datasets. The first dataset contains original images, and the second dataset includes pre-processed images. Classification with pre-processed images produces better results. R. Lavanya Devi et al. [8] developed a classification system based on GLCM for feature extraction, K-means for segmentation and probabilistic neural network (PNN) for classification. The authors favored the use of PNN over other techniques, and justify that as it is fast and provides good accuracy results.

III. PROPOSED METHODOLOGY

Figure 1 below depicts the proposed methodology.

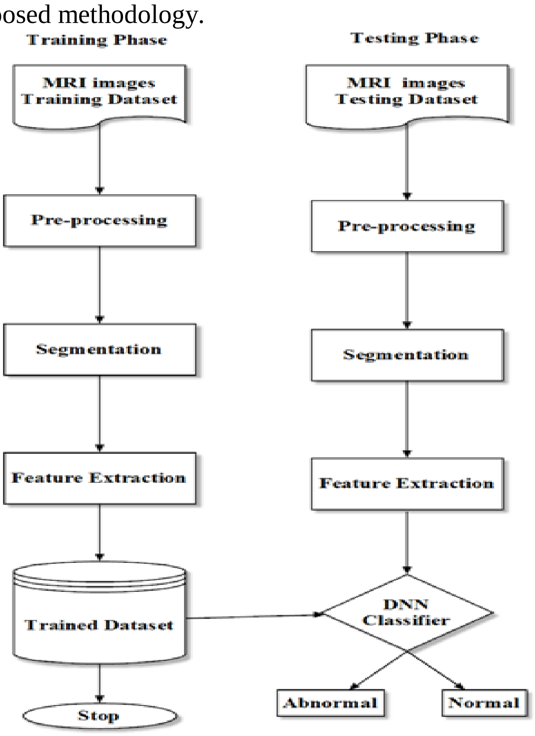

Fig. 1 proposed methodology

3.1 Preprocessing

The objective of pre-processing the image is to streamline the identification of tumor areas without discarding any significant information. Enhancing techniques are one way to perform pre-processing. The purpose of enhancement techniques is twofold. First, noise removal to generate improved images that is suitable for human reviewing. Second, contrast enhancement and sharpening details for later computer algorithm processing. [10]. Filters can smooth, sharpen, transform, and de-noise an image so that we can draw the required information to heighten edges, enumerate the edges of any holes in a particle, and make the contrast between the elements and the background. [11]

3.2 Median Filter

Image noise is an undesirable part or superfluous piece of the image. Image noise is a pixel change development discrete or isolated in space. It influences the quality of the digital image, which can restrain the valuable information thus influencing the accuracy of data extraction [14]. The median filter is applied to eliminate the noise from images. Equation 1 describes the median filter:

$$g(x,y) = median\{f(s,t)\}_{(s,t)\in sxy} \qquad (1)$$

where f is the input image, g is the filtered image and (x, y) are the spatial coordinates of the central pixel within a filtering window of size W x W pixels [12]. In median filtering, all the pixels of the image were filtered based on the neighbor pixel value median filter substitutes value with the median of those values. Neighbor pixels are also known as window [13].

3.3 Segmentation

Image segmentation is the process of constituting a label to every pixel in an image to the extent that pixels with a similar mark share certain visual properties. To draw some significant information from an image, segmentation changes the composite image into a straightforward image which helps the system to examine the image [15].The fuzzy C-means (FCM) is used for segmentation. The FCM algorithm is based on fuzzy set and fuzzy clustering, these concepts, are briefly introduced below.

3.3.1 Fuzzy Set

Fuzzy set (FS) is an extension of the classical set. In FS theory, a fuzzy set *A in* a finite set *X*= {*x*1, *x*2, …, *xn*} can be represented as $A = \{(x, \mu_A(x)) | x \in X\}$ where the function $\mu_A(x){:}X \to [0,1]$) denotes the membership degree of an element x in A. [16]

3.3.2 Clustering

A cluster is a group of items which are similar linking them and dissimilar to the object belonging to others.Clusteringis targeted to partition the given data items into groups on the basis of similarities between them.Here, data items are images when image clustering is applied for image retrieval and pixels in the case of segmentation. Clustering maintains two characteristics i.e. maximize intra-cluster homogeneity and inter-cluster heterogeneity.Fuzzy clustering (e.g. (FCM)) addresses the indistinctness in a cluster membership of the data item [17].

3.3.3 The fuzzy C-means (FCM)

FCM is a fuzzy clustering method that associates a specific level of membership of an object to the object's distance to the middle of the group. An object will incline to be a cluster member if the object has the highest level of membership in the cluster [19].A set of vectors of n (X=x1, x2, …, xn) will be grouped into c cluster center 1 <c <n + 1. Each vector has dimensions of D. The objective function in FCM is defined as the multiplication between the membership μ_{ij} value and the Euclidean distance between the object and the cluster center. The FCM objective function formula [18], [20]:

$$J_m(u,v) = \sum_{i=1}^{n}\sum_{j=1}^{c}(\mu_{ij})^m \left\| x_i - v_j \right\|^2 \quad (2)$$

The minimization of the objective function Jm in the FCM algorithm is performed by modifying reiteratively from the cluster center and the membership matrix using the following formula [21]:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\left\|x_i - v_i\right\|}{\left\|x_i - v_k\right\|}\right)^{\frac{2}{m-1}}} \qquad (3)$$

$$v_j = \frac{\sum_{i=1}^{n}(\mu_{ij})^{m_{xi}}}{\sum_{i=1}^{n}(\mu_{ij})^{m}} \qquad (4)$$

This is performed up to the maximum value of the difference μ_{ij} with the previous μ_{ij} is smaller than the error.

3.4 Features Extraction

Feature extraction is a method which gives significant information or properties of an image. Features applied for identification basically rely on location, size, shape, and texture of a tumor. The texture-based features are usually applied for feature extraction, which is additionally split in statistical-based (1st order and 2nd order texture feature). The extracted features are then utilized as an input for a machine learning algorithm for classification [22].

3.4.1 Grey Level Co-Occurrence Matrix (GLCM)

In GLCM, the texture is interpreted as a matrix by applying grey levels from the image and in addition, it involves the harshness and superfluous of the texture in the image. The number of grey levels of an image is mapped by a number of rows and columns of the GLCM matrix. P is the matrix element, which is divided by the pixel distance of the relative frequency of two pixels. Generally used texture features are contrast, energy, correlation, and homogeneity [22].

Contrast (C): Contrast is applied to check the presence of the grey level in the MRI images and its fluctuation

$$C = \sum_{i,j} |i-j|^2 \cdot P(i,j) \quad (5)$$

Correlation: It is a measure of how a center pixel is correlated to its neighboring pixel (range is between [-1,1]). μ is the mean and σ is the standard deviation.

$$Corr = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)\cdot P(i,j)}{\sigma_i \sigma_j} \quad (6)$$

Energy(E): Energy is applied to check the similarity of an image. The range for energy is between [0 ,1]

$$E = \sum_{i,j} P(i,j)^2 \quad (7)$$

Homogeneity(H): gives the nearness of the distribution of feature elements for GLCM to the diagonal of the GLCM. The GLCM diagonal presents the value 1.

$$H = \sum_{i,j} \frac{P(i,j)}{1+(|i-j|)} \quad (8)$$

3.5 Classification

Classification is the procedure of determining a model that identify data classes with the intention of applying the model to predict the class whose label is unidentified. Classification requires two steps firstly, building a classification model using training data. Secondly, test the built model by specifying class labels to data items in a test dataset [15]. Deep neural network one of the deep learning methods is used for classification.

3.5.1 Deep Learning

Deep learning is a set of learning techniques seeking to model data with Complicated architectures integrating different non-linear transformations. The base of deep learning is the neural networks, that are aggregated to make the deep neural networks [24]. A Deep Neural Network **(**DNN) is formed by several hidden layers in which all neurons of a layer n are connected to all the neurons of the n+1 layer as described in figure 2. The input layer is to obtain data, the output layer to produces predicted values and the hidden layer to works on features for prediction.

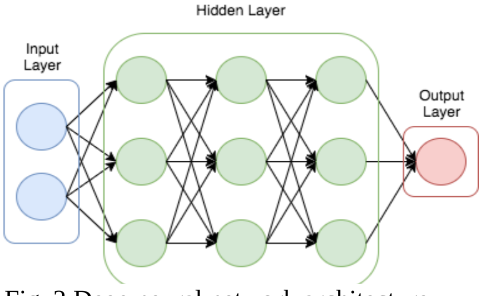

Fig. 2 Deep neural network architecture

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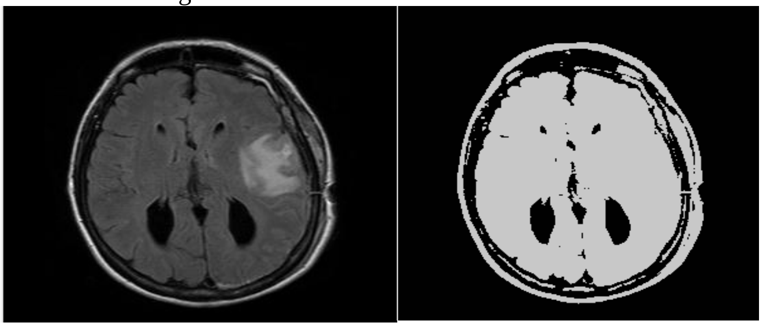
IV. RESULT AND DISCUSSION

The dataset consists of 100 MRI images collected from the open medical repositories on the web, half of them contain tumors and the rest are normal. Brain tumor images include tumorsof different size and in different locations. The images are resized, pre-processed, and segmented into various regions and the aim of segmentation is to partition an image into significant regions in order to locate the tumor spot using FCM. Figure 3 shows the results of FCM segmentation.



(a) Image before segmentation (b) Image after segmentation
Fig. 3 Segmentation results

The segmented images then submitted to feature extraction. A set of features namely, contrast, correlation, energy, and homogeneity are extracted using GLCM.Extracted features of all images are aggregated to form a feature vector as depicted in figure 4.

	A	B	C	D
1	contrast	correlation	energy	homogeneity
2	0.8781	0.8922	0.7499	0.9791
3	0.8947	0.8983	0.7313	0.9787
4	1.0054	0.8924	0.7133	0.9761
5	1.0519	0.8938	0.6965	0.975
6	1.1128	0.8928	0.6817	0.9735
7	1.197	0.8875	0.6722	0.8781
8	1.311	0.8799	0.6616	0.9688
9	1.4417	0.8726	0.6472	0.9657
10	1.5934	0.8634	0.6337	0.9621
11	1.7628	0.8601	0.6035	0.958
12	1.8497	0.8602	0.5836	0.956
13	1.8613	0.8636	0.5719	0.9557
14	1.8658	0.8664	0.5629	0.9556
15	1.8303	0.8722	0.5541	0.9564
16	1.7916	0.8773	0.5473	0.9573
17	1.7318	0.884	0.5397	0.9588
18	1.7047	0.8875	0.5342	0.95946
19	1.7512	0.8866	0.5247	0.9583
20	1.6964	0.8914	0.5211	0.9596

Fig. 4 shows the extracted features

After the features are extracted, the classification step using DNN is done on the constructed feature vector. The model implemented using Keras utilizing Tensor Flow backend. Table 1 shows the DNN performance in terms of accuracy, precision, recall, and F1-score on the average.

Accuracy: it computes the total number of normal and abnormal instances correctly classified divided by the total number of dataset instances.

Precision: it specifies the number of correctly identified normal instances.

Recall: is the ratio of correctly predicted positive instances to all instances in the actual class.

F1-score: it computes the harmonic mean of precision and true positive ratio.

Table 1 DNN Performance

Accuracy	Precision	Recall	F1-score
0.90	0.92	0.90	0.90

Table 1 shows that the DNN classifier is able to distinguish if a given image is normal or abnormal with an accuracy of 0.90. The precision of correctly classified instances within all classified instances is 0.92. The ratio of correctly identified normal instances (recall) is 0.90. The F1-score which, indicates how much the model discriminative is 0.90.

For evaluating the performance of the DNN, K-Nearest neighbor (KNN), Decision Tree (DT), and Support Vector Machine (SVM) with RBF kernel machine learning classification algorithms are used. Figure 5 depicts the comparison of performance measures for DNN with KNN, DT, and SVM.

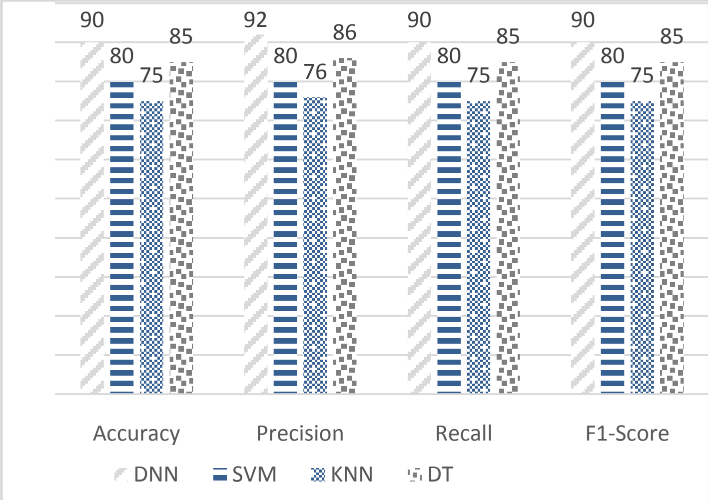


Fig. 5 Comparison of average performance metrics of the classifiers

Figure 5 indicates that the DNN classifier provided good results in all performance measures over all other classifiers.

V. CONCLUSION

The proposed classification system which combines Grey level Co-occurrence (GLCM) for feature extraction Fuzzy C-means (FCM) for segmentation, median filter for de-noising, and Deep Neural Network (DNN) to classify brain MRI images into normal and abnormal. It is implemented in Python using Keras with Tensor Flow backend. Experiments were undertaken to study the performance of the classification system in terms of performance measures such as accuracy, precision, recall, and F1-score. The results suggested that the developed system provided better performance compared with SVM, KNN and Decision Tree. The proposed methodology can be applied to some other medical images classification. Future work would investigate the performance with a larger dataset and more complex deep learning method.

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