Advanced Technique for Classification and Detection of Brain Tumor in Magnetic Resonance Images

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Abstract: In the medical world, most challenging disease is Brain tumor. Brain tumors formed inside the brain as an abnormal cell. It is a mass of tissues which results in hormonal changes results in mortality. In the recent years, various brain tumor detection techniques are evolved. We propose, a novel brain tumor detection technique is proposed to detect tumors accurately in given brain MR image and also it classifies the given brain MR image is normal or abnormal. At first the preprocessing is performed by median filtering and segmentation by means of morphological technique. Then the Gray Level Co-occurrence Matrix (GLCM) is applied to extract the texture features. Then, the derived features are applied to classification using three classifiers such as Naïve Bayes, Multilayer perceptron, and Decision Tree C4.5 classifiers. By conducting experiments, the proposed technique is assessed and validated for performance as well as quality analysis based on accuracy, sensitivity and specificity on brain MR images. In experimental section, the performance of all three classifiers are compared in which the decision tree C4.5 algorithm provides better performance with 75% of accuracy, 79% of sensitivity and 56% of specificity.

Keywords: Brain MR Images, Median filtering, morphological operation, Gray Level Cooccurrence Matrix (GLCM), Naïve Bayes, Multilayer perceptron, and Decision Tree C4.5.

1. INTRODUCTION

As we are human beings facing various kinds of diseases in our day-to-day life in which cancer is a most crucial disease among that brain tumor is one of the notable one. Tumors are of various kinds which differs in the aspect of its nature [1]. It is generally caused by the enlargement of suspicious tissues in the brain. Magnetic Resonance Imaging (MRI) is a diagnosing process done through radio waves three dimensional image and strong magnetism field for detecting the hidden organs. MRI process is considering as one of the effective medical imaging system because it is free from ionized radiations [2-4]. The accuracy of those MR images was enhanced by applying it on quality image processing techniques. Commonly known conventional machine learning-based mechanism used for detecting brain tumor are random forest (RF), k-nearest neighbor's algorithm (KNN) and support vector machines (SVM) [5-8] As we say among the image processing, the processing on brain images are most complex task then others. The medical diagnosis can be made simple by using medical image processing by viewing the internal structures of unseen human organs. It is said to be a boon for patients and the doctors in identifying the tumors as much as accurately. From the initial stage it can be further investigated by applying mathematical operations to improve its imaging quality. The medical image processing techniques is achieved by implementing following process which includes feature extraction, pre-processing, image segmentation and classification [9-11]. Among these classification is considered as final stage and those results were considered for clinical diagnosis. Pre-processing plays a vital role in eliminating noisy, irregular and insufficient data from an image. In this paper, pre-processing of given brain image is done with median filter to remove impulse noise without affecting the original image. Then the image segmentation is done by using morphological operations including image erosion, dilation, opening and closing. Next stage is implementing Gray Level Co-occurrence Matrix (GLCM) for feature extraction. It is an advanced mechanism for extracting several texture features. Final stage is the classification. In general, the classification is subdivided into supervised and unsupervised classifications and every classification has

its fundamental principles and properties. But both classifications possess a common goal to detect and extract brain tumors. In our work three classifications are performed such as Naïve Bayes, multilayer perceptron and decision tree C4.5. The structure of the proposed work is organized as follows. The section 2 discusses some existing works and the proposed methodology is explained in section 3. In section 4 result and discussion is explained and section 5 concludes the work.

2. Related work

In this section we discussed various existing brain tumor detection techniques in the field. Qiang Wang et al [12] proposed advanced mechanism for assisting clinical diagnosis by utilizing data from magnetic resonance spectroscopy (MRS) and magnetic resonance imaging (MRI). The presented technique comprises of a few stages comprising segmentation, feature selection, and feature extraction. Classification framework development is employed for classifying brain case to ordinary or anomalous. A fuzzy connectedness separation strategy was applied. They plot the boundaries of tumor mass in the MR Images. The redundant features are removed by performing feature selection. The features are extracted concentric circle strategy over the regions of interest. Simulation results show the proposed system classifying efficiency of tumors in MR images.

Yudong Zhanga et al [13] have presented a technique for classifying MR brain images as normal or abnormal by applying neural network (NN). The initial phase in this strategy was feature extraction from MR images by utilized wavelet transform. Next, principle component analysis (PCA) mechanism is used to decrease the features. And then, the obtained results are given to the input of neural network. The technique is implemented over 66 images with 18 normal images and other 48 images are abnormal. The obtained classification accuracy is 100%.

Rajeswari S. et at [14] have introduced a technique created on Grey Level Co-occurrence Matrix (GLCM) texture features of brain MR images. In order to choose discriminative features, they apply Sequential Forward selection algorithm. The presented classifies the given MR brain images as normal or abnormal by applying kernel based Support Vector Machine (SVM).

A. Jayachandran et al [15] have developed a hybrid technique to detect brain tumor in MR images by applying Fuzzy Support Vector Machine classifier and statistical features. This hybrid technique comprises of four stages. In the initial stage, anisotropic filter is applied to eliminate noise in the MRI. In the second stage, the texture feature extraction of MR images is done. In the third stage, principles component analysis (PCA) technique is applied for feature reduction to derive most important features. Finally, with the help of Supervisor classifier based Fuzzy Support Vector Machine the detected tumor is classified as normal or abnormal. The obtained classification accuracy is 95.80%.

PrachiGadpayle et al [16] have proposed a technique for the detection and classification of brain tumor MR images. Some of the image processing strategies, for example, preprocessing, segmentation, image enhancement, morphological operations, feature selection, and feature extraction are applied to detect tumors in brain MR images. Gray Level Cooccurrence Matrix (GLCM) technique is implemented to extract texture features in the detected tumor. By applying BPNN and K-NN classifiers, the classification is performed as normal or abnormal.

In this work, we perform different image processing operations to detect and extract tumor from brain MR images. From these operations texture features are extracted and classified the detected tumor as normal (benign) or abnormal (malignant). Finally, the classification is performed on the derived texture features and their results are given and compared in experimental section.

3. PROPOSED TECHNIQUE

This section explains about the proposed method for brain image classification which is comprised of four stages namely pre-processing on image, image segmentation, feature extraction and finally classification. The figure 1 shows different sample brain MR images. The below Figure 2 demonstrates proposed method overall flow and all the four stages are explained in the following subsection in a detailed manner.



Figure 2: Overall flow of the brain tumor detection system

3.1. Preprocessing

Initially the input images were considered as raw images which are not applicable for brain tumor detection, in which unwanted and redundant pixels were removed on preprocessing. Next the noises in the images were reduced by applying median filtering technique. During this stage it conserves all essential details in an image. In this process all individual pixels with its neighboring pixels were compared using median filtering. The original pixel value is replaced by median values of neighboring pixels. It replaces the entire mid pixel value by sorting the pixel values [17]. Figure 3 shows the preprocessing result of given sample MR brain images.



Image-4

Image-5

3.2. Segmentation

In this section the preprocessed image is segmented to several block, by means these images were signified for better study. This process based on two factors known as discontinuity and similarity. During which tumor region selected and unwanted regions in the images were removed effectively.





Image-4

Image-5

Fig. 4: Segmented images by morphological operation

by involving detailed analysis, the tumor region is separated and analyzed effectively. The morphological segmentation technique in the proposed brain tumor detection system is applied for partitioning foreground and background images. On that stage the tumor area is categorized as per the characteristic features such as size, location and shape. The segmented result of given sample MR brain images are given in Figure 4.

3.3. Feature Extraction

Feature extraction is the process of gathering higher-level data of an image like contrast, shade, and shape. In both human visual perception and machine learning techniques the texture feature analysis is considered as an essential parameter. It is utilized efficiently for enhancing the precision of diagnosis framework by choosing prominent image features.

Haralick et al. [18] have presented a novel Gray Level Cooccurrence Matrix (GLCM) and texture feature which are the most generally applied image processing applications. This approach has two phases to perform feature extraction from the medical images such as MRI or CT images. In the initial phase, the GLCM is estimated, and in the next phase, the GLCM based texture features are computed. Because of the complicated framework of expanded tissues, for example, WM, GM, and CSF in the MR brain images, extraction of important features is a basic operation. Textural discoveries and examination could enhance the diagnosis, distinctive phases of the tumor, and treatment reaction appraisal. Texture based features are Entropy, Energy, Mean, Variance, Contrast, Standard deviation, Correlation, Skewness, Kurtosis and Homogeneity.

Types of tumor	Mean	Standard deviation	Entropy	RMS	Variance
Image-1	41.42349	58.31566	5.31566	10.42145	2400.981
Image-2	53.87975	57.10327	6.34071	11.4013	2412.458
Image-3	87.81889	86.90351	6.10369	15.95373	910.0191
Image-4	66.329	59.5858	5.9492	15.8782	2322.934
Image-5	85.018	63.0951	6.6266	13.74	3771.372

Types of	Kurtosis	Skewness	Contrast	Correlation	Energy	Homogeneity
tumor						
Image 1	5.8978	1.86068	0.27153	0.95224	0.31489	0.91125
Image 2	3.41965	0.96835	6.34261	0.93898	0.26627	0.89769
Image 3	7.411	1.5173	0.26401	0.907	0.29145	0.96189
Image 4	2.98352	0.91261	0.18182	0.9749	0.33963	0.92691
Image 5	31.0613	0.41768	0.17367	0.97372	0.19709	0.93814

Table 1: Extracted features for given sample MR brain images

3.4. Classification

3.4.1. Naïve bayes

Naïve bayes is a type of classification method which is based on supervised learning and statistical approach. It is a fundamental probabilistic classifier that applies Bayes theorem. It supposed that the measure of specific feature is inconsequential to the existence or non-existence of some other features. The priori likelihood and probability are estimated for computing the posterior likelihood. The strategy maximal posterior likelihood is utilized for parameter computation. This technique needs just a few training data for estimating the parameters that are required for to perform classification. It takes very less time to execute the training and classification process.

3.4.2. C4.5 decision tree algorithms

Quinlan Ross was presented C4.5 algorithms an extension of ID3 algorithm. In order to develop a decision tree, it manages all the categorical and proceeding attributes [19]. It executes a depth-first initially and common to particular search to perform hypotheses by passively segmenting the dataset in every node of that tree. C4.5 endeavors to fabricate a decision tree as an amount of the data increased ratio of every single feature and spreading on the attribute that restores the maximal data gain ratio. Anytime amid the search, the selected attributes are taken to possess the maximum discriminating capacity

between the diverse ideas whose depiction is being produced [20]. Pruning happens in C4.5 by substituting the internal node by a leaf node by that the error rate is decreased. It has an upgraded strategy for tree pruning which decreased misclassification errors rate of noise or an excessive number of details in the training dataset. C4.5 utilizes critical pruning for erasing of useless branches in the decision tree because of that precision was increased [21].

3.4.3. Multilayer Perceptron (MLP)

Multilayer perceptron (MLP) is known as a type of supervised classifier. It is a feed forward neural network which operates over back propagation algorithm to execute training process. Generally, it comprises of three or more than three layers such as an input, an output, and one or more number of hidden layers. If there is no algorithmic solution is present or if the algorithmic solution is too complex, then this MLP is applied in such situation. The training process of MLP is learned through the transformation of input data to desired output. Some of the operations like pattern recognition and interpolation are done by the MLP. It is applied for the brain tumor detection in MR images or some other kinds of image processing modalities [22, 23]. Initially it is developed with several hidden layers and neurons which are varying continuously and it is known that the better performance is achieved with 2 hidden layers and 3 neurons per layer. The rate of learning is set to be 0.3.

4. Results and discussion

In this section the proposed system results are obtained and discussed through real MR brain images. The proposed technique is applied on a dataset that comprises 38 brain MR images in which 11 images are normal and 27 images are abnormal images which is the Digital Imaging and Communications in Medicine (DICOM) dataset [24]. The proposed technique is implemented in Matlab R2017a where preprocessing, segmentation, morphological operation, detection, and feature extraction is performed. The extracted features are formed as a dataset and given as an input to WEKA tool for classification. There are three classifications such as C4.5 decision tree, Multilayer Perceptron and Naïve bayes.

The proposed system's performance is evaluated through the confusion matrix can be employed which depicts all possible outputs of the forecast outputs in table format. In order to evaluate the performance of the proposed technique the confusion matrix can be employed which depicts all possible outputs of the forecast outputs in table format. The possible outputs of a two class data prediction is illustrated as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The True Positive and True Negative are normal and abnormal brain images. The False Positive is the output which is incorrectly classified as positive while it is negative whereas the false negative is the output which is incorrectly classified as negative while it is positive. In the process of classification, the False Positive is defined as the False alarm.

In our proposed work we considered,

TP - Correctly classified abnormal images.

TN - Correctly classified normal images.

FP-Incorrectly classified abnormal images.

FN - Incorrectly classified normal images.

a) Precision

Precision is the ratio of abnormal images to the correctly classified results.

$$\Pr{ecision} = \frac{TP}{TP + FP}$$

b) Sensitivity or Recall

It is the probability of the test discovering the abnormal image among all the abnormal images.

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

c) Specificity

It is defined as the ratio to the test findings of the normal image to the all normal images.

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

d) Accuracy

It is the ratio of test outputs which are correct or accurate.

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

ТР	FP	Precision	Recall	F-	MCC	ROC	PRC
Rate	Rate			Measure		Area	Area
0.636	0.222	0.538	0.636	0.583	0.396	0.778	0.557
0.778	0.364	0.840	0.778	0.808	0.396	0.778	0.898
0.737	0.323	0.753	0.737	0.743	0.396	0.778	0.799

Table 2: Results of MLP classifier

TP Rate	FP Rate	Precision	Recall	F- Measure	MCC	ROC Area	PRC Area
0.818	0.407	0.450	0.818	0.581	0.373	0.677	0.499
0.593	0.182	0.889	0.593	0.711	0.373	0.677	0.872
0.658	0.247	0.762	0.658	0.673	0.373	0.677	0.764

Table 3: Results of Naïve Bayes classifier

TP Rate	FP Rate	Precision	Recall	F- Measure	MCC	ROC Area	PRC Area
0.455	0.148	0.556	0.455	0.500	0.327	0.641	0.398
0.852	0.545	0.793	0.852	0.821	0.327	0.641	0.786
0.737	0.430	0.724	0.737	0.728	0.327	0.641	0.673

Table 4: Results of C4.5 classifier

Evaluation parameter	MLP	Naïve Bayes	C4.5
True negative	21	16	23
False positive	4	2	6
True positive	7	9	5
False negative	6	11	4
Specificity (%)	54	45	56
Sensitivity (%)	84	88	79
Accuracy (%)	74	66	75

Table 5: Comparison of classifier outputs

The statistical parameters are required to determine the test performance of the classifiers. Here, accuracy, specificity and sensitivity are taken to compare the performance of different classifiers such as MLP, Naïve bayes, and C4.5 which is demonstrated in Table 5. Moreover, the better performance is obtained from the higher accuracy of all compared classifiers. From Table 5, it can be obtained that C4.5 provides better performance by increased accuracy than other techniques. The proposed technique executes preprocessing, segmentation, texture feature extraction, and classification to detect various objects, several textures, different contrast, and brightness of an image for human visual perception. Also, if particular operators are implemented efficiently, the utilization of the proposed system can be extended for various kinds of brain tumors.

5.Conclusion

In this work, novel brain image classification mechanism is proposed. The initial preprocessing section applies median filtering techniques for MR brain images. Then it undergoes segmentation by means of morphological segmentation technique were tumor affected region are segmented perfectly. Then the feature extraction is executed using Gray Level Cooccurrence Matrix (GLCM) to derive texture features of MR brain images and finally the classification is performed through three different classifiers such as MLP, Naïve bayes, and C4.5. Among these classifiers MLP achieves the accuracy of 74%, Naïve bayes of 66% and C4.5 of 75% respectively. Finally, it is observed that the C4.5 algorithms can provide better performance than other two classifiers. In future, we extend our proposed work by including number of scenarios comprising various aspects with large dataset.

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