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DETECTION AND CLASSIFICATION OF MRI BRAIN TUMOUR USING GLCM AND ENHANCED K-NN

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Abstract

Magnetic Resonance Imaging (MRI) modality is an advanced and efficient tool in radiology to obtain the pictures of the anatomy of human brain. In this proposed work, an automated classification of brain tumour as tumour or non-tumour is presented using enhanced K-Nearest Neighbour (enhanced K-NN) classifier. Here, Median Filtering is used in the pre-processing stage; Fuzzy C-means clustering (FCM) to separate the tumour region from MRI; Grey level co-occurrence matrix (GLCM) is adopted for feature selection followed by Principle component analysis (PCA) for feature reduction. These reduced features are trained and classified using enhanced K-NN classifier. The proposed work is compared with various existing classifiers such as Naïve Bayes, Probabilistic Neural Network (PNN), Support Vector Machine (SVM) and Artificial Neural Network (ANN). The experimental result of the proposed work shows better performance in terms of Recall 97.68%, Precision 97.43% and accuracy 98.42%.
Key words: Magnetic Resonance Imaging, Enhanced K-NN classifier, Gray Level Co-occurrence Matrix, Principal Component Analysis

1. Introduction. In recent years, tumour has become the most serious disease across the world. Around 14.1 million people suffered by tumour in 2012 as reported by American Cancer Society and furthermore, it is predicted to increase up to 21.7 million in 2030. Brain tumour is the growth of abnormal cells in human brain. These are considered to be either cancerous (malignant) or noncancerous

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(benign). Tumours are classified into different types based on their own characteristics and treatments. Among them, the brain tumour is considered to be a severe disease which needs a perfect medical analysis to classify the tumour very accurately for early diagnosis. For the purpose of early diagnosis of brain tumours, MRI is commonly used as imaging modality for analyzing medical data due to its resolution and quality [15]. Brain tumour diagnosis is most difficult and tedious for the radiologists to classify the MR images based on their visual perception [16]. Hence, it is crystal clear that there is a need for an efficient system for classification and analysis of MR brain image. Both SVM and ANN were combined for the brain tumour classification as defined by AHMMED et al. [1]. Here, segmentation using Template based K-means and modified Fuzzy C-means (TKFCM) algorithm is carried out on the processed brain MRI, which extracts the necessary statistical features for classifying the tumour. The combination shows an improved accuracy and reduction in computational time and bit rate. Adaptive Regularized Kernal Fuzzy C – means algorithm (ARKFCM) proposed by MAKSUD et al. [4] enhances the accuracy and robustness of segmentation process. A methodology proposed by NICHAT et al. [11] integrates SVM and Modified FCM to classify the tumour.

The proposed work is organized as follows. Section 2 shows the literature review of existing work based on the classification techniques on the brain MRI. The proposed methodology and algorithms for brain tumour classification is discussed in Section 3. Section 4 deals with the feature extraction and feature reduction strategy. The experimental results are discussed in Section 5 and compared with existing classifiers such as SVM, ANN and PNN and finally, the paper is concluded in Section 6.

2. Literature review. This section depicts the various segmentation and classification techniques used for detecting and classifying brain tumours. A hybrid genetic-fuzzy technique for the detection of tumour is discussed by DEEPA et al. [3]. Initially, the pre-processing step is used to remove the noise in MR brain images and clustering is carried out by the combined FCM and genetic algorithm, which improves the accuracy with low computation time. An efficient image segmentation is applied by integrating K-means with Fuzzy C-means algorithm as in Maksud et al. [4]. The validation is performed on three datasets and it is a three step process: pre-processing is done using median filter for de-noising; brain surface extraction is used for skull removal; segmentation is done using Clustering technique K-means and Fuzzy C-means to extract tumour region. For larger data sets, K-means gives better output with low computation time and Fuzzy C-means detects malignant tumour with higher accuracy rate.

In order to increase the accuracy of classification, various methods are discussed in [5, 13] for automatic segmentation of MR brain image. An adaptive neuro-fuzzy inference system is proposed by SHANTHAKUMAR et al. [14] for tumour region segmentation. RAVICHANDRAN et al. [12] claim that efficient revealing of brain tumour is enhanced by skull stripping and power law transformation. The features are extracted using discrete wavelet transform (DWT) and are reduced to twelve features by applying principal component analysis (PCA) which produces 65% classification accuracy. NANDAPURU et al. [9] used SVM to classify brain tumour based on the factors such as texture features, symmetrical features and gray features. Finally, the extracted features are reduced to seven features using PCA with 84% accuracy. The researchers are focusing on hybrid techniques to improve the precision of the overall classification system. MACHHALE et al. [8] presented a hybrid classification technique, a combination of SVM and K-NN classifiers which has a maximum success rate of 98% by considering the best 24 features. DAHSHAN et al. [2] proposed a combination of ANN and K-NN classifiers, a hybrid technique is used to visualize and classify human MR images into tumour or non-tumour. Here, feature extraction is based on DWT, and most significant features are obtained using PCA. Taking into account seven features, ANN classifier produces 97% accuracy and K-NN classifier produces 98% accuracy. An automatic detection and classification technique using ANN is used by NAZIR et al. [10] to classify brain MRI. Later, for consecutive classification different features were selected and fed to ANN as input. An accuracy of 94.2% for testing data is obtained with the reduction of computational complexity to 3s. The key objective of the proposed work is to detect and classify the tumour images with more accuracy and improve the overall system performance.

3. Research methodology. The architecture of the proposed work is as depicted in Fig. 1 which consists of different phases such as Image Pre-processing,

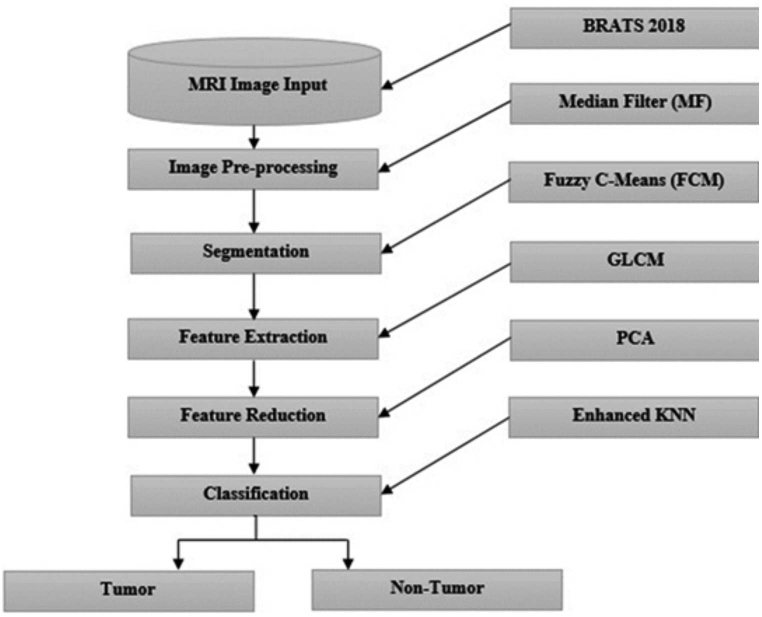

Fig. 1. Proposed architecture

Segmentation, Feature Extraction, Feature Reduction, Feature Analysis and Classification.

3.1. Image pre-processing. In this phase, noise and irrelevant information are eradicated from the input MRI brain image using median filter to improve the classification accuracy. It helps to maintain the quality of input image. The median filter computes the centre pixel of 3×3 mask, which is replaced by the median value of the neighbouring pixels intensity as in equation

$$y(x, y) = \text{median}\{f[a, b]\}, \tag{1}$$

where $(a, b) \in g_{xy}$.

3.2. Image segmentation. In this phase, pre-processed image is applied to Fuzzy C-means Clustering algorithm (FCM) to separate the tumour region which helps to achieve the objective of the research. FCM is an iterative process which gives optimistic 'm' clusters by reducing the weight within cluster and the objective function is given in the following equation

$$B_{FCM}B_{FCM} = \sum_{a=1}^{n}\sum_{b=1}^{m}(z_{ba})\sum_{a=1}^{n}\sum_{b=1}^{m}(z_{ba})_q d^2 d^2(x_b, r_a, x_b, r_a). \tag{2}$$

3.3. Feature extraction and feature reduction. In this phase, Gray Level Co-occurrence Matrix (GLCM) is used to extract second order statistical features of the segmented image. GLCM is represented as $Z(x, y)$ and is obtained by the displaced distance of matching pair of pixels between "x" and "y". Then the extracted features are applied to Principle Component Analysis (PCA) to improve the computation time by reducing its dimensionality. Extracted features and its statistical formula are given in the following equations:

(3)	Contrast	$\sum_i \sum_j \lvert i-j\rvert^2 P(i,j)$
(4)	Correlation	$\frac{1}{\sigma_i\sigma_j}\sum_i \sum_j (i-\mu_i)(j-\mu_j)P(i,j)$
(5)	Energy	$\sum_i \sum_j P^2(i,j)$
(6)	Homogeneity	$\sum_i \sum_j \frac{P(i,j)}{1+\lvert i-j\rvert}$
(7)	Entropy	$-\sum_{i=1}^{N}\sum_{j=1}^{N} P(i,j)\log P(i,j)$
(8)	Inverse Difference Moment (IDM)	$\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{1}{1+(i-j)^2}P(i,j)$
(9)	Mean	$\frac{1}{N}\sum_{i=j=1}^{N} P(i,j)$
(10)	Standard Deviation (SD)	$\sqrt{\sum_{i=0}^{N-1}(1-\mu)^2 P(i,j)}$

(11) Skewness $\frac{1}{N}\sum_{i=j=1}^{N}\left(\frac{P_{i,j-\mu}}{\sigma}\right)^3$

(12) Kurtosis $\frac{1}{N}\sum_{i=j=1}^{N}\left(\frac{P_{i,j-\mu}}{\sigma}\right)^4 - 3$

Extracted feature values for normal MRI Brain Image and abnormal MRI brain image are given in Table 1.

3.4. Classification. In this final phase, the proposed enhanced K-NN classifier classifies the MRI Brain image as non-tumour or tumour. Calculation of Manhattan distance is given as

$$M_d = \sum_{i=1}^{k} |x_i, y_i|.$$

The enhanced K-NN is given as:

1. Obtain the test image to find whether its tumour or normal.
2. Find Manhattan distance for the image to be tested and image to be trained.
3. Rearrange the computed Manhattan distance obtained from step 2 in ascending order.
4. Choose the initial k-nearest value with initial k-distances.
5. Find relationship of the adjacent majorities over the k-nearest.

4. Results and discussion. The proposed enhanced K-NN is trained by 765 MRI images from DICOM dataset for both the training phase and testing phase. DICOM dataset comprises of 522 tumour images and 243 normal images. These images are categorized for different purposes as 70% for training, 15% for testing and 15% for validation. Few experimental results were shown as in Fig. 2(a) represents the input MRI image, (b) represents the pre-processing output (c) represents the segmented tumour region. The performance of the proposed method is measured using various measures such as Precision, Recall and Accuracy.

(i) Precision = TP/(TP + FP)

(ii) Recall = TP/(TP + FN)

(iii) Accuracy = TP + TN/(TP + FP + TN + FN)

Compared with the existing techniques such as Naïve Bayes, PNN, SVM, ANN, the proposed enhanced K-NN performs the segmentation of the tumour region with more precision. The performance measures of various parameters

T a b l e 1

Table 1. Extracted feature values for normal and abnormal MRI brain image

Feature values for Normal MRI Brain Image										
Images	Features									
	Contrast	Correlation	Energy	Homogeneity	Entropy	IDM	Mean	SD	Skewness	Kurtosis
DICOM1	0.1987	0.1723	0.8623	0.9824	2.2464	0.284	0.00463	0.07784	0.9044	12.3921
DICOM2	0.2173	0.1983	0.8347	0.9548	2.2188	0.2564	0.00239	0.0756	0.8768	12.3645
DICOM3	0.2111	0.1856	0.8763	0.9964	2.2604	0.298	0.00498	0.07819	0.9184	10.3021
DICOM4	0.1876	0.1432	0.8523	0.9724	2.2364	0.274	0.00123	0.07444	0.8944	12.3821
DICOM5	0.1972	0.1103	0.8987	1.0188	2.2828	0.3204	0.00324	0.07645	0.9408	11.2341
DICOM6	0.2145	0.1198	0.9011	1.0212	2.2852	0.3228	0.00319	0.0764	0.9432	12.4309
DICOM7	0.2072	0.1174	0.9123	1.0324	2.2964	−0.349	0.00342	0.07663	0.9544	12.4421
DICOM8	0.2043	0.1278	0.8898	1.0099	2.2739	0.3115	0.00438	0.07759	0.9319	12.4196
DICOM9	0.1923	0.1382	0.8987	1.0188	2.2828	0.3204	0.00112	0.07433	0.9408	12.4285
DICOM10	0.1988	0.1563	0.8934	1.0135	2.2775	-0.332	0.00234	0.07555	0.9355	12.4232
Feature values for Abnormal MRI Brain Image										
DICOM1	0.2308	0.1857	0.8836	0.9503	2.2576	1.1051	0.00568	0.08807	1.9076	26.4553
DICOM2	0.2494	0.2117	0.856	0.9227	2.23	1.0775	0.00344	0.08583	1.88	26.4277
DICOM3	0.2432	0.199	0.8976	0.9643	2.2716	1.1191	0.00603	0.08842	1.9216	24.3653
DICOM4	0.2197	0.1566	0.8736	0.9403	2.2476	1.0951	0.00228	0.08467	1.8976	26.4453
DICOM5	0.2293	0.1237	0.92	0.9867	2.294	1.1415	0.00429	0.08668	1.944	25.2973
DICOM6	0.2466	0.1332	0.9224	0.9891	2.2964	1.1439	0.00424	0.08663	1.9464	26.4941
DICOM7	0.2393	0.1308	0.9336	1.0003	2.3076	0.4713	0.00447	0.08686	1.9576	23.0065
DICOM8	0.2364	0.1412	0.9111	0.9778	2.2851	1.1326	0.00543	0.08782	1.9351	26.4828
DICOM9	0.2244	0.1516	0.92	0.9867	2.294	1.1415	0.00217	0.08456	1.944	21.0012
DICOM10	0.2309	0.1697	0.9147	0.9814	2.2887	0.489	0.00339	0.08578	1.9387	26.4864

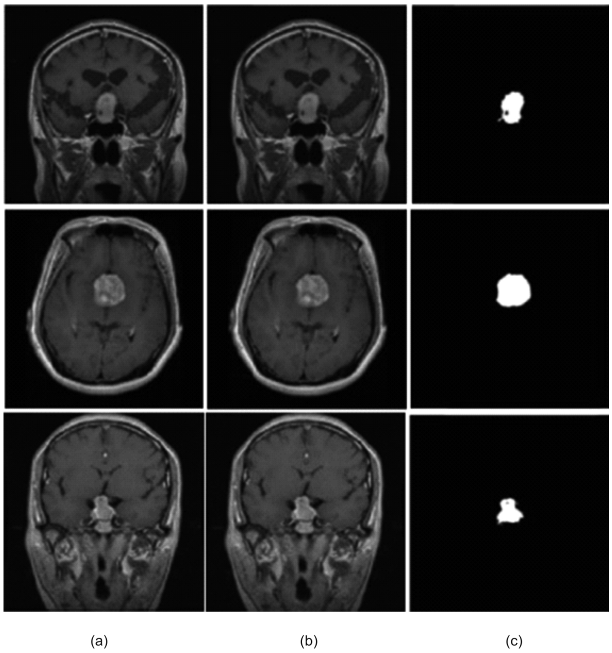

Fig. 2. Experimental analysis of proposed method

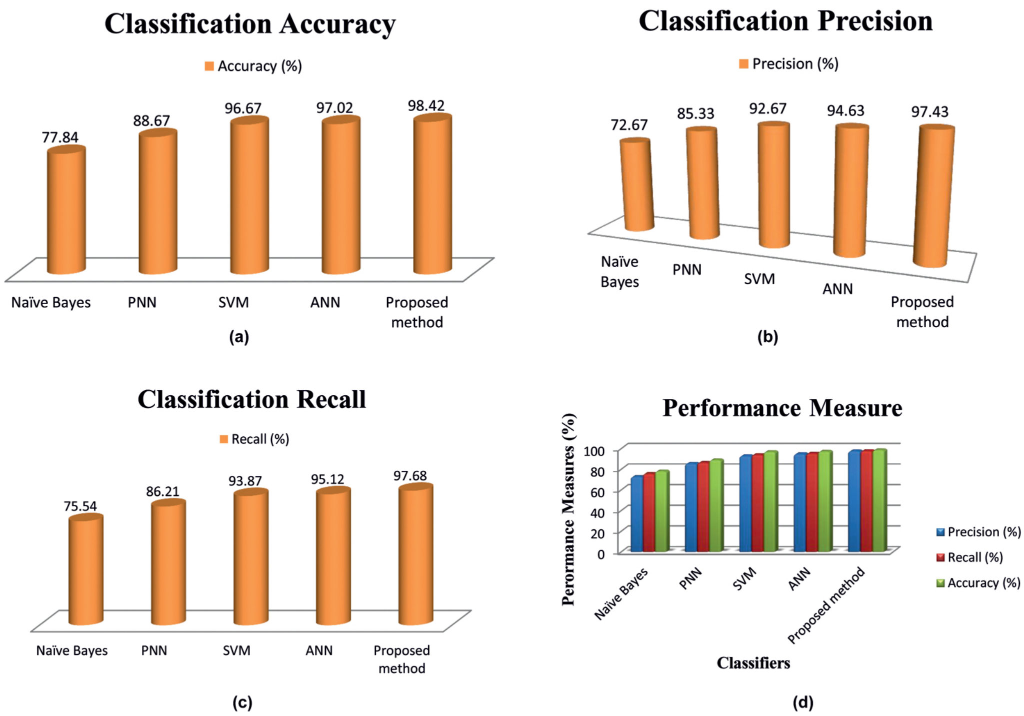

Fig. 3. Performance measure of proposed method with existing method

with different methods is shown in Fig. 3. Figure 3(a) shows the performance measure in terms of accuracy, (b) shows the performance measure in terms of precision, (c) shows the performance measure in terms of recall, and (d) shows overall performance of proposed and existing classifiers. From Fig. 3, it is clear that the performance of the proposed classifier is better when compared with existing techniques such as Naïve Bayes, PNN, SVM, ANN. The proposed method produces high accuracy rate 98.42%, 97.43% Precision and Recall with 97.68%.

Conclusion. In this proposed method, enhanced K-NN Classifier with GLCM and PCA together constitutes to differentiate MR brain image as tumour or non-tumour. The median filter removes the irrelevant noise from the input image and the Gray Level Co-occurrence Matrix extracts relevant features to classify the MRI Brain image obtained from the fuzzy C-means segmentation. Further, the selected feature dimensionality is reduced using Principal Component Analysis (PCA). The enhanced K-NN classifier analyzes the Digital Imaging and Communications in Medicine (DICOM) datasets to classify the MR brain image. Extensive experiments were conducted and the experimental results proved that enhanced K-NN classifier out performed in terms of 98.42% accuracy, 97.43% precision and 97.68% recall in classifying the MR brain image. This work can be further extended using 3D MR brain image.

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