Mithilesh Nandini Malviya, 10:6
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

MRI Image Segmentation and Classification Using KFCM and Convolution Neural Networks

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Abstract- This work focus on the stage effectual categorization of brain tumour descriptions and segmentation of exist illness images employing the segmentation and classification techniques. The major goal of the future method is to design well-organized and accurate algorithm that segmentation tumor region from brain MRI. The algorithm identifies the position of tumor in brain MRI as they are mostly preferred for tumor diagnosis in clinic. The proposed method also crops tumor region from segmented image and way growth of tumor and help in treatment planning. It also provides important information about location, dimension and shape of brain tumor region with no exposing the enduring to a high ionization radiation. The size of tumor is calculated in term of number of pixels. Similarly the primary brain tumor is considered into Benign and malignant type on MRI brain images, based on accuracy, sensitivity, specificity in MATLAB simulation.

Keywords- KFCM, CNN, Feature Extraction, MRI Image, GLCM.

I. INTRODUCTION

Traditionally the segmentation of brain tumor MRI images is done manually by Radiologists. It is time consuming as well as can cause unavoidable mistakes. So proper segmentation of tumor region is required to identify tumor location, tumor size and its surrounding structure of brain for the Radiologist. This information is very essential for appropriate treatment. So, the correct evaluation of brain tumors by means of imaging modalities is one of the key subject of radiology departments Brain tumor can influence people at any age of a person and it is the main cause of cancer death worldwide. Brain tumor is embedded in a brain, which results in development of abnormalities.

Due to the overlapped structure of cells in brain and poor quality of MRI due to noise, it's a challenging task for radiologist to diagnose.[1][2] The identification of exact location of tumor in such kind of images be a challenging task to the Radiologist. Radiologist refers to these images to get detail information about tumor to analyze the disease.

There are barrier to separate out tumor region due to Operator supervision and manual thresholding. The segmentation of brain tumor is difficult due to tumor and edema (swelling). Edema appears in white matter regions around tumor and it might hold infiltrative tumor cells. There is gradual change between tumor, edema, and surrounding brain tissue. This results in the uncertainty of the structural boundaries. So it is difficult to select a standard segmentation technique that gives acceptable results in representation dispensation.

The intelligence, non-brain rudiments and tissues are main obstacles in segmentation of brain tumor images. So the Radiologists in adding up to physician face problem during diagnosis. It is really a challenge for researcher to design an algorithm which gives accurate and detail in sequence for accurate analysis of tumor from MRI image.[3][4]

The accuracy of the segmentation and classification of brain CT images depends upon the accuracy with which the region of interests such as gray matter, white matter, cerebrospinal fluid and tumor region are segmented from the CT images.

Segmentation is a necessary image processing technique for easily distinguishing the abnormal tumor regions from normal regions. Most of the texture feature extraction methods are developed to quantify and detect the structural abnormalities in different tissues.

The stability of the images shows the variations from one equipment to another and it is also subjective. The same algorithm cannot be run successfully for all the acquired images without human intervention. The selection of features and human intervention at every slice made to excessive computation time. The selection of features to successfully and efficiently segment and it classify the tumors from all the slices of the axial view is important for the present research work. The proposed work discusses the stable and highly reliable texture feature extraction algorithms.

The selected features are used for successful segmentation of tumor, and for accurate classification. [6] The low soft tissue contrast obtained from scanning the brain CT images, it affects the edges and yields different objects within the same range of intensity. A robust texture feature extraction algorithms taking care of affecting the edges and yielding the different objects within the same range of intensity has been presented in this work. The texture feature extraction algorithms developed in this work performs better segmentation and classification accuracy based on CNN classifiers and makes the computation faster. The gradual evolutions of the algorithm are successful in segmenting the tumor without human intervention and accurately classify the benign and malignant tumors respectively.

Benign tumors are self-contained, non-lethal, and grow more slowly than malignant ones. Glioblastoma multiform is a malignant tumor and represents the most common brain neoplasm. Malignant tumors are cancerous growths which expand quickly and can metastasize, and even spread to other areas of the body. Benign brain tumor has a homogeneous structure and do not contain cancer cells. They can be either simply monitored by radio logically or surgically eradicated and they seldom grow back. Malignant brain tumors have a heterogeneous structure and contain cancer cells. They can be treated by radiotherapy, chemotherapy or a combination of both.[8][9] The exact cause of malignant brain tumor development is unknown. Men and women of any age, race or ethnicity can develop a malignant brain tumor. The clinical manifestation of the disease may be subtle, but early diagnosis is crucial to enable early drug intervention and improved prognosis.

The progression of the disease can be degenerated by early treatment and hence it becomes very crucial to detect the onset of benign, malignant tumor early in the patient. The Gradual loss of movement, Double vision and hearing loss are very subtle and goes unnoticed in the early stages of the disease. The disease manifests attention only at a very later stage. This only makes the rationale of the work more significant, to determine the diagnosis of tumor, segment and classify the tumor in a very early stage. [7]

II. RELATED WORK

Traditionally the segmentation of brain tumor MRI images is done manually by Radiologists. It is time consuming as well as can cause unavoidable mistakes. So proper segmentation of tumor region is required to identify tumor location, tumor size and its surrounding structure of brain for the Radiologist. [15] This information is very essential for appropriate treatment. So, the correct assessment of brain tumors by means of imaging modalities is one of the key subjects of radiology departments. Brain tumour can influence persons at any age of a person and it is the main cause of cancer death all-inclusive. Brain tumour is surrounded in a brain, which results in growth of defect. We have studied and extract different features for classification of tumor type.

In this work, we extracted features; features are selected for the classification of the tumor type using optimization technique. To improve the classification accuracy, the Feature extraction and selection are performed for accurate diagnosis analysis. The detection of brain tumor and then deciding the right therapy is a long process, and once it is acquainted then time to time evaluation and its progress is extremely important, The purpose of this research work is to extract relevant information from the segmented tumor region and classify healthy and infected tumor tissues for a large database of medical images. The results of this research are helpful in classifying benign and malignant tumors, fast and accurately and thus, improving the diagnosis of tumor slices. [10][13]

III. PROPOSED WORK

In this proposed, we have used k-means clustering to segment the images and find out the tumor area KFCM algorithm is proposed.

KFCM is used efficiently in the field of classification, clustering of document categories and is a well suitable technique for retrieving the documents. Kernel methods have been applied to fuzzy clustering and the version is referred to as kernel-based Fuzzy c- means clustering. The segmented images are after that used to extract kind, for this purpose GLCM is used and feature selection is a must due to the abundance of noisy, irrelevant or misleading skin tone.

By remove these factors, learning from data techniques can advantage very much. Characteristic assortment is able to be viewed as single of the most primary problems in the field of machine learning. The most effective features a generate –F is Feature selection methods used to improve the presentation of the model but also facilitate the examination of the results. Finally, CNN is used to classify the descriptions into normal or abnormal (inferior, high-grade glioma Brain tumor).

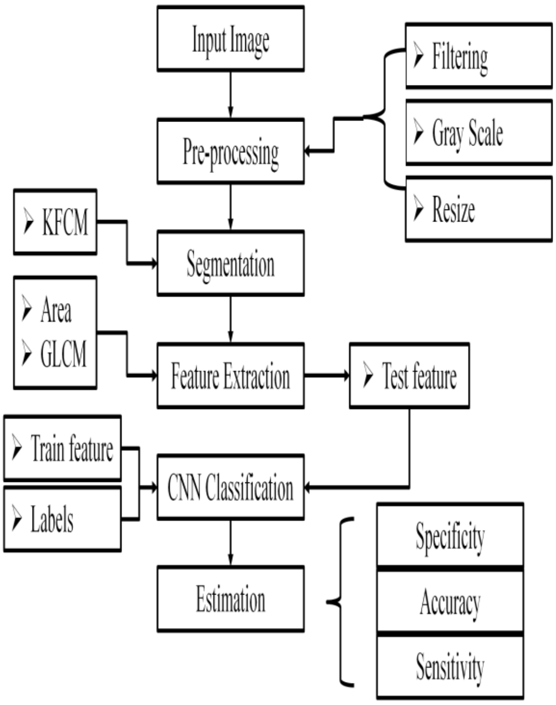

Fig 1. Proposed method Flow diagrams.

Implementation of preprocessing technique Brain CT images are noisy, inconsistent and incomplete, thus preprocessing phase is needed to improve the image quality and make the segmentation results more accurate. The Histogram Equalization can be used to enhance the contrast within the soft tissues of the brain CT images.

It is a special class of adaptive histogram equalization and maximizes the contrast throughout an image by adaptively enhancing the contrast of each pixel relative to its local neighborhood. Next the adaptive median filtering technique can also be used which is easily removes impulse noise while preserving edges to improve the image quality.

1. Segmentation of Region of interests (ROI):
The preprocessed image can be segmented into several ROIs. In this research work, the proposed segmentation methods considered are K-Fuzzy C Means clustering (FCM), Normalized cut (Ncut) image segmentation and CNN classifier. KFCM clustering has been proven to provide an easy and convenient way to perform the segmentation. KFCM clustering produced useful result as the abnormal regions (tumor) are not merged with normal regions. So abnormal tumor regions can be easily distinguished from the normal regions.

2. KFCM clustering:
A process designed to assign each sample to a cluster based on cluster membership probability. The segmentation of the image into different regions can be defined as the assignment of pixels to different clusters at the same time but in different degrees. This is an important feature of medical diagnostic systems to increase the sensitivity. The number of clusters determined for KFCM clustering is by , because the image is segmented into four regions such as, White Matter and Gray Matter including the tumor region itself.

3. CNN classifier:
The second method, **CNN classifier** is used to segment the shape of tumor information. and new edge features Contrast, angular second moment, correlation, homogeneity are extracted using gray level co-occurrence matrix method, mean, variance, entropy and energy of the gray value are extracted using histogram based method and mean, variance, energy and entropy of the edge matrix are extracted using 2 level discrete wavelet transform method.

Implementation of the classifiers Classification is the process where a given test sample is assigned a class on the basis of knowledge gained by the classifier during training.

In this 20 proposed method, an effort has been made to segment and classify the benign and malignant tumors on brain CT images the CNN classifiers used for recognizing to segment and classify the tumors. Analyze and validate the result The classification performance of the proposed computer aided diagnostic system is compared between the classifiers such as CNN The result shows that the CNN classifier has better classification performance compared with the Other classifiers.

In terms of the classification accuracy and computation time, the proposed texture feature extraction methods are compared. The result shows that the Wavelet based combined Dominant Gray Level Run Length and Gray Level Co-occurrence feature extraction method has higher classification accuracy and less computation time compared with the other texture feature extraction methods.

IV. RESULTS AND DISCUSSION

To validate the show of our algorithm,

INPUT IMAGES

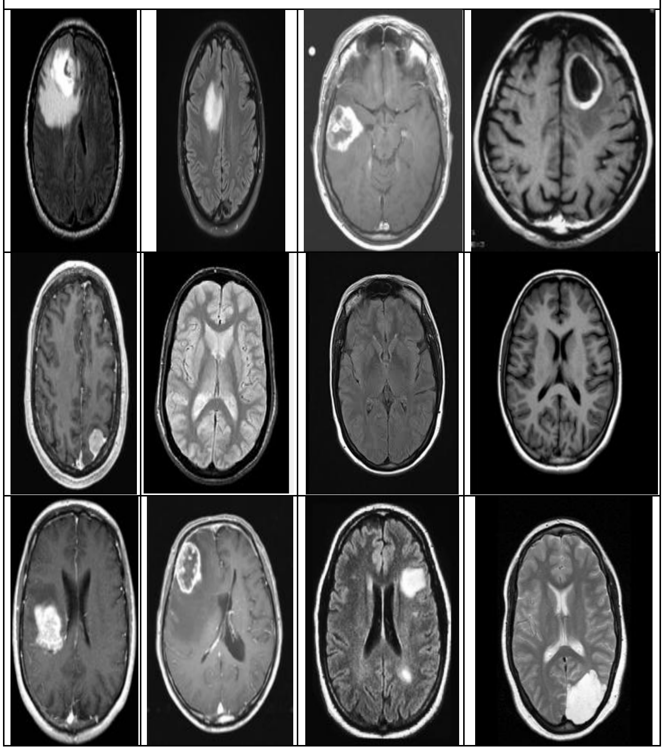

Fig 2. Input of brain MR image.

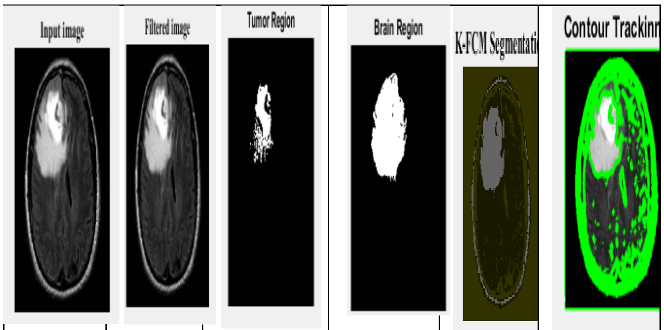

Figure (a) Original image.	Figure (b)) filter image	Segmented and area extracted result of brain MR	Enhanced image.	Brain region	Contour Tarcking

Fig 3. (a) Original image (b) filter image (c) Segmented and area extracted result of brain MR (d) Enhanced image. (e) Skull-stripped image.

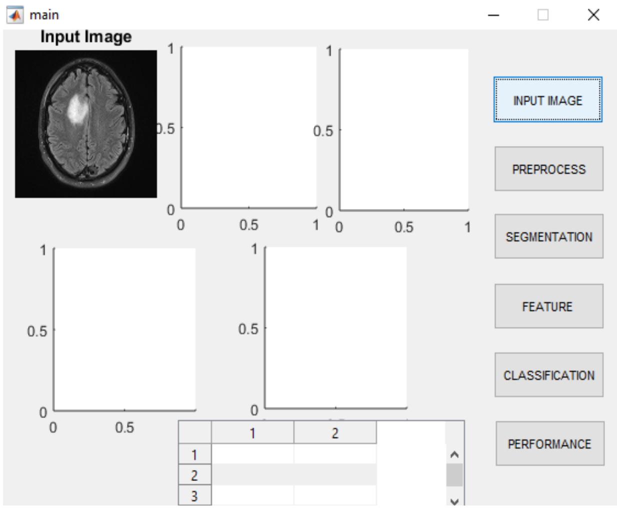

Fig 4. Input image.

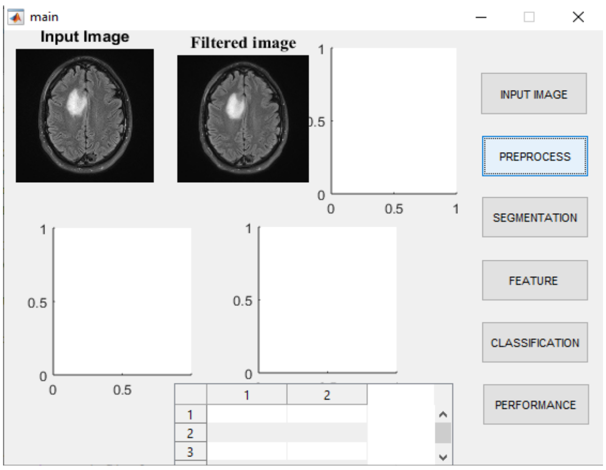

Fig 5. Filtered image.

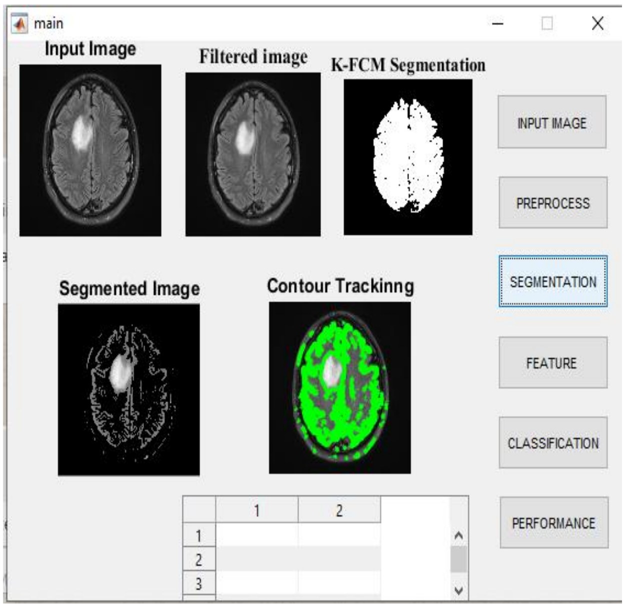

Fig 6. K-FCM segmentation image.

Segmentation is a necessary image processing technique for easily distinguishing the abnormal tumor regions from normal regions. Most of the texture feature extraction methods are developed to quantify and detect the structural abnormalities in different tissues.

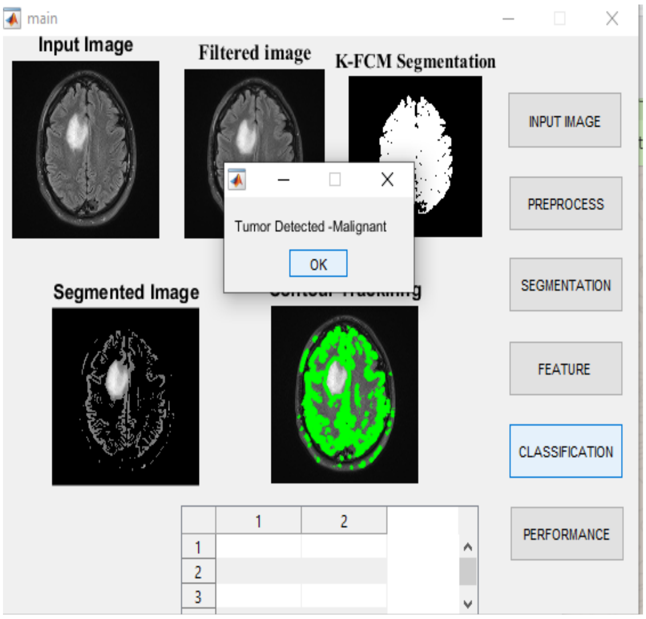

Fig 7. Tumor Classification.

The selected features are used for successful segmentation of tumor, and for accurate classification. The texture feature extraction algorithms developed in this work performs better segmentation and classification accuracy based on CNN classifiers and makes the computation faster.

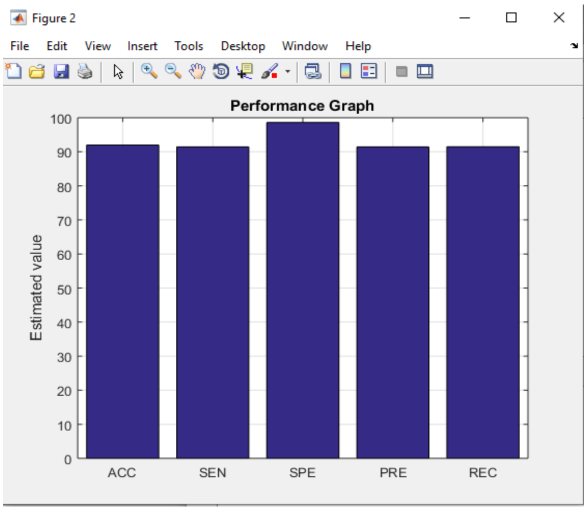

Fig 8. Performance graph.

1. Performance Evaluation:

The proposed fingerprint representation will be analyzed based on the performance measures: In terms of segmentation accuracy and similarity metric of performance scores, including Dice, Positive Predictive Value (PPV), Sensitivity, and Euclidean distance (ED). And Dice metric a comparison is made between the existing segmentation methods.

Table 1. Performance analysis parameters for segmented tissues.

DATA SET	DICE	SSIM	PSNR	MSE
Image 1	98.3260	-inf+0.00	62.44	0.0370
Image 2	98.85	-inf+0.00	66.6924	0.139
Image 3	97.5246	02806	58.6280	0.892
Image 4	98.5370	05272	61.9159	0.418
Image 5	99.0624	03124	67.1577	0.0125
Image 6	99.0657	01817	71.3121	0.0048
Image 7	97.5246	0.7793	58.6280	0.0892
Image 8	98.3801	.8095	66.6924	0.0139
Image 9	99.0721	0.7293	61.1474	0.0184
Image 10	99.2533	0.8095	65.4925	0.184
Image 11	98.5550	-inf+0.00	61.9159	0.418
Image 12	98.8773	0.3352	63.2427	0.0308

The results will show that the segmentation using CNN classifier has higher classification accuracy compared with the other classification methods. The performance of the process is measured in terms of performance metrics like Accuracy, Sensitivity, Specificity and time consumption.

- TP - is the total number of correctly classified foreground (true positives).

- TN - is the total number of wrongly classified foreground (true negatives).
- FN - is the total number of false negatives, which accounts for the incorrect number of foreground pixels classified as background (false negatives).
- FP - is the total number of false positives, which means the pixels are incorrectly classified as foreground (false positives).

Table 2. performance parameter.

Data set 1	Area in pixel	Area of tumour	Area ratio	Area in Sq.Cm.
1	76172	951	80.967	8.0097
2	65792	815	80.72	8.026
3	1367	1703	80.30	8.0301
4	3960	489	80.98	8.0982
5	68544	849	80.75	8.0735

Table 3. Area of the extracted tumor.

Reference	Segmentation	Technique	Accuracy
[1]	Automatic segmentation	CNN	91.0%
[2]	Morphological operation	Naïve bayes classifier	85.0%
[3]	OTSU's thresholding based Segmentation.	ROI (Identification)	87.5
Proposed	KFCM	CNN Proposed	92.14%

Table 4. Comparison on Different Techniques.

Data Set	Accuracy	ensitivity	pecificity	recision	Recall
mage 1	91.3528	92.2102	99.2691	91.2526	93.012
mage 2	91.9156	92.2102	99.1997	91.58	91.553
mage 3	91.7346	91.7608	98.4508	91.2454	92.668
mage 4	91.8084	91.5500	98.6652	91.054	91.233
mage 5	91.5570	91.6086	98.5174	91.4558	92.364
mage 6	91.792	91.7769	98.6291	91.2625	91.256
mage 7	92.238	91.6526	99.2457	91.5983	915530
mage 8	92.2398	92.26	91.2457	95.5983	91.30
mage 9	91.2672	99.7449	98.9058	91.9673	99.4147
Image 10	91.7993	99.1596	99.1575	91.7605	98.8614

V. CONCLUSION

According to the results of experiments, the new image segmentation method which can adaptively achieve image segmentation and get better segmentation results, has stronger robustness to deal with the noise and the out-layer data comparing with the conventional FCM algorithm and the analysis of image's histogram applied in the kernel FCM algorithm can greatly reduce the computational load and increase classification accuracy this work is driven by the motive to provide our clinicians or a radiologist is an efficient and cost effective tool for segmenting and classifying the benign and malignant tumors.

Brain tumor is any mass that results from abnormal growth of cells in the brain. It may affect any person almost in any age (age between 5 to 80). Brain tumors can have a variety of shapes and sizes; it can appear at any location in different image intensities. Brain tumors can be benign or malignant. Low grade Gliomas and Malignant are benign tumors which represent the most common type of tumor.

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