Spotting Brain and Pancreatic Tumor using Fuzzy C-Mean Segmentation and SIFT Extraction Through Sparse Representation Method

Jithendra Reddy. D, Arun Prasath. T, Pallikonda Rajasekaran. M, Vishnuvarthanan. G

Abstract: Diagnosis of Neoplasm is an utmost recurrent and lethal technique for detecting a malignant primary tumor. Imaging techniques empower researchers and medical practitioners to evaluate disorders and activities inside the human brain earlier than performing invasive surgery. Here presents the spotting and detection of brain tumor and pancreatic tumor segmentation and classification progression with several stages DBCWMF algorithm filter with histogram equation, Precise Fuzzy C-segmentation, and SIFT extraction and classification with Sparse representation. These techniques provide a better ability in clinical practices in terms of speed, accuracy, innovation. Experimental results were evaluated using TCIA database and hospital database, where the proposed approaches were verified simultaneously with data progression and incredibly effective for brain and pancreatic tumor in MR images and CT scan images both.

Keywords : Brain tumor, DBCWMF, Fuzzy C-segmentation, SIFT, Sparse representation, pancreatic tumor.

I. INTRODUCTION

Soft computing is immensely exerted in medical scrutiny medical image processing. MRI scans are exerted to create images all body parts and it dispenses an effective and rapid way for analysis of the brain tumor and pancreatic tumor exerted as an important tool while doing surgical and clinical atmosphere for the reason that of its characteristics similarly greater soft tissue diversity, higher spatial determination and with contrast significant analytical imaging method to get premature identification the brain tumor [1]. Brain imaging of MRI shows a vital key part in succor radiologists has to be approached patients for analysis and remedy [2]. The utmost eminent significant of medical image perusal in general, brain magnetic resonance image (MRI) examination in particular, is to extract clinical data that help to revamp diagnosis and remedy of ailment.

Brain tumors are one of the utmost recurrent brain ailments, so the classification of brain tumors in MRI is essential in medical diagnosis [3].

II. RELATED WORK

With CNN bounding and elective scrawls as user interactions and user afford images which are tested, nonetheless they might possibly be gained by involuntary detection [36] to auxiliary growth in efficiency Guotai, et al. [4]. The Noise reduction has made a stage in preprocessing imaging classification as stated by Sebe et al. Here the author has been analyzed exert Quadrature Mirror Filter and Gabor uses for noise reduction purposes has given emphasis to the need for preprocessing. The method is needed in order to eliminate artifacts delay additional processing of MRI images. Pre-processing images stay essential for analysis in Computer-Aided Diagnosis. The author exerted a square designed to structure element and median filtering [5]. exerted the elimination of artifacts in a preprocessing stage. It will Creates sure set 255 as a threshold value of aimed at artifacts elimination and 200 as its threshold values for the elimination of the undesirable a part of a whole of the image [6]. Author Ratan has exerted an altered type of preprocessing for decreasing the processing volume of data. Total 128 images were processed into 3 clips [7]. In Mohan et al. article, here analyzed sundry articles that ensured handle image preprocessing methods. He states that although sundry methods to eliminate noise-introducing negative result on the segmented part of the image [8]. Texture features were associations with bidirectional of associative memory category on artificial neural network is to be classifying the soft tissue parts in brain CT images Sharma,. It was combined with edge features and gray level classified using SVM for brain CT images Padma Nanthagopal, [9]. Combining of texture features with Naive Bayesian classifier from benign tumor and malignant tumor images. Kharrat combining of texture features with SVM classifier is to classify those normal tumors, benign tumors and malignant tumors images. Padma combined co-existence texture features with (PNN) probabilistic neural network classifier used to classify human brain CT scan images [10]. This paper explains about 4 Stages first conversions of noise MRI images to filtered DBCWMF images.

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After Conversion of a filtered image the second step is a detection of brain and pancreatic tumor part Fuzzy C-segmentation is carried out through Sparse Representation Classifier. Involuntary segmentation of multi-atlas process now broadly used for brain imaging.

reference section. In the case of exclusion of references, it should be less than 5%.

III. PROPOSED METHODOLOGY

The methodology proposed involves the Decision Based Couple Window Median Filter, histogram equation, Fuzzy C-segmentation SIFT extraction and classification with Sparse representation (Fig. 1).

Essential phases involved the proposed Methodology:
i) MR image and CT scanned Medical image input
ii) Preprocessing: DBCWMF image in filter and histogram equation
iii) Segmentation: Fuzzy C- segmentation with identifying Neoplasm
iv) Feature extraction: SIFT image extraction
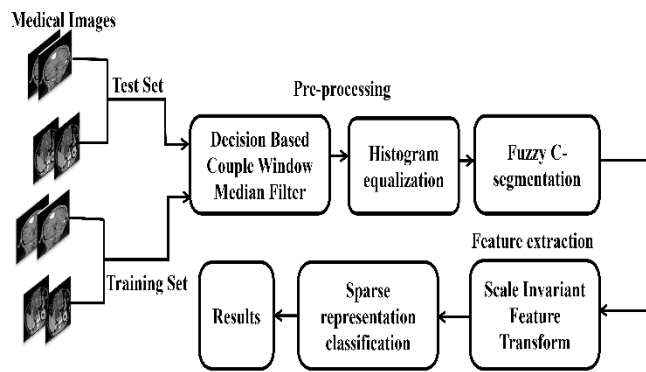vi) Classification: Sparse representation of accuracy.

Fig.1. Block diagram proposed

A. Decision Based Couple Window Median Filter algorithm

After median filter imaging leftover noise pixels free be a selection of by the window median filter with changing pixels of boisterous [11]. The method from the first image noise pixel and ultimately the pixel of a noise image ends. The scanned caused image entitled as a restored image. The mainly 3/4th or grater pixels noisy are transformed into pixels' noise-free with a median filter. Except affected pixels left over free pixel noise picks the window as pixels (i.e. 0 and 255).

$$0 < A(,n) < 255, \text{Noise free}$$
$$X(y,z) = Y(y,z) \tag{1}$$

$$M = (2n+1) \text{ a } (2n+1) \tag{2}$$

$$M(y,z) = \text{mean } \{Z(y,z)\} \tag{3}$$

B. Histogram equalization

Histogram equalization progresses the areas of the pixels that are overexposed and underexposed production the pixies histogram unchanging. Before and after histogram equation pixels find the middle element in the window compute the function of cumulative distribution of the values in the window [12].

$$\text{cdf}(l) = \text{cdf}(l) + \text{cdf}(l-1) \tag{4}$$

$$I(i,j) = round(cdf(ele)(A*B)*255) \tag{5}$$

C. Segmentation

Fuzzy C mean understand the imaging; a suitable segment is essential. Foremost task is to fit clusters with into 1 or more. The collected function is assumed as [13].

$$L_n = \sum_{a=1}^{N} \sum_{b=1}^{C} v_{ab}^r \ ||x_a - c_b||^2 \tag{6}$$

$1 \leq r < \infty$
Where,
r is real number < 1;
v_{ab} is the degree of x_a members of in the l cluster;
x_a is the d-dimensional a^{th} of data;
c_b is the center of the cluster d-dimension;

D. Feature Extraction SIFT

This is used to achieve the image feature extraction. This performance is eventually used for matching image [14]. An SIFT improvement with the comparative method of measuring the entire response belongs to the neighbor's interest point [15]. Key point identifiers can be massively repeatable.

$$A(x, y, \sigma) = (B(x, y, k\sigma) - G(x, y, \sigma) \times C(x, y)) \tag{7}$$

E. Screening Sparse representation classification

[16-17]. The principal aim of SR remains input signal linear combination done SR vector and ample dictionary. The key problems in SR are how to construct and solve vector done with ample dictionary. Widespread tools to build the dictionary contains the method of elective directions (K-SVD) k-singular value a decomposition online learning and algorithm discrete cosine transform. This effectually computed through optimization or greedy methods.

The training data matrix A, the known label vector B, and x observation.

SR Screening: Calculate

$\Omega = f_{aT1} a; a_{T2} a; \cdots ; a_{T n} a g$

T=transpose),. $Ax = f_{a(1)}; a_{(2)}; ::::; a_{(z)}g$ with

$$z = \min fn = \log(c); mg \tag{8}$$

where aT (i)a is the ith major element Ω.
Regression: Crack the normal problem of least square between Ab and a. Namely, compute $\beta = ab{-1}a$

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where ab-1 is the Moore-Penrose inverse.

SR Classification: Allocate the testing thought by
gnscr(a) = arg miny2[Y]

$$\theta(a; Aby\beta^\wedge y) \qquad\qquad (9)$$

Where θ denotes the principal angle. Break ties deterministically.

SR Output: The estimated class label gnscr (a)

IV. RESULTS

Experimental carry out with 512 x 512 brain and 256 x 256 pancreases images 30 to 60 degrees respectively via MATLAB 2013aCT scan and MR images are used. Fragmented 100 images as 40 for testing and 60 for training by TCIA database and hospital database [18].
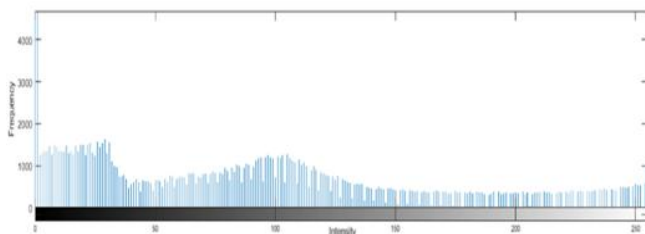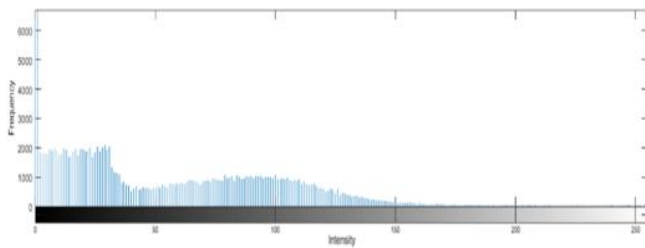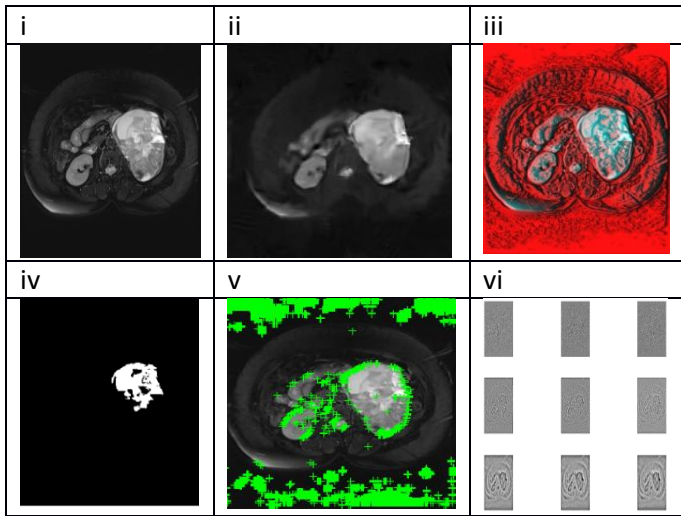
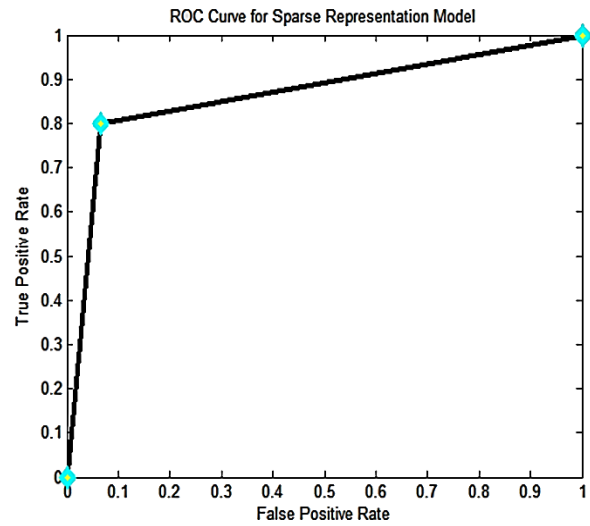

Fig.3. ROC curve –Brain

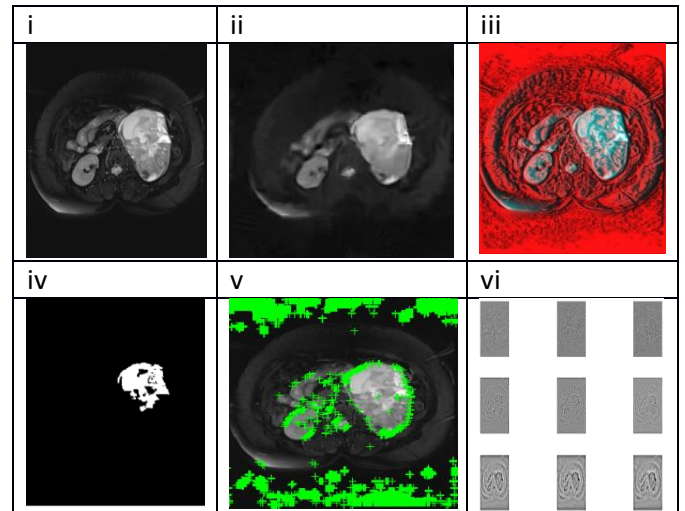
Fig.4. (i) Pancreas input (ii) Prepressing (iii)Histogram output (iv) Segmentation (v) &(vi) Feature extraction (vii) Histogram graph
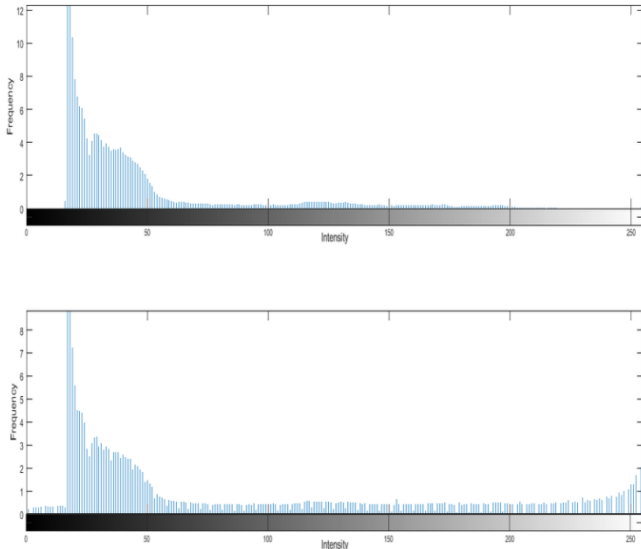

Fig.2. (i) Brain input (ii) Prepressing (iii) Histogram output (iv)Segmentation (v) &(vi) Feature extraction(vii) Histogram graph

$$PSNR = 10log_{10} \frac{255}{MSE} \qquad (11)$$

$$NCC = \frac{\sum_{y=1}^{c} \sum_{z=1}^{d} (P_{yz} * Q_{yz})}{\sum_{y=1}^{c} \sum_{z=1}^{d} (P_{yz})} \qquad (12)$$

TABLE III. Performance Analysis

	Brain	Pancreatic
Accuracy	93.67 %	89.21 %
Precision	97%	90.86 %
Specificity	97 %	91.26 %
Recall	91.24 %	84.67 %

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \qquad (13)$$

$$Precision = \frac{TP}{FP+TP} \qquad (14)$$

$$Recall = \frac{TP}{FN + TP} \qquad (15)$$

TABLE IV. Accuracy Analysis with different Models-Brain

	Probability neural networks (PNN)	ANN	Sparse Representation
Accuracy	83.33 %	82.24	93.67 %

TABLE V. Accuracy Analysis with different models-Pancreatic

	Probability neural networks (PNN)	ANN	Sparse Representation
Accuracy	80.33 %	82.24%	91.21 %

Fig.4. (i) Pancreas input (ii) Prepressing (iii)Histogram output (iv) Segmentation (v) &(vi) Feature extraction (vii) Histogram graph
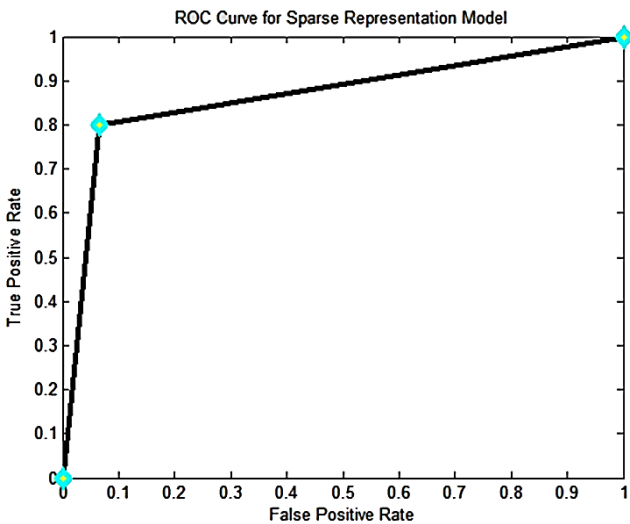

Fig.5. ROC curve –pancreases

TABLE I.   Brain-parameters

Parameters	MSE	PSNR	SSIM	NCC
Median	230.22	21.41	0.4021	1
DBCWMF	101.51	28.87	0.7735	1

TABLE II.   Pancreatic-parameters

Parameters	MSE	PSNR	SSIM	NCC
Median	176.23	26.16	0.6123	1
DBCWMF	88.34	30.27	0.8267	1

$$MSE = \left[\frac{1}{PQ}\right] \sum_{c=0}^{P-1} \sum_{d=0}^{Q-1} [F(c,d) - \hat{F}(c,d)]^2 \qquad (10)$$
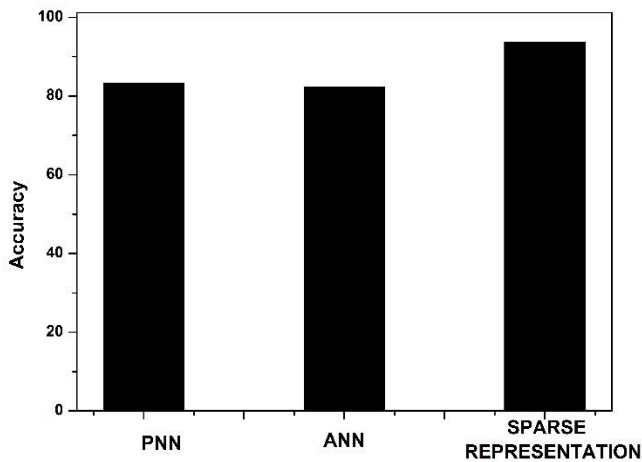
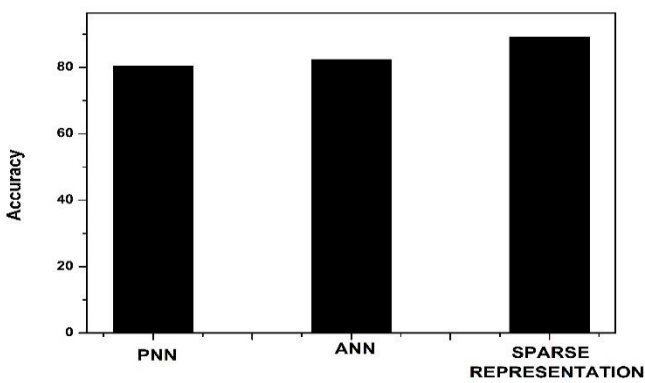Fig.6. Accuracy Analysis with different Models-Brain

Fig.7. Accuracy Analysis with different models- Pancreatic

V. CONCLUSION

Imaging technology has had rapid growth in imaging field. The proposed methodology represents spotting Tumor on both pancreatic CT scan and brain MR images filtered using DBCWMF, which is higher than median filter and Histogram equation. The segmentation with Fuzzy C-mean algorithm and the classification is done by employing Screening Sparse representation and has higher results comparing with ANN and PNN.

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