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An Amalgam Approach for DICOM Image Classification and Recognition

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***Abstract*—**This paper describes about the process of recognition and classification of brain images such as normal and abnormal based on PSO-SVM. Image Classification is becoming more important for medical diagnosis process. In medical area especially for diagnosis the abnormality of the patient is classified, which plays a great role for the doctors to diagnosis the patient according to the severeness of the diseases. In case of DICOM images it is very tough for optimal recognition and early detection of diseases. Our work focuses on recognition and classification of DICOM image based on collective approach of digital image processing. For optimal recognition and classification Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Support Vector Machine (SVM) are used. The collective approach by using PSO-SVM gives high approximation capability and much faster convergence.

***Keywords*—**Recognition, classification, Relaxed Median Filter, Adaptive thresholding, clustering and Neural Networks

I. Introduction

MEDICAL imaging is an essential component for application in the clinical track of events including clinical diagnostic settings, planning, consummation, and evaluation of surgical and radiotherapeutical procedures. Two global categories in imaging are anatomical and functional. Anatomical modalities include X-ray, CT (Computed Tomography), MRI (Magnetic Resonance Imaging, US (UltraSound), portal images, and Video sequences. Some well-known techniques are so isolated under a separate name, for example MRA (Magnetic Resonance Angiography), DSA (Digital Subtraction Angiography, derived from Xray), CTA (Computed Tomography Angiography), and Doppler (derived from US, referring to the Doppler Effect measured). Efficient modalities depicting primarily information on the metabolism of the underlying anatomy, include (planar) scintigraphy, SPECT (single photon emission computed tomography), PET (positron emission tomography), which together make up the nuclear medicine imaging modalities, fMRI (functional MRI), EEG (electro encephalography), and MEG (magneto encephalography).

The computer-aided diagnosis system (CAD) is helpful for clinical diagnosis and treatment. Content-based image retrieval (CBIR) of medical images, according to its domain specific image features, is an important alternative and complement to traditional text-based retrieval using keywords for security purpose [1].

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Obviously, feature extraction is important; many feature extraction methods of biomedical images have been collective using gray level and co-occurrence matrix features [15].

The main problem faced during diagnosis is the noise introduced due to the consequence of the coherent nature of the image capture under liquid, the noise obtain is speckle noise, during transmission the capturing devices itself has a salt & pepper noise[2],[4]. These noises corrupt the image and often lead to incorrect diagnosis. Speckle is a complex phenomenon, which degrades image quality with a backscattered wave appearance which originates from many microscopic diffused reflections that passing through internal organs and makes it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations. Thus, denoising these speckle noise from a noisy image has become the most important step in medical image processing followed by segmentation.

The purpose of segmentation is to simplify an image into a meaningful entity by defining boundaries between features and objects in an image based on some constraint, or homogeneity predicate. Specifically, the segmentation problem is defined as sufficiently partitioning an image into non-overlapping regions.Segmentation which is widely used in medical applications such as surgical planning, abnormality detection and treatment progress monitoring [19], [20]. In our approach for segmentation adaptive thresholding plays a vital role to detect objects in a given image using the techniques of separating foreground and background objects to simplify the image, which gives fine results. The four-layered model called the knowledge-based semantic temporal image model in order to describe a knowledge based image retrieval of CT and MRI images where brain lesions are automatically segmented and represented within a knowledge-based semantic model, providing a mechanism for accessing and processing spatial, evolutionary, and temporal queries.

The existing method for impulse noise reduction is referred [4], [8], [10], [11],[12]. The filters used for impulse noise reduction techniques are median, relaxed median, center weighted median and spatial median filters. Impulse noise which blurs the medical images and fine details are suppressed, for denoising the images median type of filters is used. Weighted median filter gives a clear output compare to other median filter [4],[6],[7]. After pre-processing the image is simplified using segmentation technique.

Image Classification is becoming more important for diagnosis process [18]. The lack of systematic research on features extracted and their role to the classification results forces researchers to select features arbitrarily as input to their systems. In medical image analysis, the determination of normal and infected brain is classified by using texture [20]. CT image texture proved to be useful to determine the Normal brain and to detect the abnormal brain. The need of efficient research on features extracted and their role to the classification results makes researchers to select features randomly as input to their systems. The image is normally classified by clustering method. Our approach is grouping in to distinct class normal and abnormal of brains. The extracted features are separately optimized using GA and PSO [21],[22]. This optimal feature is directed to SVM for an efficient classification.

This paper is organized as follows: The image pre-processing and segmentation is presented in Section 2. Section 3 describes the feature extraction and classification approach is presented in Sections 4. Section 5 proves the results and discussion. Finally in Section 6 future work is presented.

II. Overview of Methodology

This approach consists of various stages such as pre-processing, segmentation, recognition and classification. Each Brain CT images are characterized by certain geometrical properties through which they are identified and classified in the real world. We have adopted a new approach for classification of brain images for classification.

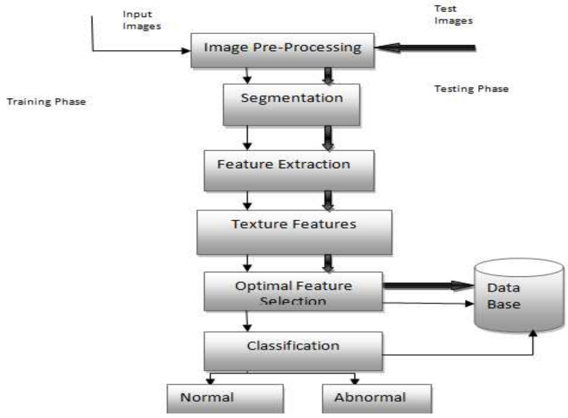
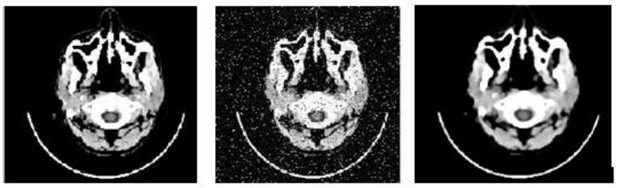


Fig. 1 Collective approach for DICOM image recognition and classification

The above figure 1 shows the collective approach for DICOM image classification and recognition. The CT brain images are classified as normal and abnormal based on the texture feature extracted. The CT brain image with normal size is considered as normal brain. A CT image with varying size of brain images is considered as abnormal brain. The following section explains the collective approach in detail.

A. Image Pre-Processing

During transmission of images, the capturing devices introduce impulse noise. The images of CT brains are filtered by relaxed median filter to remove impulse noise introduced at the time of acquisition of images. Thus, denoising this impulse noise from a noisy image has become the most important step in medical image processing [10], [11].



(a) Original (B) Noisy (c) Pre-Processed

Fig. 2 Image results for denoising impulse noise using relaxed median filter

The above figure 2 shows the image results for denoising impulse noise using relaxed median filter. The output of the relaxed median (RM) filter with parameters ℓ and ϑ is given in the following equation,

$$y_i = RM_{\ell\partial}(w_i) = \begin{cases} x_i, if\ x_i \in [[w_i]]_\ell, [w_i]_\partial \\ x_{i,otherwise} \end{cases},$$

Where ℓ and ∂ are such that $1 \le \ell \le 2N+1$. Note when $\ell = 1$ and $\partial = 2N+1$, the RM, the identity filter $\ell = 1$ and $\partial = N+1$ the output obtained is simply the median. The symmetric relaxed median filter is also called rank conditioned median filter [11]. In [12], the output distribution of the relaxed median filter is given in a more generalized form, and its corresponding statistical properties are also calculated.

B. Segmentation

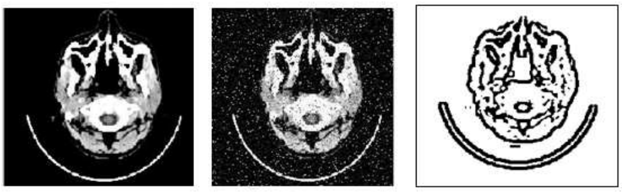
This paper uses the adaptive thresholding. When different thresholds are used for different regions in the image, it is called adaptive thresholding [21],[14]. This may also be known as local or dynamic thresholding. Consider a grayscale image in which g(x, y) € [0, 255] be the intensity of a pixel at location (x, y). In local adaptive thresholding techniques, the threshold t(x, y) for each pixel is computed,

$$O(x, y) = \begin{cases} 0, .if\,(g(x, y) \le t(x, y)) \\ 255, otherwise \end{cases}$$

In Sauvola's binarization method, the threshold t(x, y) is computed using the mean m(x, y) and standard deviation s(x, y) of the pixel intensities in a w × w window centered on the pixel (x, y) as

$$t(x, y) = m(x, y)\left[1 + k\left(\frac{s(x, y)}{R} - 1\right)\right]$$

Where R is the maximum value of the standard deviation (R = 128 for a grayscale), and k is a parameter which takes positive values in the range [0.2, 0.5]. The local mean m(x, y) and standard deviation s(x, y) adapt the value of the threshold according to the contrast in the local neighborhood of the pixel. When there is high contrast in some region of the image, s(x, y) ~R results in t(x, y) ~m(x, y). However, the difference comes in when the contrast in the local neighborhood is low. In that case the threshold t(x, y) goes below the mean value thereby successfully removing the relatively dark regions of the background. The parameter k controls the value of the threshold in the local window such that the higher the value of k, the lower the threshold from the local mean m(x, y).



(a) Original (b) Noisy (c) segmented

Fig. 3 Segmentation Image results for Adaptive Thresholding technique

The above figure 3 shows the results for image segmentation using adaptive thresholding.

III. Feature Extraction

The Gray-Level Co-occurrence Matrix (GLCM) is a statistical method that considers the spatial relationship of pixels, which is also known as the gray-level spatial dependence matrix. The pixel and the adjacent pixel are considered as the spatial relationship and also other spatial relationships can be specified between these two pixels [12],[13],[15],[16].

The GLCM texture features considered for our collective approach and the derived values for the specified features to normal and abnormal DICOM image is given in the following Table 1.

TABLE I
GLCM Features And Values Extracted From Normal And Abnormal Medical Images

S.No	Feature Name	Normal	Abnormal
1	Area	52000.96	16055
2	Centroid	13000.74	1.434
3	Major axis length	30000	1.81
4	Minor Axis Length	2.31	1.01
5	Perimeter	52000.96	4.82
6	Autocorrelation	63.8	1.23
7	Contrast	0.0859	1.71
8	Correlation	0.126	8.83
9	Cluster Performance	2.14	2574.01
10	Cluster Shade	-40.2	215.827
11	dissimilarity	0.0193	0.358529
12	Energy	0.989	0.569828
13	Entropy	0.0481	1.161687
14	Homogeneity	0.996	0.926596
15	Max Probability	0.994	0.740557

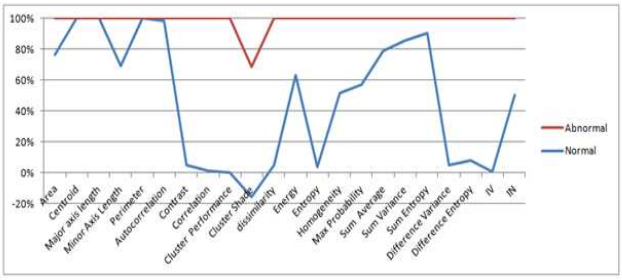


Fig.4 The Features of DICOM image

The above figure 4 shows the features of DICOM image.

IV. Optimal Feature Subset Selection

To improve the prediction accuracy and minimize the computation time, feature selection is used. Feature selection occurs by reducing the feature space. This is achieved by removing irrelevant, redundant and noisy features which performs the dimensionality reduction. Popularly used feature selection algorithms are Sequential forward Selection, Sequential Backward selection, GA and PSO. In this paper an optimal approach of GA and PSO is used to select the optimal features. The selected optimal features are considered for classification through SVM.

A. GA based Feature selection:

During classification, the number of features can be large, irrelevant or redundant. So the optimal solution is not occurred. To solve this problem, feature reduction is introduced to improve the process by searching for the best features subset, from the original features.

GA is an adaptive method of global-optimization searching and simulates the behaviour of the evolution process in nature. It is based on Darwin's fittest principle [25], which states that an initial population of individuals evolves through natural selection in such a way that the fittest individuals have a higher chance of survival.

In our approach a total of 40 features are considered for extraction. These features are optimized by applying GA technique, which minimizes to final subset of 8 suitable features.

TABLE II
Feature Subset Selection Using GA

S.No.	Features	Normal	Abnormal
1.	Area	52000.9	16055
2.	Centroid	13000.7	1.434
3.	Major axis	30000	1.81
4.	Autocorrelation	63.8	1.23
5.	Sum entropy	10.2	1.035941
6.	Difference variance	0.0442	0.523892
7.	Mean	17.9	4.816268
8.	Energy	0.989	0.569828

The above Table II shows the feature selected by GA method.

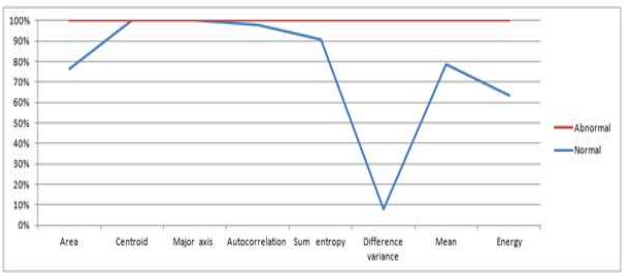


Fig. 5 The optimal feature selection using GA

The above figure 5 shows the optimal feature selection using GA.

B .Feature selection by PSO

PSO [23] is a swarm intelligence model describing behaviors of swarms of creatures, like ants looking for food. It is an optimization algorithm in multi-particle system, like genetic algorithm [25]. In PSO, hundreds or thousands of particles search the optimum while communicating with other particles. Each particle *p* has two state vectors: position x_τ^p and velocity υ_τ^p . These state vectors are simply updated as follows:

$$\upsilon_{\tau+1}^{p} = w\upsilon_{\tau}^{p} + c_s r_s (h_s^p - x_\tau^p) + c_g r_g (h_g - x_\tau^p)$$

$$x_{\tau+1}^{p} = x_\tau^p + \upsilon_\tau^p$$

Where *w* is the inertia term, *cs* and *cg* are parameters given manually, *rs* and *rg* are random values between 0 and 1, *hps* and *hg* show the best position in the history of *p*-th particle and all particles, respectively. All *P* particles search the best position up to T_{it} turns. The selected features using PSO method are tabulated as follows

TABLE III
FEATURE SUBSET SELECTION USING PSO

S.No.	Features	Normal	Abnormal
1.	Dissimilarity	0.0193	0.358529
2.	Difference Variance	0.0859	1.713906
3.	Correlation	0.126	8.83
4.	Contrast	0.0859	1.71
5.	Entropy	0.0481	1.161687

The following figure 6 shows the optimal feature selection using PSO.

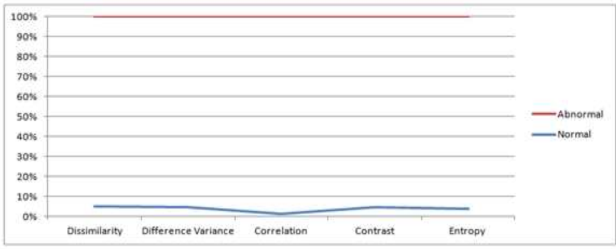


Fig. 6 The optimal feature selection using PSO

C. Feature selection

In feature selection,

N = number of Features
n1= features selected by GA
n2= features selected by PSO

1. N number of features is extracted by GLCM and Histogram texture features from the preprocessed Image
2. Apply GA algorithm to select the optimal set containing n1 number of features where n1< N
3. Apply PSO algorithm to select the best subset containing n2 number of features where n2<N
4. Use the n features where n<N for Classification.

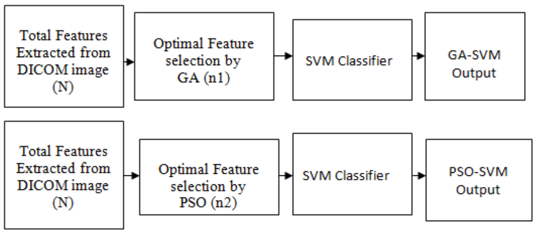


Fig. 7 Optimal approach for feature subset selection

The above figure 7 shows the feature selection by optimal approach.

V. CLASSIFICATION THROUGH SVM

Image classification analyzes the numerical properties of various image features and organizes data into categories. Classification algorithms typically employ two phases of processing: *training* and *testing*. In the initial training phase, characteristic properties of typical image features are isolated and, based on these, a unique description of each classification category, *i.e. training class*, is created. In the subsequent testing phase, these feature-space partitions are used to classify image features.

Support Vector Machine (SVM) is a powerful supervised classifier and accurate learning technique that has been introduced in 1995. It is derived from the statistical theory developed by Vapnick in 1982. It yields successful classification results in various application domains, e.g. medical diagnosis [22, 23]. Support Vector Machine (SVM) is based on the structural risk minimization principle from the statistical learning theory. Its kernel is to control the empirical risk and classification capacity in order to maximize the margin between the classes and minimize the true costs [24]. A support vector machine searches an optimal separating hyper-plane between members and non-members of a given class in a high dimension feature space [21]. The inputs to the SVM algorithm are the feature subset selected using PSO method. In our method, the two classes are normal or abnormal brain, each subject is represented by a vector in all images. There are many common kernel functions, such as:

- Linear: $x_i \cdot x_j$,
- Polynomial of degree *d*: $(x_i \cdot x_j + 1)^d$,

$$\exp\left(\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}\right)$$

- Radial basis function (RBF)

Among these kernel functions, a radial basis function proves to be useful, due to the fact the vectors are nonlinearly mapped to a very high dimension feature space. The optimal values of constants γ and C are determined, where γ is the width of the kernel function and C is the error/trade-off parameter that adjusts the importance of the separation error in the creation of the separation surface. We perform the classification for the CT image dataset with (γ, C) varying along a grid. SVM-based classification takes N training samples, trains the classifier on N-1 samples, then uses the remaining one sample to test. This procedure is repeated until all N samples have been used as the test sample. The performance of the classification for a given value (γ, C) is evaluated by computing the accuracy across all subjects.

VI. Experimental Results

The optimized classification and recognition is performed by GA-SVM and PSO-SVM. The GLCM texture features are extracted from CT DICOM brain images and used for recognition and classification. The features are trained with SVM classifier. The results are effectively obtained based on a DICOM image dataset.

Different brain images are taken into consideration for evaluation. They are categorized into Normal (N) and Abnormal (AN) brains. The sample images for normal and abnormal brain CT images are shown in Figure 8. A total of 75 images are considered for experimentation, where 50 images are considered for training the classifier and the remaining set of 25 images of each class are used for testing the classifier.

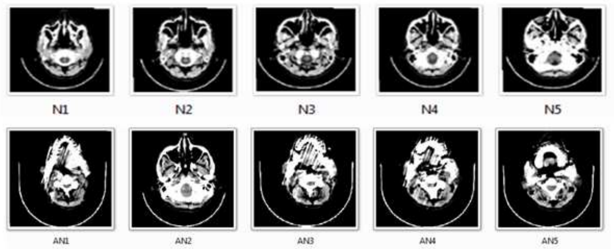


Fig. 8 Optimal approach for feature subset selection

The methodology gives the classification of brain CT images by grouping based on texture features. The CT images are classified based on structural appearances. The effectiveness of the collective method has been estimated using the following measures:

Accuracy= (TP+TN)/ (TP+TN+FP+FN)
Sensitivity= TP/ (TP+FN)
Specificity= TN/ (TN+FP)

where, True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the number of True Positive cases (anomalous cases correctly classified), the number of True Negatives (normal cases correctly classified), the number of False Positives (normal cases classified as anomalous), and the number of False Negatives (anomalous cases classified as normal) respectively. Accuracy is the proportion of correctly diagnosed cases from the total number of cases. Sensitivity measures the ability of the collective method to identify anomalous cases. Specificity measures the ability of the method to identify normal cases [22, 23].

TABLE IV
Feature Subset Selection Using GA

S.No.	Classifiers	Accuracy	Sensitivity	Specificity
1.	GA-SVM	92%	83%	89%
2.	PSO-SVM	94%	87%	92%

The above table IV shows the parametric results for classification. The collective approach shows better results in terms of accuracy, sensitivity and specificity.

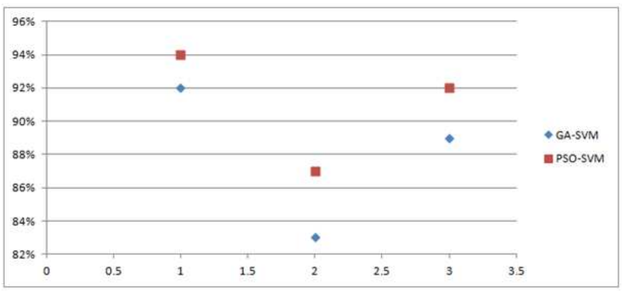


Fig. 9 Optimal Classifier Analysis

The above figure 9 shows the accuracy,sensitivity and specificity of GA-SVM and PSO-SVM optimal classifier performance. The optimal PSO-SVM method works efficiently and gives better results compared to GA-SVM.

VII. Conclusion and Future Work

This paper describes about the process of recognition and classification of brain images such as normal and abnormal based on neural network. In case of DICOM images it is very tough for optimal recognition and early detection of diseases. The experimental results using the collective approach prove that the normal and abnormal brains are fairly classified, by considering the texture features giving literal accuracy for CT brain images. For optimal recognition and classification PSO, GA and SVM is used. The collective approach by using PSO-SVM gives high approximation capability, much faster convergence and it is proved successively and concludes PSO-SVM to be an effective. Our future work will concentrate on large amount of data for experimentation using fully automatic image retrieval system.

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