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An integrated Framework Based on Texture Features, Cuckoo Search and Relevance Vector Machine for Medical Image Retrieval System

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ABSTRACT

As medical images are widely used in healthcare applications, Content Based Medical Image Retrieval (CBMIR) system is needed for physicians to convey effective decisions to patients and for medical research students to learn imaging characteristics for their extensive research based on visual features. However the performance of the retrieval is restricted due to high feature dimensionality of visual features. To reduce the high feature dimension, an integrated approach is proposed such as Visual feature extraction, Feature selection, Feature Classification and Similarity measurements. The selected feature is texture features by using Local Binary Patterns (LBP) in which extracted texture features are designed as feature vector database. Fuzzy based Cuckoo Search (FCKS) techniques are applied for feature selection to reduce the high feature vector dimensionality and addresses the difficulty of feature vectors being surrounded in local feature optima also the global optimum feature position to be special for all feature cuckoo hosts. Fuzzy based Relevance Vector Machine (FRVM) classification is an proficient method to customize the collections of relevant image features that would classify dimensionally determined optimized feature vectors of images. The Euclidean Distance (ED) is a standard technique for similarity measurement between the query image and the image database. The proposed system is implemented on thousands of medical images and achieved a high retrieval precision and recall compared with other two methods as validated through experiments.

Keywords: Texture Features, Medical Image Retrieval, Feature Optimization, Dimensionality Reduction, Feature Classification, Similarity Measurements

1. INTRODUCTION

Medical imaging field is a treasured and vital tool in healthcare systems to physicians for conveying effective decisions and to medical research students to learn imaging characteristics for their extensive research. Everyday thousands of medical images are acquired in the radiology department of hospitals. However, it is tough to assess, retrieve the historical image records and providing explanations about them in a quicker and more precise manner from the huge medical image database without a structured arrangement of the medical image database. Picture Archiving and Communications Systems (PACS) has allowed faster and wider access to medical images based on textual meta data features of image headers such as patient id, name, image modality and body parts by using the format of Digital Imaging and Communications in Medicine (DICOM). However PACS repositories are still far from being considered as the basis for ancillary meta image data storage because this meta data would not be appropriate for content based medical image query and retrieval process. Hence a

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Content-Based Medical Image Retrieval (CBMIR) (Ghosh *et al*., 2011; Kyung *et al*., 2012) system is developed by extracting the content of visual features by using low level features such as texture, shape or color in order to provide relevant medical images from the database. Prosperous CBMIR applications (Emmanuel *et al*., 2010; Akgul *et al*., 2011) has been developed by selecting a capable algorithm at several stages of catalogue and retrieval stream. From the existing systems (Esmat *et al*., 2013; Yogapriya and Vennila, 2012), it has been concluded that CBMIR system performance is limited by high visual feature dimension. Hence, the proposed CBMIR system is implemented by using an integrated approach by selecting a well-organized methods and parameters in the following four stages to obtain relevant images from the database in which feature dimensionality problem is reduced and convergence speed would be increased. The related work and proposed methods are explained in the following four stages:

- Stage I: Feature Extraction
- Stage II: Feature Selection
- Stage III: Feature Classification
- Stage IV: Similarity measurements

1.1. Stage I: Feature Extraction

The first stage of CBMIR is Feature extraction which would extract the visual features as numerical values and stored as feature vectors (Dimitris *et al*., 2009; Akgul *et al*., 2011) in medical image database. Compared to shape and color features, texture features are well suited for image retrieval also it has periodicity and scale results of gathering semantic features in images subsequently it consumes a thorough implication of finite grey levels within the images. The statistical ,spatial frequency and transform based texture descriptors such as Gray level Co-occurrence Matrix (GLCM), Tamura Features (TF) and Gabor Filters (GF) were most widely used texture descriptors for image retrieval (Yogapriya and Vennila, 2012). The Discrete Wavelet Transform (DWT) has extracted the features merely in three directions such as diagonal, horizontal and vertical. Hence, Texture image retrieval in different directions has been accomplished by Gabor Filter (GF), rotated wavelet filters, Dual Tree Complex Wavelet Filters (DT-CWF) and Dual Tree Rotated Complex Wavelet Filters (DT-RCWF). The above revolutionary methods were scramble the complete texture orientation information, so they are not appropriate for rotation invariant based texture descriptors also they requires more computational time to get the more features would be derived for representing medical image textures. Hence, there is a necessity of the texture feature extraction technique which would extract the features with less computational complexity. To overcome the above problems, the Local Binary Pattern (LBP) features are well suited for description of texture features (Liao *et al*., 2009; Subrahmanyam *et al*., 2012) in all directions. The rotational invariant and histogram equalization invariant texture features are extracted by observing the statistical distributions of the uniform LBP.LBP is used to encode the association among reference pixel and its adjacent neighbours by relating gray-level values. It is best suited for texture feature descriptors also no need to tune parameters so speed of the feature extraction have increased. But, this high dimensional histogram equalization and rotation invariant features could be interrelated and have irrelevant information for retrieval which would decline the proficiency of the retrieval process, substantial loss of the discriminative power of each feature and dropping the performance of feature classification that creates problems in assembling proficient data structures for retrieval. Definitely, these features would be reformed using feature selection and feature classification methods to retrieve images effectively.

1.2. Stage II: Feature Selection

To overcome the high feature dimension, the second stage of CBMIR uses feature selection by optimization which would be defined as selecting a specific feature set is finest among all features by applying dimensionality reduction methodologies. Existing feature selection (Wu *et al*., 2009) approaches have used Weighted Multi-Dimensional Scaling, Tabu Search Method, Principal Component Analysis and Evolutionary Algorithms for optimizing the features are Particle Swarm Optimization (PSO) (Ye *et al*., 2009), Ant Colony Optimization (ACO) (Piatrik and Izquierdo, 2009), Gravitational Search Algorithm (GSA) (Rashedi *et al*., 2009) and Genetic Algorithms (GA) (Silva *et al*., 2011). From the above methods, it is concluded that the specific feature selection approach would not provide an exact feature selection which has focused on identifying probable optimal solutions within a sensible amount of time which in turn make the system to have a spontaneous convergence in which inclusive optimal fact and the convergence speed is declined.

Generally, PSO is one of the best meta heuristic algorithms but the basic drawback of classic PSO is that the choice of parameters that have an impulsive convergence at whatever time the feature particle and bulk finest solutions are narrowed into local specks through the search process. A Fuzzy-based PSO (FPSO) method is used to astound the impulsive convergence besides to increase the speed of the CBMIR probing process. However, FPSO might change its performance during the optimization process based on information gathered at each iteration. To overcome the drawback of FPSO, Cuckoo Search[20] (CKS) algorithm (Yang and Deb, 2009) has been used which is a powerful optimization techniques and solved most of the engineering problems (Yang and Deb, 2010). The proposed system has used Cuckoo Search algorithm initially and which is inspired by the egg laying and breeding behaviour of the cuckoo bird, starts with persistent number of cuckoo nests with only few parameters as compared to the other meta heuristic algorithms. However, the size of the cuckoo nests has increased as related to the initial number of nests at the final stage of each generation. Hence, A Fuzzy-based CKS (FCKS) (Chandrasekaran and Simon, 2012) has been used to choose the best negotiation solution, which would be equal to the starting number of nests that would alive for the upcoming generations. The Fuzzy membership function should be enclosed in FCKS for maximizing the fitness function. Hence the proposed system uses FCKS as feature selection, which is able to search local and global best host nests features also it would reject the feature solution nests which are isolated from the best feature solution.

1.3. Stage III: Classification of Optimized Features

The third stage of CBMIR is feature classification which would train and classify the optimized textures features into distinct classes using classification assessment rules. The most widely used classification algorithms (Rajendran and Madheswaran, 2010; Ramamurthy and Chandran, 2012) are K-nearest neighbor, Fuzzy C-Means clustering, Decision Tree, Bayesian Classification and the machine learning algorithms are enabled to train and classify images by using Support Vector Machine (SVM), Relevance Vector Machine (RVM) (Yogapriya and Vennila, 2012). Generally, SVM is the finest machine learning algorithm for image classification, however, the major drawback of SVM's are the following: (1) SVM is unstable for the small-sized training set, (2) SVMs optimal hyper plane may be partial due to certain condition, (3) over fitting occurs when the number of feature dimensions is higher than the size of the training set, (4) SVM makes point predictions rather than generating predictive distributions, (5) SVM requires more support vectors to classify and (6) Kernel functions must satisfy Mercer conditions.

Relevance Vector Machine (RVM) is familiarized to overcome SVMs drawback also it proved a typical machine learning techniques centered on statistical learning theory and having glittering features and focused functional performance. RVM has been proved as efficient classifier than SVM since it produces an optimum solution with few relevance vectors or training samples. The limitation of RVM is to consider the training points homogeneously during training but the significance of the training points is different. Definitely, a fuzzy membership is mandatory to each input point so that dissimilar input points can generate different effects in learning. Fuzzy Relevance Vector Machine (FRVM) (Hong and Chen, 2011) is used to overcome this training scrap, a fuzzy membership is allotted to each training input point, so the dissimilar input points can make various effects in learning evolution.

1.4. Stage IV: Similarity Measurements

The Similarity Measurement is used to retrieve the relevant images from the classified image feature vector database based on the query image features. Various similarity measurement distance metrics are available such as Manhattan Distance (L1 metric), Euclidean Distance (L2 metric), Vector Cosine Angle Distance (VCAD), Chord Distance, Pearson's Correlation Coefficient, Spearman Rank Coefficient (Zhu *et al*., 2012; Ayyachamy and Manivannan, 2013). The Euclidean Distance (ED) is proved as a standard measurement to retrieve images from the medical image database.

2. MATERIALS AND METHODS

The following steps should be taken and repeated by using an integrated approach Texture-FCKS-FRVM in which an efficient CBMIR system would be developed and the proposed system is represented in **Fig. 1**.

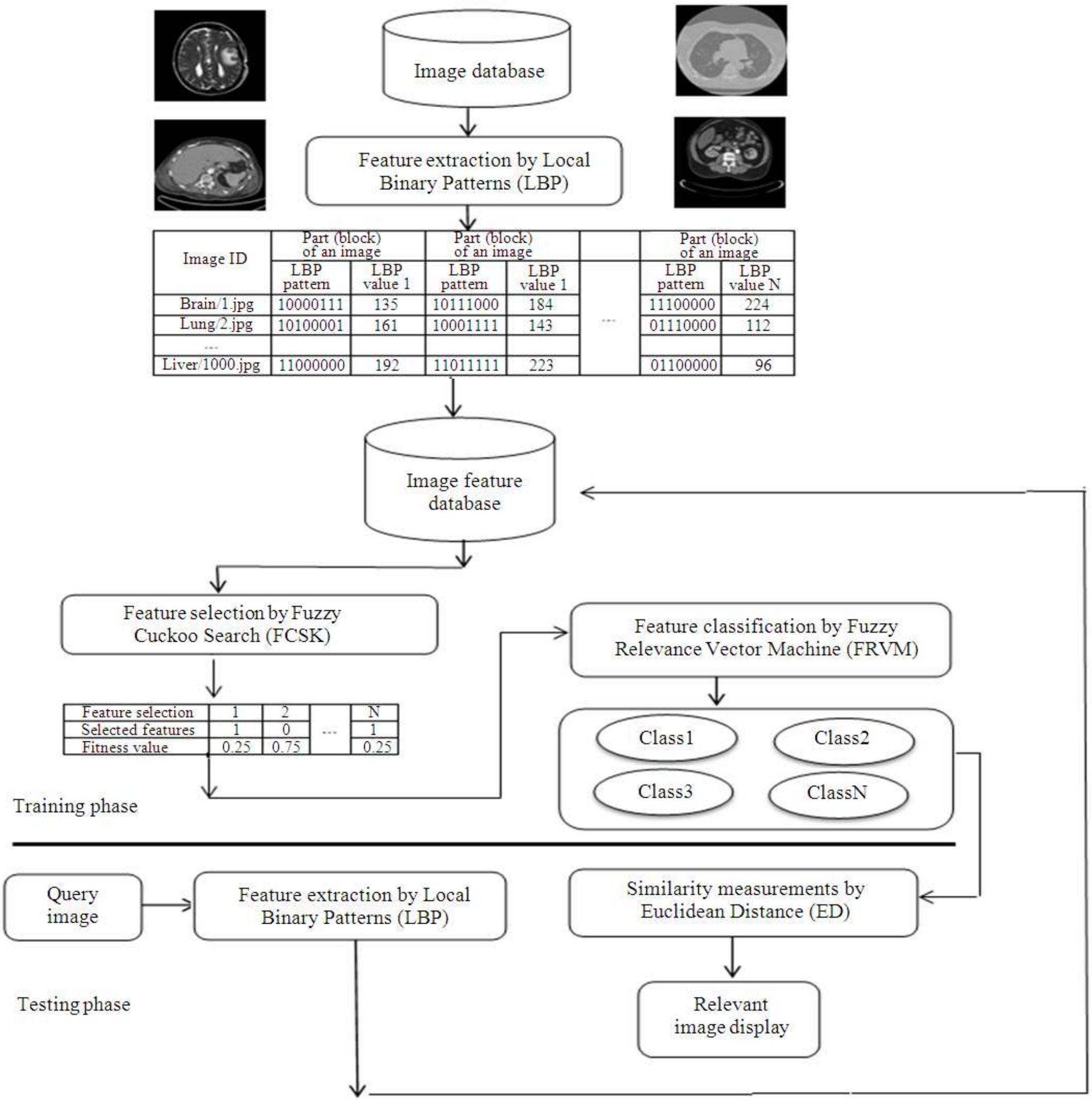


Fig. 1. The proposed medical image retrieval system based on texture-FCKS-FRVM

2.1. Feature Extraction by LBP

An image is first divided into several chunks and LBP operator provides labels for the image pixels in which threshold value to be assigned to neighbouring pixels based on centre value and summing the threshold values weighted by powers of two which results a binary number. The histogram obtained from each block (part) is summed to construct the global feature.

Given a centre pixel in the pattern, LBP value is computed by comparing its gray-scale value with its neighbourhoods based on Equation 1:

$$LBP_{P,R} = \sum_{p=1}^{P} t(I(g_{nb}) - I(g_{ct})) \times 2^{p-1}$$
$$t(x) = \begin{cases} 1 \rightarrow x \geq 0 \\ 0 \rightarrow \text{otherwise} \end{cases} \tag{1}$$

where, $I(g_{nb})$ represents the gray value of the centre pixel, $I(g_{ct})$ represents the gray value of its neighbours, t denotes the thresholding function, when the centre pixel is higher than the neighbouring pixel then value '1' is assigned otherwise '0', P denotes the number of neighbours and R is the radius of the neighbourhood.

Figure 2 represents an example of finding an LBP from a specified pattern and **Table 1** shows the sample brain image LBP Patterns and its value. **Figure 3** shows the sample LBP feature map of brain and lung images. Once the LBP pattern for each pixel (a,b) has been computed then the image is denoted by constructing a histogram as defined in Equation 2:

$$H_{LBP}(c) = \sum_{a=1}^{M_1}\sum_{b=1}^{M_2} f(LBP(a,b),c); c \in [0,(2^P - 1)$$
$$f(x,y) = \begin{cases} 1 \rightarrow x = y \\ 0 \rightarrow \text{otherwise} \end{cases} \quad (2)$$

where the size of input image $M_1 \times M_2$.

This LBP histogram contains information about the distribution of the local patterns such as edges, spots, corners and flat areas of the entire image to represent the image characteristics statistically. The significant belongings of LBP features are, tolerance against illumination variations and computational forbearance. If two transitions are exists between "0" and "1" then the patterns are uniform. For example, 01100000 and 11011111 are uniform patterns. Hence, for image retrieval, the uniform LBPs are successfully extract the fundamental information of textures.

2.2. Feature Selection by Fuzzy Cuckoo Search (FCKS)

The feature vectors are the histogram of the uniform patterns. However, if we consider all the possible patterns to perform classification, it will take more time to retrieve the needed images. So, the most important feature patterns only need to be selected and served as the best feature vectors to perform classification. The feature selection is performed by using Fuzzy based Cuckoo Search algorithm. The following steps are to be taken for best feature selection.

Step 1: Generate the Core Population of N Features of the Host Nest to Get Random Solutions

A feature vector corresponds to the nest and similarly each individual feature attribute of the feature vector corresponds to a cuckoo egg. The core host nests of each feature particle is arbitrarily generated and defined in Equation 3:

$$\text{FeatureHostnests} = \begin{bmatrix} FH_1 \\ FH_2 \\ \ldots \\ FH_{N_{Host}} \end{bmatrix}$$
$$\text{Featurehostnest}_j = [Fh_1, Fh_2, \ldots Fh_d] \quad (3)$$
$$Fh_i^{min} < Fh_i < Fh_i^{max}$$

where, Feature Hostnests_j are the j^{th} feature host nest for the i^{th} specific features of host nests. Fh_i^{max} and Fh_i^{min} are the maximum and minimum value of each feature point that are appropriate to the j^{th} feature hostnest, respectively.

Step 2: Estimate the Objective Function Value to Minimize High Dimensional Features and to Categorize the Core Feature Population (Histogram Bins)

The objective function f(x) = BFF, where BFF is the best feature fitness, to be estimated for each specific population of N Feature cuckoo eggs in order to minimize the high dimensional features into a low dimensional features and defined in Equation 4:

$$BFF = \sum_{o=1}^{N} FD_1, FD_2, \ldots FD_o \quad (4)$$

Part of an image

30	11	19
39	23	15
31	29	33

Thresholding binary image pattern 11110001

1	0	0
1		0
1	1	1

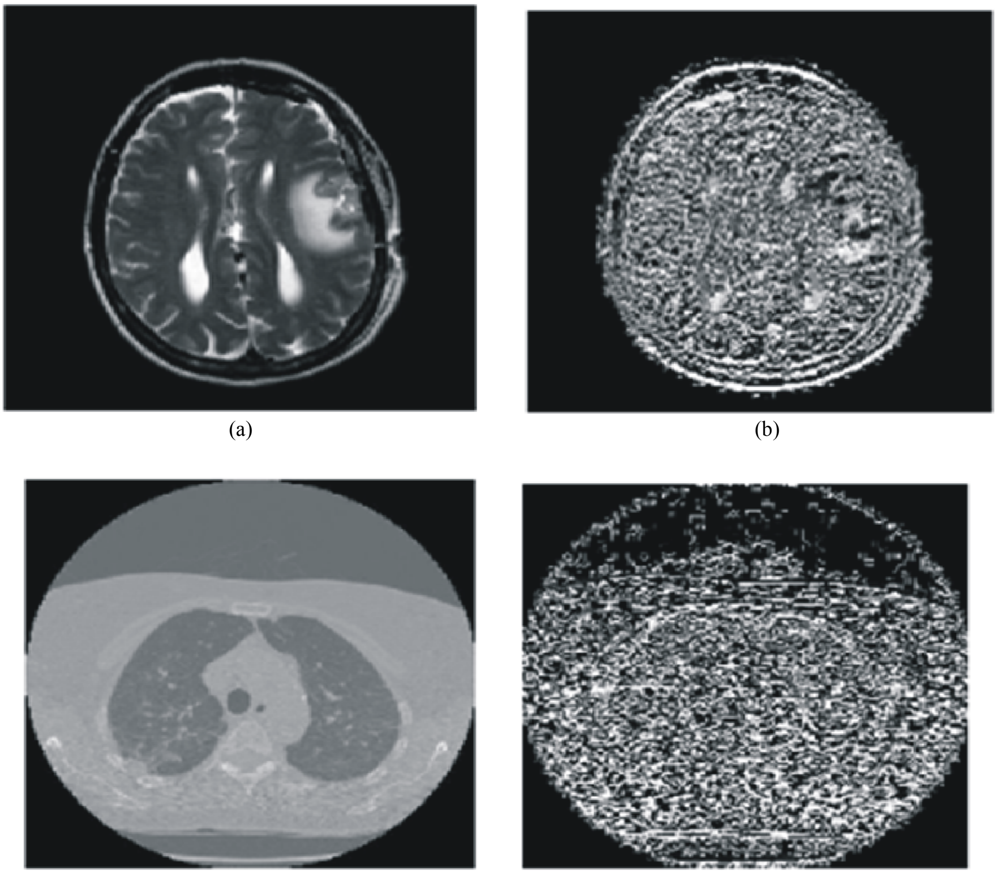
Weights

1	2	4
128		8
64	32	16

LBP value (decimal) = 128+64+32+16+1241

	241	

Fig. 2. Calculation of LBP



(a) (b) (c) (d)

Fig. 3. LBP Feature Map of Brain and Lung Images (a) Brain image (b) LBP feature map (c) Lung image (d) LBP feature map

Table 1. The LBP patterns and its value for sample brain image

Sample part of brain image	LBP pattern								LBP value
Part 1	1	0	0	0	0	1	1	1	135
Part 2	1	0	0	0	0	1	1	0	134
Part 3	1	1	1	1	0	0	0	1	241
Part 4	1	0	1	1	1	0	0	0	184
Part 5	0	1	1	1	0	0	0	0	112
Part 6	1	1	1	1	0	0	0	0	240
Part 7	1	1	1	0	0	0	0	0	224
Part 8	1	1	0	0	0	0	0	0	192
Part 9	1	1	1	0	0	0	0	0	224
Part 10	1	1	0	0	0	0	0	0	192

where, FD_1, FD2 …FD_o are the optimized low dimensional features.

Step 3: Select the ith Specific Nest Position Features then Choose the Best Local Position and a Current Best Feature Solution

Generally, each egg in a nest denotes a feature solution. Each cuckoo egg denotes selected features. The host nests and the number of cuckoo egg selection show a vital role in reducing the feature dimension. For each host nests, the quality of eggs are either 1 or 0, which represents the particular feature is selected or not. First, set the CKS parameters such as the nest size, beta value and maximum generation number.

The cuckoo randomly selects the Nest Position Feature (NPF) to lay eggs and defined in Equation 5:

$$NPF_{xy}^{pos+1} = NPF_{xy}^{pos} + L'evy(\beta) \times \alpha \quad (5)$$

The best feature local position is selected for each specific feature set and gets the current best features X_{best} as the new solution using L'evy flight and defined in Equation 6:

$$L'evy(\beta) = \left(\frac{\Gamma(1+\beta)\cdot \sin(\pi\cdot\beta/2)}{\Gamma\left(\left(\frac{1+\beta}{2}\right)\cdot\beta\cdot 2^{\frac{\beta-1}{2}}\right)} \right)^{1/\beta} \quad (6)$$

where, β is a constant that represents the Levy distribution parameter and the value assigned is β = 1.50, Γ denotes the gamma function and α is the step size which is related to the scales of feature problem.

Step 4: Calculate the Step Size

When the step size is excessively high, then the new feature solution would be far away from the old solution. Hence, such a solution would not be accepted. When the step size is excessively low, variation is minor to be substantial and subsequently such mechanism is also not acceptable.

So a standard step size is vital to preserve the search as professionally as possible. The step size is calculated using the following Equation 7:

$$\alpha = 0.010\cdot\left(\frac{p_j}{q_j}\right)^{1/\beta}\cdot(p - X_{best}) \quad (7)$$

P = Levy.rend [FD_n] and q = rand [FD_o]. Where p and q are the randomly selected keys p = {1,2,…, FD_n} where FD_n is the total feature population of nest position and q = {1, 2…FD_o} where FD_o represents the number of parameters that can be optimized for feature selection and note that the value of p and q must be different.

Step 5: Once Cuckoo Selects the Nest Features, then Evaluate the Egg Laid by a Cuckoo using Fitness Function

The Fuzzification mechanism and fitness sharing is used to select the best negotiation solution. The Fuzzy Membership Function Rules are:

- If BFF is greater than BFF_{max}, then The Membership function value is 0, not accepted for optimal feature solution
- If BFF is less than BFF_{min}, then The Membership function value is 1, accepted and maximizes the fitness function
- If BFF is between BFF_{min} and BFF_{max}, then The Membership function as Normalized Best Feature Fitness (NBFF) and defined in Equation 8:

$$NBFF = \frac{BFF - BFF_{min}}{BFF_{max} - BFF_{min}} \quad (8)$$

where, BFF_{min} and BFF_{max} are the minimum and maximum values of BFF value. This feature solution could be participated based on the fitness value. Once the host feature birds recognized the alien egg (not accepted as optimal feature) then select the high quality of egg using the probability value using Equation 9:

$$Feature\_Probability = (1 * NBFF_x / \max(NBFF)) + 0.15 \quad (9)$$

where, $NBFF_x$ is the fitness value of the feature solution x which is related to the high standard egg in the nest position feature NPF. The egg is discovered by the host bird by comparing randomly such as probability Pd∈[0, 1] with Feature_Probability. The minimum value of Feature_Probability leads to discarding the feature and the high value of Feature_Probability takes that specific feature to the next generation in which feature dimension would be reduced.

Step 6: Check the Termination Condition

The termination condition is the stated maximum number of generations. Once the termination condition is satisfied, stop the process and go to Feature Classification otherwise go to step 3. The best feature selection and the equivalent host nest feature position are remembered in the memory at the final stage of the termination criteria.

2.3. Feature Classification by Fuzzy Relevance Vector Machine (FRVM)

The dimensionally reduced best features are considered to be the initial solution for the Fuzzy RVM classification algorithm. The RVM has used the principle of Bayesian probabilistic learningapproach that would get the relevance vectors and the weights by maximizing the marginal likelihood. The RVM starts with an optimized input feature vector and their corresponding optimized output feature vector. Given a set of optimized feature values $\{ox_i,oy_i\}$, RVM makes predictions by the sum of product of weights and kernel functionswhere ox_i is the optimized feature input vector and oy_i is the corresponding outputs which are specified in Equation 10:

$$oy(ox,w)=\sum_{i=1}^{n} w_i K(ox,ox_i) \quad (10)$$

where, $K(ox,ox_i)=\exp\left[-\frac{\| ox-ox_i \|^2}{2\sigma^2}\right]$ is a Gaussian kernel function of the optimized features, σ indicates the width of the Gaussian kernel which is selected by FCKS and $\{w_i\}$ are the model weights. RVM use hyper planes in order to separate the two parts of the image classes such as relevant and irrelevant. The fuzzy membership is introduced in RVM and the likelihood is represented in Equation 11:

$$-\log\{p(t|\omega)p(\omega|\alpha)\}=-\sum MFs_n[t_n \log y_n+(1-t_n) \times\log(1-y_n)]+\frac{1}{2}\omega^T A\omega \quad (11)$$

p (t|w) -Likelihood of the optimized feature training data set p(w|α) -Gaussian distribution over w with variance α to control over fitting. MFs_n is the fuzzy membership.

Based on the different values of MFs_i , there would be control over the transaction of the respective training points (x_i, t_i) during the classification stage.

A negligible value of MFs_i grades the corresponding point (x_i, t_i) less significant in training. So RVM is the separate case of FRVM if we set all $MFs_i=1$ and if MFs_i is positive then conclude that the optimized feature set would be properly classified otherwise it would not be under the specific class and defined in Equation 12:

$$MFs_i=\left\{\frac{MFs_+, y_i=1}{MFs_-, y_i=-1}\right\} \quad (12)$$

The rules of FRVM are defined, R1, R2….R_n, as follows:

R1: If ox_1 is $K(ox_1,ox_{11})$ and …ox_D is $K(ox_D,ox_{1D})$
Then $f_1 = c_{10}+c_{11}\, ox_1+\ldots+c_{1D}\, ox_D$
R2: If ox_1 is $K(ox_2,ox_{21})$ and …ox_D is $K(ox_D,ox_{2D})$
Then $f_1 = c_{20}+c_{21}\, ox_1+\ldots+c_{2D}\, ox_D$
...
Rn: If ox_1 is $K(ox_1,ox_{n1})$ and …ox_D is $K(ox_D,ox_{nD})$
Then $f_1 = c_{n0}+c_{n1}\, ox_1+\ldots+c_{nD}\, ox_D$

D-Dimension of an optimized feature input.
ox_j is an input variable; j = 1,2…D.
f_i is ith local output feature variable.
$K(ox_j, ox_{ij})$ is a fuzzy set i = 1,2…n; j = 1,2,…D.
c_{ij} is a consequent parameter i = 1,2…n; j = 1,2,…D.

The number of rule would be selected based on the number of relevance vectors.

2.4. Similarity Measurements by Euclidean Distance

Euclidean distance is used to retrieve the needed images by finding the similarity between the query image features and the classified image features in the database based on the principle of smaller the distance and better the resemblance defined in Equation 13:

$$FS_{ED}=\sqrt{\sum_{i=1}^{N}(Q_F[i]-DB_{CF}[i])^2} \quad (13)$$

where, $Q_F[i]$ the i^{th} query image features and $DB_{CF}[i]$ is the matching feature in the classified feature vector database and N refers to the total number of images in the database.

3. RESULTS AND DISCUSSION

This proposed CBMIR is implemented with the medical image database of 1000 images which are gray level images of the human body such as Lung, Liver, Kidney, Brain. The proposed system has addressed the feature dimensionality reduction problem and effectively retrieve images based on Feature Extraction, Feature Selection, Feature Classification and Similarity measurements. This study includes the analysis of the proposed integrated algorithm FCKS-FRVM with two methods such as FPSO-FRVM and PSO-RVM.

3.1. Feature Extraction

In this experiment, texture features are extracted using LBP. To determine the optimal number of texture features, different numbers of histogram texture pattern features are used to retrieve images. **Figure 4 and 5** represents the LBP brain and lung image features and histograms in which medical image content is described.

3.2. Feature Selection

To overcome the high feature dimension, the second stage of CBMIR is feature selection by FCKS which would be defined as selecting a specific histogram feature set is finest among all features.

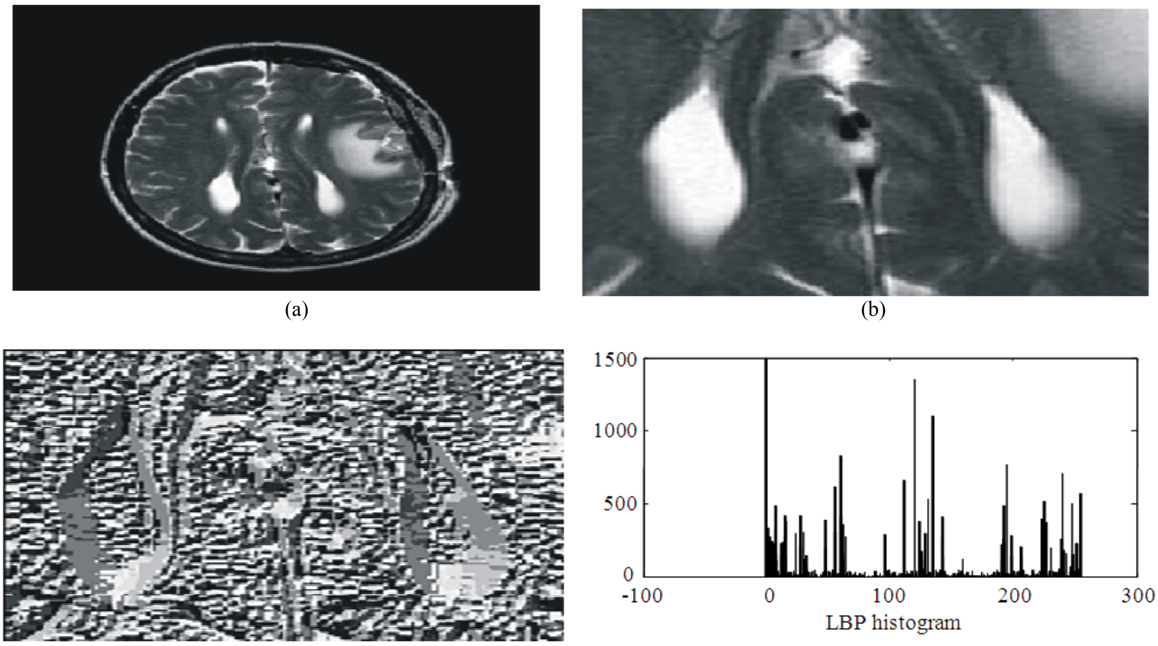


Fig. 4. The LBP Image, Features and Histogram of brain image (a) Brain image (b) LBP image (Part of Brain Image) (c) LBP Features (d) LBP histogram

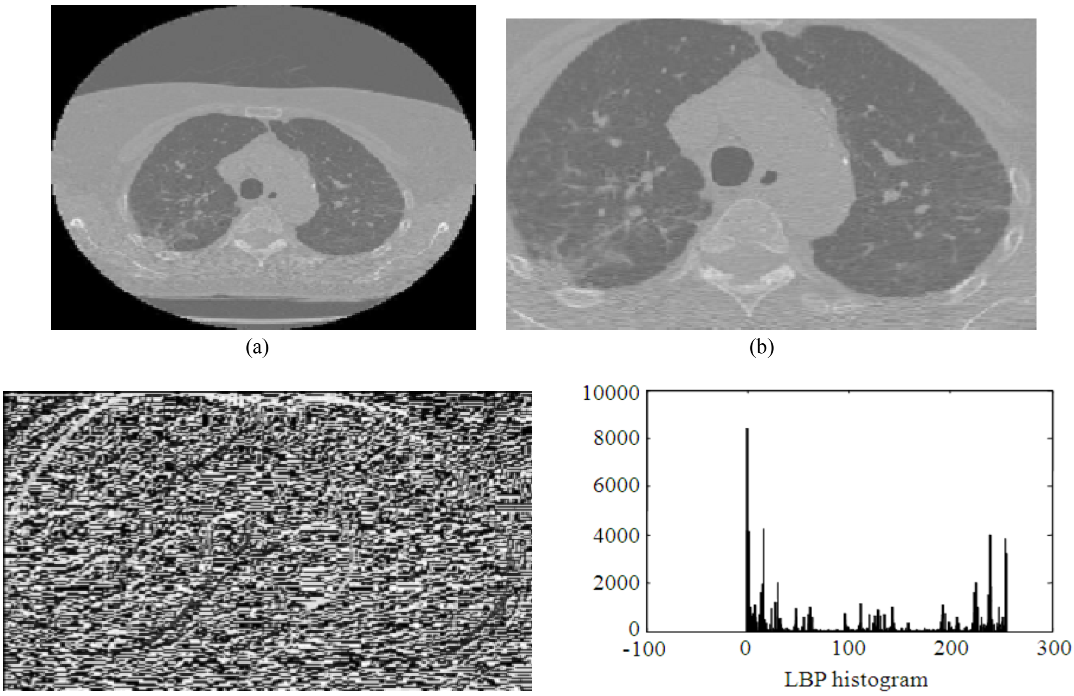


Fig. 5. The LBP image, features and histogram of lung image (a) Lung image (b) LBP image (Part of lung image) (c) LBP features (d) LBP histogram

The problem is to discover nominal feature subset whilst preserving high classification accuracy in demonstrating the original features. This study modernizes the system, progresses the accuracy and reduces the complexity of the system. FCKS algorithm starts with an initial fixed number of cuckoo nests (preferably 25). At the end of each generations of FCKS, the size of cuckoo nests is increased (Nest>25) when compared to the initial number of nests. Hence, the fuzzy CKS is used to select the best negotiation feature solution, the nest size is preferably 25 that would be alive for the forthcoming generations (maximum generations are 100). FCKS will throw away or abandon the feature which is a far away from the best features. From the experiments, it was identified that putting the part of nests would be abandoned with Feature_Probability to 0.75 and part of the nests to be placed in the top nest class with Feature_Probability to 0.25 yielded the best feature fitness results. In feature selection, the parameters are impulsive convergence whenever the particle and cluster finest solutions are narrowed into a local minimum through the search process. The FCKS-FRVM based approach is applied to astonish the impulsive convergence and besides to increase the speed of penetrating process and it gives about 96% of the performance of this phase. The FCKS and FPSO Property and their value are mentioned in the **Table 2**.

3.3. Feature Classification

For each image, the selected optimized texture features are given as input to the classification phase and approximately all the images were classified using a fuzzy membership assigned to the input point using FRVM in which unrelated optimized feature points can create improved effects in learning and produces 96% of classification performance. The total number of feature classes are 34. The number of relevance vectors would be less due to feature optimization. **Table 3** shows the ten optimization results of FPSO-FRVM and FCKS-RVM in respect to Relevance vectors and (Particle) Host nest Fitness Value. The investigational results show that σ makes a nearly perfect fit wit (5/100) and close sparse level.

3.4. Similarity Measurements and Image Retrieval

Euclidean distance is used to retrieve the needed images from the database by finding the similarity between the query image features and classified image features. In this retrieval experiments, the lung and the brain query image and retrieval of images are shown in **Fig. 6-8**. The analysis of texture features shows that most of the retrieval results are similar in respect to the query image.

3.5 Comparisons on Retrieval Performance

The proposed and other two methods performance are analysed with respect to Precision, Recall and Error Percentage. The Precision, Recall and Error Percentage are defined in Equation 14 to 16:

$$\text{Precision} = \frac{\text{Number\_of\_relevant\_images}}{\text{Number\_of\_retrieved\_images}} \tag{14}$$

$$\text{Recall} = \frac{\text{Number\_of\_relevant\_images}}{\text{Total\_Number\_of\_retrieved\_images\_in\_the\_Database}} \tag{15}$$

$$\text{Error\_Percentage} = \frac{\text{Number\_of\_images\_misclassified}}{\text{Total\_Number\_of\_images\_in\_the\_Database}} \tag{16}$$

The effectiveness of the optimization, classification testing, potential performance and accuracy is analysed with training feature samples and testing feature samples of Lung, Liver, Brain and Kidney images. For all classes, model error percentage, precision and recall of PSO-RVM, FPSO-FRVM and FCKS-FRVM is represented in **Table 4-7**, indicate that the proposed method has more accuracy than the remaining two methods. **Figure 9 and 10** represents Lung, Liver, Brain and Kidney image retrieval performance analysis based on Precision and Recall of the proposed approach FCKS-FRVM with FPSO-FRVM, PSO-RVM which shows that the proposed method has high precision, recall and high speed accuracy with less error than the other two methods. Hence, this proposed approach is able to find the optimum feature selection and classification in all runs in which it could speed up the retrieval process of CBMIR. This integrated environment is offer more confidence to the physician and medical research students.

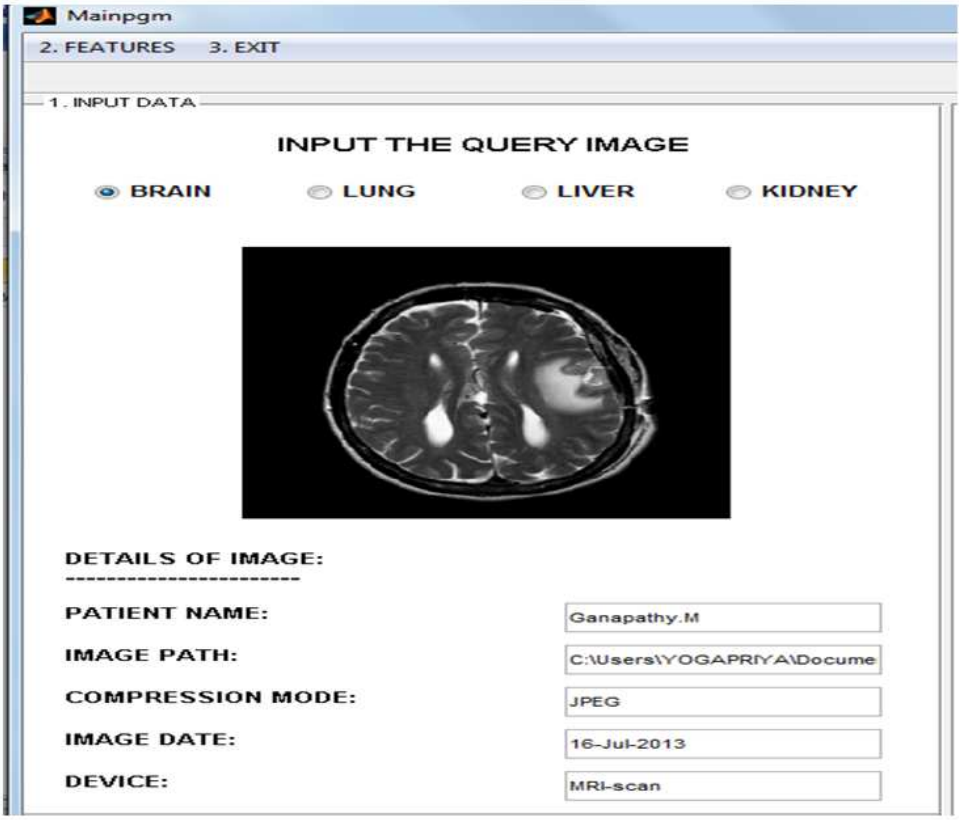


Fig. 6. Sample query image brain/1.jpg

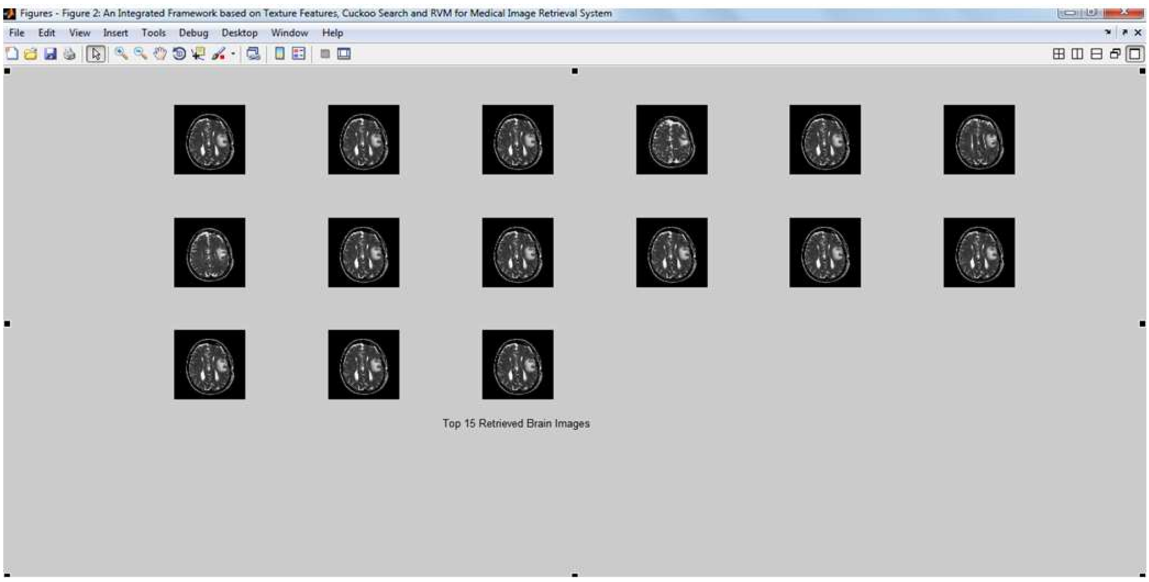


Fig. 7. Image retrieval results of brain image: Top15 retrieval results

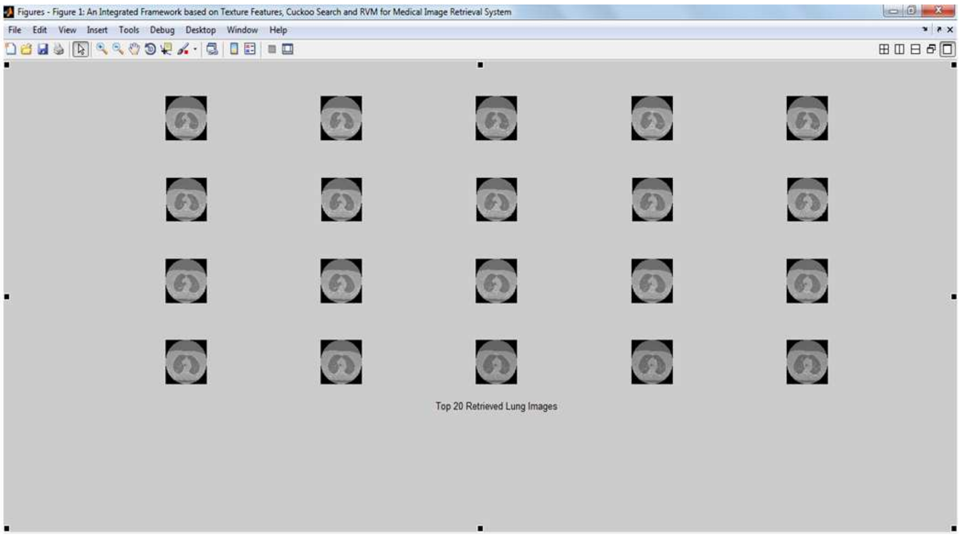


Fig. 8. Image retrieval results of lung image: Top20 retrieval results

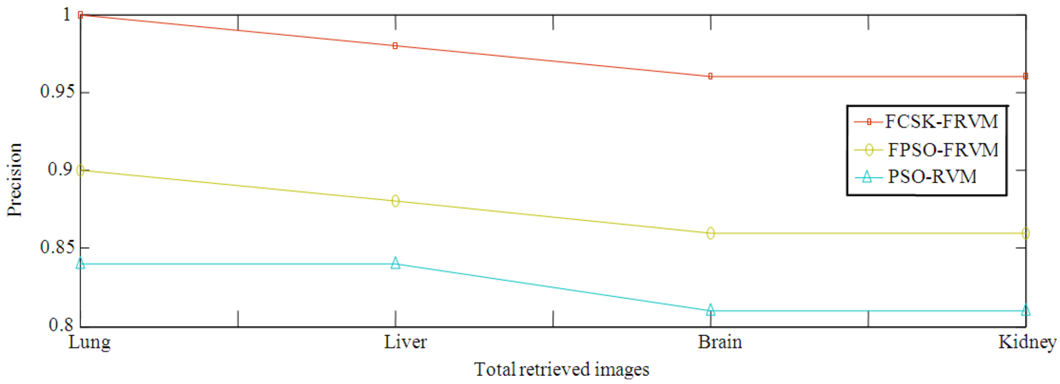


Fig. 9. Comparison of retrieval performance using precision of 3 methods

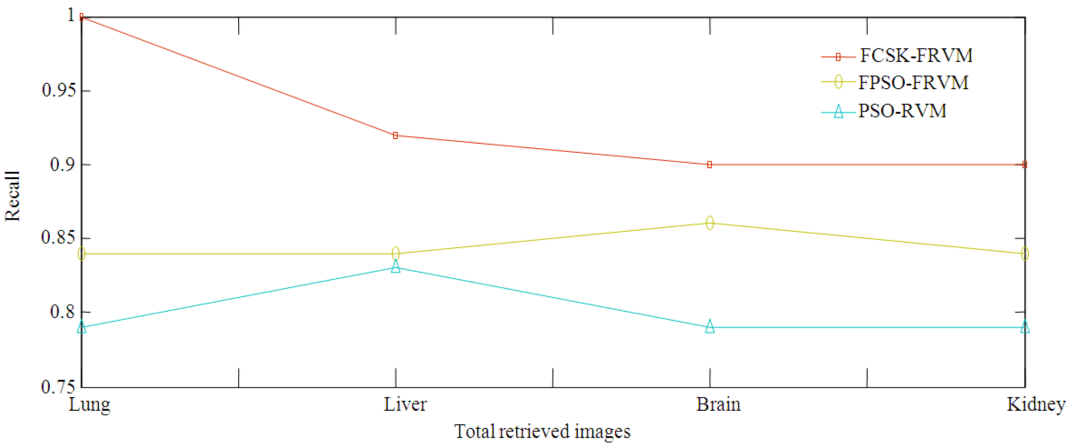


Fig. 10. Comparison of retrieval performance using recall of 3 methods

Table 2. The FCKS and FPSO property and their value

FCKS property	Value	FPSO property	Value
Number of Initial Population of cuckoos	10.0	Number of Initial Population of Particles	10
Maximum Population of Cuckoos	100.0	Maximum Population of Cuckoos	100
Nest Size	25.0	Swarm size	30
Maximum no. generations	100.0	Maximum no. generations	100
Levy distribution parameter, β	1.5	Learning Factors c1,c2	1,1 and 2,2
Step Size α	1.0	Inertia Weight ω	0.2 and 0.4
Minimum Fuzzy Rules	3.0	Minimum Fuzzy Rules	7

Table 3. The sample optimization results of FPSO-FRVM and FCKS-FRVM

Kernel function parameter value σ	Relevance vectors FRVM	Particle fitness value	Kernel function parameter value σ	Relevance vectors FRVM	Cuckoo fitness value
4.9111	7	0.1054	5.1445	5	0.25
4.9432	7	0.1049	5.1486	5	0.25
4.9334	7	0.1043	5.2434	5	0.25
4.8968	7	0.1056	5.1521	5	0.75
4.6745	7	0.1052	5.1515	5	0.75
4.6989	7	0.1054	5.2560	5	0.25
4.8832	7	0.1058	5.2932	5	0.25
4.7896	7	0.1048	5.1503	5	0.75
4.6856	7	0.1047	5.3782	5	0.25
4.8234	7	0.1053	5.3278	5	0.25

Table 4. Comparison of Retrieval performance on 3 methods for lung images

Methods	Overall lung images	No. of optimized lung classes	Model error percentage	Precision (%)	Recall (%)
PSO-RVM	185	13	48.65	84	79
FPSO-FRVM	185	11	43.24	90	84
FCKS-FRVM	185	7	10.81	100	100

Table 5. Comparison of retrieval performance on 3 methods for liver images

Methods	Overall liver images	No. of optimized liver classes	Model error percentage	Precision (%)	Recall (%)
PSO-RVM	224	16	49.11	84	83
FPSO-FRVM	224	13	40.18	88	84
FCKS-FRVM	224	7	13.39	98	92

Table 6. Comparison of Retrieval performance on 3 methods for brain images

Methods	Overall brain images	No. of optimized brain classes	Model error percentage	Precision (%)	Recall (%)
PSO-RVM	264	19	41.67	81	79
FPSO-FRVM	264	16	34.09	86	86
FCKS-FRVM	264	9	11.36	96	90

Table 7. Comparison of retrieval performance on 3 methods for kidney images

Methods	Overall kidney images	No. of optimized kidney classes	Model error percentage	Precision (%)	Recall (%)
PSO-RVM	327	20	42.81	81	79
FPSO-FRVM	327	18	33.64	86	84
FCKS-FRVM	327	11	12.23	96	90

4. CONCLUSION

An integrated approach is proposed such as Visual feature extraction, Optimized feature selection, Classification of optimized features and Similarity measurements, to address the high visual feature dimension for effective retrieval of medical images. Texture Features are extracted using Local Binary Pattern and stored in a feature vector database. The Fuzzy-based cuckoo search is used to diminish the feature vector dimensionality concerns whilst choosing the significant features in the feature vector database in which computational complexity is reduced. The Fuzzy-based relevance vector machine is used for feature classification in which the speed and response rate of the retrieval procedure is improved with small training data. Euclidean distance is used to resolve the similarity between classified features and query image features. This proposed framework is used to support the physician to obtain more assurance in their decisions for diagnosis and medical research students are passion to get the vital images successfully for additional investigation of their assessment.

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6. REFERENCES

Akgul, C.B., D.L. Rubin, S. Napel, C.F. Beaulieu and H. Greenspan *et al*., 2011. Content-based image retrieval in radiology: Current status and future directions. J. Digital Imag., 24: 208-222. DOI: 10.1007/s10278-010-9290-9

Ayyachamy, S. and V.S. Manivannan, 2013. Distance measures for medical image retrieval. Int. J. Imag. Syst. Tech., 23: 9-21. DOI: 10.1002/ima.22031

Chandrasekaran, K. and P.S. Sisha, 2012. Multi-objective unit commitment problem using cuckoo search Lagrangian method. Int. J. Eng. Sci. Tech., 4: 89-105. DOI: 10.4314/ijest.v4i2.7

Dimitris, K.I., N. Pelekis, E.E. Kotsifakos, I. Kopanakis and H. Karanikas *et al*., 2009. A pattern similarity scheme for medical image retrieval. IEEE Trans. Inform. Tech. Biomed., 13: 442-450. DOI: 10.1109/TITB.2008.923144

Emmanuel, M., D.R.R. Babu, J. Jagdale, P. Game and G.P. Potdar, 2010. Parallel approach for content based medical image retrieval system. J. Comput. Sci., 6: 1258-1262. DOI: 10.3844/jcssp.2010.1258.1262

Esmat, R., N. Hossein and S. Saeid, 2013. A simultaneous feature adaptation and feature selection method for content-based image retrieval systems. Knowel. Based Syst., 39: 85-94. DOI: 10.1016/j.knosys.2012.10.011

Ghosh, P., S. Antani, R. Long and G.R. Thoma, 2011. Review of medical image retrieval systems and future directions. Proceedings of the 24th International Symposium on Computer Based Medical Systems, Jun. 27-30, IEEE Xplore Press, Bristol, pp: 1-6. DOI: 10.1109/CBMS.2011.5999142.

Hong, L.I. and G. Chen, 2011. Image classification technique based on fuzzy-relevance vector machine. J. Inform. Comput. Sci., 8: 3989-3995.

Kyung, H.H., L. Haejun and D. Choi, 2012. Medical image retrieval: Past and present. J. Healthcare Inform. Res., 18: 3-9. DOI: 10.4258/hir.2012.18.1.3

Liao, S., M.W.K. Law and A.C.S. Chung, 2009. Dominant local binary patterns for texture classification. IEEE Trans. Image Proc., 15: 1107-1118. DOI: 10.1109/TIP.2009.2015682

Piatrik, T. and E. Izquierdoe, 2009. Subspace clustering of images using ant colony optimization. Proceedings of the International Conference on Image Processing, Nov. 7-10, IEEE Xplore Press, Cairo, pp: 229-232. DOI: 10.1109/ICIP.2009.5414503

Rajendran, P. and M. Madheswaran, 2010. Hybrid medical image classification using association rule mining with decision tree algorithm. J. Comput., 2: 127-136.

Ramamurthy, B. and K.R. Chandran, 2012. Content based medical image retrieval with texture content using gray level co-occurrence matrix and k-means clustering algorithms. J. Comput. Sci., 8: 1070-1076. DOI: 10.3844/jcssp.2012.1070.1076

Rashedi, E., H. Nezamabadi-Pour and S. Saryazdi, 2009. GSA: A gravitational search algorithm. Inform. Sci., 179: 2232-2248. DOI: 10.1016/j.ins.2009.03.004

Silva, S.F.D., M.X. Ribeiro, J.D.E.S.B. Neto, C. Traina-Jr and A.J.M. Traina, 2011. Improving the ranking quality of medical image retrieval using a genetic feature selection method. Decision Support Syst., 51: 810-820. DOI: 10.1016/j.dss.2011.01.015

Subrahmanyam, M., R.P. Maheshwari and R.B. Subramanian, 2012. Directional local extrema patterns: A new descriptor for content based image retrieval. Int. J. Multimed. Inform. Retr., 1: 191-203 DOI: 10.1007/s13735-012-0008-2

Wu, J., X. Wang, D. Yan, C. Wei and Y. Zhang, 2009. Method for medical image retrieval based on frequency layer feature. Proceedings of International Conference on Information Technology and Computer Science, Jul. 25-26, Kiev, pp: 622-624. DOI: 10.1109/ITCS.2009.321

Yang, X.S. and S. Deb, 2009. Cuckoo search via Levy flights. Proceedings of the World Congress on Nature and Biologically Inspired Computing, Dec. 9-11, IEEE Xplore Press, Coimbatore, pp: 210-214. DOI: 10.1109/NABIC.2009.5393690

Yang, X.S. and S. Deb, 2010. Engineering optimization by cuckoo search. Int. J. Math. Modell. Numerical Optim., 1: 330-343. DOI: 10.1504/IJMMNO.2010.035430

Ye, Z., B. Xia, D. Wang and X. Zhou, 2009. Weight optimization of image retrieval based on particle swarm optimization algorithm. Proceedings of International Symposium on Computer Network and Multimedia Technology, Jan.18-20, Wuhan, pp: 1-3. DOI: 10.1109 / CNMT.2009.5374753

Yogapriya, J. and I. Vennila, 2012. Medical image retrieval system using GGRE framework. Proceedings of the International Conference on Pattern Recognition, Informatics and Medical Engineering, Mar. 21-23, IEEE Xplore Press, Salem, Tamilnadu, pp: 246-251. DOI: 10.1109/ICPRIME.2012.6208352

Zhu, Z., C. Zhao and Y. Hou, 2012. Research on similarity measurement for texture image retrieval. PLoS ONE, 7: 1-14. DOI: 10.1371/journal.pone.0045302