Combined Weighted Feature Extraction and Dimension Reduction (CWFE-DR) Technique for CBIR

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Abstract: Content-Based Image Retrieval (CBIR) obtains information from images by utilizing the features lines, textures, colors and spatial data. The performance of the CBIR system can be speed up by reducing the size of the training images. This paper proposes a Combined Weighted Feature Extraction and Dimension Reduction (CWFE-DR) technique for CBIR. In this technique, the images which are onlysimilar to the query image are fetched. The performance is further enhanced by generating a combined feature vector based on color, shape and texture features. By applying multiclass Support Vector Machine (SVM), the appropriate weights of the individual features are determined adaptively, depending on the type of query image.

1.   Introduction

Image Retrieval is one of the approaches for findingdata in the image. It is demarcated as examining for image resemblance with the referred image key. It consists of two classes: manuscript and content-based. CBIR owns two elementarymethods to finddata from images by means of low-level aspects likestreaks, consistencies, colors and spatial data. CBIR investigation which executes low-level aspects has been ledregularly. [1].Owing to its confines, more encouragingsubstitutionslike CBIR by means ofseveral low-level pictorialaspects like colour, consistency and form to index images has addednumerouscare from investigators. In CBIR schemes, images are indexed by these minedaspects. Aspects attempt to signifypertinentdata from the image pixels so as todo the essentialworks such as probing, indexing, and browsing by means of this abridgeddemonstrationrather than the full image dimension [2].

The image content can be categorized into three sorts (a) spatial, (b) semantic and (c) low-level contents. Color, form and consistencyaspects are considered as low-level. Majority of the CBIR approaches are centred on low-level aspects. Content-based procedure utilises pictorial content of the image for recoveryeliminating the drawbacks of text-based recoveryschemes[3][4].So as toincrease the act of the recoveryscheme, it is an activeapproach to incorporatenumerousaspects for image recovery. Dimension level union is extensively utilised, but determining the mass of everyaspect to advance the recoveryact is still a very significantissue[6].

2.   Literature Review

Zhihao Cao et al [5] have suggested an image recovery technique centred on intricacy neural network and measurement lessening. Intricacy neural network is made use of to remove high-level structures of images, and to resolve the difficulty that the mined feature extents are too high and have robust link, multilinear chief module examination is utilised to diminish the measurement of structures. The structures after measurement lessening are dualistic hash oblique for reckless image recovery.

Xiaojun Lu et al [6] have suggested a fresh adaptive weighting technique centred on entropy theory and relevance feedback. Then, they built a transferral matrix with trust. Lastly, based on the transferral matrix, they acquired the heaviness of sole aspects via numerous repetitions. It has three exceptional benefits: (1) The recovery scheme pools the act of several structures and has improved recovery exactness and simplification capacity than sole aspect recovery scheme; (2) In each enquiry, the mass of a sole aspect is rationalized enthusiastically with the enquiry image, which makes the recovery scheme make complete use of the act of numerous single structures; (3) The technique can be practical in two cases: overseen and unverified.

Mutasem K. Alsmadi et al [7] have suggested an effectual CBIR scheme by means of MA to recover images from records. Once the operator entered an enquiry image, the suggested CBIR removed image aspects like color sign, form and consistency color from the image. Then, by means of the MA based resemblance extent; images that are appropriate to the QI were recovered proficiently. The tests done based on the Corel image record show that the suggested MA procedure has robustability to distinguish color, form and color consistency structures.

Minu et al [8] have suggested a novel image indexing system termed Basic intrinsic pattern (BIP), which utilises the image strength as the crucial variable for image indexing. The procedure is assessed regarding the magnitude of the feature vector and the recovery level.

Oluwole A. Adegbola et al [9] have integrated Relevance Feedback (RF) mechanism into an out moded Query by Visual Example CBIR (QVER) scheme. The intrinsic expletive of dimensionality relatedwas supplied by execution feature assortment by means of Principal Component Analysis (PCA). The quantity of feature measurement reserved was indomitable with loss oblige levied on average accuracy of recovery outcome.

WalaaE.Elhady et al [10] have suggested a fresh prejudiced mulit-feature balloting method which includes numerous sorts of low-level pictorial aspects like consistency, form and color in recovery procedure. The color aspect is defined by color histogram and hierarchical annular histogram while form aspect is defined by verge histogram and verge course histogram while consistency aspect by gabor filter and co-occurrancemartix.

3.   Proposed Methodology

A.Overview

The CWFE-DR based CBIR schemesuggested in this researchdefines the structures in the image like color, shape and texture features.Then a combined weighted feature vector is determined based on these individual features. After determining similarity measurements, the multiclass SVM is applied to extract the relevant images.

Figure 1 represents the block diagram of the proposed CWFE-DR method.
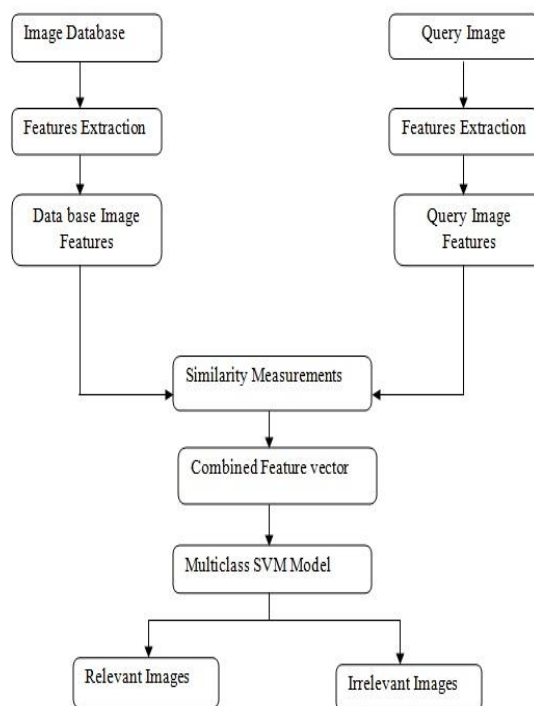

Figure 1 Block diagram of CWFE-DR based CBIR system

B Color Features Extraction

Color feature is an indispensable module for image recovery. For enormous image records, image recovery by means of color aspect is very fruitful and effectual. Even though color aspect is not a determined structure, it is endangered to numerous non-surface features, for instance, the captivating situations like lighting, features of the manoeuvre, the manoeuvre perspective

Let CM be the color matrix

Let CH be the color histogram of CM

Let V and M be the variance and median of CH.

Let Sum(V,M) denotes the sum of all row variances and medians

Let CFV be the combined feature vector

The algorithm of the color feature extraction process is shown below:

Algorithm-1

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1.   Separate the RGB color planes into Red, Green and Blue matrices

2.   For each color matrix CM

3.   Compute the CH

4.   Compute V and M of CH

5.   Compute Sum(V,M)

6.   Combine all features into CFV

7.   End For

8.   Store CFV into features database

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C Shape Features Extraction

The primary goal extractingshape featuresis to extract the shape characteristics of the images. A coloured image has three standardsforevery pixel.To extract the features, the color image is to be converted into one two-dimensional array based on Craig, formula as follows:

$$I_g = [I_r \, I_g \, I_b] * \begin{bmatrix} 0.2989 \\ 0.587 \\ 0.114 \end{bmatrix} \tag{1}$$

Where Ig is the joined 2D matrix, Ir*Ig*Ib are the modulesof the colored image. Ig is signified as the grey level pooled image. In thepreprocessingstage, noise is abridged by means of median filter. The involved noises are salt and pepper noise and speckle noise.

The algorithm for Median filter with width w and length l is as follows:

Algorithm-2: Noise removal using Median Filter

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1. Gather all pixels with length l/2 and width w/2 around every single pixel.

2. Sort all collected pixels.

3. Apprise the pixel value by the intermediate order pixel values from the earlier list.

4. Remove the noise

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After applying the median filter, the noises from the image are completely reduced.

Then Neutrosophic clustering procedure[11] is used to detach pixels with very close values and to disregardunspecified pixels from the gray image.

A novel exclusive group *A* is considered as the combination of the determinant groups and unspecified groups.

Let $A = C_j \cup B \cup R$, j = 1, ...C

where C_j is an unspecified group, B is the groups in border areas, R is related with noisy data and $\cup$ is the union action. B and R are two types of unspecified groups.

T is described as the extent to determinant groups, I is the extent to the border groups, and F is the degree belonging to the noisy data set.

The novel objective function and association are demarcated   as:

$$J(T,I,F,C) = \sum_{i=1}^{N}\sum_{j=1}^{C}(\varpi_1 T_{ij})^m \| x_i - c_j \|^2 + \sum_{i=1}^{N}(\varpi_2 I_i)^m \| x_i - \bar{c}_{i\max} \|^2 + \sum_{i=1}^{N}\delta^2(\varpi_3 F_i)^m \tag{2}$$

$$\bar{c}_{i\max} = \frac{c_{pi} + c_{qi}}{2} \qquad (3)$$

$$p_i = \arg\max_{j=1,2,\cdots C}(T_{ij}) \qquad (4)$$

$$q_i = \arg\max_{j \neq p_i \cap j=1,2,\cdots C}(T_{ij}) \qquad (5)$$

Where m is a constant. p_i and q_i are the group numbers with the leading and second leading value of T. When p_i and q_i are recognized, the $\bar{c}_{i\max}$ is intended and its value is a constant number for each data point i. T_{ij}, I_i and F_i are the association values belonging to the determinate groups, borderareas and noisy data set. $0 < T_{ij}, I_i, F_i < 1$, which gratify with the subsequent formula:

$$\sum_{j=1}^{C} T_{ij} + I_i + F_i = 1 \qquad (6)$$

The algorithm is as follows:

Algorithm-3: Neutrosophic clustering algorithm

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1. Choose k centroids pixel values.

2. For every pixel

Allot arbitrary association value to every centroid.

End For

3. Allot T, N values with the image I and F value with the converse of T.

4. Analyse the novel centroid value as the biased mean of the pixel values, where the mass is the association value to that centroid.

5. Describe the association values as per Eq.(2) to (5)

6. Apprise the image I by using the mean filter over pixels with substantial values.

7. If (Reorganized association values are identical to the values before updation) then

Stop

Else

Reprise fromStage 3

End if.

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Lastly, use the canny procedure to discover the boundaries around the like pixels (grouped pixels). After using canny verge recognition technique, diverse forms can be got which occurs in the Ig image and then the formed content directories are removed and kept in the database in form of feature vector.

The steps of the Canny edge detection are as follows [12]:

Algorithm-4 Canny Edge Detection Algorithm

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1.   Eliminate any noise by means of a filter. Gaussian filteris applied for eliminating the noise. Asample of Gaussian kernel filter of size 5 is:

$$k = \frac{1}{159} \begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} \tag{7}$$

2. Discover the incline of the image.

a. Gradient along x, and y directions are intended by means of the intricacy masks of 3x3 as given below.

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \tag{8}$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} \tag{9}$$

b. Gradient power and way of the limits are intended as given below:

$$G = \sqrt{G_x^2 + G_y^2} \tag{10}$$

$$\theta = \arctan(\frac{G_y}{G_x}) \tag{11}$$

Here Gx and Gy are inclines along x and y directions.

3. Non-maximum dominance is done. This step eliminates pixels which are not deliberated as portion of an edge. Only skinny lines will endure, these comprise pixels which are deliberated to be portion of an edge.

4. Hysteresis: Let LB – lower bound UB-upper bound
   . If the incline value of a pixel is > UB, then
        The pixel is deliberated as an edge pixel.
   .Else if the incline value of a pixel is < LB, then
        The pixel is prohibited.
Else if the incline value of the pixel is > LB and <UB, then
   If the pixel is associated to a pixel which is > UB, then
        The pixel will be recognized
   Else
        The pixel is prohibited
   End if
End if

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D. Texture Features Extraction

Color texture features cataloguing is an indispensable stage for image subdivision by means of CBIR. Thus, this paper suggests a method that is based on texture investigation to categorize color texture rather than separation only

Grey-level co-occurrence matrix (GLCM)

The GLCM is a vigorous image statistical investigation method. GLCM can be demarcated as a matrix of two sizes of combined prospects amid pixels pairs, with a distance d amid them in a specified direction *h*. Haralick removed and demarcated 14 aspects from the GLCM for the texture features cataloguing. But these 14 features are extremely connected.So, in our investigation we eluded this issue by means of five structures for the assessment.

The Steps of the color texture features extraction is shown below:

Algorithm-5 Texture Feature Extraction using GLCM

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1. Filter the input image by applying the 5x5 Gaussian Filter.

2. Divide the filtered image into 4x4 blocks.

3. For each block apply GLCM

4.   Compute Standard Deviation,

5.   Compute Homogeneity

6.   Compute mean value

7.   Compute Contrast

8.   End For

9. Store the extracted features in texture database

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E. Similarity Measure

In CBIR schemes, rather than precise matching, distance measure really calculates the level of "intimacy" of an inquiry image to the imageries in the database. Thus, the recovery outcome is a list of images graded in order of their resemblances with the inquiry image.

$$D_{LP}(X,Y) = \left[\Sigma_{i=1}^{n}|x_i - y_i|^{p}\right]^{1/p} \tag{12}$$

$$D_{L1}(X,Y) = \sum_{i=1}^{n}|x_i - y_i| \tag{13}$$

$$D_{L2}(X,Y) = \left[\Sigma_{i=1}^{n}|x_i - y_i|^{2}\right]^{1/2} \tag{14}$$

F Adaptive Weighted Policy for Combined Feature Vector

In order to generate a combined weight of color, shape and texture features, the common weighted fusion method of sum fusion is applied. It is obtained by adding of different weighted similarity measures of each feature.

Everyprocess of synthesis is exposed as given below

$$sum(q) = \sum w_q^{(i)}[SD_i(q)+, CD_i(q) + TD_i(q)]\{i = 1,2,....K\} \tag{15}$$

Where SD, CD and TD are the similarity measures of shape, color and texture features, respectively, K is number of selected features, q is the query image and W is the combined feature weight.

This article suggests a novel technique to attain the pooled feature weight. Our technique can be used for controlled learning.

Under the conditions of management, the mass of a distinct aspect is got based on Relevance Feedback. $CD(q) \in \{CD_1(q), CD_2(q), ...CD_K(q)\}$ is the resemblance vector of color features amid the inquiry image q and images of database, which is intended based on feature $CF_i \in CF_1, CF_2, ...CF_k$

.We sort the similarity vector and return search results by it. The outcomes are branded as $a^i = \{a_1^i, a_2^i, ..., a_t^i\}$ Here, t signifies the predefined number of reverted images. The recovered outcomes are assessed based on relevant feedback.

G. Classification using SVM

a. Support Vector Machines (SVM)

In SVM, the training set is given by

$(x_1,y_1),(x_2,y_2),....(x_n,y_n)$, $x_j \in R^n$, $y_j \in \{+1,-1\}$.

Here x_j is the input feature vector of jth model and y_j is the output index which is +1 or -1.

SVM splits the +ve and –ve samples by means of a hyperplane as

$$w..x + b = 0, w \in R^n, b \in R \tag{16}$$

Here w.x signifies the inner invention of w and x.

A border splits the +ve and –ve samples. SVM calculates the best hyperplane by exploiting the border.

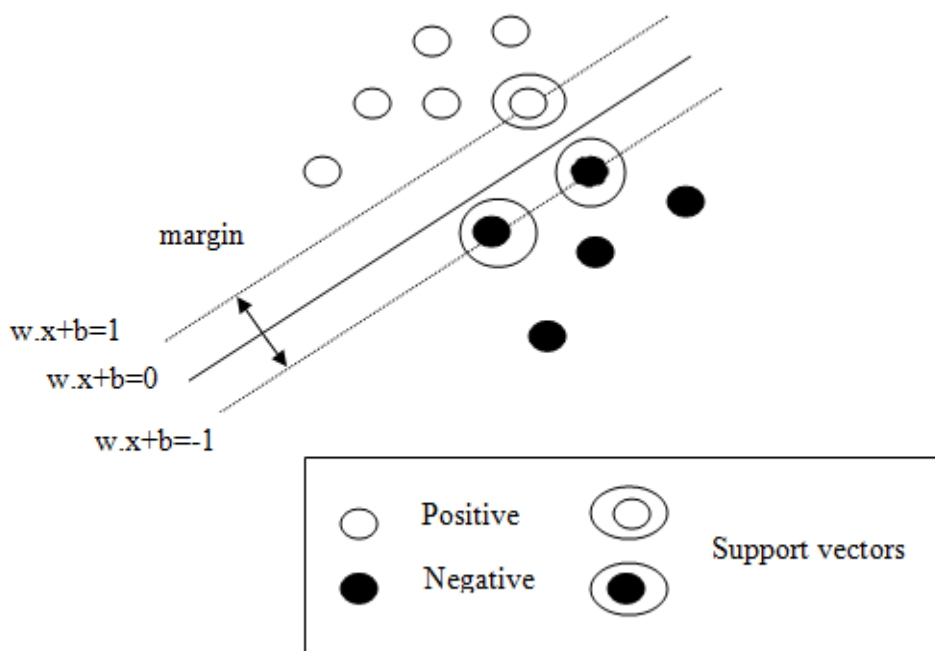Figure 2 offers the pictorial image of SVM notion.

Figure 2 Concept of SVM

The choice function f(x) = sgn(g(x)) for linearly divisible circumstance is as follows

$$g(x) = \left(\sum_{i=1}^{l} \lambda_i y_i x_i..x + b \right) \tag{17}$$

where λ_i is the scalar parameter for future vector x_i

For non-linear circumstances, the choice function is specified by

$$g(x) = \left(\sum_{i=1}^{l} \lambda_i y_i K(x_i.x) + b \right) \qquad (18)$$

where K(x$_i$.x) is a kernel function given by

K(x$_i$,x) = (x$_i$ .x + 1)^d (19)

b. M-class SVM Classifier

A SVM is a binary classifier such that the class labels can only accept two values: +1 or -1. But in our situation, as there are numerous sorts of procedures want to be categorized, M-class classifiers are used. It includes subsequent stages:

To build M-class classifiers, let us first create a group of twofold classifiers f$_1$, f$_2$, . . . ,f$_M$, each proficient to isolate one class from the remaining. Then these M-class classifiers are joined to acquire a multi-class cataloguing by assessing the best output by using equation (7).

argmaxg^j(x), j=1,2….M (20)

$$g^j(x) = \sum_{i=}^{M} \lambda_i y_i k(x_i, x) + b^j \qquad (21)$$

Here g^j(x) revenues a contracted real-valued value which can be construed as the distance from the hyper plane to the point x. Hence point x ought to be allotted to the class whose buoyancy value is prevalent for this point.

c. Classification of Good features

By using the M-class SVM classifier, we split the features into good features and bad features

Good features and bad features are precisely demarcated as given below:

If   pre$_y$>= pre$_x$

Prey ϵ {good_feature}

Else

Pre$_x$ϵ {bad_feature}

$pre_y \in \{pre_1, pre_2,....., pre_k\}$ is the retrieval performance of $F_y \in \{F_1, F_2,....., F_k\}$, $pre_x \in \{pre_1, pre_2,....., pre_k\}$ is the retrieval performance of $F_x \in \{F_1, F_2,....., F_k\}$.

4. Results and Discussion

The intention of retrieving images for a given query image evaluate with following investigations. The investigation includes four different medical images such as brain, lung, mammogram and ultrasound.

The performance of each query image is evaluated with three standard measures precision (P) Recall (R) and F measure (Fm) by comparing the proposed M-SVM with the approaches GA, PSO and MBO.

Particle swarm optimization (PSO): It is a population-based optimization technique simulated from the social behavior of particles. Each particle has a position in source multidimensional search space. The position of a particle is determined according to its own personal best experiences of a particle (Pbest) and the common best experience (Gbest) among several swarms. In every iteration of PSO position and velocity for every particle is updated according to simple mechanisms.

Genetic Algorithm (GA): It is a technique applied for handling conditional and unconditional optimization problems that are based on natural choice. It performs the operations mutation, crossover, selection, etc. to provide accurate solutions for the optimization problems

Monarch Butterfly Optimization (MBO): In order to make the migration behavior of monarch butterflies address various optimization problems, the migration behavior of monarch butterflies can be idealized.
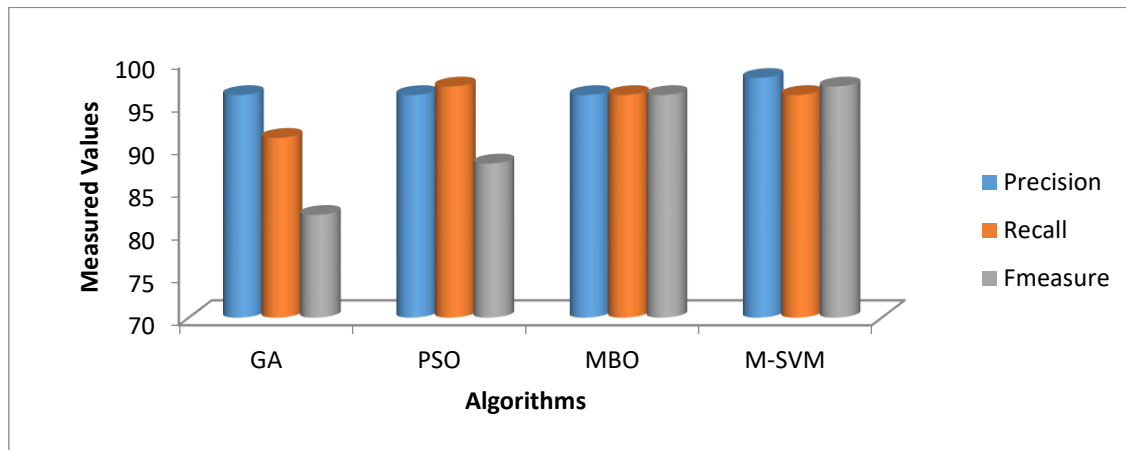
Figure 3 Performance graph for Brain image

Figure 3 exhibits average performance measures of a set of given brain query images for different optimization techniques. Whereas in GA the precision is 96, the recall is 93 and f-measure is 82 respectively.In PSO, the precision is 96, recall is 97 and f-measure is 88 respectively. In MBO, the precision is 96, the recall is 96 and f-measure is 96 respectively.Finally in M-SVM, the precision is 98, the recall is 96 and the f-measure is 96 respectively.
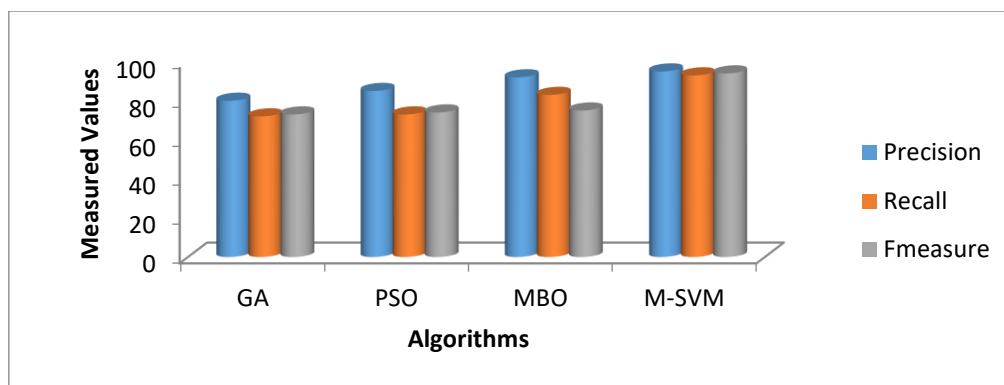

Figure.4 Performance graph for Lung image

Figure 4 exhibits average performance measures of a set of given lung query images for different optimization techniques. In GA, the precision is 80, recall is 72 and f-measure is 73.In PSO, the precision is 85, recall is 73 and f-measure is 74. In MBO, the precision is 92, recall is 83 and f-measure is 75.Finally in M-SVM, the precision is 95, recall is 93 and f-measure is 94.
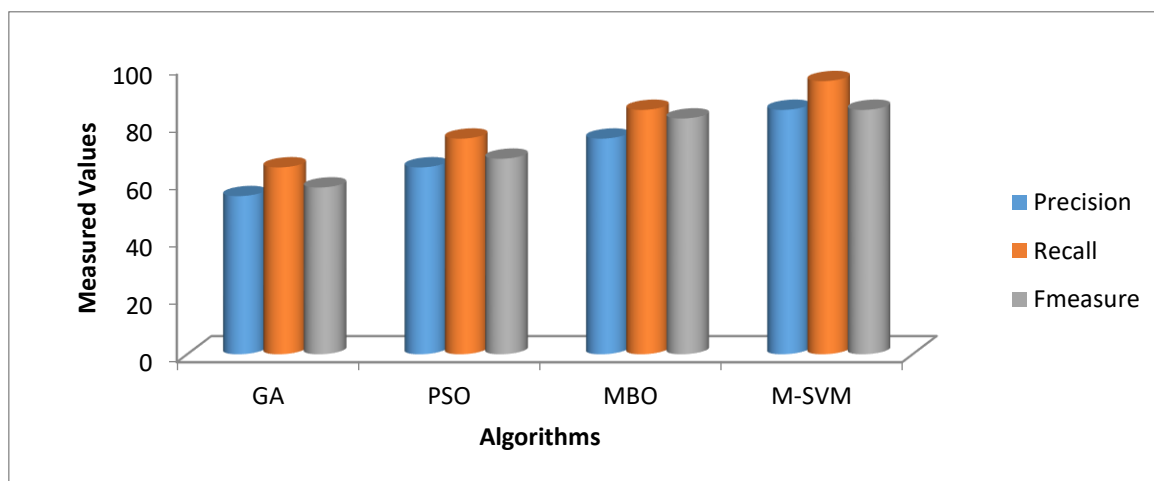

Figure.5 Performance graph for Mammogram image

Figure 5 exhibits average performance measures of a set of given Mammogram query images for different optimization techniques. In GA, the precision is 55, recall is 65 and f-measure is 75.In PSO, the precision is 65,

recall is 75 and f-measure is 85. In MBO, the precision is 75, recall is 85 and f-measure is 82.Finally in M-SVM, the precision is 85, recall is 95 and f-measure is 85 respectively.
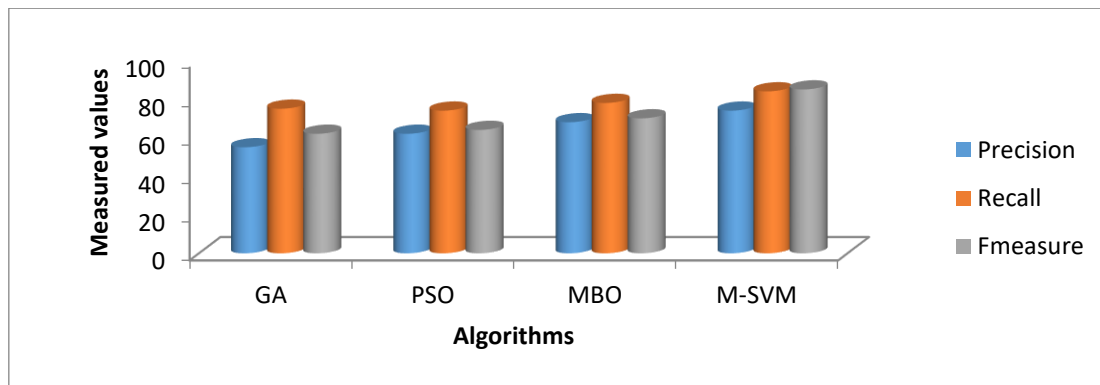

Figure 6 Performance graph for Ultrasound image

Figure 4 exhibits average performance measures of a set of given Ultrasound query images for different optimization techniques. In GA, the precision is 55, recall is 75 and f-measure is 62.In PSO, the precision is 62, recall is 74 and f-measure is 64. In MBO, the precision is 68, recall is 78 and f-measure is 70.Finally in M-SVM, the precision is 74, recall is 84 and f-measure is 85 respectively.

Table.1 Retrieved images with query images for different optimization techniques

Medical Images	Retrieved Images (GA)	Retrieved Images (PSO)	Retrieved Images (MBO)	Retrieved Images (M-SVM)	Query Images
Brain					
Lung					
Mammogram					
Ultra sound					

4.   Conclusion

This paper proposes a Combined Weighted Feature Extraction and Dimension Reduction (CWFE-DR) technique for CBIR. In this technique, the images which are not relevant to the query image are eliminated from the retrieval. The performance is further enhanced by generating a combined feature vector based on color, shape and textute features. By applying multiclass SVM, the appropriate weights of the individual features are determined adaptively, depending on the type of query image. In experimental section, four different medical images such as brain, lung, mammogram and ultrasound are considered and the performance of each query image is evaluated with three standard measures precision (P) Recall (R) and F measure (Fm). By results, it has been proved that the proposed M-SVM attains better results when compared to the approaches GA, PSO and MBO

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