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Gray Level Cooccurrence Matrix Feature Extraction and Fuzzy Based Discriminative Binary Descriptor for Medical Image Retrieval

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***Abstract*:-**Medical image retrieval plays an more important role in the medical research environment which needs to done fastly and accurately for improved performance. In our previous research method it is done by introducing coiflets wavelet based feature extraction and SVM based classification. However this research method cannot perform well with the presence of increased noise level and the minuter feature information. This is resolved in this research method by introducing method namely Gray Level Co occurrence Matrix Feature Extraction and Fuzzy Based Discriminative Binary Descriptor (GLCMFE-FBDBD). It contains five major steps such as deblurring, preprocessing, feature extraction, detection of most discriminative bin and subspace clustering. In this research method, the image deblurring is accomplished by utilizing Artificial Bee Colony (ABC) algorithm. Preprocessing is done by using min-max normalization; feature extraction is done by using gray level concurrence matrix Then FSK Function is used to discover the most discriminative bin selection. SC is presented for quick image retrieval. The MRI brain tumor images are used for evaluation. Finally, the results show that the proposed work gives greater performance compared to the previous work.

***Keywords*:** Image retrieval, Edge Scale-Invariant Feature Transform (ESIFT), Image deblurring, Artificial Bee Colony (ABC), Subspace Clustering (SC) algorithm, Fuzzy Sigmoid Kernel (FSK).

I. INTRODUCTION

In recent times there becomes known a class of image search applications whose query images taken from a mobile device similar to a camera mobile phone. For specified a query image, the technique is to place its next to- and partial-duplicate images in a huge amount of web images and medical images. There are a lot of applications for such a system, such as identifying copyright violations or placing super quality or canonical, versions of a less-resolution or changed image. In image-based object retrieval, image deviations could be because of 3D view-point change, lighting, object deformations, or even object-class variability [1].

Local image patch descriptors have turn out to be a broadly utilized tool in computer vision, utilized for image retrieval, object/scene identification, face alignment face verification, and image stitching. Their helpfulness and significance are confirmed by the huge amount of publications which presented diverse descriptors. In recent times binary key point descriptors [2] gained substantial interest since they need fewer storage and give sooner matching times matched up to descriptors which encode the patch appearance since a vector of real numbers.

A codebook-free algorithm is utilized for extensive mobile image search [3]. In this technique, it uses a new scalable tumbled hashing method to make sure the recall rate of local feature matching. After that, it improves the matching precision by proficient confirmation with the binary signatures of these local features [4]. As a result, this technique attains rapid and exact feature matching without an enormous visual codebook. Furthermore, the quantization and binarizing functions in the method are free of little groups of training images and simplify well for varied image datasets.

Content-Based Image Retrieval (CBIR) has been a main issue in multimedia for years. There are numerous techniques utilized invariant local features to signify images that use the bag-of-visual-words model [5] and the typical inverted index structure for scalable image search. Usually, such an image search structure comprises four essential key modules, with feature extraction, feature quantization, image indexing, and image ranking. For feature extraction, the very well-liked and effectual local descriptor is the SIFT [6], that is extorted on main points or regions identified by Difference of Gaussian (DoG) and Hessian affine detector. Afterwards, there have been more attempts on intending local descriptors with a superior effectiveness and equivalent discriminability e.g., edge-SIFT [7].

At feature quantization, every local descriptor is plotted or hashed to one or various visual words and after that an image is denoted by a collection of visual words. Subsequently, inverted index structures are willingly taken up to index significant image databases for image search. At the online retrieval phase, the shared visual words among a query image and database images could be effortlessly recognized by searching the inverted index lists. The likeness amid the query and database images is deliberated by a weighted formulation dependent upon those shared visual words. At last, those appropriate database images are ordered by their likeness scores and offered to users. The primary retrieval outcomes possibly will be re-ranked by certain post-processing methods, for instance the query expansion, feature augmentation, or geometric verification.

II. RELATED WORKS

Zhou et al. [8] utilized to alter SIFT descriptors to 256-bit binary vectors by a scalar quantization method. Devoid of guiding a codebook, this technique chooses 32 bits from the 256-bit vector as a codeword for indexing and search. The disadvantage of this method is that the respite 224-bit per feature ought to be stored in the inverted index that casts a weighty memory load. A new query-sensitive ranking algorithm to order PCA-based binary hash codes to look for neighbors for image retrieval that successfully progresses the precision of feature matching however at the risk of missing certain exact matches. The review work done in the recent work is described as follows:

Liu et.al [9] introduced the problem of the loss of aspects discriminative power because of quantization and the low usage of spatial relationships amongst visual words. This work proposes new methodology coupling visual and spatial information constantly to advance discriminative power; features of the query image are primarily clustered by both equivalent visual features and their spatial relationships. Afterwards clustered features are gently matched to ease quantization loss. Experimentations on both UK Bench database and a gathered database with over one million images prove that the technique attains 10% enhancement over the technique with a vocabulary tree and bundled feature methodology.

Grauman et.al [10] research kernel based classification methodology that plots unordered feature sets to multi-resolution histograms and calculates a weighted histogram intersection in this space. This “pyramid match” calculation is linear in the amount of features, and it completely discovers associations dependent upon the optimum resolution histogram cell where a matched pair foremost comes out. Because the kernel does not castigate the existence of additional features, it is vigorous to litter. This technique proves the kernel function is positive-definite, making it legal for utilize in learning algorithms whose best possible solutions are assured only for Mercer kernels. Nevertheless it contains problem with system complexity.

Jegou et al [11] offers two contributions to progress accurateness and speediness of an image search system dependent upon bag-of-features: a contextual dissimilarity measure (CDM) and a competent search structure for visual word vectors. This measure (CDM) considers the local distribution of the vectors and iteratively guesstimates distance correcting terms. These terms are consequently utilized to bring up to date a previous distance, thus changing the neighbourhood structure. Experimentation outcomes on the particular dataset prove that the technique considerably does better than the state-of-the-art in regards to accurateness.

Hong et al [12] concentrates on biased duplicate web image retrieval, and bring in a new method, spatial coding, to encode the spatial relationships amongst local features in an image. This spatial coding is both competent and effectual to find out false matches of local features amid images, and could significantly get better retrieval performance. Experimentations in partial-duplicate web image search, utilizing a database of one million images, expose that the technique attains a 53% enhancement in mean average precision and 46% decrease in time cost over the baseline bag-of-words technique.

Xu, et al [13] presented a New Artificial Bee Colony (NABC) algorithm that alters the search pattern of both working and observer bees. A solution pool is built by storing up certain most excellent solutions of the present swarm. Novel candidate solutions are produced by looking for the neighbourhood of resolutions arbitrarily selected from the solution pool. Experimentations are carried out on a group of twelve benchmark functions. Simulation outcomes prove that this method is extensively superior or no less than similar to the original ABC and seven other stochastic algorithms.

Rosten et.al [14] introduced a well-organized corner detection algorithm. Corners are favoured cues because of their two dimensional restraint and quick algorithms to identify them. Newly, a new corner detection approach, fast, has been presented which outperforms previous algorithms in both computational performance and repeatability. On the other hand it contains issue with attaining quality of images for extremely major dataset. PCA is winning method which has been utilized in image processing. PCA is a statistical technique underneath the broad title of factor analysis. The point of PCA is to decrease the huge dimensionality of the data space (observed variables) to the minor intrinsic dimensionality of feature space (independent variables) that are required to explain the data inexpensively. This is the case while there is a sturdy correlation amid noticed variables [15].

III. ACCURATE AND FAST MEDICAL IMAGE RETRIEVAL

The structure defines that the research ABC algorithm and Gray level co occurrence matrix and Fuzzy Sigmoid Kernel (FSK) based edge compression shown in Figure. 1.

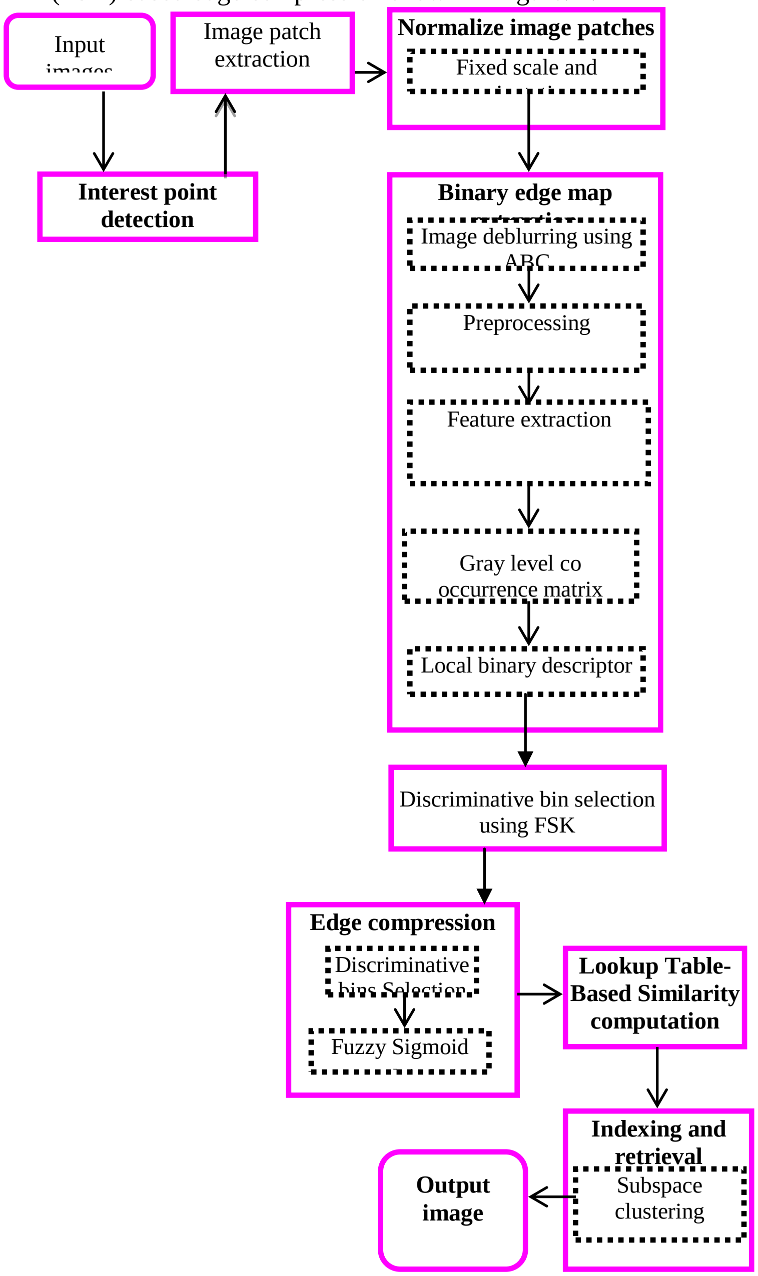

Figure 1: Overall Architecture Diagram

III.I. ABC For Image Deblurring

The ABC contains the benefit of applying less control parameters when matched up with other swarm optimization algorithms. Both approximate image and blur function are discovered via this depiction. In ABC, a colony of artificial forager bees (agents) looks for well-off artificial food resources (fine way out for a specified issue). In order to employ ABC, believed optimization issue is initially trans formed to the issue of identifying the finest parameter vector that reduces an objective function. After that, the artificial bees arbitrarily find out a population of preliminary solution vectors and afterwards iteratively get better them by applying the methods: Approaching improved solutions via a neighbours search method whilst discarding poor solutions. The colony of artificial bees consists of three sets of bees: applied bees linked with accurate food resources, onlooker bees inspecting the dance of used bees within the hive to select a food resource, and scout bees looking for food resources arbitrarily.

Both onlookers and scouts are as well-known as jobless bees. At first, all food source positions are found by scout bees. Afterwards, the nectar of food resources are utilized by applied bees and onlooker bees, and this repeated exploitation will eventually root them to turn out to be bushed. After that, the applied bee that is exploiting the exhausted food resource turn out to be a scout bee looking for additional food resources another time. In other phrases, the applied bee whose food resource has been shattered turns out to be a scout bee. In ABC, the place of a food resource denotes a probable resolution to the issue and the nectar amount of a food resource in relation to the quality (fitness) of the related resolution. The amount of employed bees is equivalent to the amount of food resources (solutions) a sever applied bee is related with unique one food resource. The common method of the ABC algorithm is in this manner Initialization Phase. Every vectors of the population of food resources x_{ij}, are initialized (m = 1,...,SN), SN: population size) by scout bees and control parameters are set

$$X_{ij} = l_j + rand(0,1) * (u_j - l_j) \qquad (1)$$

Here l_j and u_j are e the lower and higher bound of the parameter correspondingly. rand is the random generator function of values with zero mean and unity variance.

REPEAT

Employed Bees Phase

$$fitness = \begin{cases} 1/(1 + f_i) & f_i \geq 0 \\ 1 + abs(f_i) f_i < 0 \end{cases} \qquad (2)$$

Here f_i is the best fitness function value

Onlooker Bees Phase

$$p_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i} \quad (3)$$

Scout Bees Phase

Remember the best solution attained until now

UNTIL (Cycle = Maximum Cycle Number (MCN))

When using ABC algorithm first need to compute the fitness function f_i. In this work, the fitness function is obtained by using equation (4). It produced local bees best and global bee best values based on the highest intensity and lower error values. Thus it is used to provide deblurred image with high quality. It is used to reduce the Peak Signal To Noise Rates (PSNR) in the given blurred images more optimally. PSNR value is calculated by measuring the quality of restored image alongside original image.

$$f_i = PSNR = 10log_{10}\left(\frac{Max_I^2}{\frac{1}{N_1 \times N_2\left(\sum_{i=1}^{N_1}\sum_{j=1}^{N_2}(I(i,j-\hat{I}(i,j))^2\right)}}\right) \quad (4)$$

Where: N_1 and N_2 = The size of the image 'I' = The original image for evaluating the quality of the various filters $\hat{I}$ = The image obtained after applying the respective filter 'Max' = The maximum possible intensity of the image. It is utilized to amplify the PSNR in the specified blurred images best possibly. The corner points are identified and the intensity pixel values of images are improved by utilizing ABC algorithm together with superior PSNR rate. PSNR value is computed by measuring the quality of restored image alongside real image.

3.2. MIN-MAX Normalization For Contrast Enhancement

In this technical work, a Min –Max normalization method [2] that makes the adjustment in the range of pixel intensity values for better clarity is utilized. This method conducts a linear transformation function on the actual input image. It is assessed that the same minimum and maximum range of pixel intensity values inthe input image should be followed by the Min-max normalization method. If there is a variation in the intensity values of original input image values (A), it will be counted as out of range error for future prediction of normalization process.

3.3. Gray Level Co-occurrence Matrix Feature Extraction For Multiple Static Feature Extraction

Gray Level Co-occurrence Matrix (GLCM) is a matrix that depicts the number of occurrences of one gray level for fake and live fingerprint image making appearance in a given spatial linear relationship with another gray level within the area of detection. GLCM calculates second order texture features, which in turn, are of greater significance in human vision and realizes a similar level of categorization performance. This mechanism is normally employed in texture analysis as it is capable for providing for each sample a huge collection of fake and live fingerprint image features and it can be assumed that at least any one of these features are able to present even a smaller variation of texture between multiple classes. GLCM of an $N_x \times N_y$ image, which comprises of pixels with gray levels $(0, 1, \dots, G-1)$ is a two dimensional matrix $P(i,j)$, where each element of the matrix shows the probability of joint occasion of intensity levels k and l at a particular distance d. GLCM features selected are as shown below:

Contrast (CON): Contrast is the main diagonal close to the moment of inertia, which specifies how the values of the matrix are allocated and number of images of local transformations which is the reflection of the image clarity and texture of shadow depth. Larger Contrast means deeper texture.

$$CON = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1,|i-j|=n}^{N_g} \sum_{j=1}^{N_g} p(i,j) \right\} \quad (5)$$

Correlation (CORR): Correlation is defined as a measure of gray level linear dependency of the pixels at the particular locations which are relative to each other.

$$CORR = \frac{\left[\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i,j)p(i,j)\right] - \mu_x\mu_y}{\sigma_x\sigma_y} \quad (6)$$

$$\mu_x = \sum_{i=1}^{N_g}\left[i\sum_{j=1}^{N_g}p(i,j)\right] \quad (7)$$

$$\mu_y = \sum_{j=1}^{N_g}\left[j\sum_{i=1}^{N_g}p(i,j)\right] \quad (8)$$

$$\sigma_x = \sum_{i=1}^{N_g}\left[(i-\mu_x)^2 j\sum_{j=1}^{N_g}p(i,j)\right] \quad (9)$$

$$\sigma_y = \sum_{i=1}^{N_g}\left[(j-\mu_x)^2 i\sum_{i=1}^{N_g}p(i,j)\right] \quad (10)$$

where μ_x , μ_y are the mean values and σ_x , σ_y are the standard deviations of P_x and P_y, respectively

Energy (ENER): This value is also referred to as Uniformity or Angular second moment. It figures the textural consistency which is pixel pair repetitions. It performs the identification of disarray in textures. The maximum value of energy reaches to one. High energy values occur when gray level distribution is uniform or in a periodic form. Energy has a normalized range. The GLCM of less uniform image will have a large number of smaller entries.

$$ENER = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P(i,j)^2 \quad (11)$$

Entropy (ENT): It is quite tricky to define the term Entropy. The concept comes from thermo dynamics, which refers to the quantity of energy that is lost in a persistent manner to heat each time a reaction or a physical transformation takes place. Entropy cannot be rejuvenated to do useful work. As a result of this, the term can be taken as q quantity of irrecoverable chaos or disorder.

$$ENT = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} [P(i,j)\log(P(i,j))] \quad (12)$$

Inverse Difference Moment (IDM): IDM is generally called homogeneity that calculates the local uniformity of an image. IDM feature learns the measures of the proximity of the distribution of the GLCM elements with respect to the GLCM diagonal. IDM weight value is the reverse of the contrast weight, with an exponential decline in weights away from the diagonal.

$$IDM = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\left[\frac{1}{1+(i-j)^2}P(i,j)\right] \quad (13)$$

Sum of Squares (SOS): The estimated variance of the source population is denoted by the sum of squared deviates of the images.

$$SOS = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i-\mu)^2 p(i,j) \quad (14)$$

Sum Average (SA): Sum average is the average of normalized gray tone image in the respective spatial domains.

$$SA = \sum_{i=2}^{2N_g}\left[iP_{x+y}(i)\right] \quad (15)$$

Sum Variance (SV): This characteristic applies relatively high weightage on the elements that vary from the average value of $P(i,j)$.

$$SV = \sum_{i=2}^{2N_g}\left[(i-SA)^2 P_{x+y}(i)\right] \quad (16)$$

Sum Entropy (SE): The sum entropy is a quantity of stochasticity within an image and it is given as,

$$SE = -\sum_{i=2}^{2N_g}\left[P_{x+y}(i)\, log\left[P_{x+y}(i)\right]\right] \quad (17)$$

Difference Variance (DV): The difference variance is the variation of the image in a normalized co-occurrence matrix.

$$DV = -\sum_{i=0}^{N_g-1}[(i-f')P_{x-y}(i)] \quad (18)$$
$$where\ f' = \sum_{i=0}^{N_g-1}\left[iP_{x-y}(i)\right]$$

Difference Entropy (DE): The difference entropy is also an *amount of an image randomness indicator.

$$DE = -\sum_{i=0}^{N_g-1}[P_{x-y}(i)]log[P_{x-y}(i)]] \quad (19)$$

Area (A): The area A_i is calculated in pixels and is an indication of the relative size of the object.

$$A_i = \sum\sum I_i(r,c)\,, 0 \le r, \le N-1 \quad (20)$$

where:

$$I_i(r,c) = \ 1\ if\ I(r,c)\ =\ ith\ object$$
$$0 \qquad otherwise$$

Perimeter (P): The perimeter is a measure of the count of the number of ‘1’ pixels that have ‘0’ pixels as neighbours in the original binary image.

Mean (M): Standard deviation or variance represents the contrast of an image. Image with good contrast should have a big variance. Standard Deviations (SD) also depict the cluster.

$$mean\colon \mu = \sum_{i=1}^{L} k_i p(k_i) \quad (21)$$

Variance (V): Variance denotes the variations of an image.

$$variance\colon \sigma^2 = \sum_{i=1}^{L}(k_i-\mu)^2 p(k_i) \quad (22)$$

Skewness (SK): Skew is a measure of thenon-uniformity (imbalance) of the distribution of the gray level.

$$skewness\colon \mu_3 = \sigma^{-3}\sum_{i=1}^{L}(k_i-\mu)^{-3}p(k_i) \quad (23)$$

Kurtosis (K): It denotes the level of sharpness which is relatively the curve of an image,

$$Kurtosis\colon \mu_4 = \sigma^{-4}\sum_{i=1}^{L}(k_i-\mu)^{-4}p(k_i) - 3 \quad (24)$$

Standard deviation (STD)

$$standard\ deviation : \sqrt{variance} \quad (25)$$

Where k_i =gray value of the i^{th} pixel, $L =$ number of distinctive gray levels, $p(k_i)$ normalized texture feature gray level value.

$$p(k_i) = \frac{number\ of\ pixels\ with\ gray\ level\ of\ I}{total\ number\ of\ pixels\ in\ the\ region} \quad (26)$$

Gradient (G)is a vector which has certain magnitude and direction:

$$\nabla f = \frac{\partial f}{\partial x}\hat{x} + \frac{\partial f}{\partial y}\hat{y} \quad (27)$$

Where : $\frac{\partial f}{\partial x}$ is the gradient in the x direction, $\frac{\partial f}{\partial y}$ is the gradient in the y direction. The gradient direction can be calculated by the formula :

$$\theta = atan2\left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right) \quad (28)$$

Circularity(Cir) : Circularity is ratio involving area of the leaf A and square of perimeter P of the leaf. It can be defined as A/P2.

Eccentricity(Ecc): Eccentricity is defined as a scalar value which specifies the eccentricity of the ellipse and has the same second moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The range value of eccentricity is from 0 to 1.

Zero-crossing is a measurement of the number of edges in a given image and by perception may show how "busy" a given textured image is. The calculation of the zero-crossing values it is first necessary to threshold each of the high-pass variant wavelet decomposition outputs in order to obtain binary images. The threshold value for each of the wavelet decomposition outputs is chosen to be its mean.

Rectangularity of the feature is determined by ,

$$\text{Rectangularity} = \frac{Area(\text{BOUNDING BOX})}{Area} \quad (29)$$

3.4. Fuzzy Sigmoid Kernel (FSK) for Discriminative Bins Selection

According to the above mentioned strategy, to compress initial HC-ESIFT as well as to preserve its discriminative power need to choose an ideal threshold. However, such threshold is hard to decide. To conquer this issue, first select several initial bins with high compactness from initial HC-ESIFT, and then identify and add discriminative bins to get the final compressed HC-ESIFT. The matching value is determined between two images A and B is computed according to the number of matched descriptors between them. Specifically, assume that there are two images $A = \{d_A^{(k)} \in \mathbb{R}^d, k = 1,2,..,N_A\}$, $B = \left\{d_B^{(k)} \in \mathbb{R}^d, k = 1,2,.. ,N_B\right\}$, where $d_A^{(k)}$, $d_B^{(k)}$ → d-dimensional local edge descriptor, in which the values are extracted from the images. A measurement of the generic image-level is defined as,

$$S(A,B) = f\left(\left[k\left(d_A^{(k)}, d_B^{(k)}\right)\right], \forall d_A^{(k)} \in A, d_B^{(k)} \in B\right) \quad (30)$$

Where N→total number of local descriptors, i.e., 'd', in an image. Where $\left[k\left(d_A^{(k)}, d_B^{(k)}\right)\right]$→ local kernel matrix of a feature pair combinations of A,B respectively. f (.)→Mapping function from local to Fuzzy Sigmoid Kernel (FSK) function.

The feature mapping edge pixels existing in images implying the membership functions could be personalized throughout the learning. For example, three neurons could be used to indicate "small", "medium" and "large" fuzzy values of a variable. The Fuzzy Sigmoid Kernel (FSK) function does the modelling of the hyperbolic tangent function through linguistic variables [19]. Its description to the kernel framework is extended as below:

$$K(A,B) = \begin{cases} -1\ A.B\ is\ low \\ +1\ A.B\ is\ high \\ m.A.B\ \ A.B\ is\ medium \end{cases} \quad (31)$$

where m refers to a constant factor denoting the smoothness of the sigmoid tract. In the pretext of fuzzy logic, the sigmoid kernel can be made with a series of membership functions. In case the activation function has to be continuous, the membership limits are provided by $\gamma \pm 1/a$where $\gamma = -r/a$. That is, the final form of the newly introduced FSK function obtained from fuzzy tanh function. The important benefits of this function is that being differentiable at each point in its whole domain, it enforces quicker trainings as the final solution will be represented in a set of saturated samples (Eq. (28)), and it allows to choose various degrees of non-linearity by selecting the amount and complexity of the membership functions. This method is used to select n number of bins.

3.5. Subspace Clustering Algorithm

To generate BoWs representation, first quantize HC-ESIFT into code words. SIFT into code words. Visual vocabulary tree can be generated through clustering with the defined similarity measurement. In this research, subspace clustering algorithm is introduced for retrieval of higher similarity measure. Subspace clustering is focused to identify the subspaces of the feature space in which clusters exist. It is efficient approach to the subspace clustering visual word generation problem. Subspace clustering is the task of automatically detecting clusters in subspaces of the original feature space. Visual vocabulary tree is generated via clustering with the defined similarity measurement. To reduce the price of the in word, it decides that subspace utilizing best Subspace $\subset$ word from S_k in which a least amount number of objects are in the cluster.

BoWs representation is computed via quantizing local features into visual words. Consequently, quantization error is predictable and it could reduce the image retrieval competence. By dividing SC-ESIFT after discriminative bins selection (α and β), this technique could evade the quantization error. It is for example, Quantization Code (QC) and Verification Code (VC). QC is used for visual vocabulary tree generation and SC-ESIFT quantization, i.e., BoWs representation totalling. VC is maintained in the index file for online verification. The indexing approach is dependent upon the standard inverted file indexing framework. It is utilized to get better the more appropriate similarity outcomes and decrease the unrelated word subspaces.

If suppose the mobile image retrieval is implemented based upon client-server architecture, here the server keeps an image index and the mobile device uploads the amount of queries after that gets retrieval outcomes. With the research retrieval structure, two types of information must be sent for query from mobile devices, specifically visual word ID and VC of every SC-ESIFT. Therefore, maintaining a well-built VC would potentially advance the retrieval performance and gives low transmission cost. In addition it concentrated the amount of iterations and therefore the calculation speed is enlarged and time complexity is condensed efficiently. The image quality is gets as superior and detection accurateness is enhanced more willingly than preceding research.

IV. RESULTS AND DISCUSSION

Materials

There are 50 MRI brain tumor images are used for Evaluation database. The medical image database was obtained from the adults ranging from 18 to 60 years old people. The sample images are collected from this https://basicmedicalkey.com/von-hippel-lindau-syndrome-2/ and images are also referred from this work [20]. The results showed that the retrieval result in MRI image samples was considerably provides higher results when compared to other existing methods. An MRI brain tumor image with four samples (Figure 2) was performed to analyze the retrieval results. The HC-ESIFT edge descriptor for MRI Brain Tumor Images are shown in Figure 3.

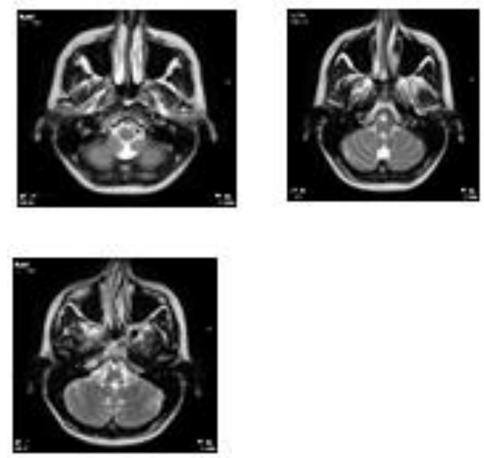

Figure 2: MRI brain Tumor Images

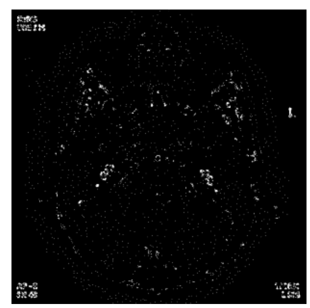

Figure 3: HC-ESIFT edge Descriptor for MRI Brain Tumor Images

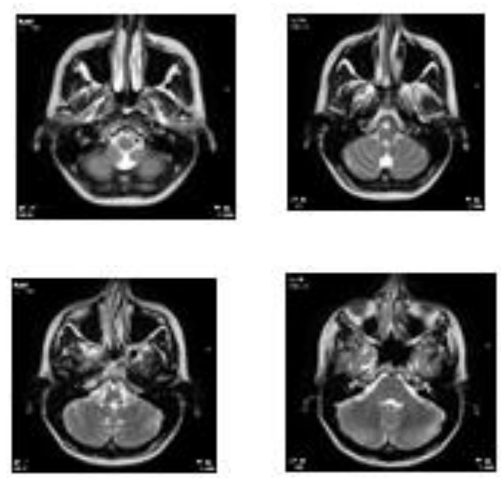

Figure 4: MRI Brain Tumor Images

Our proposed GLCMFE-FBDBD technique performance is evaluated by two quantitative performance metrics are given below,

(i) Average Retrieval Rate (ARR)

$$ARR = \frac{1}{N_q}\sum_{q=1}^{N_q} RR(q) \leq 1 \qquad (32)$$

The first quantitative evaluation metric is Average Retrieval Rate (ARR) is given in Equation above where N_q represents the number of queries that are used for verifying the retrieval performance and RR, represented the retrieval rate of a single query image. The RR can be computed by the following Equation,

$$RR(q) = \frac{N_r(q)}{N_{dr}(q)} \leq 1 \qquad (33)$$

In the above Equation $N_{dr}(q)$ denotes the number of relevant images in the database D of the query q and $N_r(q)$,denotes the number of retrieved relevant images of the queryq. The high ARR value indicates the good performance of image retrieval whereas low value indicates a bad retrieval rate.

(ii) Average Precision Rate (APR)

$$AP = \frac{1}{r}\sum_{k=1}^{r} p_k$$

AP represents the mean of precision values of all relevant images which is calculated by using Equation given above

Precision and recall are used to evaluate the performance of the proposed approach. Precision is the number of the returned relevant images over the total number of returned images, and recall is the number of the returned relevant images over the total number of relevant images in the database. To calculate precision and recall, only those returned images from the same semantic category as the query are counted as relevant. The average precision and recall of all queries are used as the overall performance.

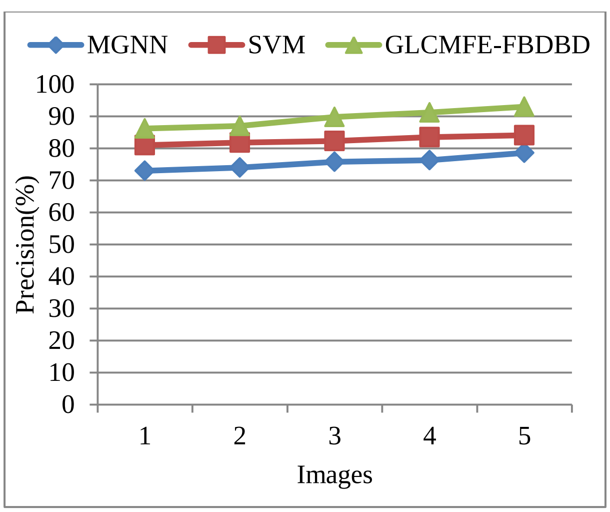

Figure 5. Precision performance results

In Figure 5 shows the different retrieval results are analysed in terms of precision. The graph result shows that the proposed GLCMFE-FBDBD has given high precision rates than the other methods such as SVM and MGNN. From the results it concludes that the proposed GLCMFE-FBDBD produces precision results of 93% for image 5 which is 8.9% and 14.4 % higher when compared to SVM and Mixture Gaussian Neural Networks (MGNN) methods respectively.

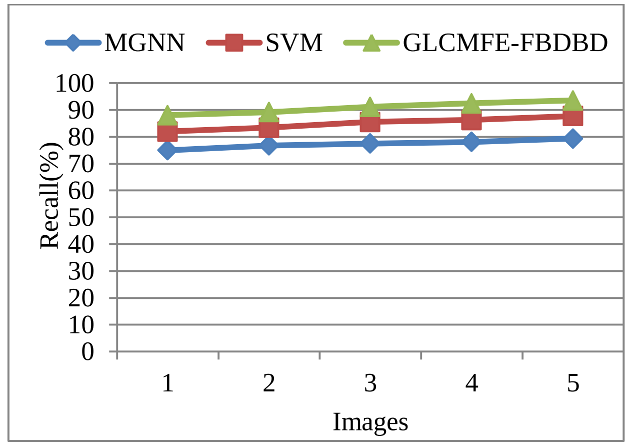

Figure 6 Difference RM learning methods performance results vs Recall

Figure 6 shows the different retrieval results are analysed in terms of recall. The graph result shows that the proposed GLCMFE-FBDBD has given high recall rates than the other methods such as SVM and MGNN. From the results it concludes that the proposed GLCMFE-FBDBD produces recall results of 93.6% for image 5 which is 5.8% and 14.22 % higher when compared to SVM and MGNN methods respectively. The tabulated values of these parameters are discussed in table 1.

Table 1. Performance evaluation metrics

Image	Precision(%)			Recall(%)		
	MGNN	SVM	GLCMFBDB	MGNN	SVM	GLCMFBDB
1	73	81	86.2	75	82	88.1
2	74	81.8	87	76.8	83.4	89.2
3	75.8	82.3	89.8	77.5	85.6	91.2
4	76.3	83.5	91.2	78.12	86.3	92.5
5	78.6	84.1	93	79.38	87.8	93.6

V. CONCLUSION

In this work, the algorithms are improved to raise the system accurateness and effectiveness considerably for the real images. The image normally comprises noise and therefore it leads to blurred images. To rebuild the images, the process includes for instance image denoising, feature extraction, feature quantization and image matching/retrieval. In image deblurring, the ABC algorithm is utilized to eliminate the noise by improving the fitness value of intensity. Peak Signal To Noise Ratio (PSNR) value is utilized to make sure the noise level after obtaining the deblurred image. To retrieve the matching medical images for query image, features in the medical is extracted as feature vector. The separate training phase was carried out for database feature vector extraction. To make SC-ESIFT more robust and more compact, discriminative bins selection utilizing Fuzzy Sigmoid Kernel (FSK) is research named as GLCMFE-FBDBD. In feature quantization step, visual vocabulary tree could be produced via SC with the described similarity measurement. The indexing approach is dependent upon the standard inverted file indexing structure. Therefore the GLCMFE-FBDBD is more well-organized, discriminative and robust for large-scale mobile partial-duplicate image retrieval.

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