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# Comparative Study of Content Based Image Retrieval using Segmentation Techniques for Brain Tumor Detection from MRI Images

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**Abstract:** ***In this discussion the need for alternate access approaches of medical information processing against the already dominant text-based methods. The vast volume of visual data generated, the growing diversity of medical imaging data, and evolving usage habits all contribute to this need. Significant volumes of unused information are contained in the visual data, which can be used to aid diagnosis, training, and testing if properly used. Before addressing technology introduced in the medical sector, the chapter briefly discusses the history of image retrieval and its general processes. We will go into how to assess medical content-based image retrieval (CBIR) technologies, as well as their capabilities, drawbacks, and future innovations. The Med GIFT project and the IRMA (Image Retrieval in Medical Applications) platform are used as examples.***

**Keywords:** Content Based Image Retrieval (CBIR), Shape, Feature Extraction, Segmentation, color, Texture

## 1. INTRODUCTION

Image properties such as color and texture are used in content-based image retrieval (CBIR) to index images with limited human interference. Medical information retrieval can use content-based image retrieval to identify patient photographs in vast databases. The technique of a CBIR system for collecting digital images from an MRI database is defined in this paper. This is used to preserve several photographs of a human brain captured at various times in order to determine if the image shows the presence of a malignant tumor. It would even tell you when the cancer is in stages I, II, or III. In this paper, the creation of medical images, medical image categorization, and a content-based access approach are briefly described. Hospitals have produced a vast amount of digital medical imagery over the last decade. X-ray, computed tomography (CT), magnetic resonance imaging (MRI),ultrasound (US), nuclear medical imaging, endoscopy, microscopy, and scanning laser ophthalmoscope images are among the large-scale image collections (SLO). Using an image quality specification, the most critical aspect of image database management is deciding how to display requested images in a reliable manner. The method of extracting photographs from a database using information extracted solely from the content of the pictures themselves, rather than relevant text or annotation, is known as content-based image retrieval (CBIR).

## 2. RELATED WORK

Content-based image retrieval is a very demanding application in the medical field since it can provide the physician a decision support in the diagnosis of diseases by retrieving relevant cases. The features used to retrieve general images may not apply to medical images. The knowledge of the acquired medical images and disease characteristics is necessary to extract appropriate features of the medical images. Training present a retrieval system where the shape information about various regions of the brain is extracted to retrieve similar images from the database. The system was not able to retrieve similar images in all the cases as it is based on global features which consider information of the entire image. In medical radiology, the clinically useful information consists of variations in the highly localized region of the image. Hence, attributes characterizing the local regions are required. The pathology bearing region (PBR) has to be segmented on the medical image to extract local features. There exist several brain tumor segmentation techniques such as region-based, cluster-based and deformable models. Ahmad et al. experimented with both global features obtained from whole image and local features obtained from non-overlapping image blocks in retrieving similar CT brain images from the database. Retrieval precision of only 94% was reported since PBR was segmented manually. Automatic segmentation of PBR is necessary in CAD as it is more accurate and consistent. Color has got limited expressive power in the MR image retrieval as these images are in grey scale. most vital features of medical images are shape and texture. The shape of the tum or can be characterized with shape descript or such as Fourier descriptors(FD),Zernike moment sand fractals. The malignant brain tumors are more irregular in shape compared to benign tumors. Among the visual features of medical images, texture acquires distinguished importance in identifying tissues. Various texture description methods are proposed in the literature of CBIR such as co-occurrence matrix, auto regressive model , Tamura , wavelets and Gabor filters . Among these methods, multichannel analysis algorithms such as wavelets and Gabor filters have gained a lot of attention due to their ability to characterize features at different frequencies and orientations. The similarity measure used for comparing images in CBIR also has an impact on image retrieval results. Tsang et al. experimented with various similarity measures and achieved a highest precision of 91.7%with Jeffrey divergence and local texture features. However, good precision was not achieved since tumors were characterized using only texture features. One of the inherent problems in CBIR is the semantic gap due to the inconsistency between the features extracted and the user interpretation of an image. In the recent years, several methods are proposed to eliminate the semantic gap based on supervised classification, unsupervised classification and relevance feedback . Li-Xinet al.filled the semantic gap by incorporating the relevance feedback into the CBIR system. But, the relevance feedback consumes a lot of time to fine tune the system parameters as it involves the user. K-means clustering is the widely used unsupervised classification method because of its simplicity. However, the K-means algorithm is sensitive to initial cluster centers. Thus , it may give unstable and empty clusters in case of random initialization. There exist several methods for cluster center initialization such as the one based on genetic programming , binary splitting and KD-tree. But these methods have increased computational complexity and are parameter dependent. Also K-means clustering requires the user to specify the number of clusters in the dataset. This becomes the difficult process if the user does not have any prior knowledge about the data. The existing methods such as the one proposed by Zhaoetal.Kotharietal.and Fangetal.solved this problem by running the clustering algorithm for a wide range of clusters and selecting the number of clusters that optimize the cluster validity index. But a single index may not give optimum results in all the cases. In addition to accuracy, efficiency is also one of the important performance fact or to be considered in the development of CBIR system. Thus, the existing CBIR systems make use of various indexing schemes such as KD-tree, R-tree, R*-tree and quad trees to improve the efficiency of the image retrieval system. The indexing techniques retrieve images similar to the query image without comparing each image in the database and thus reduce the retrieval time. All these indexing structures give worst performance in case of large dimensional feature vectors. Extracting a large number of visual features of an image leads to the dimensionality curse problem, where the indexing, retrieval and similarity matching techniques collapse, due to the fact that it is not possible to well separate the data. Thus, the retrieval accuracy and efficiency can be improved using a feature reduction technique on the feature vector dimensions.

## 3. METHODOLOGY

Content-based retrieval uses the contents of images to represent and access the images. A typical content-based retrieval system is divided into off-line feature extraction and online image retrieval. In offline feature extraction, the contents of the images in the database are extracted and described with a multi-dimensional feature vector, also called descriptor. The feature vectors of the image constitute a feature dataset stored in the database. In online image retrieval, the user can submit a query example to the retrieval system in search of desired images. The system represents this example with a feature vector. The distances (i.e., similarities) between the feature vectors of the query example and those of the media in the feature dataset are then computed and ranked. Retrieval is conducted by applying an indexing scheme to provide an efficient way of searching the image database. Finally, the system ranks the search results and then returns the results that are most similar to the query examples. If the user is not satisfied with the search results, the user can provide relevance feedback to the retrieval system, which contains a mechanism to learn the user's information needs. The following sections will clearly introduce each component in the system.

### 3.1: Feature Extraction:-To extract the features of an image color and texture method is used.

#### 3.1.1: Color

Color is a powerful descriptor that simplifies object identification and is one of the most frequently used visual features for content-based image retrieval. To extract the color features from the content of an image, a proper color space and an effective color descriptor have to be determined. But gray level and pseudo color is insufficient to give the whole description of an image. But for a color image the results are better.

#### 3.1.2: Texture

Texture in CBIR can be used for at least two purposes. First, an image can be considered to be a mosaic that consists of different texture regions. These regions can be used as examples to search and retrieve similar areas. Second, texture can be employed for automatically annotating the content of an image. For example, the texture of an infected skin region can be used for annotating regions with the same infection Textural representation approaches can be classified into statistical approaches and structural approaches. Statistical approaches analyze textural characteristics according to the statistical distribution of image intensity. Approaches in this category include gray level co-occurrence matrix, fractal model, Tamura feature, Wold decomposition, and so on. Structural approaches characterize texture by identifying a set of structural primitives and certain placement rules.If medical images are represented in gray level, texture becomes a crucial feature, which provides indications about scenic depth, the spatial distribution of tonal variations, and surface orientation. For example, abnormal symptoms on female breasts include calcification, architectural distortion, asymmetry, masses, and so forth. All of those reveal specific textural patterns on the mammograms. However, selection of texture features for specifying textural structure should take account of the influence from the modulation transfer function on texture. As the intensifying screens are used to enhance the radiographs, the blurring effect also changes texture features, that is, spatial resolution, contrast, and sharpness are all reduced in the output. Low resolution and contrast result in difficulties in measuring the pattern of tissue and structure of organs.

## 4.LITERATURE SURVEY

B.Jyothi, P.G.Krishna Mohan, Y.MadhaveeLatha, "Region Based Texture Descriptor for Content Based Medical Image Retrieval Using Second Order Moments" [1],as Present, With the growing popularity of large-scale image databases in a variety of applications, it's critical to develop a fast retrieval system that can search the whole database. The image is divided into equal-sized blocks, and the average intensity is computed on the pixels in each block. This feature extraction method is as follows: the image is splits into equal-sized blocks, and the average intensity is computed on the pixels in each block. These values are saved for image matching, with Euclidean distance, City block of absolute value metric, and Murkowski distance used as resemblance measures. We checked various database images in the image retrieval experiment and calculated Recall rate and Error rate as a performance metric, indicating that the proposed Texture features are an effective retrieval technique with apparent advantages and a higher recall rate than the histogram technique.

B.Jyothi, Y.MadhaveeLatha, P.G.Krishna Mohan, "An Effective Multiple Visual Features for Content Based Medical Image Retrieval"[2],as Present, Accurate diagnosis is important for effective treatment in the medical profession. With the exponential advancement in technology, hospitals are producing an ever-increasing number of diagnostic photographs for diagnosis. CBMIR (Content-Based Image Retrieval) is a technique that uses visual attributes like colour, texture, and form to recover identical medical images from a large archive. The aim of this paper is to present a novel approach for improving the efficiency of a Content Based Medical Image Retrieval System (CBMIRS). When compared to a single feature, a multiple feature vector offers higher quality performance. This paper introduces a novel solution that maximizes the benefits of each individual function. The image's material was derived using texture and region-based form descriptors, which are more resilient to noise and have greater feature representation capabilities. Gabor filter and chebichef Moments are used to remove texture features, and chebichef Moments are used to extract shape features. Using Euclidian distance as a similarity measure, the query image's feature vector will be compared to the corresponding feature vectors of the data base images to retrieve identical medical images. In contrast to individual feature-based retrieval systems, experimental findings suggest that the proposed approach achieves the best retrieval efficiency.

Ashnil Kumar, Falk Nette, Karsten Klein, Michael Fulham, and Jinman Kim, "A Visual Analytics Approach using the Exploration of Multi-Dimensional Feature Spaces for Content-based Medical Image Retrieval"[3].as present, CBIR is a search strategy focused on visual feature similarity that has shown success in medical diagnosis, education, and research. The semantic distance, which is the contrast between computed image similarity and the user's search purpose, is a barrier to clinical acceptance of CBIR. As a consequence, appropriate images with outlier features can be missed. Furthermore, most CBIR algorithms do not offer user-friendly reasons for why the recovered images were deemed identical to the question (e.g., which subset of features were similar), making it impossible for users to determine if valid images containing a small subset of outlier features were skipped. As a result, consumers are required to examine irrelevant photographs, and there are few options for locating these "missed" images. We suggest a new approach to medical CBIR in this paper by using a technique called Visual Analytics for Medical Image Retrieval to allow directed visual exploration of the search space (VAMIR). The visual analytics approach allows for immersive visualization of the entire dataset by using the query image as a point of reference. We performed a consumer analysis and several case studies to show VAMIR's capabilities in the retrieval of CT images and multi-modality PET-CT images.

Shiv Ram Dubey, Satish Kumar Singh, and Rajat Kumar Singh, "Local Wavelet Pattern: A New Feature Descriptor for Image Retrieval in Medical CT Databases"[4].as presentThis paper introduces a new image feature specification based on the local wavelet pattern to identify medical CT images for content-driven CT image retrieval (LWP). In the proposed work, the LWP is measured for each pixel of the CT image using the relationship between the center pixel and the local neighboring detail. Unlike the Local Binary Pattern, which only considers the relationship between a center pixel and its neighboring pixels, the presented approach uses local wavelet decomposition to consider the relationship between neighboring pixels before going on to the relationship with the center pixel. A centre pixel transition scheme is used to match the collection of center values with the selection of local wavelet decomposed values. In addition, the proposed local wavelet decomposition scheme is symmetric in the middle and suitable for CT images. This paper is special in two ways: (1) it encodes local neighboring information using local wavelet decomposition, and (2) it computes LWP using local wavelet decomposed values and transformed center pixel values. In terms of precision and recall, we tested our method on three CT image databases. We compared the proposed LWP descriptor to other cutting-edge local image descriptors, and the results reveal that the proposed system outperforms other CT image retrieval methods.

J.Yogapriya and B.Nithya, "Fuzzy Based Grey Wolf Optimization for Effective Medical Image Retrieval System"[5].as present, — Picture databases are exploding all over the place in today's digital world. To make use of these large databases, an efficient image retrieval strategy is needed. The CBMIR method has been the subject of extensive research. The CBMIR scheme is suggested in this contribution by extracting image texture characteristics, selecting the best features, classifying the best features, and determining image similarities. Local Binary Patterns (LBP) is the preferred feature, and all derived functions are stored as a feature database. To pick the right features from the high-dimensional texture features, Fuzzy based Grey Wolf Optimization (FGWO) is used. For determining the best subset of functions, the classification algorithm is used as an evaluation criterion. The subset of texture features in the images is classified using a fuzzy based Relevance Vector Machine (FRVM). The Euclidean Distance (ED) is used to determine how close the query image and the database of images are. Accuracy, precision, and recall are used as performance indicators to test the proposed CBMIR scheme.

Liu Yang, Rong Jin, Lily Mummert, Rahul Sukthankar, Adam Goode, Bin Zheng, Steven C.H. Hoi, and Mahadev Satyanarayanan, "A Boosting Framework for Visuality-Preserving Distance Metric Learning and Its Application to Medical Image Retrieval"[6].as present, In content-based image retrieval systems, similarity calculation is important, and knowing a good distance metric will greatly increase retrieval efficiency. Nonetheless, despite thorough studies, there are some major deficiencies in current methods for distance metric learning that can have a direct effect on their application to medical image retrieval. In image retrieval, for example, "similarity" can mean many different things: resemblance in visual appearance (e.g., two images that look similar to one another) or similarity in semantic annotation (e.g., two images of tumors that look quite different yet are both malignant). Present approaches to distance metric learning usually address only one target without concern for the other. This is troublesome for medical image retrieval, where the aim is to support doctors in making decisions. Provided a query image, the purpose of these applications is to retrieve related images from a reference library whose semantic annotations may provide the medical professional with more insight into the potential meanings of the query image. Users would be less likely to believe the machine if it returned images that did not look like the query; on the other hand, returning images that are superficially identical to the query but are semantically unrelated is unacceptable since it may lead users to an inaccurate diagnosis. As a result, developing a distance metric that retains both visual and semantic similarity is critical. We stress that, though our research focuses on medical image retrieval, the issue discussed in this work is important to many image retrieval systems. We propose a boosting system for distance metric learning that seeks to maintain both visual and semantic parallels. The boosting method first learns a binary representation from side knowledge in the form of labeled pairs, and then computes the distance as a weighted Hamming distance using the acquired binary representation. To learn the distance function effectively, a boosting algorithm is presented. We test the proposed algorithm on a mammographic image reference database using an Integrated Search-Assisted Decision Support (ISADS) system and a medical image data collection from Image CLEF. Our findings show that the boosting system outperforms state-of-the-art approaches for distance metric learning in retrieval accuracy while having a much lower computational cost. Additional testing with the COREL array demonstrates that our algorithm performs very well with standard image data sets.

A. Nikoukar1, I. S. Amiri, J. Ali, “Generation of Nanometer Optical Tweezers Used for Optical Communication Networks”[7].as Present, To build ultra-short nanometer (nm) optical tweezers, a Half-Panda microring resonator (MRR) device is proposed. Within nonlinear MRR, the dark soliton propagates. When the dark soliton is used as an input pulse, molecules or photons travel across the device. Nano optical tweezers can be made and used in a variety of optical communication network applications. The smallest nano optical tweezers signals are obtained here, with a full width at half limit (FWHM) of 9 nm and a free spectrum range (FSR) of 50 nm.

Ankur Gupta , “A review on various approaches for content based image retrieval based on shape, texture and color features”[8].as present, It's a way of removing secret information from a vast volume of raw data. It must be novel insight that can be put to use. This paper describes a process for easily extracting an image's color and texture features for content-based image retrieval (CBIR). CBIR refers to image information that is obtained directly from an image database by searching for images with specific features or containing specific material. CBIR's key principle is to evaluate image details using low-level features of an image, such as color, texture, shape, and object spatial relationships, and to use feature vectors as an image's index. Various approaches to image retrieval focused on color, form, and texture have been discussed in this article.

Poulami Haldar, Joydeep Mukherjee, “Content based Image Retrieval using Histogram, Color and Edge”[9].as present, CBIR (Content-Based Image Retrieval) is a way of extracting a captured image from a database by using an image as a parameter rather than text. This can be accomplished by a thorough function extraction and querying procedure. In order to retrieve an image correctly, features such as histogram, color values, and edge detection are very important. We've used the histogram, colour, and edge detection functionality to introduce an image retrieval system. We used image segmentation in this process to increase the accuracy percentage, and it proved to be a very good technique. We used some Matlab functions as well as our own computation nmethod. Our method has a higher degree of precision thanks to Canny's edge detection technique and color values extraction after image segmentation. Finally, we use the Euclidean Distance method to find the best images that match our query image.

Sreena P. H, David Solomon George,” Content Based Image Retrieval System with Fuzzified Texture Similarity Measurement”[10] A content-based image retrieval (CBIR) system is a database management system that retrieves images based on image content similarities to the query image. Tamura texture attributes are derived as image material in the proposed CBIR scheme. A fuzzified distance metric called fuzzy hamming distance (FHD) is used to compare query images to images in the database. The index is ordered by similarity measure and made accessible to the customer in ascending order. The suggested methodology is applied in Matlab, and the Bordatz texture database is used to validate its efficacy.

SHAO Hong, CUI Wen-cheng, TANG Li,” Medical Image Description in Content-Based Image Retrieval”[11] In content-based medical image retrieval, medical image classification is a significant issue. Currently, a hierarchical medical image semantic features description model is proposed based on the primary sources of semantic features. It is based on this that a medical image representation model is proposed that combines low-level and semantic functions. The inclusion of text as part of semantic functionality increases image retrieval accuracy and memory, according to experimental findings.

Robert J. Curry Michael M. Marefat Fan Yang,” Content-Based Image Retrieval Using Similarity”[12] With the rapid growth of digital image data and its wide range of uses, a reliable image retrieval system is needed. This paper suggests a similarity-based context-based image retrieval scheme that takes advantage of the complementary benefits of all current approaches, Retrieval by Image Example (RIE) and Retrieval by Semantic Content (RSC) (RSC). A content-based image synthesis framework produces a list of exemplar images, which are then used as examples in the GNU Image Finding Tool (GIFT) for image matching. In this experiment, queries on battlefield images will be tested, and the results will be addressed for two separate image matching algorithms. The results of the study demonstrate that the method mentioned in this paper can be used to extract images using semantic queries.

p.s.suhasini , dr. k.sri rama krishna, dr. i. v. murali krishna,” cbir using color histogram processing”[13] advances in data storage and image processing technologies have enabled the development of large image datasets. In this case, proper database structures must be built in order to efficiently maintain these collections. The most popular approach is content-based image retrieval (CBIR). CBIR systems are intended to extract images based on details such as shape, color, and texture. For color extraction and contrast, three color histograms were used in this paper: standard color histogram (CCH), invariant color histogram (ICH), and fuzzy color histogram (FCH). An image's traditional color histogram (CCH) displays the frequency of which each color appears in the image. Because of its simplicity and ease of computing, the CCH is appealing. The CCH, on the other hand, has a range of disadvantages. The first of these is the CCH's high dimensionality, which often results from dramatic quantization of the color space. Another drawback of the CCH is that it cannot rotate or convert and does not allow for color similarities across bins. To address the problem of rotation and localization, an invariant color histogram (ICH) based on color gradients is used, while a fuzzy binding color histogram (FCH) is used to address the problem of spatial correlation.

Yinghui Zhang , Fengyuan Zhang , Yantong Cui , Ruoci Ning," classification of biomedical images using content based image retrieval systems"[14] Because of the multiple applications of the Content-based image retrieval (CBIR) method in various fields, it has always piqued the researchers' interest. The key purpose of the CBIR is to retrieve the most comparable image from the entire archive by comparing it to the input image in the shortest period of time. The object of the CBIR will range from various types of criteria such as a physician's diagnosis of a disease, a criminal investigation, product reviews by e-commerce firms, and so on. CBIR is used in this study to find related patients with breast cancer. CBIR systems are built using a Gray-Level CoOccurrence Matrix, a histogram, and a correlation coefficient. Comparing the photographs of a current patient's area of focus with the whole set of images of a previous patient will aid in the early identification of the disease. CBIR is so effective that it can detect illness even though the signs are not visible on the body's surface.

Nikita Upadhyaya and Manish Dixit," A Review: Relating Low Level Features to High Level Semantics"[15] Content-based image retrieval is a strategy for rapidly extracting digital photographs from a large image archive. The primary goal of CBIR is to remove features from the queried image and images stored in the database in order to detect visual similarities between these features and retrieve visually equivalent images. CBIR gets more complex as the focus switches to close the semantic gap, or linguistics gap, between low level features and high level semantics. This survey gives a brief summary of the low-level features and high-level linguistics considered by CBIR for efficient and accurate retrieval.

Igor F. Amaral, Filipe Coelho, Joaquim F. Pinto da Costa and Jaime S. Cardoso," Hierarchical Medical Image Annotation Using SVM-based Approaches"[16], When looking for images in a database, automatic image annotation or image classification can be very helpful. Common approaches to medical image annotation with the Image Retrieval for Medical Applications(IRMA)code make little or no use of the code's hierarchical structure, in which separate dense sampled pixel-based information methods outperform global image descriptors. We build a Content Based Image Retrieval (CBIR) system to investigate the combination of three different methods using Support Vector Machines (SVMs): first, we concatenate global image descriptors with an interest points Bag-of-Words (BoW) to build a feature vector; second, we perform an initial annotation of the datum; and third, we perform an initial annotation of the datum. Our findings indicate that, while almost all fusion approaches outperform standalone classifications, none specifically outperforms the others. However, as opposed to similar works using the same database, they are very successful.

Senthilkumaran Nand Vaithegi S," image segmentation by using thresholding techniques for medical images",[17] The method of splitting pixel values into two classes, black for the background and white for the foreground, is known as image binarization. External thresholding and local thresholding are two types of thresholding. This paper discusses a locally adaptive thresholding strategy that uses local mean and standard deviation to eliminate context. Thresholding is the most popular and straightforward method for segmenting an image. We present an effective thresholding implementation in this paper, as well as a quantitative comparison of the Niblack and Sauvola local thresholding algorithms. On medical photos, the Niblack and Sauvola thresholding algorithm is used. Statistical parameters such as the Jaccard Similarity Coefficient and the Peak Signal to Noise Ratio are used to determine the quality of a segmented image (PSNR).

Serge Belongie, Chad Carson, Hayit Greenspan, and Jitendra Malik, "Color- and Texture-Based Image Segmentation Using EM and Its Application to Content-Based Image Retrieval"[18] as present, Using picture content as a key to retrieve images from wide and diverse collections is a complicated and significant issue. We introduce a new image representation in this paper that allows us to convert raw pixel data into a limited number of image regions that are color and texture coherent. This so-called "blobworld" representation is built on segmentation of combined color and texture features using the Expectation-Maximization algorithm. The texture features we use for segmentation are the product of a novel texture definition and scale selection strategy. We define a device that retrieves images using the blob world representation. The ability to see the internal representation of the requested image and the query findings in the light of similarity-based querying is an essential and special feature of the method. Similar programs do not provide the consumer with this degree of visibility into the system's operations; as a consequence, despite the existence of knobs for changing the similarity measure, the effects of certain inquiries on these systems may be very inexplicable.

Deepak Sharma, Dr. Tarun Gulati, "Rotation Invariant Content Based Image Retrieval System for Medical Images"[19] Content-Based Image Retrieval (CBIR) is the application of computer vision to the image retrieval dilemma, i.e. locating digital images in a broad database. Because of the increased use of medical imaging, the medical image archive is increasing by the day. CBIR (Content-Based Image Retrieval) is in high demand in the medical sector these days. Based on the literature review, we believe that the engineering and science communities are working hard on CBIR. The key focus of this paper is on a rotation-invariant Content-Based Image Retrieval (CBIR) method for medical image databases that uses a dual tree complex wavelet transform. After implementing dual tree complex wavelet transform in CBIR, which is used for medical image databases, very strong rotation invariant results were obtained.

Ms.A.Bhagyalaksluni, Dr.V.Vijaya chamundeeswari, "A Survey on Content Based Image Retrieval Using Various Operators"[20].as present, Image retrieval is important in a variety of fields, such as medical diagnosis, biometrics, industry inspection, geographic information satellite systems, web searching, and historical research. "As the size of the archive grows, image-based systems face new obstacles and critical issues such as resource management, indexing, information management, and retrieval presentation. To retrieve images from the multimedia database, we need a fast retrieval method. Content-based image retrieval (CBIR) is an image retrieval technique that utilizes low-level image features such as form, form, and color to effectively retrieve images. An image query in the CBIR system is described by primitive, functional, and abstract attributes. This survey paper focuses on various feature descriptors for image retrieval and study of various retrieval operators such as LBP-Local Binary patterns, LTP-Local Ternary patterns, LDP-Local Derivative Patterns, and LTrP-Local Tetra patterns utilizing high level features to increase the efficiency and accuracy in the CBIR system.

## 5. CBMIR SYSTEM

A typical conceptual content-based retrieval system is illustrated in Figure (1) divided into off-line feature extraction process and online image retrieval process. In offline feature extraction process, the contents of the database images are extracted and described with a feature vector. The same process is repeated for query image in online process. The database consist of various classes of medical images characterized by certain objects such as liver, body outline, spine for CT or MRI images of the skull, abdomen, ventricles for images of the head etc. In online image retrieval process, the user submits a query images as an example to the retrieval system for searching similar medical images. The system retrieves related images by computing the similarity matching between the feature vectors of the query image and those of the feature vector of the data base images. Finally the system returns the results that are most similar to the query image. The various phases of CBMIR have shown in below figure.

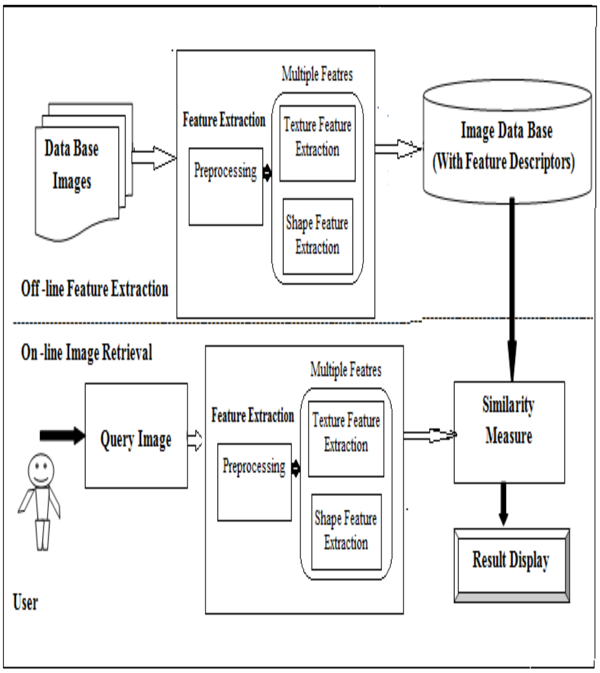


**Figure 1.** Content based Medical Image Retrieval System

## 6. EXPERIMENTAL RESULTS

### 6.1 Figures and Tables

To test the effectiveness of the proposed algorithm our experimental data base consist large collection of medical images acquired from different modalities images such as lung, liver and brain etc . The proposed method is implemented using MATLAB. The feature vector of the query image is compared with the feature vectors of the images in the database using Euclidian distance method, and then the most similar images are reported. To evaluate the overall performance of a retrieval system we used recall rate (RR) mean average precision (MAP) and error rate as a performance measures defined in [16]. Recall is defined as the number of retrieved relevant images over the total number of relevant images in the database. Precision is defined as the number of relevant images retrieved over all the images retrieved by the system. From the experimental results conducted on the retrieval system, it is clear that the proposed approach is more prominent for the content based medical image retrieval as it compares with the existing system shown in figure (3),figure(4) and figure(5).

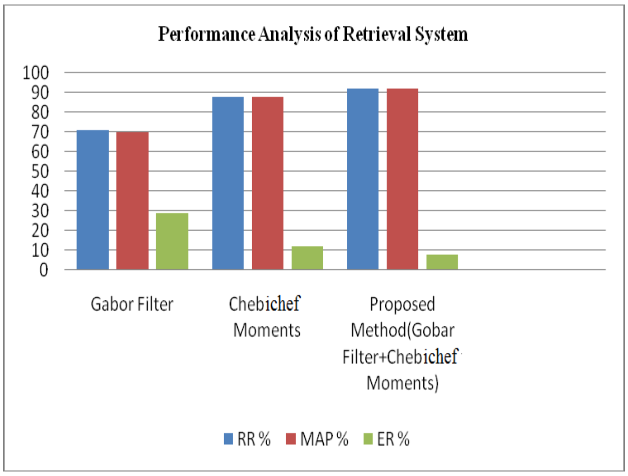


**Figure.2 .**Retrieval Result using Gabor Filter

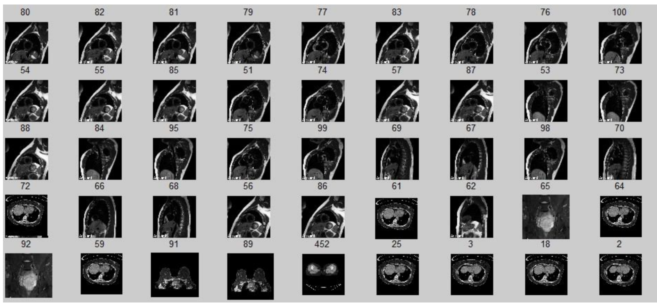

**Figure..3.**Retrieval Result using Chebyshev Moments

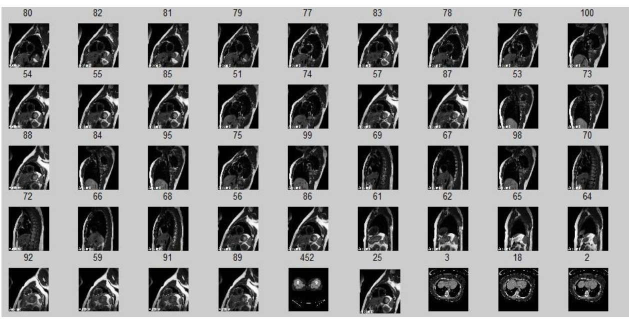

**Figure.4.**Retrieval Result using proposed Multiple Features

**FIGURE.5.**PERFORMANCE ANALYSIS USING VARIOUS METHODS

## 7. TECHNIQUES

### 7.1.Dimension Reduction

To reduce the dimensionality of a large feature set, the most widely-used technique in image retrieval is principal component analysis (PCA). The goal of principal component analysis is to specify as much variance as possible with the smallest number of variables. Principal component analysis involves transforming the original data into a new coordinate system with low dimension, thus creating a new set of data. The new coordinate system removes the redundant data, and the new set of data may better represent the essential information.

### 7.2. Similarity Measure

Selection of similarity metrics has a direct impact on the performance of content-based image retrieval. The kind of feature vectors selected determines the kind of measurement that will be used to compare their similarity If the features extracted from the images are presented as multi-dimensional points, the distances between corresponding multi-dimensional points can be calculated. Euclidean distance is the most common metric used to measure the distance between two points in multi-dimensional space For other kinds of features such as color histogram, Euclidean distance may not be an ideal similarity metric or may not be compatible with the human-perceived similarity. Histogram intersection was proposed by Swain and Ballard (1991) to find known objects within images using color histograms. A number of other metrics, such as Mahalanobis Distance, Minkowski-Form Distance, Earth Mover’s Distance, and Proportional Transportation Distance, have been proposed for specific purposes. used several approaches to code the shape features for different classes of spine Xrays. Each class used a specific similarity metric to compare the distance between two feature vectors.

### 7.3. Multi-Dimensional Indexing

Retrieval of an image is usually based not only on the value of certain features, but also on the location of a feature vector in the multi-dimensional space. A retrieval query on a database of multimedia with multi-dimensional feature vectors usually requires fast execution of search operations. To support such search operations, an appropriate multi-dimensional access method has to be used for indexing the reduced but still high dimensional feature set. Popular multi-dimensional indexing methods include the R-tree (and the R*-tree [20]) T R-tree, which is a tree-like data structure, is mainly used for indexing multidimensional data. Each node of an R-tree has a variable number of entries. Each entry within a non-leaf node can have two pieces of data. The goal of the R tree is to organize the spatial data in such way that a search will visit as few spatial objects as possible. The decision on which nodes to visit is made based Hence, the R-tree must be able to hold some sort of spatial data on all nodes.

### 7.4.Relevance Feedback

Relevance feedback was originally developed for improving the effectiveness of information retrieval systems. The main idea of relevance feedback is for the retrieval system to understand the user's information needs. For a given query, the retrieval system returns initial results based on pre-defined similarity metrics. Then, the user is required to identify the positive examples by labeling those that are relevant to the query. The system subsequently analyzes the user's feedback using a learning algorithm and returns refined results.

A typical relevance feedback mechanism contains a learning component and a dispensing component. The learning component uses the feedback data to estimate the target of the user. The approach taken to learn feedback data is key to the relevance feedback mechanism.

## 8. CONCLUSION

An ideal medical CBIR system from a user perspective would involve semantic retrieval, in which the user submits a query like "find MRIs of brain with tumor". This kind of open-ended query is very difficult for the current CBIR systems to distinguish brain MRI's from spine MRIs even though the two types of images are visually different which are malignant tumor or not. Current medical CBIR systems mainly rely on low-level features like texture, color, and shape.

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