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A Survey on Local and Global Feature Extraction Techniques in Content Based Medical Image Retrieval

Jasmine Samraj[1*] , R.Dhivya[2]

[1]PG & Research Department of Computer Science, Quaid-e-Millath Government College For Women (Autonomous), Chennai-600002.
[2] M.Phil. Scholar PG & Research Department of Computer Science, Quaid-e-Millath Government College For Women (Autonomous), Chennai -600002.

[*]*Corresponding Author: jasminesamraj@gmail.com*

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Abstract—Content-Based Image Retrieval (CBIR), also known as Query by Image Content and Content-Based Visual Information Retrieval is the application of Computer Vision Techniques and Image Processing Algorithms to the image retrieval problem which is the problem of searching for digital images in large databases. "Content-based" means that the search analyses the contents of the image rather than the metadata such as keywords, tags, or descriptions associated with the image. The term "Content" refers the low – level features of the image such as colour, shape, texture, or any other information that can be derived from the image itself. Content based image retrieval uses these extracted features to retrieve the relevant images from the database. The Local and Global features extracted from these image also plays an important role in the Content Based Medical Image Retrieval (CBMIR). The global features are extracted from the whole image whereas the zone based local features are computed from individual regions of the image to form the local features. Recent studies show that content based image retrieval is an important area of research in the multimedia databases in retrieving similar images based on user defined specification or pattern. In this paper we analyse the different state-of-art local and global feature extraction techniques used by the content based image retrieval system for medical images.

Keywords—CBIR,CBMIR,FeatureExtraction,GlobalandLocalFeature,Color,Texture,Shape,ImageRetreival.

I. Introduction

Digital Image Processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords, or descriptions to the images so that retrieval can be performed over the annotation words. In computer vision and image processing, a feature is a piece of information which is relevant for solving the computational task related to a certain application. This is the same sense as feature in machine learning and pattern recognition generally, though image processing has a very sophisticated collection of features. Features may be specific structures in the image such as points, edges or objects. Features may also be the result of a general neighbourhood operation or feature detection applied to the image. Content-based image retrieval (CBIR) has been the traditional paradigm to index and retrieve images. Content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. In CBIR the images are retrieved from databases on basis of their contents. In early days, retrieval was based of keywords, references of text, etc. It was developed to resolve the problem of searching digital images from large databases. One of the fields that may benefit more from CBIR is medicine, where the efficiency of digital is huge. Medical Image has been increasingly applied in clinical diagnosis and treatment. It is an important to make use of large numbers of images in medical image management system in order to help clinician to analyze and diagnose. The structure of the Content-based Medical Image Retrieval System (CBMIR) as in Fig. 1 is introduced and the key problems are mainly investigated, which included image segmentation, feature extraction, similarity searching and feedback mechanism. The medical imaging field has grown substantially in recent years and has generated additional interest in methods and tools for the management, analysis, and communication of the medical images.

Medical image explanation include of three key tasks, they are recognition of image findings, interpretation of those findings to submit a diagnosis or differential diagnosis, and commendation for clinical management or further imaging if a firm diagnosis has not been established. Now a days, a large number of digital medical images have been produced in medical diagnostic centres. Some of the Comprehensive image databases are prepared having various images, including MRI (magnetic resonance imaging), X ray, CT (computed tomography), US (ultrasound) etc. The CBIR system mainly contains two phases named as feature extraction phase and classification phase.

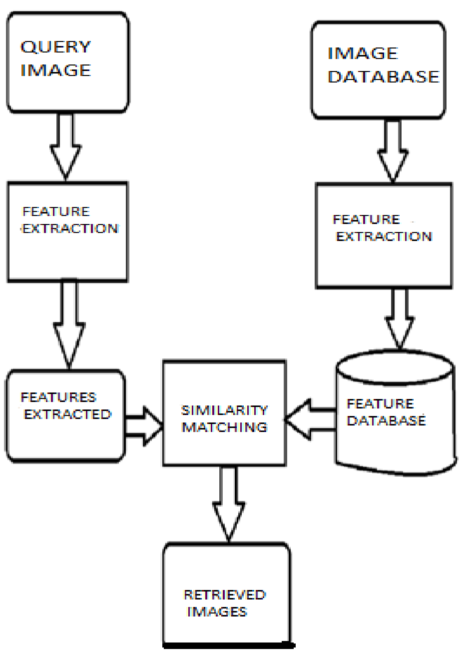

Figure.1 Overview of CBIR

An effective visual words fusion technique based on speeded-up robust features (SURF) and histograms of oriented gradients (HOG) feature descriptors. HOG is used to extract global features, whereas SURF is used for the extraction of local features. Global features are preferred for large-scale image retrieval, whereas local features perform better on those systems that support semantic queries with close visual appearance. Global features are used to extract semantic information of the whole image. Local and global features can be employed together to represent images in a very powerful way. Local features are unable to give an accurate results in different image categories. Global features also perform better for various low level applications such as classification and object detection, whereas local features are more robust due to image representation in the form of local patches and perform better in object recognition based higher-level applications. There are different ways to measure image features similarity, For example, using the distance metrics (i.e. Euclidean distance) where the features are represented as a vector, or via graph matching where the objects in the images are arranged in the form of relationships among them. In addition, statistical classifiers can also be trained to categories the query image into respective known classes. This approach would overcome the semantic gap by training the similarity of measurement on known and labelled data. In this paper we analyse those techniques and methods which are used to retrieve an image from a large databases. And also we find which is the best method or techniques on feature extraction to retrieve a relevant image. It shows an accurate results from these analyses.

II. LITERATURE SURVEY

Nor AsmaMohd Zin, RozianiwatiYusof, Saima Anwar Lashari, Aida Mustapha &NorhalinaSenan et.al focuses the performance of CBIR system. This is improved by introducing relevance feedback techniques in the system. Several feature modification and subspace learning based relevance feedback methods are studied. Various systems use feature modification of each image and tries to retrieve relevant images. But these systems are not suitable for high dimensional images. Several subspace learning relevance feedback methods provides more relevant images compared with feature modification based methods. It also considers local information of images and aims those similar images close to but dissimilar images are far away from query image [1].

Y. FanidFathabad et.al researches the several research papers on CBIR and summarise few of them. Content based image retrieval has frequently been proposed for use in medical and medical image management, only a few content based retrieval systems have been developed specifically for medical images. IRMA (Image Retrieval in Medical Applications) is an approach and it permits queries on a heterogeneous image collection and helps identify images that are similar with respect to global features. The IRMA system lacks the ability for finding particular pathology that may be localized in particular regions within the image; NHANES II is a program of studies designed to assess the health and nutritional status of adults and children in the United States, it contains the Active Contour Segmentation (ACS) tool, which allows the users to create a template by marking points around the vertebra; Yottalook is a search engine and it is optimized to be used as a decision support tool at the time if interpretation when you need the information quickly; iMedline is a multimodal search engine . Build tools employing a combination of text and image features to enrich traditional bibliographic citations with relevant biomedical images, charts, graphs, diagrams and other illustrations; ALIPR (Automatic Linguistic Indexing of Pictures in Real-Time) is a on a mission to assign relevant tags to digital images based on their content, and wants you to help it learn; In FIRE system query by example image is implemented using a large variety of different image features that can be combined and weighted individually and relevance feedback can be used to refine the result; RadLex (Radiology Lexicon) is a controlled terminology for radiology-a single unified source of radiology terms for radiology practice, education, and research; ASSERT (Automated Search and Selection Engine with Retrieval Tools) a CBIR system for the domain of HRCT (High Resolution Computed Tomography) images of the lung with emphysema-type diseases. Content- based image retrieval of medical images has achieved a degree of maturity, albeit at a research level, at a time of significant need. However, the field has yet to make noticeable inroads into mainstream clinical practice, medical research, or training. In this paper the author focused on the applications of medical domain, challenges and opportunities in the medical domain and also speculations (finding a result from other sources) for future enhancements [2].

Soumya Mathew et.al looks the effectiveness of content based image retrieval depends on the feature extraction method. The efficiency of the system increases with the meaning of extracted features. As the time passed, the researches has flourished on this topic. For a decent retrieval the success lies in developing the similarity metrics for effective ranking. In CBIR systems, features are computed automatically for the characterization of images present in the databases. But an undeniable fact is that, the application of this concept has always experienced a limitation in its success [3].

Amandeep Kaur et.al focuses 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 by using PCA(Principal component analysis) classifier, the system ranks the search results and then returns the results that are most similar to the query image [4].

K. Srinivasa Reddy, R. Anandan& K. Kalaivani et.al proposed for Medical image retrieval spine x-ray and functional photon emission tomography (PET). When several images are available for diagnosis, there is a need for finding similar medical cases as references and the Image retrieval system can be used as a guideline that might gives a correct diagnosis. CBIR proposed for wide use in medical and medical management, but only a few CBIR systems have been developed specially for medical images. One of the important among them is IRMA (Image Retrieval in medical images) [5].

Neha Ghosh &Shikha Agrawal et.al focuses an Image pre-processing. They developed an approach for improving images previous to computational processing, the main aim of image pre-processing is to enhance the visual appearance of images and database manipulation. Here, the paper minimize the problem associated with large dataset, then overall manipulation of the database will be decreased, and it will give better result of an image retrieval process [6].

V. Murugesh& V. Sivakumar et.al proposes comparative performance that exhibits better results for segmentation and detection of brain diseases in multimodal brain MR images. In this paper the final outcome of performance development, the proposed method is efficient for automatic segmentation and detection of disease regions in Brain MR Images [7].

Zahid Mehmood, Fakhar Abbas, Toqeer Mahmood & Muhammad Arshad Javid et.al proposed technique based on visual words fusion that significantly improves the performance of CBIR due to the more compact representation of image visual contents as compared to the features fusion, standalone SURF, and standalone HOG feature descriptor techniques that are also based on the BoVW methodology as well as state-of-the-art CBIR techniques [8].

MahyaSadeghi&Parmit K. Chilana et.al use an intuitive and scalable method on CBIR as an explainable artificial intelligence application, and investigate to what extent a CBIR system can help a non-dermatologist make an accurate classification of a given skin lesion image. They also explored to what extent the use of CBIR affects the confidence levels of these users. The findings shed new insights into how user-centered design techniques can improve non-expert user interaction with CBIR systems and open up new opportunities for non-experts to explore, trust, and learn from medical image collections [9].

Khawaja Tehseen Ahmed &AunIrtaz et.al is accomplished with an improved Moravec method using the covariance matrix of the local directional derivatives. These directional derivatives are compared with a scoring factor to identify which features are corners, edges or noise. Located interest point candidates are fetched for the sliding window algorithm to extract robust features. These locally-pointed global features are combined with monotonic invariant uniform local binary patterns that are extracted a priory as part of the proposed method [10].

AbdolraheemKhaderAlhassan et.al describes a Content Based Image Retrieval (CBIR) as an interface between a high level system (the human brain) and a low level system (a computer). The human brain is capable of performing complex visual perception, but is limited in speed while a computer is capable of restricted visual capabilities at much higher speeds. In a CBIR, visual image content is represented in form of image features, which are extracted automatically and there is no manual intervention, thus eliminating the dependency on humans in the feature extraction stage [11].

Rafael S. Bressan, Daniel H. A. Alves, Lucas M. Valerio & Pedro H. Bugatti et.al proposed a methodology, called here as DOCToR, to analyze the important role of deep features obtained through transfer learning in the CBIR process, specifically for mammographic images. Their extensive experiments showed improved precisions, using deep descriptors through transfer learning joined with a trivial query refinement process, reaching gains of up to 82.6% in comparison with the best hand-crafted descriptor. From experiments, they demonstrated that it is possible to take advantage of such general context features, when they are refined by a post process (e.g. query refinement) [12].

BehzadMerhrbakhshChoobari et.al explore deep features into the CBMIR process. The majority of works focus on just apply transfer learning to quietly similar contexts, not a high specific one like mammographic images. In this paper the author focuses the best of our knowledge, the majority of works focus on just apply transfer learning to quietly similar contexts, not a high specific one like mammographic images [13].

N. Parvin et.al used Corel 1000 database to compare their proposed method with LBP and local tetra pattern (LTrP), the proposed method shows significant progress in both average precision and recall. In this paper the author propose a novel image retrieval method, which uses the texture structures for indexing and retrieval [14].

G. M. Galshetwar, L. M. Waghmare& A. B. Gonde et.al describes the primitive features namely the color and texture which are extracted from the JPEG compressed image and as the second stage they have used the genetic algorithm in fine tuning the retrieved results. Here the proposed idea can be extended towards DWT compressed images as used in JPEG 2000 methodology. Though the proposed system have tested against an animal data set, the proposed approach can be tested against different commercial applications including crime prevention, security checks, medical diagnosis, intellectual properties, architectural and engineering designs [15].

Amin Khatami, MortezaBabaie , H.R. Tizhoosh , Abbas Khosravi& Thanh Nguyen et.al uses a deep structural method with the employment of transfer learning to obtain a robust feature extraction stage, resulting in an accurate classification system. This shrunk data categories along with the further shrinking steps, derived by a projection-based selection pool, result in a two- step hierarchical shrinking phase which enables a robust feature representation system for CBIR tasks. This contribution beats sev- eral state-of-the-art methods, especially dictionary approach on a strongly imbalanced IRMA dataset [16].

B. Prasanthi& Suresh Pabboju et.al access efficient image with annotation, and they introduced and implemented an effective and novel computational evaluation approach, i.e., non-training-based label index refinement approach with convex optimization classification for applying large data preprocessing for weakly labeled data in image indexing. They also have developed an approximation-based grouping algorithm to improve precision and recall efficiency in large web-based image retrieval tasks. The experimental results show efficient image indexing with different experimental studies on large scale web-based images. The experiments in search-based annotation yield scalability measure results in the range of 85–90% as compared to the existing approaches in image retrieval [17].

Nisha Tiwari et.al focuses on the RGB colors that are extracted and used to form the feature vector. Then the distance between the query image and the images in the database is calculated, and gives the similarity in percentage between query image and retrieved similar images. At last the retrieval system retrieves the 5 best matches and displays the result [18].

R. Rani Saritha& Varghese Paul et.al focuses on the similarity measurements and the representation of the visual features as the two important tasks in Human Activity Detection using RGBD. Here, given a query image, the work is to retrieve similar kind of images from the database based on the features extracted from the query image [19].

Vikram M Kakade et.al proposes a system that is reliable compared to the existing algorithms, the DBN generates a huge data set for learning features and provides a good classification to handle the finding of the efficient content extraction [20].

III. FEATURE EXTRACTION

Feature extraction is a term used with computers and machine learning. In conjunction with image processing, feature extraction begins with a set of measured data and then creates a series of derived values that are intended to informative and non-redundant. Related to dimensionality reduction, this process is intended to facilitate subsequent learning and generalization steps that can lead to better human interpretations. In short, dimensional data is entered into a computer to build a simulated 3-dimensional figure. From this simulation, humans can then manipulate these dimensions to create a desired form. When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Many machine learning practitioners believe that properly optimized feature extraction is the key to effective model construction. Basically there are two types of features are extracted from the images based on the application. They are **local** and **global** features. Features are sometimes referred to as descriptors. Global descriptors are generally used in image retrieval, object detection and classification, while the local descriptors are used for object recognition/identification. There is a large difference between detection and identification. Detection is finding the existence of something/object (Finding whether an object is exist in image/video) where as Recognition is finding the identity (Recognizing a person/object) of an object. Global features describe the image as a whole to the generalize the entire object where as the local features describe the image patches (key points in the image) of an object. Global features include contour representations, shape descriptors, and texture features and local features represents the texture in an image patch. Shape Matrices, Invariant Moments (Hu, Zerinke), Histogram Oriented Gradients (HOG) and Co-HOG are some examples of global descriptors. SIFT, SURF, LBP, BRISK, MSER and FREAK are some examples of local descriptors. Generally, for low level applications such as object detection and classification, global features are used and for higher level applications such as object recognition, local features are used. Combination of global and local features improves the accuracy of the recognition with the side-effect of computational overheads. Some of the techniques in feature extraction are given below.

- **Color**

Computing distance measures based on color similarity is achieved by computing a color histogram for each image that identifies the proportion of pixels within an image holding specific values. Examining images based on the colors they contain is one of the most widely used techniques because it can be completed without regard to image size or orientation. However, research has also attempted to segment color proportion by region and by spatial relationship among several color regions.

- **Texture**

Texture measures look for visual patterns in images and how they are spatially defined. Textures are represented by texels which are then placed into a number of sets, depending on how many textures are detected in the image. These sets not only define the texture, but also where in the image the texture is located. Texture is difficult concept to represent the identification of specific textures in an image.

- **Shape**

Shape does not refer to the shape of an image but to the shape of a particular region that is being sought out. Shapes will often be determined first applying segmentation or edge detection to an image. Other methods use shape filters to identify given shapes of an image. Shape descriptors may also need to be invariant to translation, rotation, and scale.

- **Spatial**

Spatial analysis or spatial statistics includes any of the formal techniques which study entities using their topological, geometric, or geographic properties. Spatial analysis includes a variety of techniques, many still in their early development, using different analytic approaches and applied in fields as diverse as astronomy, with its studies of the placement of galaxies in the cosmos, to chip fabrication engineering, with its use of "place and route" algorithms to build complex wiring structures. In a more restricted sense, spatial analysis is the technique applied to structures at the human scale, most notably in the analysis of geographic data.

- **Transform**

A distance transform, also known as distance map or distance field, is a derived representation of a digital image. The choice of the term depends on the point of view on the object in question: whether the initial image is transformed into another representation, or it is simply endowed with an additional map or field. Distance fields can also be signed, in the case where it is important to distinguish whether the point is inside or outside of the shape.

- **Edge and boundary**

Edge enhancement is an image processing filter that enhances the edge contrast of an image or video in an attempt to improve its acutance. The filter works by identifying sharp edge boundaries in the image, such as the edge between a subject and a background of a contrasting color, and increasing the image contrast in the area immediately around the edge. This has the effect of creating subtle bright and dark highlights on either side of any edges in the image, called overshoot and undershoot. Boundary tracing (also known as contour tracing) of a binary digital region can be thought of as a segmentation technique that identifies the boundary pixels of the digital region. Boundary tracing is an important first step in the analysis of that region. These features are used to retrieve the relevant image from the image database. They are used to extract the image based upon the features.

IV. GLOBAL AND LOCAL FEATURE EXTRACTION

Principal Component Analysis

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables (entities each of which takes on various numerical values) into a set of values of linearly uncorrelated variables called principal components. If there are n observations with p variables, then the number of distinct principal components is min (n − 1, p). This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors (each being a linear combination of the variables and containing n observations) are an uncorrelated orthogonal basis set. PCA is sensitive to the relative scaling of the original variables. There are two applications in PCA. They are Quantitative Finance, Neuroscience. It is also relation with other methods. They are Correspondence analysis, Factor analysis, k-means clustering, Non-negative matrix factorisation, independent component analysis, Network component analysis.

Limitations of PCA

The results of PCA depend on the scaling of the variables. A scale-invariant form of PCA has been developed. The applicability of PCA is limited by certain assumptions made in its derivation. The other limitation is the mean-removal process before constructing the covariance matrix for PCA. In fields such as astronomy, all the signals are non-negative, and the mean-removal process will force the mean of some astrophysical exposures to be zero, which consequently creates unphysical negative fluxes and forward modeling has to be performed to recover the true magnitude of the signals. As an alternative method, non-negative matrix factorization focusing only on the non-negative elements in the matrices, which is well-suited for astrophysical observations. See more at Relation between PCA and Non-negative Matrix Factorization.

Linear Discriminant Analysis

Linear discriminant analysis (LDA) is a generalization of Fisher's linear discriminant, a method used in statistics, pattern recognition and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification. LDA is closely related to analysis of variance (ANOVA) and regression analysis, which also attempt to express one dependent variable as a linear combination of other features or measurements. LDA is applied in Bankruptcy prediction, Face recognition, Marketing, Biomedical studies, Earth science.

Independent Component Analysis

Independent component analysis (ICA) is a computational method for separating a multivariate signal into additive subcomponents. This is done by assuming that the subcomponents are non-Gaussian signals and that they are statistically independent from each other. ICA is a special case of blind source separation. A common example application is the "cocktail party problem" of listening in on one person's speech in a noisy room. Some Independent component analysis applications are given below.

- optical Imaging of neurons
- neuronal spike sorting
- face recognition
- modelling receptive fields of primary visual neurons
- predicting stock market prices
- mobile phone communications
- colour based detection of the ripeness of tomatoes
- removing artifacts, such as eye blinks, from EEG data
- analysis of changes in gene expression over time in single cell RNA-sequencing experiments
- Studies of the resting state network of the brain.

Texture Feature Extraction

Gray Level Co-Occurrence Matrix (GLCM)

A co-occurrence matrix or co-occurrence distribution is a matrix that is defined over an image to be the distribution of co-occurring pixel values (grayscale values, or colors) at a given offset. Co-occurrence matrices can also be parameterized in terms of a distance, d and an angle θ, instead of an offset (Δ x , Δ y). GLCM relates between two pixels at a time, they are reference pixel and a neighbor pixel. Co-occurrence matrices are also referred to as:

- GLCMs (gray-level co-occurrence matrices)
- GLCHs (gray-level co-occurrence histograms)
- spatial dependence matrices

Texture measures like the co-occurrence matrix, wavelet transforms, and model fittinghave found application in medical image analysis in particular. A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. (The texture filter functions, described in Texture Analysis cannot provide information about shape, that is, the spatial relationships of pixels in an image).

Speeded UP Robust Features (SURF)

In computer vision, speeded up robust features (SURF) is a patented local feature detector and descriptor. It can be used for tasks such as object recognition, image registration, classification or 3D reconstruction. It is partly inspired by the scale-invariant feature transform (SIFT) descriptor. The standard version of SURF is several times faster than SIFT and claimed by its authors to be more robust against different image transformations than SIFT. To detect interest points, SURF uses an integer approximation of the determinant of Hessian blob detector, which can be computed with 3 integer operations using a pre-computed integral image. Its feature descriptor is based on the sum of the Haar wavelet response around the point of interest. These can also be computed with the aid of the integral image. SURF descriptors have been used to locate and recognize objects, people or faces, to reconstruct 3D scenes, to track objects and to extract points of interest. The image is transformed into coordinates, using the multi-resolution pyramid technique, to copy the original image with Pyramidal Gaussian or Laplacian Pyramid shape to obtain an image with the same size but with reduced bandwidth. This achieves a special blurring effect on the original image, called Scale-Space and ensures that the points of interest are scale invariant. The SURF algorithm is based on the same principles and steps as SIFT; but details in each step are different. The algorithm has three main parts: interest point detection, local neighborhood description and matching.

Detection

SURF uses square-shaped filters as an approximation of Gaussian smoothing. (The SIFT approach uses cascaded filters to detect scale-invariant characteristic points, where the difference of Gaussians (DoG) is calculated on rescaled images progressively.) SURF uses a blob detector based on the Hessian matrix to find points of interest. The determinant of the Hessian matrix is used as a measure of local change around the point and points are chosen where this determinant is maximal. In contrast to the Hessian - Laplacian detector by Mikolajczyk and Schmid, SURF also uses the determinant of the Hessian for selecting the scale, as is also done by Lindeberg. Given a point p=(x, y) in an image I, the Hessian matrix H(p, σ) at point p and scale σ, is:

$$H(p,\sigma) = \begin{pmatrix} L_{xx}(p,\sigma) & L_{xy}(p,\sigma) \\ L_{yx}(p,\sigma) & L_{yy}(p,\sigma) \end{pmatrix}$$

Descriptor

The goal of a descriptor is to provide a unique and robust description of an image feature, e.g., by describing the intensity distribution of the pixels within the neighbourhood of the point of interest. Most descriptors are thus computed in a local manner, hence a description is obtained for every point of interest identified previously. The dimensionality of the descriptor has direct impact on both its computational complexity and point-matching robustness/accuracy. A short descriptor may be more robust against appearance variations, but may not offer sufficient discrimination and thus give too many false positives. The first step consists of fixing a reproducible orientation based on information from a circular region around the interest point. Then we construct a square region aligned to the selected orientation, and extract the SURF descriptor from it.

Matching

By comparing the descriptors obtained from different images, matching pairs can be found.

- **CLASSIFICATION**
- **Support Vector Machine (SVM) Classifier**

Support vector machines (SVMs, also support vector networks [1]) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. When data is unlabelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups.

Applications:

SVMs can be used to solve various real world problems:

- SVMs are helpful in text and hypertext categorization as their application can significantly reduce the need for labeled training instances in both the standard inductive and transductive settings.
- Classification of images can also be performed using SVMs. Experimental results show that SVMs achieve significantly higher search accuracy than traditional query refinement schemes after just three to four rounds of relevance feedback. This is also true of image segmentation systems, including those using a modified version SVM that uses the privileged approach as suggested by Vapnik.
- Hand-written characters can be recognized using SVM
- The SVM algorithm has been widely applied in the biological and other sciences. They have been used to classify proteins with up to 90% of the compounds classified correctly. Permutation tests based on SVM

weights have been suggested as a mechanism for interpretation of SVM models. Support vector machine weights have also been used to interpret SVM models in the past. Posthoc interpretation of support vector machine models in order to identify features used by the model to make predictions is a relatively new area of research with special significance in the biological sciences.

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➢ **K- Nearest Neighbour Classifier (KNN)**

The k-nearest neighbor's algorithm (k-NN) is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression:

- In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor.
- In k-NN regression, the output is the property value for the object. This value is the average of the values of its k nearest neighbors.

k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms. Both for classification and regression, a useful technique can be used to assign weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/d, where d is the distance to the neighbor. The neighbors are taken from a set of objects for which the class (for k-NN classification) or the object property value (for k-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required. A peculiarity of the k-NN algorithm is that it is sensitive to the local structure of the data.

- *The 1-nearest neighbor classifier*

The most intuitive nearest neighbour type classifier is the one nearest neighbour classifier that assigns a point x to the class of its closest neighbour in the feature space, that is $C_n^{1nn}(x) = Y(1)$. As the size of training data set approaches infinity, the one nearest neighbour classifier guarantees an error rate of no worse than twice the Bayes error rate (the minimum achievable error rate given the distribution of the data).

- *The weighted nearest neighbour classifier*

The k-nearest neighbour classifier can be viewed as assigning the k nearest neighbours a weight 1 / k and all others 0 weight. This can be generalised to weighted nearest neighbour classifiers.

A. Properties

k-NN is a special case of a variable-bandwidth, kernel density "balloon" estimator with a uniform kernel. The naive version of the algorithm is easy to implement by computing the distances from the test example to all stored examples, but it is computationally intensive for large training sets. Using an approximate nearest neighbor search algorithm makes k-NN computationally tractable even for large data sets. Many nearest neighbor search algorithms have been proposed over the years; these generally seek to reduce the number of distance evaluations actually performed. k-NN has some strong consistency results. As the amount of data approaches infinity, the two-class k-NN algorithm is guaranteed to yield an error rate no worse than twice the Bayes error rate (the minimum achievable error rate given the distribution of the data). Various improvements to the k-NN speed are possible by using proximity graphs.

An example of a typical computer vision computation pipeline for face recognition using k-NN including feature extraction and dimension reduction pre-processing steps (usually implemented with OpenCV):

- Haar face detection
- Mean-shift tracking analysis
- PCA or Fisher LDA projection into feature space, followed by k-NN classification

Dimension reduction

Dimension reduction is usually performed prior to applying the k-NN algorithm in order to avoid the effects of the curse of dimensionality. The curse of dimensionality in the k-NN context basically means that Euclidean distance is unhelpful in high dimensions because all vectors are almost equidistant to the search query vector (imagine multiple points lying more or less on a circle with the query point at the center; the distance from the query to all data points in the search space is almost the same). Feature extraction and dimension reduction can be combined in one step using principal component analysis (PCA), linear discriminant analysis (LDA), or canonical correlation analysis (CCA) techniques as a pre-processing step, followed by clustering by k-NN on feature vectors in reduced-dimension space. In machine learning this process is also called low-dimensional embedding. For very-high-dimensional datasets (e.g. when performing a similarity search on live video streams, DNA data or high-dimensional time series) running a fast approximate k-NN search using locality sensitive hashing, "random projections" , "sketches" or other high-dimensional similarity search techniques from the VLDB toolbox might be the only feasible option.

- *k-NN regression:*

In *k*-NN regression, the *k*-NN algorithm is used for estimating continuous variables. One such algorithm uses a weighted average of the *k* nearest neighbors, weighted by the inverse of their distance. This algorithm works as follows:

1. Compute the Euclidean or Mahalanobis distance from the query example to the labeled examples.
2. Order the labeled examples by increasing distance.
3. Find a heuristically optimal number *k* of nearest neighbors, based on RMSE. This is done using cross validation.
4. Calculate an inverse distance weighted average with the *k*-nearest multivariate neighbors.

- **HISTOGRAM OF ORIENTED GRADIENTS (HOG)**

The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy.

- **LOCAL BINARY PATTERNS (LBP)**

Local binary patterns (LBP) is a type of visual descriptor used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990. LBP was first described in 1994. It has since been found to be a powerful feature for texture classification; it has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, it improves the detection performance considerably on some datasets. The feature vector can now be processed using the Support vector machine, extreme learning machines, or some other machine-learning algorithm to classify images. Such classifiers can be used for face recognition or texture analysis.

- **HAAR-LIKE FEATURES**

Haar-like features are digital imagefeatures used in object recognition. They owe their name to their intuitive similarity with Haar wavelets and were used in the first real-time face detector. Historically, working with only image intensities (i.e., the RGBpixel values at each and every pixel of image) made the task of feature calculation computationally expensive. A publication by Papageorgiou et al. discussed working with an alternate feature set based on Haar wavelets instead of the usual image intensities. Viola and Jones adapted the idea of using Haar wavelets and developed the so-called Haar-like features. A Haar-like feature considers adjacent rectangular regions at a specific location in a detection window, sums up the pixel intensities in each region and calculates the difference between these sums. This difference is then used to categorize subsections of an image. For example, let us say we have an image database with human faces. It is a common observation that among all faces the region of the eyes is darker than the region of the cheeks. Therefore a common Haar feature for face detection is a set of two adjacent rectangles that lie above the eye and the cheek region. The position of these rectangles is defined relative to a detection window that acts like a bounding box to the target object (the face in this case). The key advantage of a Haar-like feature over most other features is its calculation speed. Due to the use of integral images, a Haar-like feature of any size can be calculated in constant time (approximately 60 microprocessor instructions for a 2-rectangle feature).

- **COLOR HISTOGRAMS**

A color histogram is a representation of the distribution of colors in an image. For digital images, a color histogram represents the number of pixels that have colors in each of a fixed list of colour ranges that span the image's color space, the set of all possible colors. The color histogram can be built for any kind of color space, although the term is more often used for three-dimensional spaces like RGB or HSV. For monochromatic images, the term intensity histogram may be used instead. For multi-spectral images, where each pixel is represented by an arbitrary number of measurements (for example, beyond the three measurements in RGB), the color histogram is N-dimensional, with N being the number of measurements taken. Each measurement has its own wavelength range of the light spectrum, some of which may be outside the visible spectrum. If the set of possible color values is sufficiently small, each of those colors may be placed on a range by itself; then the histogram is merely the count of pixels that have each possible color. Most often, the space is divided into an appropriate number of ranges, often arranged as a regular grid, each containing many similar color values. The color histogram may also be represented and displayed as a smooth function defined over the color space that approximates the pixel counts. Like other kinds of histograms, the color histogram is a statistic that can be viewed as an approximation of an underlying continuous distribution of colors values.

- **Characteristics of a color histogram**

A color histogram focuses only on the proportion of the number of different types of colors, regardless of the spatial location of the colors. The values of a color histogram are from statistics. They show the statistical distribution of colors and the essential tone of an image.In general, as the color distributions of the foreground and background in an image are different, there might be a bimodal distribution in the histogram.For the luminance histogram alone, there is no perfect histogram and in general, the histogram can tell whether it is over exposure or not, but there are times when you might think the image is over exposed by viewing the histogram; however, in reality it is not.

- **Drawbacks**

The main drawback of histograms for classification is that the representation is dependent of the color of the object being studied, ignoring its shape and texture. Color histograms can potentially be identical for two images with different object content which happens to share color information. Conversely, without spatial or shape information, similar objects of different color may be indistinguishable based solely on color histogram comparisons. There is no way to distinguish a red and white cup from a red and white plate. Put another way, histogram-based algorithms have no concept of a generic 'cup', and a model of a red and white cup is no use when given an otherwise identical blue and white cup. Another problem is that color histograms have high sensitivity to noisy interference such as lighting intensity changes and quantization errors. High dimensionality (bins) color histograms are also another issue. Some color histogram feature spaces often occupy more than one hundred dimensions.

V. RESULT ANALYSIS

The Table 1 gives a complete table with the methods taken for literature review. This table gives a bird's eye view of the various feature extraction methods used in CBIR with their respective merits and demerits.

Table.1 Comparison of Results

SI. NO	PAPER	TECHNIQUES / METHODS	MERITS	DEMERITS
1.	Content-Based Image Retrieval in Medical Domain: A Review	This paper focuses on the different relevance feedback techniques in digital image processing. In additionto the dimensionality reduction problem caused by the low-level features, current features arealso insufficient to convey the semantic meaning of the images. This paper reviews the recentworks in CBIR that attempts to reduce the semantic gap in extracting the features from medical Images [1].	The advantages are dimensionality reduction, solve singular problem in the high dimensional space, increases generalization and robustness using Laplacian regularization.	The disadvantage is computational complexity is very high due to the large scale dataset.
2.	Content Based Image Retrieval For Medical Images	Content Based Image Retreival with image enhancement, feature extraction and image segmentation Shape features may also be local or global. A shape feature is local if it is derived from some proper subpart of an object, while it is global if it is derived from the entire object. A shape-based representation of the image content in the form of point sets, contours, curves, regions, or surfaces should be available for the computation of shape-based features. [2].	The main aim of CBIR in medical is to efficiently retrieve images that are visually similar to a query.	The IRMA system lacks the ability for finding particular pathology that may be localized in particular regions within the image.
3.	Survey on Various Biomedical CBIR Methods	LBP, LTP, LTrP, LWP To determine the similarity between images measures the distance between their corresponding feature vectors. For medical images shape and texture are the two important low level features which describe the content of the image [3].	The main advantage of the above mentioned system is that it encodes the relationship between the center and neighboring pixels. Another advantage is that system remained insensitive to the change of parameters.	The noticeable factor is that precision and recall is high on comparison with other existing methods.
4.	Survey On Cbir Of Biomedical Images	PCA (Principle component analysis). CBIR systems mainly rely on low level features and most medical	A comparison of the query image with the database of images will result in an exact match.	The accuracy of the system can be further improved by using more sophisticated shape features.

		retrieval systems are designed for one particular type of medical images and current research on medical CBIR rarely evolves the relationship between CBIR and user interface design [4].		
5.	A Comprehensive survey on content based image retrieval system and its applications in medical domain.	Here, we described the significance of CBIR systems and retrieval of images using feature extraction methods and also discussed about the overview of CBIR systems Query. By Image Content (QBIC) which uses low level features only such as shape, text and color and does not include any semantic level. CBIR also known as Content based Visual Information Retrieval (CBVIR) and uses the application of computer vision techniques to overcome the problems found in image retrieval [5].	This paper is also given a direction for future researchers there is a need to develop new methods and tools which are required to manage the increasing amount of medical images.	Text Based Image Retrieval systems are used in many hospitals, but for large databases these are inefficient.
6.	A Survey of Feature Extraction for Content-Based Image Retrieval System.	Content-based image retrieval techniques [6].	Fused features are used which gives better Visual retrieval than the single characterized feature retrieval	Spatial distribution of color information is lost
7.	An Ingenious Segmentation Application for Brain Lesion Detection in Multimodal MR Images	FCMC Method, Watershed Method, Proposed Method, Bilateral Filter, Brain MRI, Multimodal. Fuzzy C-Means Clustering (FCMC) is most accepted method under unsupervised technique which has been effectively used in many applications and several areas like clustering, segmentation, etc. [7].	The major focus of the proposed method is to enhance the segmentation results of disease detection.	The drawback of FCMC method is the less segmentation accuracy for the detection of anomalies in multimodal brain MR images.
8.	Fusion of local and global features for effective image extraction	Here, they proposed a novel method for effective and accurate feature vector extraction and image classification. Global features are preferred for large-scale image retrieval, whereas local features perform better on those systems that support semantic queries with close visual appearance. Moreover, SURF is scale and rotation-invariant as compared to HOG descriptor and it works better for low illumination. [8].	Contribution presents a feature descriptor that combines the benefits of local interest point detection with the feature extraction strengths of a fine-tuned sliding window in combination with texture pattern analysis.	Here they identify such results with limitations.
9.	Color and Texture Fusion-Based Method for Content-Based Image Retrieval	CBIR, Gabor function. The content based image retrieval system is technology for search in the image database by it is visual content such as color, texture and shape Features [9].	Uses low-level feature extraction	the major drawback is that the user of a Text Based Image Retrieval must describe an image using nearly the same keywords that were used by the annotator in order to

				retrieve that image.
10.	DOCToR: The Role of Deep Features in Content-based Mammographic Image Retrieval	Deep learning, transfer learning, medical image analysis. The current large application of deep learning architectures in several medical problems, to the best of our knowledge, the majority of works focus on training state of-the-art architectures from the scratch. Unfortunately, this not only leads to a huge computational cost, but also require a large volume of data to present a good generalization [10].	The generalized deep features are able to improve in a great extend the precision of similarity queries both in the traditional process and applying query refinement strategies.	These deep architectures could be not only efficiently transferred on small subproblems, but also fine-tuned to it.
11.	A Robust Content Based Image Retrieval Using Local Full-Directional Pattern (LFDP)	LFDP[11]	The idea of pre-processing phase comes from the fact that for image Retrieval purpose very small texture structures are not needed which in the contrary for texture classification and fingerprint detection they are very important	It is time consuming. .
	Content Based Image Retrieval using Feature Extraction in JPEG Domain and Genetic Algorithm	DCT (Discrete Cosine Transform), GA (Genetic Algorithm), CH (Color Histogram), Colour Moments; Precision and Recall. The visual contents of an image include color,	We will be able to integrate human perception in to the query and evaluate the results as well.	As the human psycho-visual system does not give importance to the high frequency information, this transformation in the process of quantization
		texture and shape. These features can be extracted through different mechanisms that are discussed in depths across the literature. But most of the research work focuses on extracting these features from the spatial domain on the RGB or HSV values directly [12]		removes all these redundant information and stores back only the required details to reproduce the image.
12.	Content Based Image Retrieval using Feature Extraction in JPEG Domain and Genetic Algorithm	DCT (Discrete Cosine Transform), GA (Genetic Algorithm), CH (Color Histogram), Colour Moments; Precision and Recall. The visual contents of an image include color, texture and shape. These features can be extracted through different mechanisms that are discussed in depths across the literature. But most of the research work focuses on extracting these features from the spatial domain on the RGB or HSV values directly [12]	We will be able to integrate human perception in to the query and evaluate the results as well.	As the human psycho-visual system does not give importance to the high frequency information, this transformation in the process of quantization removes all these redundant information and stores back only the required details to reproduce the image.
13.	Multi-dimensional multi-directional mask maximum edge pattern for bio-medical image retrieval	Local binary pattern (LBP) · Local mesh pattern (LMeP) ·Multi-dimensional multi-directional mask maximum edge patterns [(MD)2MaMEP	The local depth information, further it accesses the local information in multiple directions and finds directional	Efficiency issues.

		]	edges, and due to this processor method is able to retrieve images accurately.	
14.	A Novel Indexing and Image Annotation Structure for Efficient Image Retrieval	Image re-ranking, Pre-processing, Annotation, Semantic signatures, Visual Features, Convex optimization clustering. They extract index features of images by applying some image indexing technique such as using locality sensitive hashing (LSH), a very popular indexing approach to define image features. Other than the indexing approach, another key approach is to use an unsupervised classification procedure to extend quality of the weakly labeled images. [14].	This approach is less time-consuming.	It takes more execution time to retrieve the topmost images for automatic image annotation with their names from the image data source
15.	Human Activity Detection Using RGBD	RGB, Melanoma, JAI [15].	The problems with text-based access to images have reduced which increases the interest in the development of image based solutions	Limitation of our system is that, the result displayed does not give 100% accuracy, as image similarity is based on many feature vectors collectively, but we are limiting our similarity measurement to the color only.
16.	Content based image retrieval using deep learning process	In this paper they use Deep learning [16].	The deep belief network (DBN) method of deep learning is used to extract the features for classification and is an emerging research area, because of the generation of large volume of data.	Due to the computation time requirement, some good algorithms are not been used.
17.	Review on Content Based Image Retrieval (CBIR) Technique	Indexing, query specification, query visualization, effectiveness measures, color, texture, shape, Semantic retrieval, Relevance feedback [17]	CBIR is desirable because searches that rely purely on metadata are dependent on annotation quality and completeness.	The problem of retrieving images on the basis of their pixel content remains unsolved.
18.	A Survey Over the Content Based Image Retrieval Techniques	K-Means Clustering algorithm, Feature Extraction (FE), Similarity Measurement (SM), Euclidian distance, Haar Transform [18].	Suggested improvement will also help in solving the storage space problem.	An existing technologies use a lot of computation time and also require large storage space.
19	A Survey on Different Relevance Feedback Techniques in Content Based Image Retrieval	Semantics gap, Relevance feedback, Feature modification, Subspace learning [19].	The advantages are there is no need for the explicit class label information for images in the dataset and also consider local information of each image.	Performance of CBIR system is poor due to the semantics gap between the input image and low level visual features. The main drawbacks are less efficient for large databases. The disadvantage is increasing time complexity to take both user data and user feedback log

				data.
20.	An Overview of Content-based Image Retrieval Techniques	Feature extraction, indexing and Retrieval techniques [20].	The purpose of ordering of image feature vectors, a vector cosine distance measure is used.	the drawback of the histogram techniques of color image retrieval which consider only global properties and hence cannot effectively define an image, a scheme to capture local properties has been developed for more accurate retrieval
21.	Melanoma Detection in Dermoscopic Images using Global and Local Feature Extraction	Gray level co-occurrence matrix (GLCM), Speeded Up Robust Features (SURF), Scale Invariant Feature Transform (SIFT), Support vector machine (SVM), K-Nearest Neighbor (KNN). The spatial dependence of gray levels is represented by a two dimensional matrix known as GLCM and it is used for global texture analysis of an image. [21]	The advantage of support vector machine is that it works effectively in high dimensional spaces.	The textural features represent the spatial distribution of gray tonal variations within a specified area.

VI. CONCLUSION

In this paper we have discussed about the various feature extraction methods and applications of content based image retrieval and also the overview of CBIR. This paper also analyses the different CBIR techniques in medical images. The various techniques of CBIR were studied to find the best method that gives an accurate result. This paper can be used by researchers for getting an overall picture of the feature extraction techniques in CBIR. If we minimize the problem associated with large dataset, then overall classification result increases and it will give better result of an image retrieval process. In our future work we are going to design a better approach with dimensionality reduction for the extracted feature dataset for accurate results.

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Authors Profile

Dr. (Mrs.) Jasmine Samrajfrom Quaid – e-Millath Government College For Women(Autonomous). She is currently working as an Associate Professor with 24 years of teaching experience in PG & Research Department of Computer Science.

R.Dhivya from Quaid-e-Millath Government College For Women(Autonomous). She is a Research Scholar in PG & Research Department of Computer Science.