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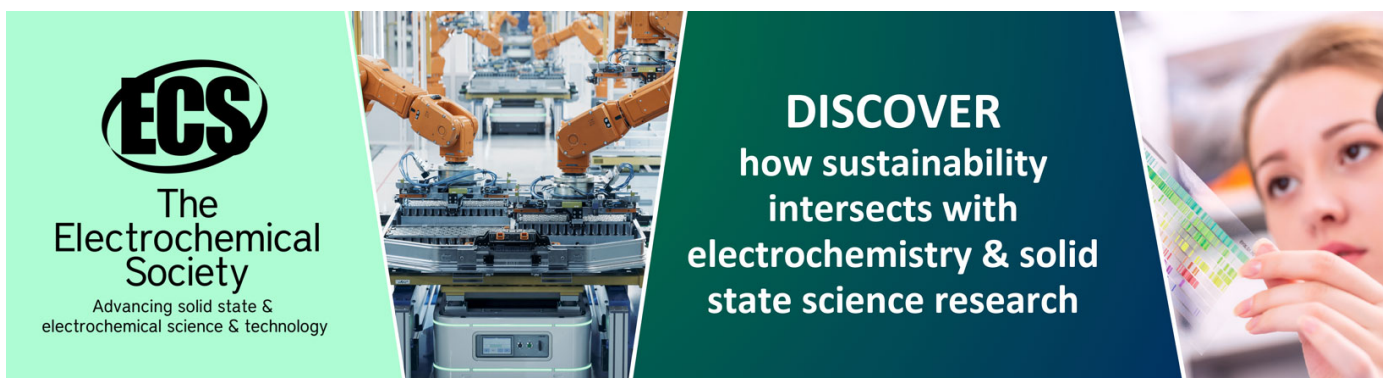
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# Content-Based Image Retrieval in Medical Domain: A Review

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**Abstract.** Content-based Image Retrieval (CBIR) aids radiologist to identify similar medical images in recalling previous cases during diagnosis. Although several algorithms have been introduced to extract the content of the medical images, the process is still a challenge due to the nature of the feature itself where most of them are extracted in low level form. In addition to the dimensionality reduction problem caused by the low-level features, current features are also insufficient to convey the semantic meaning of the images. This paper reviews the recent works in CBIR that attempts to reduce the semantic gap in extracting the features from medical images, precisely for mammogram images. Approaches such as the use of relevance feedback, ontology as well as machine learning algorithms are summarized and discussed.

## 1. Introduction

In recent times, the usage of digital images is becoming more popular across different sectors including medical, scientific experiments, educational and so forth. Hospitals and medical institutions are generating a great number of digital images such as x-ray, mammogram and magnetic resonance imaging (MRI) as part of their daily routine. Interpreting the medical images is certainly a complex task which requires extensive knowledge. In order to assist radiologists in interpreting the medical images, researchers have developed support systems such as Computer Aided Diagnosis (CAD) system and Content Based Image Retrieval (CBIR) system. CAD would help radiologists in diagnosis and also serve as a second opinion [1]. On the other hand, Content-based Image Retrieval (CBIR) uses visual content to help users browse, search and retrieve similar medical images from a database based on the user's interest [2-3].

CBIR systems such as QBIC, PhotoBook or VisualSeek which help retrieve similar images would assist radiologists in analysing previous similar cases [4]. Researches in CBIR were initiated back in early 1990s to support the emergence of large image collection. The research area becomes more active with the advancement of the availability of multimedia technologies in the medical industry as well as the advancement in image processing and medical informatics [5]. Researchers study the retrieval of images in two parts: text- and visual-based. To retrieve image that is text-based, keywords are used to annotate the images. This manual annotation process is done by human and it has the potential of offering very precise information when images are well-named or annotated [1]. However, this process becomes much more difficult to execute as the size of image collection increases. Thus, it becomes labor-intensive and time consuming. In addition, some images cannot be annotated because



they contained too much information. The other difficulty is because of the subjectivity of human perception during annotation [6]. In overcoming the problems of the retrieval of text-based image, researchers have shifted the focus to visual-based image retrieval.

Two main components in visual-based are feature extraction and feature reduction with application of certain similarity measurement. In CBIR systems, image content includes the colour, texture, and shape. They are extracted for subsequent uses during indexing and retrieval process. These features are considered low level and are usually presented in numerical forms and assigned in feature vectors. Nonetheless, the majority of users are always more interested in specific regions rather than the entire image. Thus, most of the current CBIR systems are region-based where the features are extracted only from the Regions of Interest (ROI). Representation of the images at regional level is identified to be closer to human perception system [7-8].

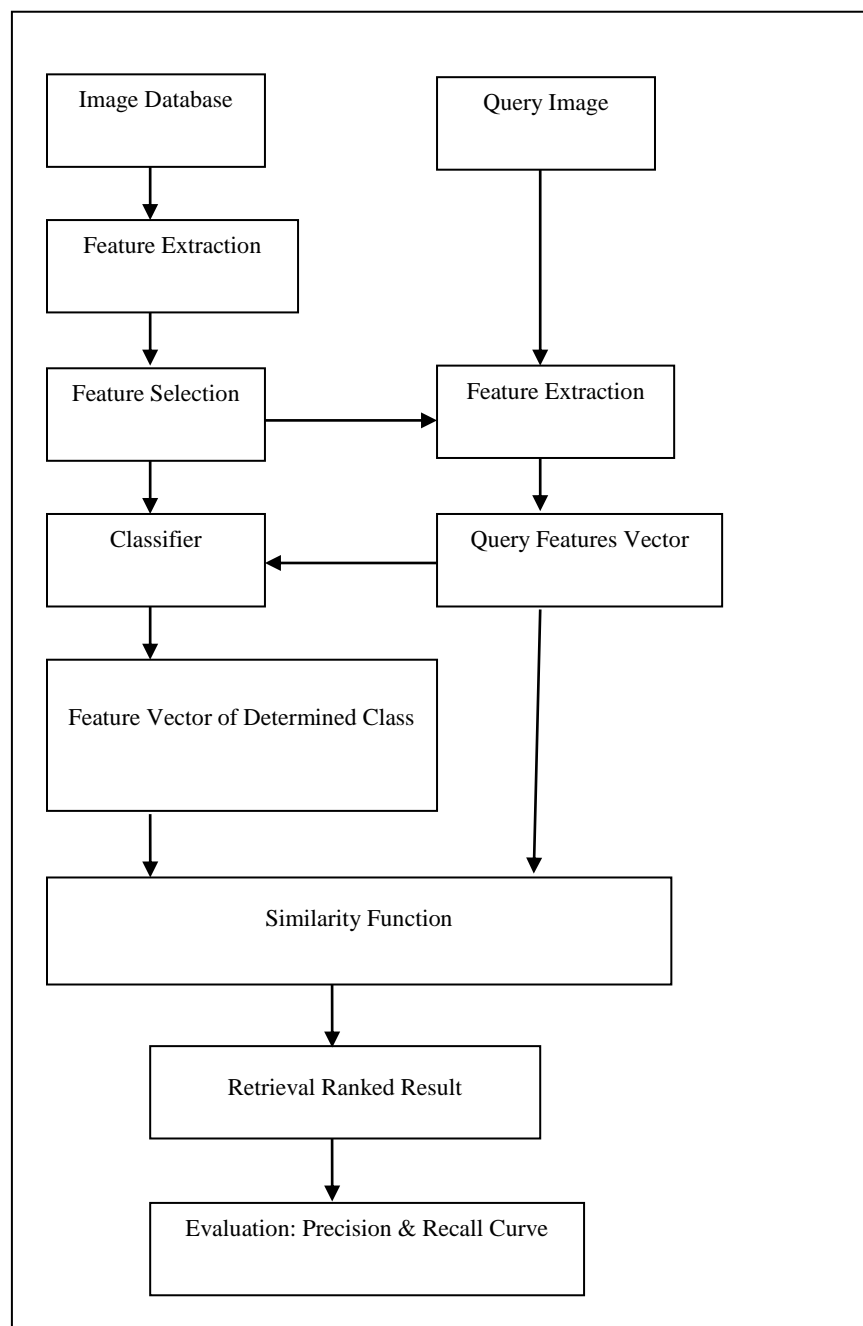
In the past, the extraction of these low- level features were done by different algorithms. It is then followed by features reduction process to form a good feature representation from larger collection of image features. However, these algorithms are not able to adequately represent the semantic information or high-level features (concept) including keywords and text descriptions that are commonly used by human during interpretation. The algorithms are somehow limited when dealing with larger numbers of rich content images in the database. Researchers, in overcoming these issues, have provided resolutions to reduce the semantic gap in retrieving the images via (1) ontology high-level concepts are defined by ontology, (2) machine learning tools associating low-level features with query concepts, with machine-learning tools and (3) relevance feedback (RF) to promote continuous learning of user interest.

Besides semantic annotation, another key challenge in CBIR research is the similarity measurement. By calculating the distance between their corresponding feature descriptors (feature vectors) in the featured space, the similarity between any two images can be determined, However, 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 labeled data [9-10].

Section 2 of this paper presents a summary of research in CBIR which includes the process of image segmentation, low-level image extraction and feature selection. This section would also detail out the similarity measurement as well as the performance measurement. Section 3 reviews the related works of CBIR in medical domain and Section 4 provides the discussion on reducing the semantic gap. Finally, Section 5 ends the paper by providing future directions in CBIR research.

## **2. Content-Based Image Retrieval**

Most of the Content-based Image Retrieval (CBIR) systems are based on image similarity, whereby a user inputs a query image and the system responds by providing the most similar image based on a certain similarity measurement. The results of the similar images are then displayed in descending rank. The fundamental bases of CBIR system are feature extraction and feature selection, classification and similarity measure as illustrated in Figure 1.



*Figure 1:* Framework for a CBIR system.

Features such as colour, texture and shape are often used to describe the content of the image similarity. Many algorithms have been proposed to extract image features. Image features can be extracted from the entire image or from certain regions. Thus, image segmentation process is necessary prior to feature extraction for Region-based Image Retrieval (RBIR) [11].

### 2.1. Image Segmentation

The selection of the types of features, global (involving the colour and texture of the histograms and the entire image layout) and local (the colour, texture and shapes of sub-images, segmented regions

and interest points) features, significantly affect CBIR research. The explanations of these features mentioned are as follows:

**Colour:** Colour features are designed based on colour space. Colour representations that are commonly used in RBIR are RGB, LAB and LUV, HSV (HSL), YCrCb, and Hue-Min-Max-Difference (HMMD). All of these are designed to be closer to human perception. They are represented using colour-covariance matrix, colour histogram, colour correlogram, dominant colour descriptor, colour moments, colour coherent vector or colour co-occurrence matrix. Colour features are reported to be very stable and robust due to their resilience towards rotation, translation and changes during scaling [12]. However, most medical images are in grayscale except for colour photographs that are used for diagnosis in ophthalmology, pathology and dermatology [13][14]. Bunte et al. [3] used elective colour features to retrieve similar skin lesions when comparing to an actual case to verify the diagnosis or confer with similar symptoms. The colour feature representations used are limited to rank matrix learning vector quantisation (LiRaMLVQ) and a Large Margin Nearest Neighbor (LMNN) approach. They performed a comparison on the retrieval rates achieved with extracted and original features for eight different standard colour spaces, and the research has achieved a significant result for each colour space.

**Shape:** Shape features, in comparison to colour and texture features, have not been used commonly. Past research have shown that it is challenging to apply shape features as compared to textual and colour features as they may be inaccurate during the segmentation process [15]. Shape features are useful in cases where images comprise objects that can evidently be separated from the background. Shape features include aspect ratio, circularity, Fourier descriptor, moment invariants and Zernike moments. In retrieving medical images, shape features are the best descriptors in detecting disease, lesion or mass. Wei et al. [16] applied features of shape and margin using Zernike moments to identify mass lesions in the mammogram. The result showed that the retrieval system was capable of achieving the highest precision among all mass lesion types when retrieving round-shaped and circumscribed margin masses,

**Texture:** Texture refers to the visual patterns that contain homogeneity properties and is not a result of the presence of only a single colour or intensity. Texture features are represented by using the gray-level co-occurrence matrix, Tamura feature, wavelet coefficients, gabor filter and Haralick's feature. For Tamura feature, six visual texture properties which include coarseness, contrast, directionality, line likeness, regularity, and roughness are used. In Haralick's approach, the texture features are represented using the co-occurrence matrix based on the orientation and distance between image pixels. Meaningful statistics are then extracted from the matrix as the texture representation [19]. In medical domain, researchers usually use texture features because organs and tissue anomalies are well characterised by texture properties [13][16]. Tissues are expected to have consistent and homogeneous texture. Thus, it is the best option to discriminate among organ tissues in CBIR system, for instances, texture features have been used for brain tumor diagnosis [17] and mass lesion detection in mammogram images [18].

## 2.2. Feature Selection

For each image in CBIR systems, a feature vector is processed and stored in a visual feature database. When a query is made by a user, the feature vector for this query is first computed. By using a similarity criterion, all the vectors in the visual feature database are compared to this query vector. The images that are most similar to the query image are returned to the user. It is obvious that the CBIR systems strongly depend on the characteristics extracted from the images. Features extracted from images are represented in the form of feature vector. Then, using these features, CBIR system will index and find the most similar and relevant images.

Intuitively, a single feature is not able to describe the image visual content very well. Therefore, researchers have proposed a combination of several features so that the content of the images can be well-characterised. However, a substantial amount of features could affect the efficiency of the retrieval process. Large number of features normally would result in feature redundancy and irrelevant

features. This would then lead to high dimensionality and eventually affect the efficiency of the retrieval process. There would be a considerable loss of the discriminative power of each feature when the number of features is added. This calls for the need for an elective feature selection algorithms to reduce the feature dimensionality. One of the key challenges in optimising the CBIR systems is feature selection. Feature selection can be defined as the process of selecting the combination of features among a given larger set that describes a particular data collection best. Feature selection has been applied as pre-processing technique in data mining, pattern recognition, classification of medical images, genomic data analysis, speech recognition and others. The function of feature selection is to decrease the features in order to generate precise results. It is therefore critical to choose the optimal features [19][20].

Three categories of feature selection methods are filter-, wrapper- and hybrid-based. Filter-based methods utilise general characteristics of the data independently from the classifier for the evaluation process. The evaluation process is classifier-dependent in wrapper methods. Finally, hybrid models use both filtering and wrapping methods to improve the performance of the selection process. Filter methods also do not include any induction algorithms. Thus, they are not computationally expensive. There is possibility that subsets of features that are not compatible with the algorithm in the users' application are selected [21].

In learning to rank approach, feature selection is used, whereby only parts of raw features are chosen. Importance and similarity are two properties of each feature which are defined. In the computation of feature importance, each dimension of the feature is used to rank the database images. The ranking performance such as mean average precision (mAP) or normalised discounted cumulative gain (NDCG) is taken as its importance. To calculate feature similarity between two features, the first step is to rank the database images individually. Subsequently, the correlation of these two-ranking list would be taken as the feature similarity. Based on these two properties, the loss function of feature selection is defined as choosing the most important (high importance) and representative (low similarity) features [22].

De Oliveira *et al.*, [23] implemented a two-dimensional principal component analysis (PCA) to overcome the existing PCA as it is claimed to be simpler and more straightforward to use for the characterisation of breast density texture. The retrieval process was carried out using support vector machine (SVM) which solved varied learning, classification, and prediction problems. On the other hand, Marinakis *et al.* [24] used a set of evaluation functions for CBIR, which is also known as the Fitness coach (Fc). The researchers, focusing on improving the quality of each query answer by retrieving a substantial amount of pertinent images during ranking, inserted feature selection function in the GA-based algorithm.

### 2.3. Similarity Measures

Similarity measures are used to identify the similarity between query image and database images. Thus, a good similarity measure would need to be employed in order to retrieve the most similar and relevant images. Many similarity measures have been introduced by researchers to improve the effectiveness and efficiency in CBIR. The measurement required for the similarity comparison is determined by the selected feature vectors. The extraction of the multi-dimensional points' features from the images allows the calculation of the distances between the multi-dimensional points. Popular metrics that are utilised to gauge the distance between two points in multi-dimensional space are Euclidean distance, Weighted Euclidean distance, Manhattan distance, Cross Correlation distance, Minimum Mean distance rule and Statistical distance [2].

Another similarity measure is performed using graph-based approach. Graph representations have received more attention recently because it is an elective tool to represent relational information. Sharma *et al.* [25] proposed a new method to determine the similarity between histological images through graph-theoretic description and matching in retrieving histological images from larger databases. In contrast to the above methods that directly measure the similarity in terms of image



information alone, Classifier-based similarity measures do not directly measure similarity in terms of image information as compared to the method mentioned earlier. It uses the classification of a query image based on a fixed set of predetermined labels to assess similarity [26].

### 3. Previous Works in CBIR

This section examines current practices and prospects of CBIR systems. The emphasis is placed on the summarization of major advanced CBIR approaches used for improving information retrieval. A considerable amount of literature has been published on CBIR systems, while looking into large and growing body of literature; it appears that CBIR systems techniques have been proven to be successful for information retrieval tasks. Town [27] described a system called the “Immense Picture Search” that is based on automated analysis and recognition of image content. This system provided two searching modalities which are (1) exploratory search where users could use keyword or a more complex theory and (2) similarity-based refinement where user could find the similar images based on the returned search result. The proposed system is highly suitable for medical area due to the diverse corpus of medical images. The Gray Level Neighbors Matrix (GLNM) was used to extract texture features for the retrieval of mammograms from the MIAS database. The performance of GLNM was compared to the Gabor, CDF 9/7 and Db4 wavelets, GLAM and GLCM based texture extraction methods. The Precision Recall (PR) graphs showed that the retrieval performance of the proposed method is much better than the competing methods. As for the future works, the proposed GLCM approach may be applied for texture feature extraction problems involving other databases, for example diabetic retinopathy and bloats.

Popova & Neshov [28] attempted to improve the retrieval effectiveness and accuracy of image search in huge databases. Their works recommended two sets of different feature combinations that perform well for medical image categories, IRMA. The top three features used in the research were Colour Layout, Edge Histogram and DCT Coefficients, which were all combined for a higher image re-trivial ranking than others that were based on individual features. The results returned a 14.49% improvement of the retrieval MAP (50.68% for combined features Set). In the future, the research is set to investigate new features and apply appropriate weights for the particular features used in the combination. In handling noisy image in Relevance Feedback CBIR systems, Huang *et al.*, (2013) proposed a two-step strategy. The first step was to apply a noisy elimination algorithm. The second step was to adopt Fuzzy Support Vector Machine (FSVM) to re-rank the images. Noisy-Smoothing Relevance Feedback (NS-RF) was reported to yield better retrieval performance as compared to the Support Vector Machine-Noisy-Smoothing-Relevance Feedback (SVM-NS-RF). The justification was that NS-RF can further handle the noisy images by considering different relevant images with different relevance probabilities in the image re-ranking procedure, whereas SVM-NS-RF treated the retained relevant image equally. In addition, the research noted that the effect of noisy elimination algorithm in NS-RF is sensitive to the slack factor in the proposed formula. Hence, it is proposed to conduct further investigation on the value in order to improve the noisy elimination algorithm in the future.

Burdescu et al. [30] include Cross Media Relevance Model (CMRM) and Continuous Space Relevance Model (CRM) to annotate the medical images with a segmentation algorithm based on hexagonal structure. The research resulted in an ontology created using Medical Subject Heading (Mesh). Their results showed that the CRM model produced better results as compared to CMRM for image annotation and semantic-based image retrieval. Annotation of mammograms has also been explored using the mammography. For Annotation Ontology, a model was proposed for similarity calculation between breast masses based on their high, mid and low-level features. They also used the Semantic Query-enhanced Web Rule Language (SQWRL) to retrieve similar masses from annotated mammography collection in OWL. The proposed approach was tested with DEMS, which is a fully-annotated digital mammography dataset. The mid-level feature also helped to effectively rank the

result set. Future work was set to include more mid-level features as well as to integrate the low-level features into reasoning phase [31].

Da Silva et al., [17] conducted three experiments using mammograms taken from the University of South Carolina and University of Sao Paulo. This technique of feature selection enhanced similarity search accuracy and lowered substantially data dimensionality, which consequently improved access methods efficiency and the CBIR system. For future work, it is recommended that a new local search into GA and the synergy between filter-based methods and the GA wrapper-based method in CBIR systems can be introduced to improve the efficiency of the proposed method. Besides those, all textual information on patients' clinical history can be incorporated into the search mechanism.

Similarly, Wei et al. [16] proposed a set of mammogram descriptors according to the BI-RADS definition. The proposed learning approach improved the classification accuracy as high as 72% and 74%. The calcification Query-By-Example (QBE) was reported to be slightly higher than the mass QBE is more effective in extracting calcification lesions as compared to mass lesions. This study resolved that in the process of feature extraction, the calcification features are able to withstand possibilities of inaccuracies, noises and misses in spot detection. Mass lesions, in feature comparisons with those of calcification, are found to be more sensitive to segmentation imprecision and extraction. This study intends to investigate long-term learning in relevance feedback for a real-time system to develop users' search information. Ramamurthy & Chandran [30], presented the texture-based image retrieval system for medical images. Gray Level Co-occurrence Matrix (GLCM) and k-means clustering algorithm were utilised in the proposed system to improve its retrieval competence. However, as the system solely used texture feature, retrieval performance was only at 50%.

To characterize the texture of breast density, MammoSys was introduced based on Two-dimensional Principal Component Analysis (2DPCA). Support Vector Machine (SVM) was used to aid the retrieval process. 2DPCA was able to extract the features of the texture of breast tissues by capturing the difference between the gray level intensities among different breast densities. This research has also produced another positive consequence, i.e. all retrieved images, sharing the same view and direction, originated from BI-RADS category of the query image. This research anticipated that there could be a combination of texture attributes with the grey-level histogram, and also with other retrieval patterns, for example, breast lesions, masses and calcifications [23].

To abridge, different researchers have conducted study on different parts of CBIR to improve the efficiency of the CBIR system as a whole. Some of researches focused on feature extraction and combine several features to improve images retrieval. In medical, researchers usually used texture and shape features to represent the images content because medical images such as breast cancer [23][13][32] and brain tumor are in grayscale except for ophthalmology, pathology and dermatology [12]. Outside of the medical area, colour features are used because it is the most recognised feature to represent the image content as compared to other features like textures and shapes [33][34]. Researchers also combine different features for a better characterisation of images content. Nonetheless, the efforts resulted in high dimensionality of feature set and hence lead to the research in feature selection. It is a common belief that selecting the best features that best describe the image content will help retrieve the most relevant ranked images [28]. There are also researchers who work on similarity measure such as new matching strategy to enhance the performance of the CBIR as well as a novel relative comparison-based similarity learning strategy to enhance CBIR performance [35][36].

Zhang [37] stated that only colour features cannot produce good results. Therefore, the author combined the colour features with texture features. In this approach, the similar images are firstly searched based on the colour features. Then, from these searched images, the searching process is performed again using texture features. For colour features, perceptually weighted histogram is generated using  $L^*u^*v$  colour space. Gabor filter is used to extract the texture features. To assess the proposed techniques, experiments were performed on the MPEG-7 natural image database. Validation



was done by calculating the precision and recall value for retrieval result. Likewise, Singh & Hemachandran [38] proposed a CBIR system using Colour moments and Gabor texture features. To extract the colour information from the image, the image is divided into three non-overlapping segments. The first three moments of the colour distributions are extracted from each segment. HSV colour space is used for the colour feature extraction. Texture features are extracted using Gabor texture descriptor and combined with the colour feature vector. They used the Canberra distance to compute the distance between the query image and the database images. For experimental purpose, they used the Coral image gallery and the results are compared with the previous CBIR techniques. To measure the performance of the proposed techniques, precision and recall were used on the performance metrics. The authors also performed experiments using only colour or texture features but the results demonstrated that only colour or texture cannot represent the image well.

Yue *et al.*, [39] used the co-occurrence matrix for extracting the colour and texture features. They compared the performance of local colour histogram, global colour histogram and texture features for a CBIR system. For this comparison, they designed a CBIR approach using fused colour and texture features. Sakhar & Nasre [40] used the local colour histogram, global colour histogram and fuzzy colour histogram for the colour feature extraction. To extract texture, they used Tammura features and the wavelet transform. Euclidean distance was used to compute the distance between the query image and the database images. Reddy and Prasad [41] proposed a CBIR approach using colour correlogram for colour features and multi wavelet transform for texture feature extraction. RGB colour space was used to generate the colour correlogram. They separated each colour space and then apply the correlogram in  $0^0$ ,  $45^0$ ,  $90^0$  and  $135^0$ . Soman *et al.*, [42] used the discrete block wise cosine transform to extract the texture features and colour moments such as mean, skewness and deviation used to compute the colour feature vector. In this proposed approach, images are firstly searched based on texture features. Then, from these searched images, searching process was performed again using colour feature vector. Coral database was selected to perform the experiments and the results were compared with previous techniques.

#### 4. Reducing The Semantic Gap

Semantic is one of the crucial issues in CBIR system. Researchers who worked on low level features have employed several techniques to reduce the semantic gap in CBIR. Based on the previous works, some researchers improved the efficiency of CBIR systems by means of ontology, machine learning tools as well as employing Relevance Feedback (RF) to ensure high relevant images. High-level features are semantically meaningful labels which describe the shape of a mass that can be round, oval, lobular or irregular [43]. Relevance feedback is a powerful tool and online learning to retrieve most relevant images. This strategy ask user to give some feedbacks on the results returned in the previous query round and come up with a better result based on these feedbacks. A variety of relevance feedback techniques designed to bridge the semantics gap between low level visual features and high level semantic concept of each image. The general process of Relevance Feedback is as follows: First user labels a number of relevant images as positive feedback and a number of irrelevant images as negative feedback from retrieved images. Then the CBIR system then refines its retrieval procedure based on these labeled samples. These processes carried out iteratively. RF techniques are classified into two categories: that is query movement and biased subspace learning. In this biased subspace learning, all positive samples are alike and each negative sample in negative in its own way [44].

Furthermore, these descriptors form a simple vocabulary, the so-called ‘object-ontology’ that provides a qualitative definition of high-level query concepts. Database images can be classified into different categories by mapping such descriptors to high-level semantics (keywords) based on our knowledge<sup>7</sup>. Researchers could automate the images according to this ontology. In medical, ontology is developed based on some standard such as the BI-RADS standard. Similar work has been done to annotate the mammogram images using Mammography Annotation Ontology (MAO) that was developed via MAO and was also based on BI-RADS standard [44]. DeOliveira *et al.*, [23] also used SVM for

retrieval task as it is able to solve a variety of learning, classification and prediction problems. For medical applications, Liu et al., [46] presented a new image retrieval method. It utilises a convolutional neural network (CNN) that is merged with neural codes for global classification and equipped with the latest Radon barcodes for the final retrieval. The researchers investigated image search based on regions of interest (ROI) that are matched after image retrieval. Relevance Feedback (RF) is another approach to reduce semantic gap in retrieving images. RF is a supervised learning technique because user has to give feedback by labeling the returned images. In conventional text-based information retrieval systems, relevance feedback is a very reliable technique used. This technique regulates automatically existing query relevant to the preceding objects retrieved through information fed back by users to the system. This allows users to have a query which is more attuned based on their information need.

The main aim of the medical image databases therefore is to organize, search, and index the vast corpus of medical images. It is therefore crucial to have, an intelligent system that enables the capture, recognition, and comprehension of the intricate content of medical images. For these tasks to be fulfilled, content-based retrieval, by which a number of techniques used in medical images has been developed, is a promising approach. In spite of the current progress, medical content-based image retrieval has the potential to develop further and there should be more research into this area. Eventually, a competent image database, together with an intelligent retrieval system will be able to improve clinical treatment, and offer a platform for better medical research and education [47].

To enhance performance in relevance feedback scheme, Wang et al., [7] proposed a Feature Line Embedding Biased Discriminant Analysis (FLE-BDA). The margin between relevant and irrelevant samples in the local neighbourhood is maximised by reducing the gap between the query and relevant images. This subspace learning method allows a linear transformation matrix from relevant or irrelevant images that is used in dimensionality reduction. The process of retrieval comprises: 1) Keying-in a query image into the IR system. Gallery images are ranked subsequent to the calculation of the similarity values. 2) The labelling of the relevant or irrelevant images as per users' preference 3) Adopting users' feedback for a new transformation. 4) Re-ranking the gallery images to acquire the retrieval results in the next round. Two labels are ascribed to the top-ranking images according to users' preference.

Users' preference is signified by the feedback of relevant or irrelevant labels. The within class scatter is calculated from the image samples with positive labels, while the between-class scatter is calculated from those with negative labels. Based on these assigned labels, the within class and between-class weighted graphs are constructed for maximizing the margin of relevant and irrelevant samples. Then new distance between query and images are calculated. 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. Early relevance feedback method has been classified into the query point movement and the reweighting method. Basically, the query point movement method enhances the estimation of the 'ideal query point' by shifting positive examples nearer to it, and negative ones afar. Fundamentally, the reweighting method is to amend the weight of each image feature element. These methods strongly assume that the target class, with an elliptical shape, significantly limits their performance. The main goal of this system is to get the best relevant and similar image as preferred by user.

## 5. Conclusion And Future Directions

Content based image retrieval is a technique to retrieve more relevant images. Retrieve similar images only is a standing problem in digital image processing. The performance of CBIR system 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 do 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. This paper focuses on the different relevance feedback techniques in digital image processing.

Researchers have proposed several approaches to provide a linkage in the use of low level features with high-level ones to bridge the semantic gap in the medical field. Past and current researches suggested of using ontology in CBIR, applying machine learning to classify images in retrieval task and employing RF to refine the retrieved images in the first iteration. Various algorithms have been conducted by the researchers to solve this matter. However, to build a working CBIR with high-level semantic requires many efforts such as extraction salient low-level features, selection of significant features, effectiveness of learning process, user friendly interface usually in case of RF and efficient similarity measure to index the images.

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