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Content Based Medical Image Retrieval System (CBMIRS) Using Patch Based Representation

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***ABSTRACT*:** *This research work is to develop an efficient and powerful medical search engine to classify and search the radiographic medical images. It focuses on bag of visual words image representation and a similarity matching technique to represent match and retrieve the similar images. This work addresses the issues in content based image retrieval for medical images. In this system can handles different categories of medical images in organ level and the pathology level for chest X-ray images. This simple, efficient medical image categorization and retrieval system in large radiographic archives (IRMA database) is developed for a medicine physicians and researchers those who are interested in being able to retrieve medical images based on low level features. This would make these systems more helpful for radiologists in medical settings, researches in medical analysis and medical students as well as teachers in academic healthcare environments. The methodology presented is based on local patch representation of the image content using a bag of visual words approach with a kernel based SVM classifier. The system supports the classification of X-ray images and retrieval of similar medical images for given input query image.*

***Key terms*:** *CBIR, IRMA, Picture archiving and Communication System, Bag of Visual Words, Computer Aided Diagnosis, Chest Radiography, image Patches.*

I. INTRODUCTION

The main motivation of this thesis is to review the current state of the art in Content-Based Image Retrieval (CBIR) need to deal with X-ray images technique for retrieving images on the basis of automatically-derived features. In this research work, develop an efficient and powerful medical search engine to classify and search the radiographic medical images. The system focus on bag of visual words image representation and a similarity matching technique to represent match and retrieve the similar images. The objective of this research is to address the issues in content based image retrieval for medical images. The simple, efficient medical image categorization and retrieval system in large radiographic archives (IRMA database) is developed for a medicine physicians and researchers those who are interested in being able to retrieve medical images based on low level features. This would make these systems more helpful for radiologists in medical settings, researches in medical analysis and medical students as well as teachers in academic healthcare environments. The methodology presented is based on local patch representation of the image content using a bag of visual words approach with a kernel based SVM classifier. The system supports the classification of X-Ray images and retrieval of similar medical images for given input query image.

The rest of the paper organised as follows. Section 2 discusses the overview of the chest X-ray pathology detection. Section 3 denotes the related works of this paper. Section 4 is comparative analysis of existing approaches. Section5 denotes the experiments of this paper. Section 6 discusses about the results and analysis. Section 7 and 8 discusses the conclusion and future work of this paper.

Medical Imaging System (MIS)

During the next years, profound changes are expected in computer and communication technologies that will offer the medical imaging systems industry a challenge to develop advanced telemedicine applications of high performance. Medical industry, vendors, and specialists need to agree on a universal MIS structure that will provide a stack of functions, protocols and interfaces suitable for coordination and management of high-level image consults, reports and review activities. Most hospital imaging departments have to computerise information systems in which patient images and reports are to be stored. The stored information can be handled by two major types of medical applications, the integrated Report and Review applications.

The former is performed by experts (eg. radiologists) in four steps :

1. Retrieving and viewing images
2. Processing, interpretation and annotation of the diagnosis
3. Composition of final diagnostic multimedia report and
4. Permanent storing in the database. The latter allows many simultaneous users (authorized patient-care personnel) to view, read, and listen to the diagnostic report; these users do not alter the handled data.

Content Based Image Retrieval System

In content-based image retrieval systems, images are indexed and retrieved from databases based on their visual content (image features) such as colour, texture, shape, etc. Commercial content-based image retrieval systems have been developed, such as QBIC, Photo book Virage , Visual SEEK , Netra . Eakins has divided these image features into three levels as followings:

1) Level 1 - Primitive features such as colour, texture, shape or the spatial location of image elements. Typical query example is 'find pictures like this',
2) Level 2 - Derived attributes or logical features, involving some degree of inference about the identity of the objects depicted in the image. Typical query example is 'find a picture of a flower',
3) Level 3 - Abstract attributes, involving complex reasoning about the significance of the objects or scenes depicted. Typical query example is 'find pictures of a beautiful lady.' The majority of content-based image retrieval systems mostly offer level 1 retrieval, a few experimental systems level 2, but none level 3.

II. CHEST X-RAY PATHOLOGY DETECTION AND CLASSIFICATION: SHEBA ARCHIVE

The medical image retrieval system that has demonstrated very strong classification rates and also providing efficiency in the retrieval process. The system has been applied to several large radiograph archives. The system have recently applied it within the Image Clef competition and demonstrated strong results. The topic of retrieval becomes of value on the clinical front, once the content involves a diagnostic-level categorization, such as healthy vs pathology. In a collaborative effort with Sheba medical center, a large academic medical facility, address this concept in the identification and categorization of x-ray lung disease.

In this section the system is shift from organ-level analysis to a pathology-level analysis. Applied our system to chest X-rays obtained in the emergency room of Sheba Medical Center. The system used 98 frontal chest images in DICOM format from the hospital PACS[5], taken during routine examinations. The radiologists examined all of the images independently; then they discussed and reached a consensus regarding the label of every image. For each image and pathology type, a positive or negative label was assigned: 38 of the images were diagnosed as normal, 55 images had at least one pathology and the other five images were labelled as inconclusive. Fig. 5 shows a set of healthy (a)–(c) and pathological images (d)–(m). Pathology data include 24 images with enlarged heart shadow [three examples shown in Fig. 5(d)–(f)], 19 images with enlarged mediastinum, Fig. 5(g)–(i), 17 images with right pleural effusion and 21 images with left pleural effusion, Fig. 5(j)–(l). Some patients had multiple pathologies. For example, Fig. 5(m) exhibits all Pathologies. The system treated the multiple pathology detection as a Set of binary classification tasks, where in each task we tried to detect an individual pathology.

The system started by resizing the original high-resolution DICOM images to a maximal image dimension of 1024 pixels and maintained the aspect ratio. The followed the Feature extraction step to extract features, build a Visual dictionary and represent an image as a histogram of visual words in multiple scales. Then detected each of the four pathologies using a binary SVM classifier with a histogram intersection kernel. In addition to individual Pathology detection trained a classifier to distinguish between healthy images vs. a non-healthy image (with any Kind of pathology). This type of classifier can be useful for initial screening of suspicious images, in order to prioritize the radiologist's work**.**

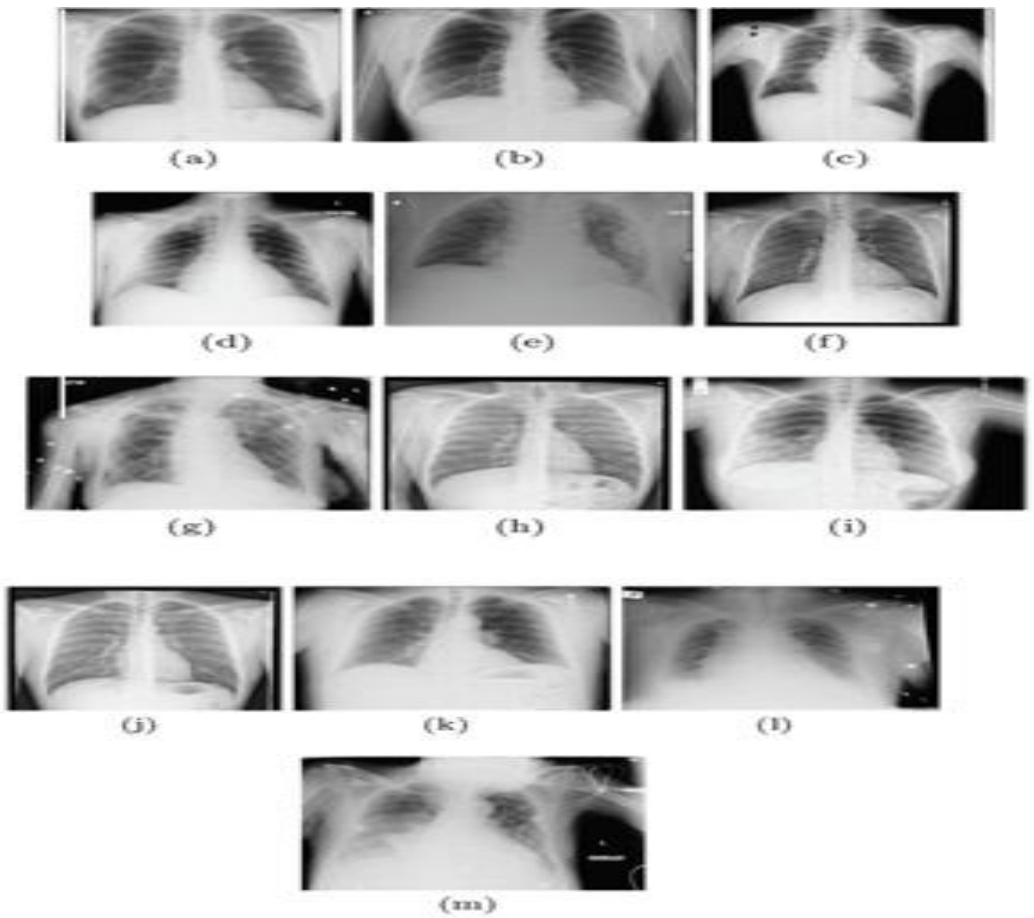

Figure no 1: Frontal chest x-ray images, Sheba medical-centre: (a-c) Healthy; (d-f) Enlarged heart; (g-i) Lung infiltrate; (j-l) Left or right effusion; (m) Multiple pathologies: enlarged heart, lung infiltrate, left and right effusion.

In the task of individual-pathology detection, performance depended on the pathology type: it was fairly accurate in detecting enlarged hearts, with a sensitivity of 75:56% and specificity of 83:46%, and slightly less accurate in detecting lung infiltrates and effusions, which are more subtle findings. Frequently, research focuses on lung nodules. In this work we Looked at other areas beyond pulmonary nodules that could Benefit from computer-aided detection and diagnosis (CAD) in chest radiography. These include interstitial infiltrates, Right and left pleural effusion and cases of enlarged heart.

III. RELATED WORKS

3.1 Medical Image Retrieval Using the GMM-KL Framework

GMM-KL framework as a localized statistical framework for medical image retrieval. Image representation and matching framework for image categorization in medical image archives are done using this framework. The GMM-KL Gaussian Mixture Modelling framework is used for matching and categorizing X-ray images by body regions [2]. Unsupervised clustering via the GMM is used to extract coherent regions in feature space that are then used in the matching process. The GMM-KL framework is evaluated for image categorization and image retrieval on a dataset of 1500 radiological images [2].

The disadvantages of this approach is extending the GMM-KL framework to work on such a large dataset is yet a challenge, especially due to the computational load involved with the KL measure. GMM is a very crude (and lossy) image representation, it suffices for classification and retrieval tasks and higher resolution image representation will be needed. Matching across images that have large variations in the alignment or zoom. Intelligent search and retrieval of visual information is needed for the diagnosis procedure currently developing more efficient approximations for KL in order to enable such large archive processing.

3.2 X-ray Categorization and Spatial Localization of Chest Pathologies

An efficient image categorization system is presented for medical image databases utilizing a local patch representation based on both content and location. Image categorization is concerned with the labelling of images into predefined classes. The principal challenge of image categorization is to capture of the most significant features within the images that facilitate the desired classification. The user can select the Region of Interest (ROI) among the regions of a particular image [11]. After finding an ROI and refining it for each image in the healthy/pathological labelled training set and run a second training stage, where sub images are cropped to the region of interest of the pathology. A new dictionary is generated for each pathology and the SVM classifiers are trained using the word histograms from the cropped regions [11]. Given a training labelled image dataset, patches are extracted from every pixel in the image. Each small patch shows a localized view of the image content. In the visual dictionary learning step, a large set of images is used. To reduce both the computational complexity of the algorithm and the level of noise, to apply a Principal Component Analysis procedure (PCA) to this initial patch collection. The final step of the visual-words model is to convert vector-represented patches into visual words and generate a representative dictionary. A visual word can be considered to be a representative of several similar patches. The vectors are clustered into k groups in the feature space using the k-means algorithm.

3.3 Distinctive Image Features from Scale-Invariant Key Points

This paper presents a method for extracting distinctive invariant features from images that can be used to perform reliable matching between different views of an object or scene. The cost of extracting these features is minimized by taking a cascade filtering approach, in which the more expensive operations are applied only at locations that pass an initial test [1].

Following are the major stages of computation used to generate the set of image features:

1. Scale-space extrema detection: The first stage of computation searches over all scales and image locations. It is implemented efficiently by using a difference-of-Gaussian function to identify potential interest points that are invariant to scale and orientation.
2. Key point localization: At each candidate location, a detailed model is fit to determine location and scale. Key points are selected based on measures of their stability.
3. Orientation assignment: One or more orientations are assigned to each key point location based on local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned orientation, scale, and location for each feature, thereby providing invariance to these transformations.
4. Key point descriptor: The local image gradients are measured at the selected scale in the region around each key point. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination.

For image matching and recognition, SIFT features are first extracted from a set of reference images and stored in a database [1]. A new image is matched by individually comparing each feature from the new image to this previous database and finding candidate matching features based on Euclidean distance of their feature vectors.

3.4 Automatic Classification of Medical X-ray Images

Image representation is one of the major aspects of automatic classification algorithms. In this paper different feature extraction techniques have been utilized to represent medical X-ray images [7]. They are categorized into two groups

(i) Low-level image representation such as Gray Level Co-occurrence Matrix(GLCM), Canny Edge Operator, Local Binary Pattern(LBP) , pixel value, and

(ii) Local patch-based image representation such as Bag of Words (BoW).

These features have been exploited in different algorithms for automatic classification of medical X-Ray images. Then analyzed the classification performance obtained with regard to the image representation techniques used [7]. These experiments were evaluated on Image CLEF 2007 database consists of 11000 medical X-Ray images with 116 classes. Experimental results showed the classification performance obtained by exploiting LBP and BOW outperformed the other algorithms with respect to the image representation techniques used.

3.5 Similarity Analysis of Images Using Content Based Image Retrieval System

The Content Based Image Retrieval (CBIR) is one of the digital image processing system [9]. Most of the available image search tools are based on textual explanation of images. In these tools, images are manually annotated with keywords and then retrieved using text-based search means. This method would not produce promising results. The goal of CBIR is to extract visual features and display the required image [9]. This paper aims to introduce the problems and challenges concerned with the design and the creation of CBIR systems using SBIR With the help of the existing methods, a possible solution how to design and implement a task specific descriptor which can handle the informational gap among a sketch and a colored image making an opportunity for the efficient search hereby. The results show that the sketch-based system allows users a shrewd access to search-tools.

This technology can be used in several applications such as digital libraries, crime prevention, and photo sharing sites. Such a system has great value in apprehending suspects and identifying victims in forensics and law enforcement. A possible application is matching a forensic sketch to a gallery of mug shot images. This paper focus on retrieval of images based on the visual content of the query picture which demands on the quite wide methodology spectrum on the area of the image processing [9].

3.6 Automatic Classification of Medical X-ray Images: Hybrid Generative-Discriminative Approach

This work is presented to improve the classification performance of medical X-ray images based on the combination of generative and discriminative classification approach. A set of labelled X-ray images were given from 116 categories of different parts of body and the aim is to construct a classification model [8]. This model was then used to classify any new X-ray images into one of the predefined categories.

The classification task started with extracting local invariant features from all images. A generative model such as Probabilistic Latent Semantic Analysis (PLSA) was applied on extracted features in order to provide more stable representation of the images. Subsequently this representation was used as input to discriminative support vector machine classifier to construct a classification model. The experimental results were based on Image CLEF 2007 medical database [8].

The classification performance was evaluated on the entire dataset as well as the class specific level. It was also compared with other classification techniques with various image representations on the same database. The comparison results showed that superior performance has been achieved especially for classes with less number of training images. Thus only 7 out of 116 classes were left with accuracy rate below 60% as it differs from the results obtained using other classification approaches. This was attained by exploiting the ability of PLSA to generate a better image representation discriminative for accurate classification and more robust when less training data are available. The total classification rate obtained on the entire dataset is 92.5%.

3.7 Local Tetra Patterns: A New Feature Descriptor for Content-Based Image Retrievals

In this paper, we propose a novel image indexing and retrieval algorithm using local tetra patterns (LTrPs) for content-based image retrieval (CBIR)[12]. The standard local binary pattern (LBP) and local ternary pattern (LTP) encode the relationship between the referenced pixel and its surrounding neighbours by computing gray-level difference. The proposed method encodes the relationship between the referenced pixel and its neighbours, based on the directions that are calculated using the first-order derivatives in vertical and horizontal directions. In addition, we propose a generic strategy to compute th-order LTrP using th-order horizontal and vertical derivatives for efficient CBIR and analyze the effectiveness of our proposed algorithm by combining it with the Gabor transform.

3.8 An Approach toward the Efficient Indexing and Retrieval on Medical X-Ray Images

Today content-based image retrieval (CBIR) has become one of the most active areas of research in computer vision. With rapid advances in digital imaging modalities, the use of CBIR to search for the clinically relevant and visually similar medical images is highly felt nowadays. This paper proposes a system for content based image retrieval of X-ray images. The six classes of X-ray images used for this work are from the IRMA Image CLEF med 2008 database. Discrete Cosine Transform (DCT) coefficients [13] were used as features and the X-rays were classified using Support Vector Machine (SVM). The classified images along with the features were stored in the database using hierarchical index structure. Euclidean distance is used as the metric for retrieving the top three images from the database relevant to the given query image.

SYSTEM ARCHITECTURE

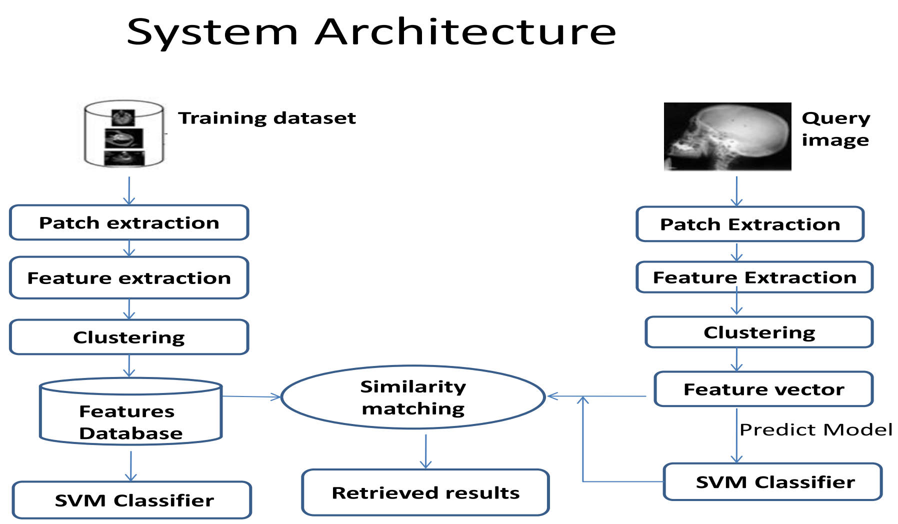

Figure No.2: Bag of visual words based medical image retrieval framework

IV. COMPARATIVE ANALYSIS

Table 1: Comparative Analysis

Feature extraction	Classification techniques	Accuracy obtained,%
GLCM, canny edge detector, pixel value	SVM with RBF	70.45
GLCM, canny edge detector, pixel value	KNN, k = 9	65.95
Local binary pattern	SVM with RBF	90.7
Local binary pattern	KNN, k = 9	86.0
Bag of visual words	SVM with RBF	90.0
Bag of visual words	Multi-modal PLSA and SVM	90.5

V. EXPERIMENDS

5.1 IMAGE PREPROCESSING

5.1.1 Patch Extraction

The existing system need to describe locally the content of images, the first task is to extract visual patches. In our implementation, patches are extracted from every pixel in the image. For a 250* 250 image, there are several hundred thousand patches. An image feature detection approach regular grid method was used to extract several small local patches. Each patch shows localized view of the image content. These patches are considered as candidates for basic elements or visual words. The patch size needs to be larger than a few pixels across in order to capture Higher-level semantics such as edges or corners. At the same time the patch size should not be too large if it is aimed to serve as a common building block for many images. To utilize all the information in the image by sampling rectangular patches of fixed size around every pixel. This simple feature detection approach has been shown to be effective we chose a patch size of 20* 10. We extract roughly 25000 patches per image.

5.1.2 Feature Extraction

In a CBIR system, a very important step is to extract appropriate features from the images. SIFT is an algorithm in computer vision to detect and describe local features in images. Following points of interest detection the feature representation method involves representing the patches using feature descriptors SIFT. In this step, a large set of images used (ignoring their labels). Patches have a single intensity value are abundant in X-Ray images. These patches are common in all categories much like stop words in text documents. The empty patches are ignored and left with a large collection of several million vector. A popular alternative approach to raw patches is the SIFT representation, a scale and rotation invariant description based on a local edge histogram. SIFT has been shown to be advantageous in medical images, where object scales can vary. To examine this option in the experiments defining the system parameter set.

5.2 CLUSTERING FOR GENERATING THE FEATURE DATABASE

In this section Features collection is given input to the clustering process. K-means clustering is applied over the vectors of initial features collection. Features are clustered them in to K groups in the feature space. Feature values obtained for each image is combined to form a Feature vector. The addition of spatial co-ordinates to the feature vector. This introduces spatial information into the image representation. We will pre compute feature vector for all train dataset images then feature vector stored in a feature database. Feature database consists of feature vector for train dataset images. Feature vector of the image describes information about image such as image name, size, and location Figure 3.

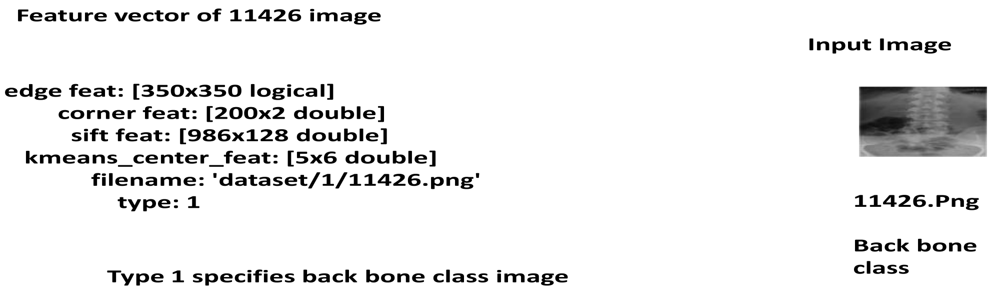

Figure No.3: Feature Vector for 11426.png Image

5.3 IMAGE CLASSIFICATION

Image classification is one of the important steps in image retrieval process because it saves more time while searching the images from huge volume of database. Image classification deals with grouping the same objects into the pre-defined classes or finding the class to which an object belongs, categorization goes beyond the act of assigning the object to categories by adding other use full information for building metadata that systems use for the retrieval task.

5.3.1 Support Vector Machine

A support vector machine (SVM) is a supervised learning methods that analyze data and recognize patterns used for classification and regression analysis. The standard SVM takes a set of input data and predicts for each given input, which of two possible classes forms the input, making the SVM a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other.

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

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into that same space and predicted to belong to a category based on which side of the gap they fall on support vector machine constructs a hyper plane or set of hyper planes in a high or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training data point of any class (so-called functional margin). Since in general the larger the margin the lower the generalization error of the classifier.

5.4 IMAGE RETRIEVAL

Image retrieval requires way to measure similarity between the images using the image representation the distance between images is defined as the sum of the bin-to-bin distance of the representing histograms. For query image and target image the distance where runs on the bins. A popular choice for the image-to-image distance is the Euclidian distance: Instead of exact matching, CBIR calculates visual similarities between a query image and images in the database. Users can select the any query image as the main theme of the query image. The retrieval is the relevance between a query image and any database image. The relevance similarity is ranked according to closest similar measures computed by euclidean distance. The retrieval result is not a single image but a list of images ranked by their similarities with the query image. The images in the database will be ranked according to their similarities to the query image. The top most similar images will be returned as the retrieval results.

Organ Level Image Retrieval Process

Given input query image 6039.png image was taken from test dataset and given as input to the system. Further SVM Test function predicts the class label of given input query image. The system then searches and retrieves the corresponding images belonging to the pelvis organ class from train dataset. Elapsed time for given query image retrieval 21 seconds. Output of retrieved images was shown in figure 4.

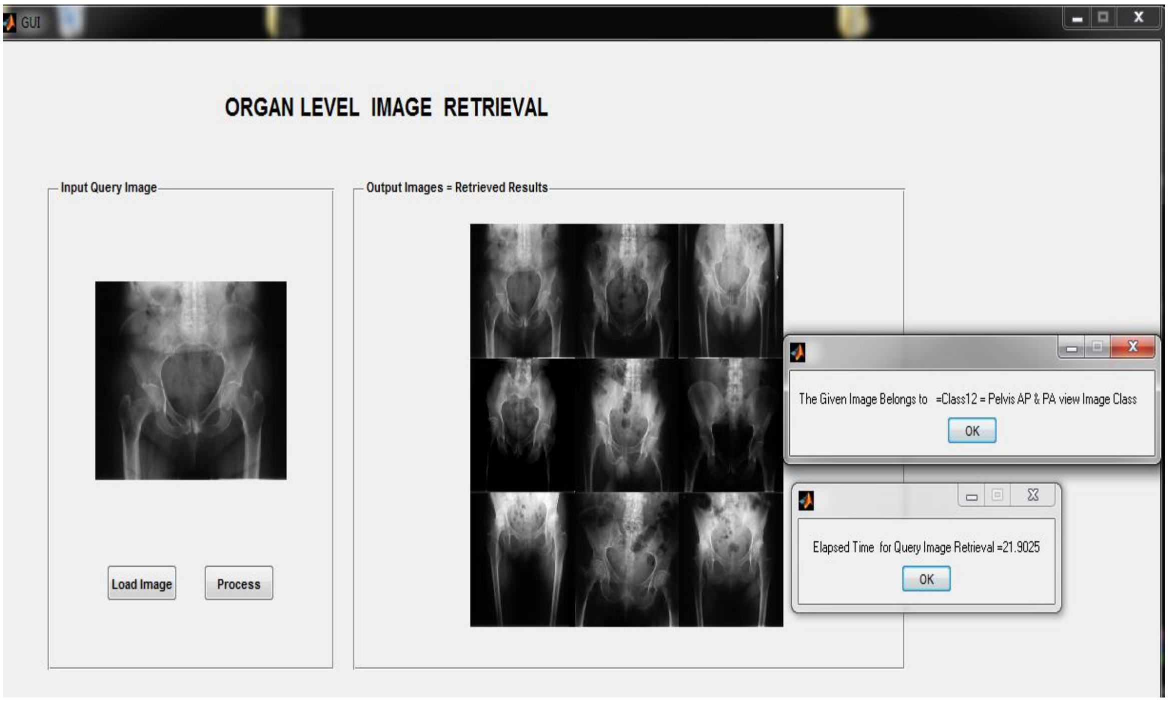

Figure No.4: Organ Level Image Retrieval Process

Pathology Level Image Retrieval Process

Given input query image 3145.png image was taken from test dataset and given as input to the system. Further SVM Test function predicts the class label of given input query image. The system then searches and retrieves the corresponding images belonging to the Enlarge Mediastinum disease image class from train dataset. Elapsed time for given query image retrieval 6 seconds. Output of retrieved images was shown in figure 5.

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Figure No.5: Pathology Level Image Retrieval process

5.5 PERFORMANCE EVALUATION

Performance of our system was analyzed using precision and recall method. Our system achieved high performance compared to existing system. So that the performance of the retrieval process has been improved by comparing the classified images with user's query image medical images Standard formulas have been computed for determining the precision and recall measures.

Precision (P) is the ratio of the relevant images to the total number of images retrieved

$$P=r/n1 \qquad \text{Eq. (1)}$$

Where,

r-number of relevant images retrieved
n1-total number of images retrieved

Recall(R) is the percentage of relevant images among all possible relevant images

$$R=r/n2 \qquad \text{Eq. (2)}$$

Where,

r-number of relevant images retrieved

n2-total number of relevant images in the database

By randomly selecting some sample query images from the training dataset, the system was tested and the results are shown in the following Table 2.

In Table 3 shows that performance measures-retrieval time for various number training dataset images. We are increasing Training dataset images like 150, 250, 500, 750, 1000, 1250, 1500, 1750, 2000, 2250, 2500. Our system was evaluated for this various dataset images. We achieve a retrieval time as a stable at certain stage 1500 train dataset then we increasing train dataset images 1750 we achieve a same retrieval time. Our system give same retrieval time for large radiographic archives.

TABLE 2 PRECISION AND RECALL VALUES IN %

Query Image	Precision	Recall
Image1	90	10
Image2	85	20
Image3	82	25
Image4	80	28
Image5	75	42
Image6	70	58
Image7	68	62
Image8	64	60

TABLE 3 PERFORMANCE MEASURES-RETRIEVAL TIME

Number of Images	Retrieval Time
150	2 sec
250	5 sec
500	7 sec
750	11 sec
1000	14 sec
1250	19 sec
1500	22 sec
1750	22 sec
2000	22 sec
2250	22 sec
25000	22 sec

VI. RESULTS AND ANALYSIS

In this section we evaluate the proposed system. We first investigate the sensitivity to various parameters that define the system. We then show classification and retrieval experiments on large radiograph archives. A key component in using the Bow paradigm in a categorization task is the tuning of the system parameters. An optimization step is thus required for a given task and image archive. We focus on three components of the system: finding the optimal set of local features, finding the optimal dictionary size, and optimizing the classifier parameters. We use a large generic archive of radiographs (IRMA) to tune the system parameters. We then show comparative results of automated organ and orientation detection and image retrieval in the Image CLEF med competition. We conclude with classification results in a chest image pathology detection application.

The system validation was conducted using a database of 2,500 categorized radiographs. This dataset is the basis for the Image CLEF med 2009 medical image classification competition. A set of 2,500 images are used for training, and 500 serve for testing. There are 25 different categories within the archive, differing in either the examined region, the image orientation with respect to the body or the biological system under evaluation. Several of these images are presented in figure 5.1. We optimized the system parameters using the training portion of this set, by running 20 cross-validation experiments trained on 2,500 images and verified on 500 randomly drawn test images. Each parameter was optimized independently. We used dense extraction of features around every pixel in the image using SIFT descriptor.

As a result of the dense sampling, a single image (following the border removal step) yields a large feature set of between 100 000 to 200 000 features. Using the normalized raw patches proved marginally preferable to the SIFT descriptors in this task, in terms of classification accuracy. Most of the running time was spent in the image representation step; this step took over three seconds per image with the SIFT features, but less than half a second with the simpler variance-normalized raw patches. Time was measured on a Intel 5 Xeon 2.33 GHz. Incorporating spatial coordinates of the patch as additional features improves the classification performance.

Using SIFT features with the SVM classifier increased significantly the feature extraction time, and achieved an average of 85:4% classification accuracy; well below the classification rate of the raw patch based classifiers. We used the SVM classifier with three possible kernels: the histogram intersection, the Radial Basis Function and the kernels. We used the optimal features and dictionary size consistently across all experiments. The SVM cost parameter, and free kernel parameter were scanned simultaneously over a grid to find the classifier's optimal working point. The histogram intersection kernel does not have a free kernel parameter, and the optimization is one dimensional over the SVM cost parameter.

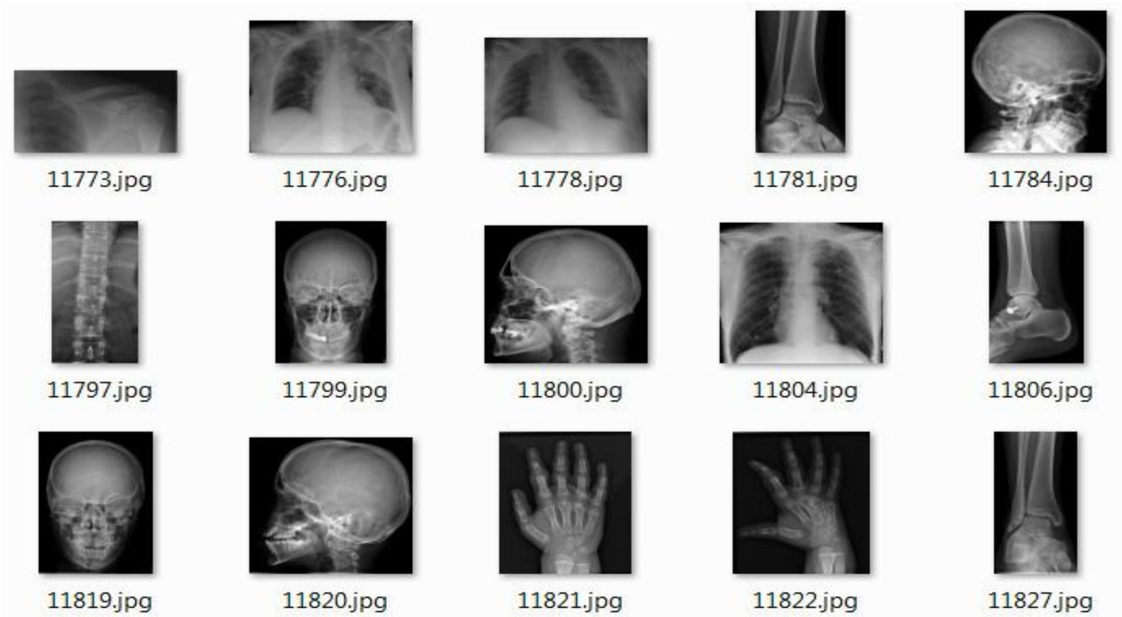

Figure No.6: Sample Images From The IRMA Database.

In Table 2 shows the 90% precision and 10 % recall means score means from 32 images returned by the system, 29 images are relevant to the users. Retrieved images were ranked by the distance between the target histogram and the histogram of the query image. When there were multiple query images, we used the minimal distance between the target and the query set. In our system we achieved overall classification rate was 95%.

The application is shown to discriminate between healthy and pathology cases, as well as identify specific pathologies on a set of 266 chest radiographs taken from a routine hospital examination. We conclude with an initial set of experiments on data obtained in a clinical setting, in which we deal with pathology screening as well as the identification of individual pathologies including right and left pleural effusion, enlarged heart and cases of enlarged mediastinum, multiple disease. This is a first step towards similarity-based categorization that has a major clinical importance in computer-assisted diagnostics. The total running time for the whole system, training and classification, was approximately 40 minutes. The retrieval system is also computationally efficient, with an average retrieval time of less than 20 sec per query. Times was measured on Intel 5 Xeon 2.33 GHz.

In Class-confusion matrix-Organ level image retrieval 25 organ image classes and the correct classification rates per class and miss classification rates per class;. Columns: predicted classes by automated classification; Rows: Pre-labeled classes. Classes are ordered by size. Overall correct classification rate for Organ level image retrieval is 95 %.

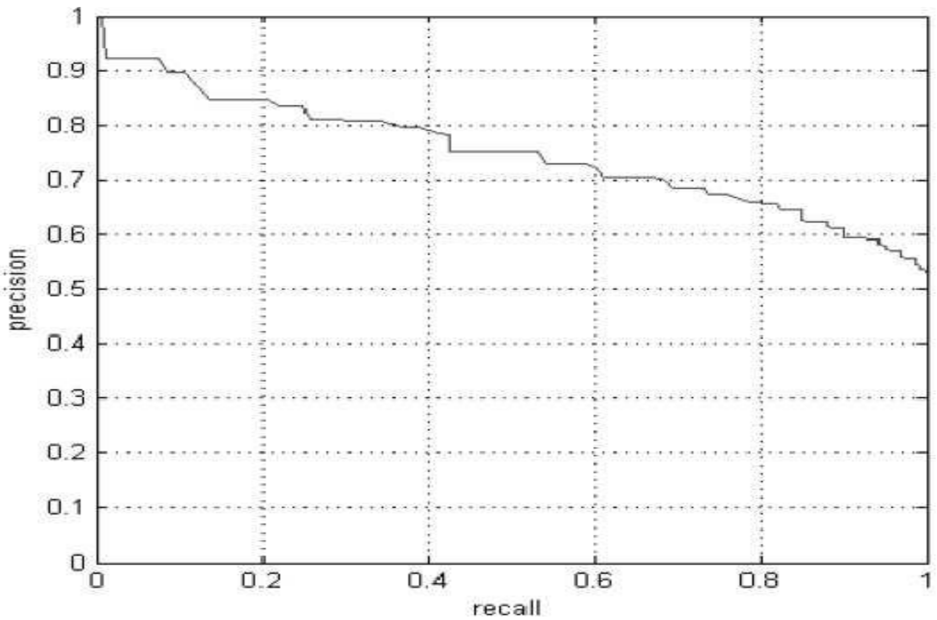

Figure No.7: Precision and Recall Curve

Table 4: CLASS-CONFUSION MATRIX-Pathology Level Image Retrieval

Class Name	AP Normal	Enlarge Heart	Enlarge Mediastinum	LT-PE	Multiple Disease	PA Normal	Plural Effusion	RT-PE	Total	Miss Classified Images	Classification [%]
AP Normal	18		1	1		2			22	4	81
Enlarge Heart		121							121	0	100
Enlarge Mediastinum		2	28	2					32	4	88
LT-PE				9					9	0	100
Multiple Disease	1	4	2	1	48		2		58	10	83
PA Normal						12	1	1	14	2	86
Plural Effusion							3		3	0	100
RT-PE								7	7	0	100
									Total Images=266	Total Errors=20	Correct 93%

In Table 4 shows that Class-confusion matrix-pathology level image retrieval eight disease image classes and the correct classification rates per class and miss classification rates per class;. Columns: predicted classes by automated classification; Rows: Pre-labeled classes. Classes are ordered by size. Overall correct classification rate for pathology level retrieval is 93 %.

VII. CONCLUSION

In existing work present a new way of medical image categorization and retrieval system using bag of visual words framework. The methodology presented is based on local patch representation of the image content and a bag-of features approach for defining image categories with a kernel based SVM classifier. In a recent international competition the system was ranked as one of the top schemes in discriminating orientation and body regions in X-ray images and in medical image retrieval. The existing system handles only limited number of image categories in the organ level retrieval and the classification accuracy also comparatively less.

The system shows initial capabilities in image categorization into healthy vs. pathology along with discrimination into one of the pathology states. These capabilities can be generalized to larger data collections as well as additional pathology families. Categorization is conducted on the entire image with no need for segmentation algorithms or any geometrical rules.

VIII. FUTURE WORK

The future work of this project is to develop a medical image retrieval system for both organ level and the pathology level by using the bag of visual words approach for different classes of X-ray images. This proposed method is a first step towards similarity-based categorization that has a major clinical importance in Computer Assisted Diagnostics (CAD). It can identify suspicious pathological X-rays and alert the referring clinicians to potential emergencies. Overall it is hoped that the development of such systems will contribute to the improvement of safety and quality of medical services. The proposed system can be tuned to achieve high accuracy in general medical image classification and retrieval. Statistical analysis of the results is shown on both the Image CLEF medical dataset on the organ-level and the Sheba chest X-ray dataset, on the pathology level. Extended the system to pathology - level discrimination and obtained results for different chest disease categorization.

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