Content based medical image retrieval using dictionary learning

By-
Aparna PL(14IT132)
Rajat N(14IT134)
Balakoti(14IT238)

Content-Based Image Retrieval-What and Why?

- The problem of searching for similar images in a large image repository based on content of the image is called Content Based Image Retrieval (CBIR).
- Traditional Method: Text Based Image Retrieval (TBIR) approach
- Practical limitations of TBIR:

    1. Images in the collection annotated manually, which becomes more difficult as the size of the image collection increases.
    2. Inadequacy in representing the image content through text.
- CBIR approaches proposed to overcome the limitations of TBIR

Why CBIR for medical domain?

- Increasing dependence on modern medical diagnostic techniques like radiology, histopathology and computerized tomography has led to an explosion in the number of medical images stored in hospitals.

- Digital image retrieval technique is crucial in the emerging field of medical image databases for clinical decision making process.

- It can retrieve images of similar nature(like same disease) and characteristics.

Limitations of existing IR systems

- The major limitations associated with existing medical IR are:

  (1) Physicians have to browse through a large number of images for identifying similar images, which takes lot of time.

  (2) Most of the existing tools for searching medical images use text based retrieval techniques

Problem statement

- To devise an efficient clustering method to group large medical databases and give the user the most relevant images ranked according to their relevance to the user input query.

Related Work

Authors	Method of retrieval	Type of images	Year
Guimond et.al.[1]	User selected volume of interest	Brain MRI images	1997
Chu et. al.[2]	Knowledge based semantic model	Brain images	1998
Adrien et.al[3]	Reisz wavelets	Lung CT images	2004
Yang et. al.[4]	Local patch descriptors using SIFT	Liver images	2011
Fei et. al.[5]	Dictionary learning based denoising	Abdomen CT images	2013

Proposed Method

- Uses dictionary learning approach for clustering and uses sparse coding technique to assign image to their respective clusters.
- Uses the idea that two images belonging to the same cluster will have decomposition in terms of similar atoms in dictionary.
- Categorizes medical images that are not restricted to any specific context, unlike many existing methods.
- Requires no training data for the classification (and retrieval) of medical data, which is in contrast to existing methods.

Feature Extraction

- **Method 1:**
- An image is partitioned into concentric circular regions of equal area. Mean and variance of each circular region is obtained.
- Number of concentric circles:17
- Size of feature vector: 34

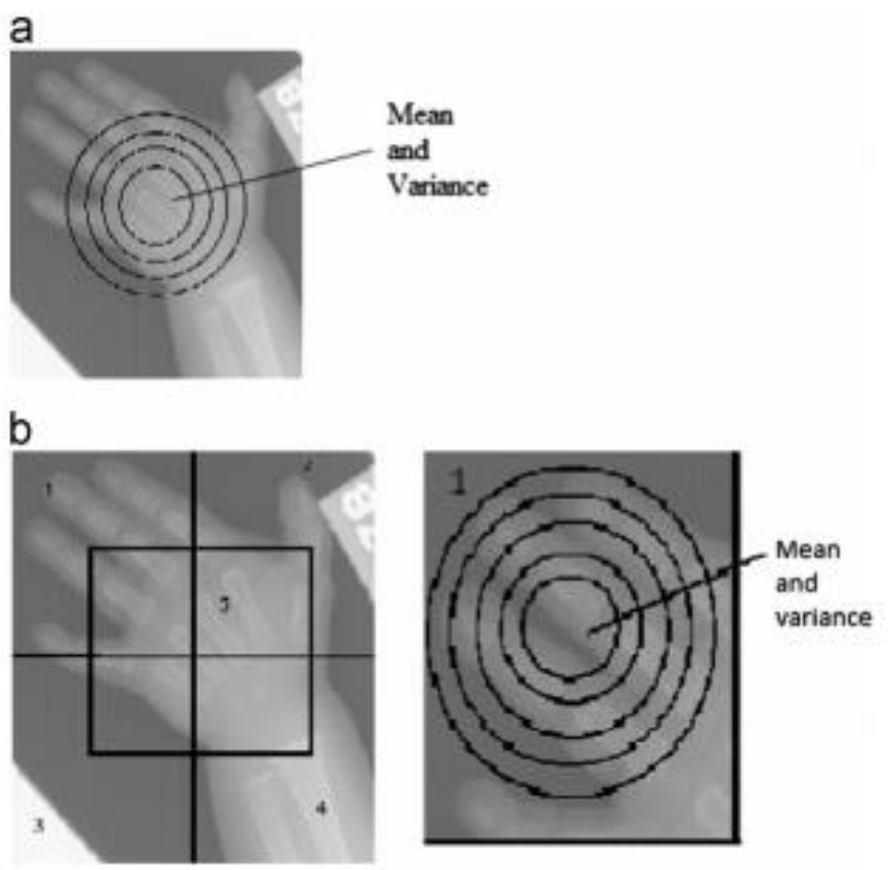
- Mean and variance:

$$\mathbf{y}_{j,2k-1} = \frac{1}{P_k} \sum_{l \in J_k} I_l$$

$$\mathbf{y}_{j,2k} = \sum_{l \in J_k} I_l^2 - \mathbf{y}_{j,2k-1}^2,$$

- j=1,2,..M and k=1,2,..L
- M: Number of images, L:Number of concentric circles, J_K :set of pixels falling in the kth concentric circle, I_l: l^{th} pixel value

Feature Extraction



Feature Extraction

- **Method 2:**
- An image is divided into four blocks resulting in four sub-images as shown in Fig. 1(b). Another sub-image which is of same block size as other four sub-images is considered.
- Each sub-image is partitioned into concentric circular regions of equal area from which the mean and variance of pixel intensity values are computed.
- No of concentric circles in each sub-image: 4
- Size of feature vector: 40

Sparse Coding

- Sparse coding involves the representation of an image as a linear combination of some **atoms** in a **dictionary**.
- The aim of sparse coding is to find a set of basis vectors such that we can represent an input vector x as a linear combination of these basis vectors.
- Widely used by image and signal processing communities.

Orthogonal Matching Pursuit

- Matching pursuit (MP) is a sparse approximation algorithm which involves finding the "best matching" projections of multidimensional data onto the span of an over-complete (i.e., redundant) dictionary ***D***.

- The sparsity problem that matching pursuit is intended to approximately solve is:

$$\alpha^j = \arg\min_{\omega} \|y_j - D\omega\|_2^2 \quad \text{subject to } \|\omega\|_0 \le T_0.$$

  where D is the overcomplete dictionary, y_j is the signal to be approximated , T_0 is the sparsity parameter.

- The optimization problem is NP-complete. Hence, approximation methods like MP is used.

- Orthogonal Matching Pursuit is a variation of MP where after every step, *all* the coefficients extracted so far are updated, by computing the orthogonal projection of the signal onto the set of atoms selected so far.

Dictionary Learning (K-SVD)

- The Dictionary Learning (DL) methods aim at designing a basis type set (called Dictionary) that provides all signals of a class with sparse representation.

- Given a set of vectors $\{v_i\}^n_{i=1}$, the K-SVD based DL method finds the dictionary D by solving the following optimization problem:

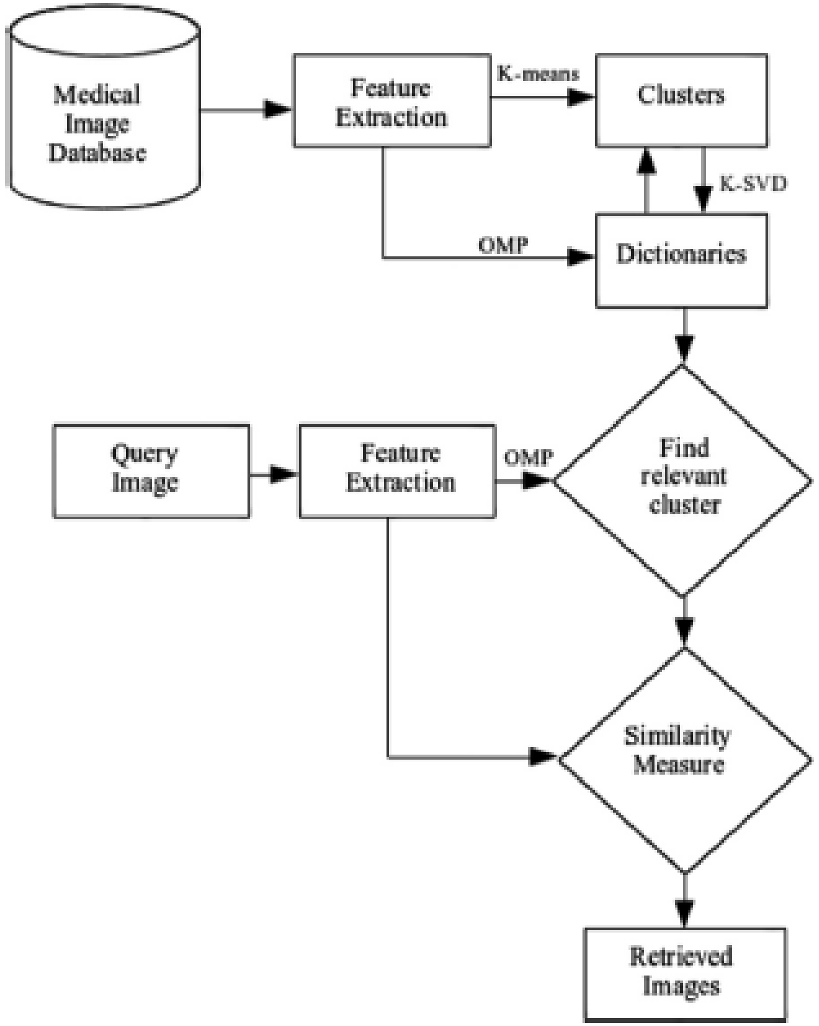
$$(D, \Phi) = \arg\min_{\hat{D},\hat{\Phi}} \|V - \hat{D}\hat{\Phi}\|_F^2 \quad \text{subject to } \|\hat{\gamma}_i\|_0 \leq T_0 \ \forall i,$$

  where gamma_i represents ith column of phi, V is the matrix whose columns are v_i , $|A|_F$ represents Frobenius norm $|A|_F = \text{sqrt}(\text{sum}(A_{ij}{}^2))$, $|v|_0$ represents the number of non-zero elements in v.

Steps in proposed approach

- Step 1: Extract features from the members of medical database.
- Step 2: Apply K-means clustering algorithm on the extracted features to generate initial clusters.
- Step 3: Generate dictionary for each cluster using K-SVD method.
- Step 4: Create new cluster for each dictionary by assigning the images that are sparsely represented by it.
- Step 5: Repeat steps 3 and 4 till clusters converge
- Step 6: For the query image x_q, search for relevance in C_i , where D_i provides sparest representation to x_q.
- Step 7: Rank the images in the cluster obtained in step 6 using similarity measures such as Eucledian distance.

Flow of the proposed approach



Implementation details

- Implementation language used: Python
- Dataset used: IRMA database consisting of 12000 images of 193 categories
- Python libraries used:
  - Scikit-image: For image processing functions
  - K-svd: For implementation of ksvd in Python
  - Numpy: for matrix manipulation
  - Scikit-learn: For k-means

Work done

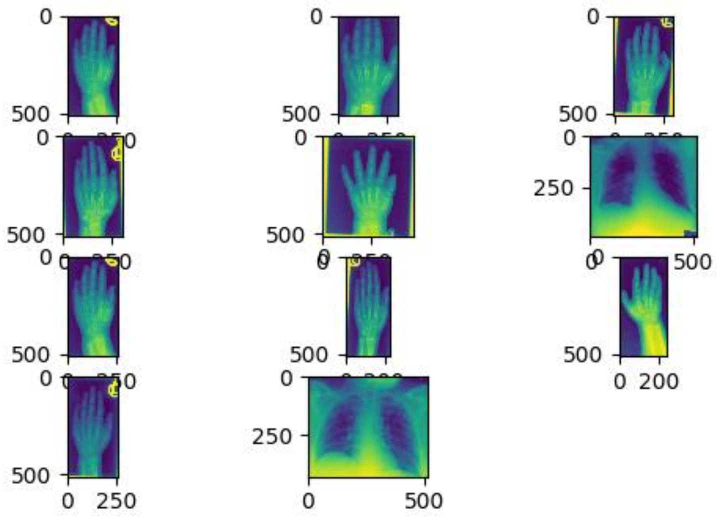
- 1. Feature extraction for 300 images using FE-II
- 2. K-means on the extracted features to obtain initial clusters
- 3. K-SVD on obtained clusters for dictionary learning
- 4. OMP for all features to re-assign each image to a cluster
- 5. Assign image to a cluster based on their Eucledian distance to each cluster
- 6. Repeated steps 3 and 4 till there was no significant change in the clusters.

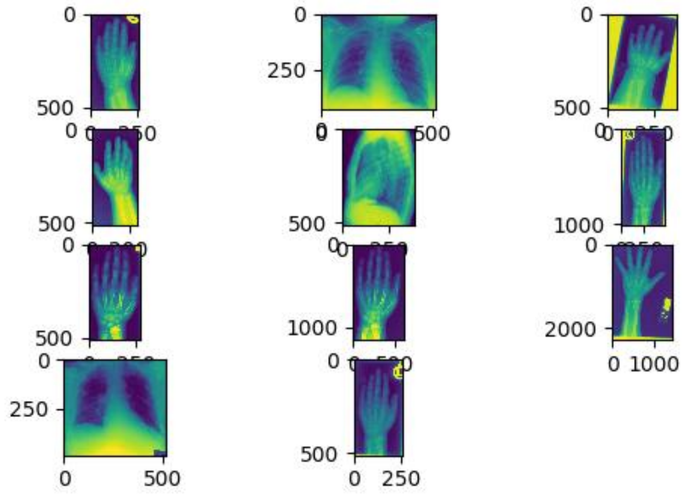
Results and discussion

- ED – Eucledian distance
- CS – Cosine similarity
- DL – Dictionary Learning

Results and discussion

- ED



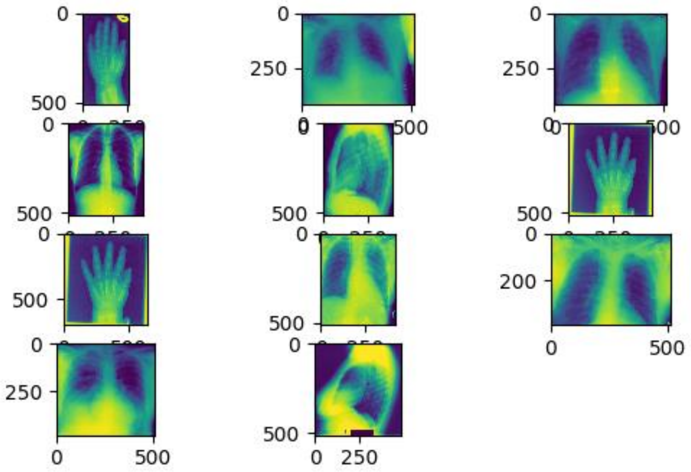


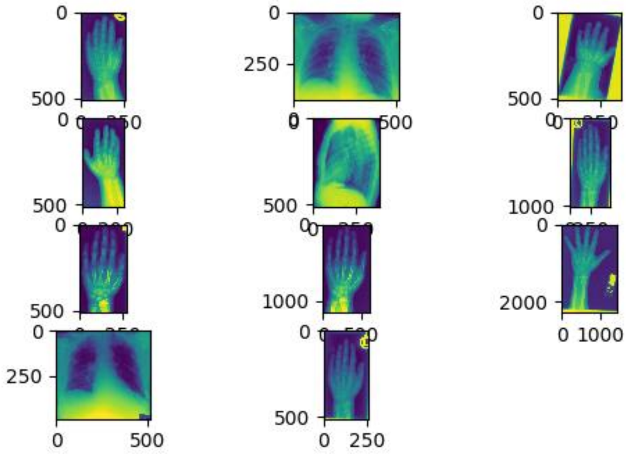
DL, Precision = 0.7

Kmeans, Precision = 0.6

Results and discussion

- CS



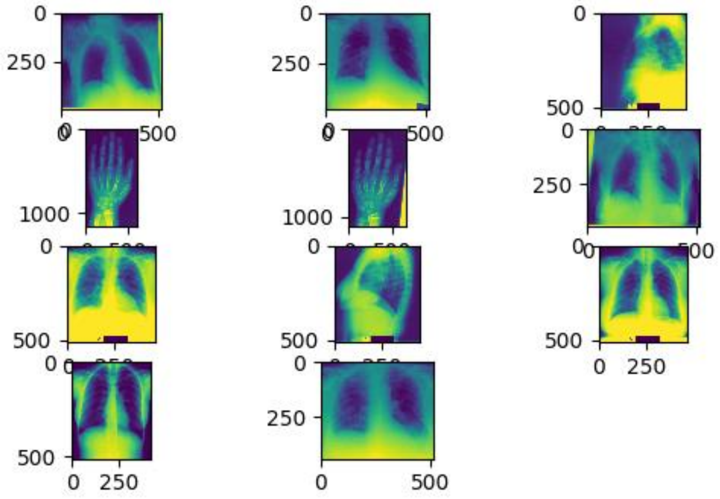


DL, Precision = 0.2

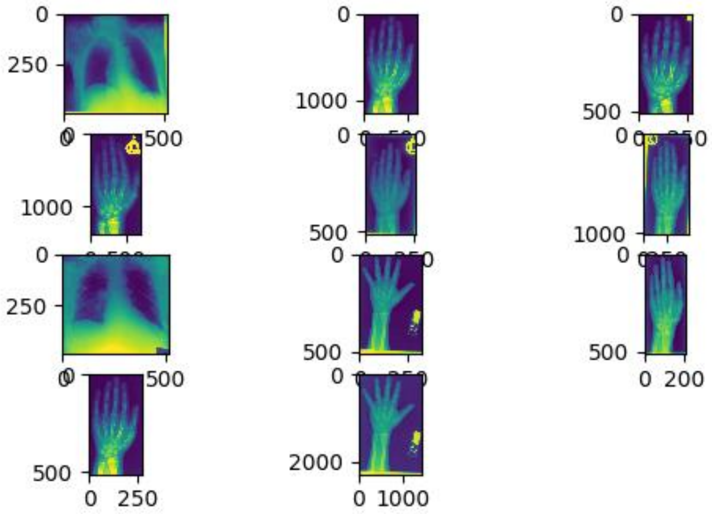
K-Means, Precision = 0.6

Results and discussion

- ED



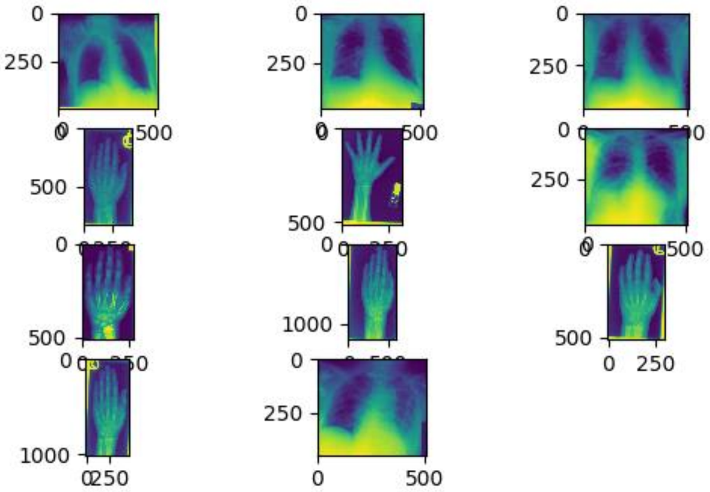
DL, Precision = 0.3



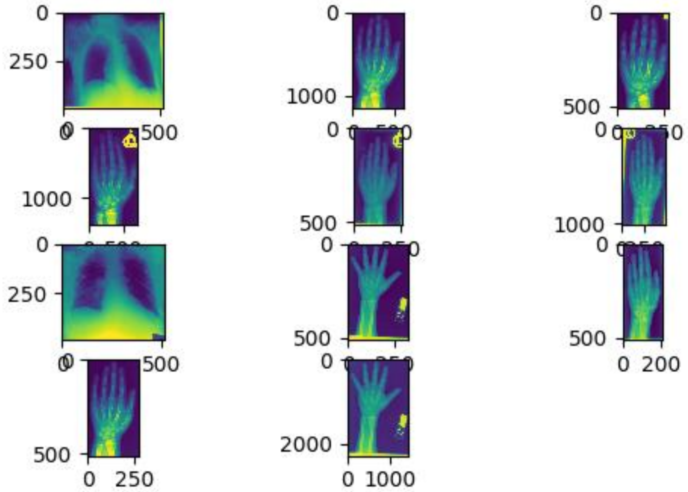
K-Means, Precision = 0.1

Results and discussion

- CS



DL, Precision = 0.4



K-Means, Precision = 0.1

Results and discussion

Mean average precision for 4 queries

	CS	ED
DL	0.282	0.572
K-Means	0.237	0.237

Table 1: Mean average precision for 4 queries

Challenges

- Cluster convergence could not be achieved, iterations were stopped when the difference between number of items per cluster was less than certain threshold
- Feature extraction for each image takes 60 s on an average, feature extraction for 500 images requires approximately 9 hours.
- Choosing number of columns for each dictionary and the number of non-zero elements in sparse representation of signal for OMP

Conclusion and Future Work

- DL approach found to be better than K-Means for both ED and CS.
- Using CoSaMP[6] instead of OMP for sparse coding
- Relevance Feedback
- Similarity Measures
- Optimizing time taken for feature extraction

References

[1] Srinivas, M., et al. "Content based medical image retrieval using dictionary learning." *Neurocomputing* 168 (2015): 880-895.

[2] Guimond, Alexandre, Gérard Subsol, and Jean-Philippe Thirion. "Automatic MRI database exploration and applications." *International Journal of Pattern Recognition and Artificial Intelligence* 11.08 (1997): 1345-1365.

[3] Chu, Wesley W., et al. "Knowledge-based image retrieval with spatial and temporal constructs." *IEEE Transactions on Knowledge and Data Engineering* 10.6 (1998): 872-888.

[4] Depeursinge, Adrien, et al. "Lung texture classification using locally–oriented Riesz components." *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer Berlin Heidelberg, 2011.

[5] F.Yu,Y.Chen,L.Luo,CT image denoising based on sparse representation using global dictionary,in:Proceedings of IEEE Conference on Complex Medical Engineering, 2013,pp.408–411.

[6] http://www.sciencedirect.com/science/article/pii/S1063520308000638

Thank you!