Performance evaluation of Different Annotation retrieval methods

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Abstract- Medical images play a central role in patient diagnosis, therapy, surgical planning, medical reference and medical training. Demand for automatically annotating and semantics retrieving is growing faster in medical images.As amount of databases increases rapidly so as images so it is needed to increase the annotation reading process for better and fast results. Automatic image annotation is the process of assigning meaningful words to an image taking into account its content. This paper presents performance analysis of methods used in the medical domain for image annotation, semantic based image retrieval and content based image retrieval. Different image annotation models like cross media relevance model and continuous space relevance model and their performance is also defined in the paper.

Keywords –annotation, crossmediarelevancemodel, continuous space relevancemodel, semantics retrieval

I. INTRODUCTION

The image annotation and meta-data explanation can provide high level description for the image data. It is however time consuming and thus expensive to find different information in the huge annotated image databases. Creating annotation based on automatic feature extraction and image processing techniques provides too low level information for many applications. The difference between the low level feature descriptions provided by image analysis tools and the high level content descriptions required by the applications is often referred to in the literature, as the "Semantic Gap". The manually or (semi-)automatic text-based explanation of image data enables the information publishers to fulfil this gap. The description of medical data is normally presented in terms of controlled, but diversely expressedvocabulary and natural language specifications. These descriptions usually require additional human intervention for data processing determination of relevancy between different data items. In order to facilitate machine-based reasoning for better information retrieval additional interpretive semantics must be attached to the data. This requires a move from datacentric approach to knowledge and semantics description models.

This process is used in image retrieval systems to organize and locate images of interest from a database. This task can be regarded as a type of multi-class image classification with a number of classes equal with vocabulary's size. AIA[14]can be seen also as a multi-class object recognition problem which is a challenging task and an open problem in computer vision. The importance of this task has increased with the growth of the digital images collections. A text retrieval system can be used for finding rapidly related documents from a vast amount of doc content remains a difficult and very challenging task. A text retrieval system can be used for finding rapidly related documents from a vast amount of documents containing keywords. Search engines like Google offers the possibility to search for images using surrounding text and file name. This image search is based on text retrieval because the content of the image is ignored. For this reason sometimes the search performed does not lead to satisfactory results. In order to avoid this drawback the researchers are looking for another way to search for images. A possible approach is to obtain a textual description from the image and then use text retrieval for searching. A different approach is to combine two modalities for example text and visual features when indexing images. Image retrieval based on text is sometimes called Annotation Based Image Retrieval (ABIR). The systems based on ABIR can have some draw-backs. Researchers working in CBIR[2] have identified two limitations. The first limitation is that ABIR requires manual image annotation which is time consuming and costly. The second limitation is that human annotation is subjective and sometimes it is difficult to describe image contents by concepts. An AIA system can solve the first limitation. The second limitation remains a general question and an unsolved problem for computer vision. AIA is situated on the frontier of different fields: image analysis, machine learning, media understanding and information retrieval. Usually image analysis is based on feature vectors and the training of annotation concepts is based on machine learning techniques. Automatic annotation of new images is possible only after the learning phase is completed. General object recognition and scene understanding techniques are used to extract the semantics from data. This is an extremely hard task because AIA systems have to detect at least a few hundred objects at the same time from a large image database. AIA is a challenge that has been identified as one of the hot-topics in the new age of image retrieval. Image annotation is a difficult task for two main reasons:

1. Semantic gap problem – it is hard to extract semantically meaningful entities using just low level image features. Low-level features can be easily extracted from images but they are not completely descriptive for image content. High-level semantic information is meaningful and effective for image retrieval.
2. The lack of correspondence between the keywords and image regions in the training data.

The semantic gap is due to at least two main problems:

1. Semantic extraction problem - how to extract the semantic regions from image data? Current object recognition techniques do not cover completely this problem.
2. Semantic interpretation problem – is represented by complexity, ambiguity and subjectivity in user interpretation. Representing the content of the image using image features and then performing nontextual queries like color and texture is not an easy task for users. They prefer instead textual queries and this request can be satisfied using automatic annotation.

There are many annotation models proposed and each model has tried to improve a previous one. These models are splitted in two categories:

(1) Parametric models: Co-occurrence Model.

(2) Non-parametric models: Cross Media Relevance Model (CMRM), Continuous Cross-Media Relevance Model (CRM) [9], Multiple Bernoulli Relevance Model (MBRM), Coherent Language Model (CLM).

The annotation process implemented in our system is based on CMRM [9]. Using a set of annotated images [Segmented and Annotated Corel15k dataset] the system learns the joint distribution of the blobs and concepts. The blobs are clusters of image regions obtained using the vector of blobs for each test image using Kullback– Liebler (KL) divergence and the resulting KL distance is used to rank the images. Having the set of blobs each image from the test set is represented using a discrete sequence of blobs identifiers. The distribution is used to generate a set of concepts for a new image.

Each new image is segmented using anoriginal segmentation algorithm which integrates pixels into a grid-graph. The usage of the hexagonal structure improves the time complexity of the used methods and the quality of the segmentation results.

The meaningful keywords assigned by the annotation system to each new image are retrieved from an ontology created in an original manner starting from the information provided by [Medical Subject Heading]. The concepts and the relationships between them in the ontology are inferred from the concepts list, from the ontology's paths and from the existing relationships between regions.

II.RELATED WORK

Visual information retrieval is widely research area. The availability of large and steadily growing amounts of visual and multimedia data, and the development of the Internet underline the need to create thematic access methods that offer more than simple text-based queries or requests based on matching exact database fields. Automatic image annotation is the process of assigning meaningful words to an image taking into account its content. This process is of great interest as it allows indexing, of large collections of image data. This paper presents a discussion about the system used in the medical domain for two distinct tasks: image annotation,semantic based image retrieval. Retrieval task is evaluated for two annotation models:Cross Media Relevance Model and Continuous- space Relevance Model [9].An original image segmentation algorithm based on a hexagonal structure was used to perform the segmentation of medical images. Image's regions are described using a vocabulary of blobs generated from image features using the K-means clustering algorithm. Semantic based image retrieval is performed using the methods provided by the annotation models.The ontology used by the annotation process was created in an original manner starting from the information content provided by the Medical Subject Headings (experiments were made using a database containing color images retrieved from medical domain using an endoscope and related to digestive diseases.

III. ONTOLOGIES AND MEDICAL SUBJECT HEADINGS (MESH)

ONTOLOGIES: A GENERAL OVERVIEW

The term ontology originated as a science within philosophy but evolved over time being used in various domains of computer science. Ontologies are enabling knowledge sharing and support for external reasoning. Ontologies can be used for improving the process of information retrieval, for solving the problem of heterogeneous information sources that utilize different representations, to analyze, model and implement the domain knowledge. A taxonomy represents a classification of the data in a domain. Ontology is different than taxonomy from two importantperspectives: it has a richer internal structure as it includes relations and constraints between the concepts, it claims to represent a certain consensus about the knowledge in the domain. This consensus is among the intended users of the knowledge, for example doctors using a hospital ontology regarding a certain disease. Computational ontologies are a means to formally model the structure of a system, the relevant entities and relations that emerge from its observation [15]. The ontology engineer analyzes relevant entities and organizes them into concepts and relations, being represented, respectively, by unary and binary predicates. The backbone of an ontology consists of a generalization/specialization hierarchy of concepts, a taxonomy. Ontologies can be very useful in improving the semantic information retrieval process by allowing an abstractization and an explicit representation of the information. Ontologies can possess inference functions, allowing more intelligent retrieval. According to their level of generality, ontologies can also be categorized by top-level ontologies, domain and task ontologies, and application ontologies. Top-level ontologies describe very general concepts, independent of a particular problem or domain. Domain ontologies describe the vocabulary related to a generic domain. Task ontologies describe a generic task or activity, such as diagnosing, advertising, etc. Domain and task ontologies inherit and specialize the terms introduced in the top-level ontology. Application ontologies describe concepts depending on both a particular domain and task. An ontology[10] represents an explicit and formal specification of a conceptualization containing a finite list of relevant terms and the relationships between them. A ''conceptualization'' is an abstract model of a phenomenon, created by identification of the relevant concepts of the phenomenon. The concepts, the relations between them and the constraints on their use are explicitly defined. ''Formal'' means that ontology is machine-readable and excludes the use of natural languages. In medical domains, the concepts are diseases and symptoms, the relations between them are causal and a constraint is that a disease cannot cause itself. A ''shared conceptualization'' means that ontologies aim to represent consensual knowledge intended for the use of a group.

In an ontology is a formal explicit description of concepts in a domain of discourse (classes sometimes called concepts), properties of each concept describing various features and attributes of the concept (slots sometimes called roles or properties), and restrictions on slots (facets sometimes called role restrictions). Classes are the focus of most ontologies. Classes describe concepts in the domain and slots describe properties of classes and instances. From practical point of view the development of an ontology includes: defining classes in the ontology, arranging the classes in a taxonomic (subclass–superclass) hierarchy, defining slots and describing allowed values for these slots, filling in the values for slots for instances. For the ontology design process applied for our system we have taken into account three fundamental rules:

(a) There is no one correct way to model a domain—there are always viable alternatives;

(b) Ontology development is necessarily an iterative process;

(c) Concepts in the ontology should be close to objects(physical or logical)and relationships in the domain of interest

The generalprocessofiterativedesignusedtoobtainthe ontology foroursystemcontainsseveralsteps:

(a) Determining thedomainandthescopeoftheontology – to define thedomainandthescopearesponseshouldbegiven to thefollowingquestions:whatisthedomaincoveredbythe ontology? Forwhatpurposewillbeusedtheontology?Inour case the domain is represented by medical domain and the ontology is used for the annotation process.

(b) Reusing existing ontologies – it is a good approach to consider what someone else had one, to check if something can be refined and if existing sources for our particular domain and task can be extended. Reusing existing ontologies can be a requirement if the system needs to interact with other applications that have already committed to particular ontologies or controlled vocabularies. Existing ontologies like Open Biological and Biomedical Ontologies can have formats that are not always easy to interpret. For this reason we have decided to create a custom ontology.

(c) Enumerating important terms in the ontology – it is useful to write downalistofalltermswewouldlikeeithertomake statements aboutortoexplaintoauser.Whatarethetermsn we wouldliketotalkabout?Whatpropertiesdothoseterms have?Whatwouldweliketosayaboutthoseterms? The descriptors provided by MESH arepresentingthetermsthat should betakenintoaccount.
(d) Defining theclassesandtheclasshierarchy – thereareseveral possible approachesindevelopingaclasshierarchy: – A top-downdevelopmentprocess starts with the definition of themostgeneralconceptsinthedomain and subsequent specializationoftheconcepts – A bottom-updevelopmentprocess starts with the definition of themostspecificclasses,theleavesofthehierarchy, with subsequentgroupingoftheseclassesintomore general concepts. – A combinationdevelopmentprocess is acombinationofthe top-down andbottom-upapproaches.Wehaveuseda top-down developmentprocessforourontology.Thefollowing classes wereidentified: concept, hierarchical,child,parents.
(e) Defining the properties of classes (slots) –once we have defined some of the classes, we must describe the internal structure of concepts. For example the fields associated with a descriptor will be used to define the properties of the concept class.
(f) Defining the facets of the slots– slots can have different facets describing the value type, allowed values, the number of the values (cardinality), and other features of the values the slot can take.
(g) Creating instances – the last step is creating individual instances of classes in the hierarchy. Defining an individual instance of a class requires: choosing class, creating an individual instance of that class, filling in the slot values. Each descriptor will be represented as an instance of the concept class and each hierarchical relationship existing between any two descriptors will be represented as an instance of the hierarchical class.

MESH description

Medical Subject Headings (MeSH) represents comprehensive controlled vocabulary for the purpose of indexing journal articles and books in the life Sciences and can also serve as a thesaurus that facilitates searching. Created and updated by the United States National Library of Medicine (NLM) it is used by the MEDLINE/ PubMed article database and by NLM's catalog of book holdings. In MEDLINE/PubMed, every journal article is indexed with some 10–15 headings or sub headings, with one or two of them designated as major and marked with an asterisk. When performing a MEDLINE search via PubMed, entry termsare automatically translated into the corresponding descriptors. The Medical Subject Headings staffs continually revise and update the MeSH vocabulary. Staff subject specialists are responsible for areas of the health sciences in which they have knowledge and expertise.MeSH's structure contains a high number of subject headings also known as descriptors. Most of these are accompanied by a short description or definition, link storelated descriptors, and a list of synonyms or very similar terms known as entry terms. Because of these synonym lists, MeSH can also be viewed as a thesaurus. The descriptors or subject headings are arranged in a hierarchy and a given descriptor may appear at several places in the hierarchical tree. The tree numbers indicate the places within the MeSH hierarchies, also known as the Tree Structures, in which the MH appears. Thus, the numbers are the formal computable representation of the hierarchical relationships. The tree location scarry systematic labels known as tree numbers, and one descriptor may have several tree numbers. The tree numbers of a given descriptor are subject to change as MeSH is updated. Every descriptor also carries a unique alphanumerical ID called DescriptorUI that willnotchange.
Two important relationship types are defined for MeSH content: hierarchical relationships and associative relationships [16]. The hierarchical relationships are fundamental components in a thesaurus and MeSH has long formalized its hierarchical structure in an extensive tree structure, currently at nine levels, representing increasing levels of specificity. This structure enables browsing for the appropriately specific descriptor. Many examples of hierarchical relations are instances of the part/whole and class/ subclass relationships, which are relatively well understood. Since its hierarchical relationships are between descriptors a MeSH descriptor can have different children indifferent trees .Hierarchical relationships in the MeSH thesaurus are at the level of the descriptor. Hierarchical relationships are seen as parent–child relationships. Associative relationships are used to point out in the thesaurus, the existence of other descriptors, which may be more appropriate for a particular purpose. They may point out distinctions made in the thesaurus or in the way the thesaurus has arranged descriptors hierarchically. Many associative relationships are represented by these related cross reference. The categories of relationships seem to be greater in number and are certainly more varied than hierarchical relationships. One attribute which can be thought of as an associative relationship within the MeSH thesaurus is the Pharmacologic Action. Limited to chemicals this relationship allows the aggregation of chemicals by actions or uses. MeSH content that can be obtained from and is offered as an xml file named desc2010.xml (2010 version) containing the descriptors and a txt file named mtrees2010.txt containing the hierarchical structure.

IV. ANNOTATION PROCESS

4.1Annotation models

4.1.1. CMRM model

The Cross Media Relevance Model is a non-parametric model for image annotation and assigns words to the entire image and not tospecificblobs.Atestimage I is annotatedbyestimatingthe joint probabilityofakeyword w and asset of blobs:

$$P(w,b_1,\ldots,b_m) = \sum_{J \in T} P(J)P(w,b_1,\ldots,b_m|J).$$

For the annotation process the following assumptions are made:
(a) It is given a collection C of un-annotated images;
(b) Each image I from C to can be represented by a discrete set of blobs: I = b1. . .bm.
(c) There exists a training collection T, of annotated images, where each image J from T has a dual representation in terms of both words and blobs: J =b1. . .bm;w1. . .wn
(d) P(J) is kept uniform overall images in T;
(e) The number of blobs and words in each image(m and n) may be different from image to image;
(f) No underlying one to one correspondence is assumed between the set of blobs and the set of words; it is assumed that the set of blobs is related to the set of words.
$P(w,b_1,\ldots,b_m|J)$
represents the joint probability of keyword w and the set of blobs $(b_1,\ldots,b_m)$ conditioned on training image J. In CMRM it is assumed that, given image J, the events of observing a particular keyword w and any of the blobs$(b_1,\ldots,b_m)$ are mutually independent.

4.1.2. CRM model

CRM is based on a statistical formalism that allows to model a relationship between the contents of a given image and the annotation of that image. It will be described an approach for learning a joint probability distribution over the regions of some image and the words in its annotation. It is supposed that T is the training set off annotated images, and let J be an element of T. J is represented as a set of image regions $r_J=\{r_1\ldots r_n\}$ along with the corresponding annotation$w_J=\{w_1\ldots w_m\}$ .Itisassumedthatthe process that generated J Tis based on three distinct probability distributions. The words area random sample from some underlying multinomial distribution$P_V(\cdot|J)$ and the regions r_J are produced from a corresponding set of generator vectors $g_1 \cdots g_n$according to a process $P_R(r_i|g_i)$which is independent of J. Finally, the generator vectors are themselves a random sample from some underlying multivariate density function $P_G(\cdot|J)$. The joint probability of observing an image defined by $r_a$together with annotationw_B as $P(r_a, w_B)$ is defined as

$$P(r_A,w_B) = \sum_{J \in T} P_T(J) \prod_{b=1}^{n_b} P_V(w_b|J) \prod_{a=1}^{n_a} \int_{R^k} P_R(r_a|g_a)P_G(g_a|J)dg_a$$

V. SEMANTIC BASED IMAGE RETRIEVAL

5.1. Methods for semantic based image retrieval

The task of semantic image retrieval in this context is similar to the general ad-hoc retrieval problem. It is given a text query $Q=w_1\ldots w_k$ and a collection C of images. The goal is to retrieve the images that contain objects described by the keywords $w_1\ldots w_k$, or more generally rank the images I by the likelihood that they are relevant to the query. Text retrieval systems cannot be used because the images $I \in C$are assumed to have no caption. The Cross Media Relevance Model allows two methods for semantic based image retrieval:
Probabilistic Annotation-based Cross-Media Relevance Model (PACMRM): Given a query$Q=w_1\ldots w_k$ and the image$I=\{b_1\ldots b_m\}$ the probability of drawing Q from the model of I is defined as

$$P(Q|I) = \prod_{j=1}^{k} P(w_j|I)$$

(b) Direct-Retrieval Cross-Media Relevance Model (DRCMRM): Given a query $Q = w_1 \ldots w_k$ and the image $I = \{b_1 \ldots b_m\}$ it is supposed the existence of an underlying relevance model $P(.|Q)$ such that the query itself is a random sample from that model. It is also assumed that images relevant to Q are random samples from $P(.|Q)$. The query is converted into the language of blobs and the probability of observing a given blob b from the query model can be expressed in terms of the joint probability of observing b from the same distribution as the query words $w_1 \ldots w_k$:

$$P(b|Q) \approx P(b|w_1 \ldots w_k) = \frac{P(b, w_1 \ldots w_k)}{P(w_1 \ldots w_k)}$$

$$P(b, w_1, \ldots, w_k) = \sum_{J \in T} P(J) P(b|J) \prod_{i=1}^{k} P(w_i|J)$$

Based on this approach images are ranked according to the negative Kullback–Liebler divergence between the query model $P(.|Q)$ and the image model $(.|I)$:

$$-KL(Q \| I) = \sum_{b \in B} P(b|Q) \log \frac{P(b|I)}{P(b|Q)}$$

For CRM model it is given a text query w_{qry} and a testing collection of un-annotated images. For each testing image J it is used to get the conditional probability $P(w_{qry}|r_J)$. All images in the collection are ranked according to the conditionallikelihood $P(w_{qry}|r_J)$. An image is considered relevant to a given query if its manual annotation contains all of the query words.

5.2. Evaluation of the annotation task

Evaluation measures [23] are considered to evaluate the annotation performance of an algorithm. Let T' represent a test set, $J \in T'$ be a test image, W_J be its manual annotation set and W_J^a be its automatic annotation set. The performance can be analyzed from two perspectives:

1. Annotation perspective: Two standard measures that are used for analyzing the performance from the annotation perspective are:

(a) Accuracy: The accuracy of the auto-annotated test images is measured as the percentage of correctly annotated words and for a given test image $J \in T'$ is defined as

$$accuracy = \frac{r}{|W_J}$$

Where variable represents the number of correctly predicted words in J. The disadvantage of this measure is represented by the fact that it does not take into account for the number of wrong predicted words with respect to the vocabulary size $|W|$.

(b) Normalized score (NS): It is extended directly from accuracy and penalizes the wrong predictions. This measure is defined as

$$NS = \frac{r}{|W_I|} - \frac{r'}{|W| - |W_I|}$$

where variable r' denotes the number of wrong predicted words in J.

2. Retrieval perspective: Retrieval performance measures can be used to evaluate the annotation quality. Auto-annotated test images are retrieved using keywords from the vocabulary. The relevance of the retrieved images is verified by evaluating it against the manual annotations of the images. Precision and recall values are computed for every word in the test set. Precision is represented by the percentage of retrieved images that are relevant. Recall is represented by the percentage of relevant images that are retrieved. For a given query word wq, precision and recall are defined as

$$precision\ (w_q) = \frac{|J \in T' | w_q \in W_J^a \wedge w_q \in W_J|}{|J \in T' | w_q \in W_J^a|}$$

$$recall(w_q) = \frac{|J \in T' | w_q \in W_J^a \wedge w_q \in W_J|}{J \in T' | w_q \in W_J}$$

It can be useful to measure the number of single-concept queries for which at least one relevant image can be retrieved using the automatic annotations. This metric compliments average precision and recall by providing in formation about how wide the range of concepts that contribute to the average precision and recall .It is defined as

$$|w_q | precision(w_q) > 0 \wedge recall(w_q) > 0|$$

Retrieval perspective: The precision and recall charts are presented in Figs. 7and 8. It was used the following convention to distinguish between the two models: the values corresponding belong to the CRM model and the other values belong to the CMRM model.

VI. RESULTS AND DISCUSSIONS

The dataset used are from Lung Image Database Consortium, it is a publicly available, well characterized repository of Lung CT images, with annotations of more than one experienced radiologists done by consensus between them. Further, help from Jawaharlal Nehru Post Graduate Institute of Medical Education and Research, Chandigarh is taken. In this research work, 8 scan set, each one consists on an average of 190 slices were taken under consideration. The images were acquired with a 512*512 matrix and quantized with 16 bits. These images were transferred into the Digital Imaging and Communications in Medicine (DICOM) format at which, the Hounsfield units for attenuation were translated into brightness values. The databases have been since then available online to the public, and have been used by many researchers.

Figure 6.1 illustrates images acquired in Dicom format that are annotated and converted into .jpg format.

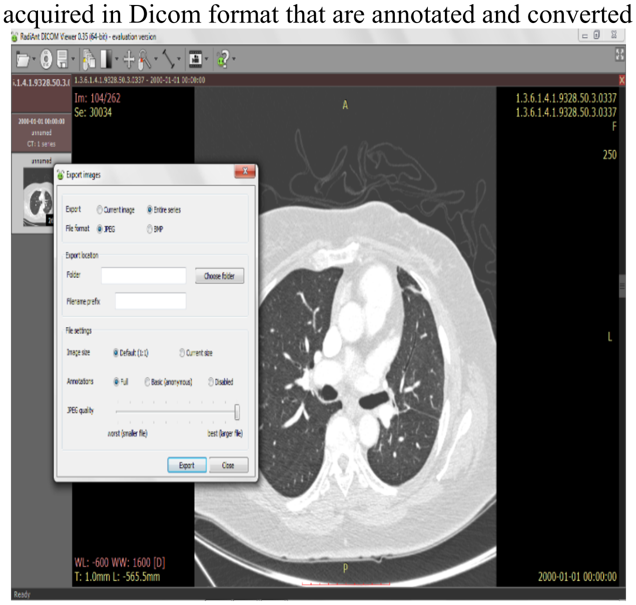
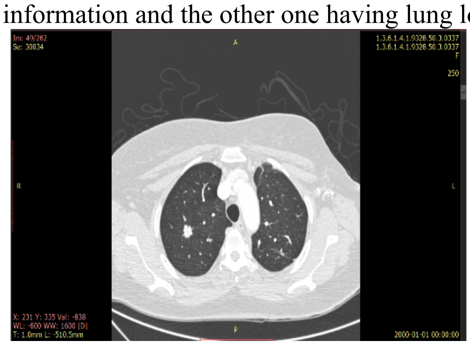


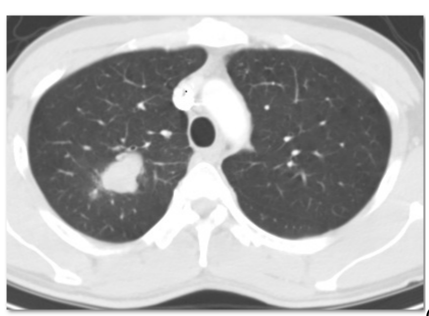
Fig.6.1: Acquired Dicom images being exported into .jpg file format and annotated.

6.2 Results of Pre- Processing phase

Figure 6.2 shows images with Meta information and the other one having lung lobes extracted using AOI.



(a)



(b)

Fig.6.2: a) Image containing Meta information b).jpg image showing AOI (lung lobes).

Before we put dataset into our implementation we have extracted and collected some of the features from the meta information like its HSV,RGB etc. Then we have implemented to calculate the two main parameters recall and precision and comparative results are mentioned in a tabular form in fig 6.3.It clearly shows that CMRM is far better than CRM algorithm for annotations and retrieval purpose.

ALGORITHM	CLASSIFY	TotalKWnum	RECALL	PRECISION
CRM	0.4260	110	0.2291	0.1872
CMRM	0.4260	110	0.6183	0.8983

Fig 6.3 comparison of CMRM and CRM algorithm.

VII. CONCLUSIONS AND FUTURESCOPE

In this paper we have given an overview of methods used in the medical domain. The CMRM and CRM annotation models are discussed and overviewed here which were proven to be very efficient by several studies.In general the words assigned to a medical image are retrieved from a controlled vocabulary and the usage of ontologies satisfies this requirement. A time consuming analysis was needed to generate the ontology. It can be concluded that CMRM model produces better results for the semantic and annotation based image retrieval task than CRM. Wehave evaluated and compared here that CMRM model produces better results than CRM for image annotation and semantic based image retrieval tasks. In future we can implement these algorithm to implement on bigger medical datasets to create new and more efficient semantics retrieval environment.

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