Web Image Search Reranking Using CBIR

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Abstract — The existing image retrieval process is based on text-based approach where the input to the search engine is given as the text. Typically, in the development of an image requisition system, semantic image retrieval relies heavily on the related captions, e.g., file-names, categories, annotated keywords, and other manual descriptions. Unfortunately, this kind of textual-based image retrieval always suffers from two problems: high-priced manual annotation and inappropriate automated annotation. To overcome this drawback the proposed work is defined based on CBIR system. The mission of this work is to present an image conceptually, with a set of low-level visual features such as color, texture, and shape and retrieve similar kind of images from the database based on features extracted from the query image. Input to the search engine is given as "Image" itself and this method serves to visually represent the query. Subsequently based on the multi-feature image extraction, Rerankers are constructed which are used to rank the top N output based on the query image. This ensures high accuracy and reliability with less noise in the displayed result.

Key Words — Image retrieval, Visual Reranking, Content Based Image Retrieval, Histogram, Meta Rerankers.

I. INTRODUCTION

1.1 Image Mining

Image mining is the new focus for data mining, which is concerned with knowledge discovery in image databases. Image mining deals with the extraction of implicit knowledge, image data relationship, or other patterns not explicitly stored in the images. It is more than just an extension of data mining to image domain.

1.2 Information Retrieval

Information retrieval is the activity of obtaining information resources relevant to an information need from a collection of information resources. Searches can be based on metadata. An information retrieval process begins when user enters a query into the system. Queries are formal statements of information needs, for example search strings in web search engines. In information retrieval a query does not uniquely identify a single object in the collection. Instead, several objects may match the query, perhaps with different degrees of relevancy.

1.3 Image Retrieval

An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords, or descriptions to the images so that retrieval can be performed over the annotation words. Image search is a specialized data search used to find images. To search for images, a user may provide query terms such as keyword, image file/link, or click on some image, and the system will return images "similar" to the query.

1.4 Content-Based Image Retrieval

Content-based image retrieval (CBIR) aims at avoiding the use of textual descriptions and instead retrieves images based on features in the image contents like textures, color, shapes etc. Thus the input to the CBIR model is the user-supplied query image or user-specified image features (Fig.1). The existing web image search engines rank images mostly based on the textual information associated with the image in the hosting web pages, such as the title and the surrounding text. In contrast to it, the main advantage of CBIR method is that the name or additional details of the image are not mandatory in the search criteria.

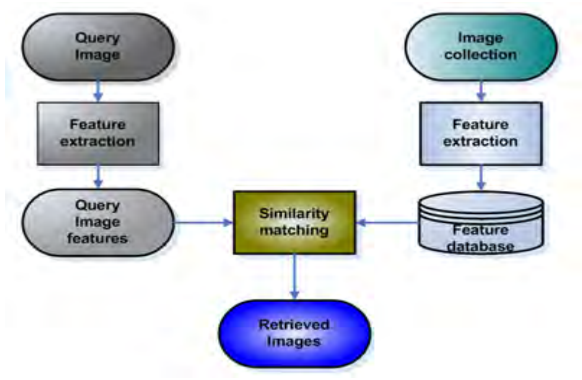


Fig.1 Content-based image retrieval framework

The paper is organized as follows. In Section II, brief review is done on the related work for Image retrieval and visual reranking methods. In Section III, overview of CBIR techniques is covered. Section IV and V focuses on the proposed Iterative Reranking Model and the construction of Meta Rerankers The experimental results are presented and analyzed in Section VI along with the Performance Measure and Comparison, while Section VII concludes the paper with a brief overview of the main results of the paper and the prospects for future work.

II. RELATED WORKS

All the existing search engines retrieve images from the database based on the text-based image search approach [1]. The main challenge in the prevailing methods is to exactly know the additional details, manual descriptions and keywords of the image that is to be searched. The required result cannot be achieved when the text-based information is unknown to the users. Further the retrieved images also contain irrelevant images and hence suffer from ranking incapability.

The ranking of the relevant images can be classified into two types:

1. **Supervised Ranking**
2. **Unsupervised Ranking.**

The Unsupervised Ranking method do not rely on human intervention to order the output images but require prior information on how to employ the information contained in the underlying text-based search criteria. The well-known method of this type is the PRF assumption [2]. Pseudo relevance feedback (PRF) is an existing technique widely used in information retrieval and also adopted in solving the visual search reranking problem [3]. The basic idea of PRF in the visual search reranking context is to regard the top ranked images in the initial result as the relevant ones, and then to apply a relevance feedback technique on this “pseudo” relevant image set to refine the search result.

The other widely-adopted image search reranking assumption is the cluster assumption [4], which says that the visually similar images should be ranked nearby. Some previous work keeps an eye on investigating what visual features are measured to be more important for those images to be considered as positive samples and to be ranked nearby.

To improve the retrieval performance and to scale up to a large number of concepts that are required to cover a realistic query space, human intervention is mandatorily needed. This method is called “Supervised Ranking Method” [5] where user should be allowed to interact with the system to “refine” the results of a query until he/she is satisfied.

This paradigm derives the reranking function in a supervised fashion from the human-labeled training data. Although supervised learning is introduced, it does not suffer from scalability issues since a unified reranking model is applied to all the queries. In other words, a query-independent reranking model will be learned for all queries using query-dependent reranking features.

Though human supervision helps alleviate the problems of unsupervised methods, the existing methods are still far from optimal. While text-based image ranking is often effective to search for relevant images using Supervised and Unsupervised paradigm, the precision of the search results, may lead to mismatching outputs. Thus to improve the precision of the text-based image search ranking, the method proposed in this paper makes a further step in retrieving images using CBIR method. Content-Based image retrieval aims in building the scalable and reliable image retrieval architecture which further targets in ranking the retrieved images in optimal and robust mode.

III. CONTENT BASED IMAGE RETRIEVAL

The proposed approach is based on the Multi-feature extraction of Content- Based Image retrieval that is used for better retrieval accuracy. Content- Based Image Retrieval also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR). “Content-based” means that the search makes use of the contents of image themselves, rather than relying on human-inputted metadata such as captions or keywords. The similarity measurements and the representation of the visual features are two important issues in Content-Based Image Retrieval (CBIR).

The main objective of this thesis work is to retrieve images that are similar to query image from a large database. The proposed work (Fig. 2) uses content- based search, for high accuracy multiple features like color, texture and shape.

- ***Color feature*** extraction is implemented by

  “Histogram Techniques”

  Histogram method are further classifies into three categories.

  1. Global Histogram Approach (GCH)
  2. Local Histogram Approach (LCH)
  3. Edge Histogram Approach (ECH)

- ***Shape feature*** extraction is incorporated via

  “Geometric Moments”

- ***Texture feature*** extraction is using

  “Gray Level Co-occurrence Matrix”

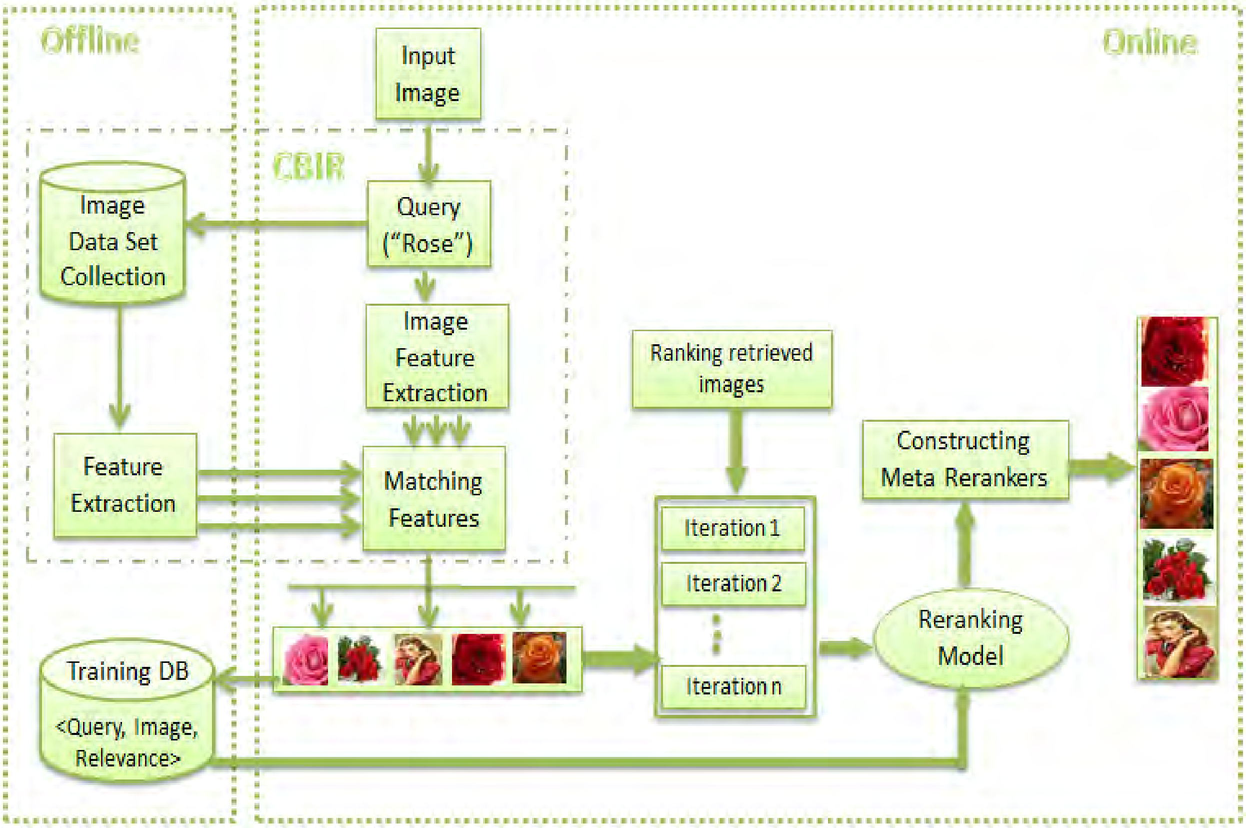


Fig.2 Overview of proposed CBIR based Image Search Reranking framework.

3.1. *Color Feature Extraction*

The most intuitive information that can be extracted from images for comparison is the color characteristics of an image [6]. Computers represent all visible colors with a combination of some set of base color components, generally Red, Green and Blue (RGB). They are considered the "additive primaries" since the colors are added together to produce the desired color. The RGB model uses the Cartesian coordinate system (Fig.3) where the diagonal from (0, 0, 0) black to (1, 1, 1) white, which represents the grey-scale. The image retrieval further utilizes the similarity of three different histograms, one for each component of a RGB pixel. Retrieval was then carried out by searching for images with the minimum distance to a query image. Additionally, the proposed method also utilizes HSV (hue, saturation and value) color pixels to retrieve the images.

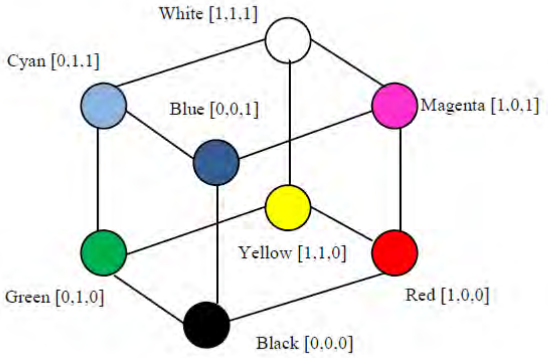


Fig.3 RGB coordinates system

A. Global Histogram Based Approach

The objective of this approach is to study the effectiveness of using the global HSV color space histograms of images as the descriptors in image clustering. The goal is to calculate the HSV (Hue, Saturation and Value) global histograms for all the images reduce the dimensions of the image descriptor vectors using Principal Component Analysis and calculate the similarity measures between the images. The clustering results are then analyzed to see if the results have any semantic meaning shows the general stages in this clustering technique from image acquisition to the final clusters.

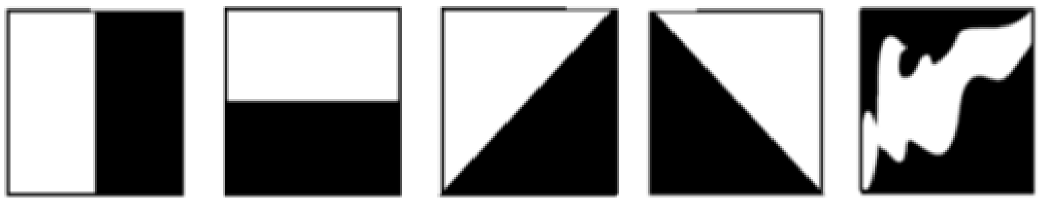
B. Local Histogram Based Approach

The goal of LCH approach includes information concerning the color distribution of regions. The first step is to segment the image into M x N local blocks and then to obtain a color histogram for each block. In general, the image is initially partitioned into 8x8 blocks. An image will then be represented by these histograms. A color histogram H for a given image is defined as a vector:

$$H=\{ H[0], H[1], H[2],\dots\dots H[I],\dots\dots H[N] \} \quad (1)$$

C. Edge Histogram Based Approach

The image array is divided into 4x4 sub images. Each sub image is further partitioned into non-overlapping square image blocks whose size depends on the resolution of the input image. The edges in each image-block are categorized into one of the following six types: (Fig.4) vertical, horizontal, 45± diagonal, 135± diagonal, non-directional Edge and no-edge. Now a 5-bin edge histogram of each sub image can be obtained. Each bin value is normalized by the total number of image-blocks in the sub image. The normalized bin values are nonlinearly quantized.



a) vertical edge b) horizontal edge c) 45 degree edge d) 135 degree edge e) non-directional edge

Fig.4 Sub Images of Edges in Edge Histogram

3.2. *Shape Feature Extraction*

Shape features of objects or regions have been used in many content-based image retrieval systems [7, 8, and 9]. Compared with color and texture features, shape features are usually described after images have been segmented into regions or objects. Since robust and accurate image segmentation is difficult to achieve, the use of shape features for image retrieval has been limited to special applications where objects or regions are readily available.

A good shape representation feature for an object should be invariant to translation, rotation and scaling. The state-of-art methods for shape description can be categorized into either boundary-based method or region-based method. The proposed approach uses “Region-based” Method that implements a technique named “Geometric Moments”.

A. Geometric Moments

Geometric moments are one of the efficient tools for image analysis and retrieval. They are also known as Cartesian moments or regular moments which are the simplest among moment functions, with the kernel function defined as a product of the pixel coordinates. Functions of geometric moments that are invariant with respect to image plane transformations have found many applications in object identification and object pose estimation.

B. Geometric Moment Descriptor

Shape descriptions are an important task in content-based image retrieval. It is a mapping that converts the shape space into a vector space and satisfies the requirement that two similar shapes will also have close-to-identical shape descriptors [9]. The two-dimensional moment (for short 2-D moment) of a 2-D object R is defined as:

$$m_{pq} = \iint_R x^p y^q f(x, y) dxdy \tag{2}$$

where f (x,y) is the characteristic function describing the intensity of R, and p+q is the order of the moment.

In the discrete case, the double integral is often replaced by a double sum giving as a result:

$$m_{pq} = \sum \sum_R x^p y^q f(x, y) \tag{3}$$

The three-dimensional geometric moment (for short 3-D Moment) of order p+q+r of a 3-D object is defined as:

$$m_{pqr} = \iiint_R x^p y^q z^r f(x, y, z) dxdydz \tag{4}$$

The distance between the query and the target shape feature gives the measure of the geometric moment where this distance is used as the local score of the image.

3.3. *Texture Feature Extraction*

Texture is another important property of images. Texture is a description of the spatial arrangement of color or intensities in an image or a selected region of an image. Various texture representations have been investigated in pattern recognition and computer vision. Texture analysis includes:

(i) Texture classification

(ii) Texture segmentation and

(iii) Texture synthesis.

Texture Classification deals with the recognition of image regions using texture properties. Each region in an image is assigned a texture class.

Texture segmentation deals with detecting the texture boundaries in an image to obtain a boundary map.

The goal of ***texture synthesis*** is to extract three-dimensional information from texture properties. An original approach to texture-based classification regions, for image indexing and retrieval, is presented.

Basically, texture representation methods can be classified into two categories:

(i) Structural method

(ii) Statistical method

Structural methods describe texture feature by identifying structural primitives and their placement rules. They tend to be most effective when applied to textures that are very regular.

Statistical methods characterize texture by the statistical distribution of the image intensity. In this proposed approach, the extraction is implemented using ***gray-level co-occurrence matrices.***

A. Gray-Level Co-occurrence Matrices

One of the statistical methods that consider the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM) [10, 11], also known as the gray-level spatial dependence matrix. The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. The adjacency of the image can be defined to take place in each of the four directions (horizontal, vertical, left and right diagonal) as shown in Fig.5. The final texture features are calculated for each of these directions of adjacency. The texture features are calculated by averaging over the four directional co-occurrence matrices.

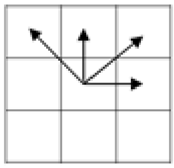


Fig.5 Adjacency calculation

For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset. In order to obtain efficient descriptors, the information contained in GLCM is traditionally condensed into a few statistical features. Four GLCM's for four different orientations (horizontal 00, vertical 900, and two diagonals-450 and 1350) are obtained and normalized to the entries [0, 1] by dividing each entry by total number of pixels. Higher order features, such as energy, entropy, contrast, homogeneity and maximum probability are measured based on averaging features in GLCMs to form a 20-dimensional feature vector for an entire image. The grey-level intensity values in a section of an image is depicted in Fig 6.

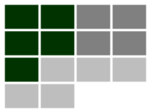


Fig.6 Sample Image

Grey-level values can be represented as shown below.

$$a = \begin{bmatrix} 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 2 & 2 & 2 \\ 2 & 2 & 3 & 3 \end{bmatrix}$$

The 0 GLCM for matrix A is shown below.

$$glcm = \begin{bmatrix} 2 & 2 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Each cell of the GLCM shows how many times the pair (reference, neighbor) occurs. For examples when considering the horizontal direction only, (0,0) occurs 2 times, (0,1) occurs 2 times, (0,2) occurs 1 time, (0,3) occurs 0 time, (1,0) occurs 0 time and so on.

B. GLCM Measure

Gray level co-occurrence matrix (GLCM) is the method proposed by Haralick [11] using 14 statistical measures. This method is considering the distribution of gray levels and their interrelationship. The pixel values are used to construct numerical structures which are associated to the texture pattern of an image. This pattern is based mainly on the interrelationship between one pixel and its neighbors. In this matrix, the indexes of rows and columns represent the given range of the image gray levels, the value C(i ,j) stored at the position (i ,j) is the frequency that gray levels i and j occurs with, at a given distance and at a given direction.

Following are the four measures of texture extracted from the matrix into a feature vector.

i. Energy
ii. Entropy
iii. Contrast and
iv. Inverse Difference Measure.

Energy, also called Angular Second Moment and Uniformity is a measure of textural uniformity of an image. Energy reaches its highest value when gray level distribution has either a constant or a periodic form.

Entropy measures the disorder of an image and it achieves its largest value when all elements in C matrix are equal.

Contrast is a difference moment of the C and it measures the amount of local variations in an image.

Inverse Difference Moment measures image homogeneity. This parameter achieves its largest value when most of the occurrences in GLCM are concentrated near the main diagonal.Table.1 is used to calculate the features extracted from Gray Level Co-occurrence Matrix.

Table.1 Features extracted from GLCM

Feature	Formulae
Energy	$\sum_{i=1}^{N}\sum_{j=1}^{N} C(i,j)^2$
Entropy	$\sum_{i=1}^{N}\sum_{j=1}^{N} -C(i,j)\log_2 C(i,j)$
Contrast	$\sum_{i=1}^{N}\sum_{j=1}^{N} (i-j)^2 C(i,j)$
Inverse Difference Measure	$\sum_{i=1}^{N}\sum_{j=1}^{N} \frac{C(i,j)}{\lvert i-j\rvert^2}, i \neq j$

Where C (i,j) is conditional-joint probabilities of all pair wise combinations of grey levels for a fixed window size.

The feature value is calculated by using the distance vector formula,

$$D(k) \quad \sqrt{\sum_{k=0}^{N}[f_j[x]-f_j[k]]^2} \quad = \qquad (5)$$

where, N is the number of features in f , f_j (x) represents the j^{th} texture feature of the test sample x , while f_j (k) represents the j^{th} feature of k^{th} texture class in the library. Then, the test texture is classified as k^{th} texture, if the distance D(k) is minimum among all the texture classes available in the library.

IV. ITERATIVE RERANKING MODEL

As depicted in Fig.2, the proposed reranking model comprises of an online and an offline set up.

A. *Online Set Up*

In the on-line part, an input image is given as a query to the database by the user. Image search is performed by the above discussed CBIR technique and set of similar images are retrieved from the available set of images. These images are ranked in the relevant order using the Reranking Model available in the online part. This is achieved by associating a L-dimensional score vector for every highest N pictures displayed within the initial search result. Finally, the score vector is employed as input to a re-ranking model, which is already trained offline in the Training DB in order to estimate the ranking scores within the reranked image search list.

B. *Offline Set Up*

The offline part is dedicated to learn the re-ranking model from the feature extracted in CBIR method. It consists of two parts.

- **Image Dataset**
- **Trained Database**

1. *Image Dataset*

This consists of the initial set of input images that are collected randomly and stored in the unstructured form. The images are stored as the dataset and not as database. They are not grouped based on any similarity. Hence, it does not contain any formatted structure and indexes to retrieve the images more efficiently during initial CBIR Search.

2. *Trained Database*

This trained database will be used in re-ranking the retrieved images. Learning process is implemented in the iterative manner in the proposed approach where the results are looped through the subsequent steps. The features of each image are stored in the array format and similar images are clustered together based on Visual Similarity (S).

C. Training the Re-Ranking Model

The existing linear re-ranking model ranks the images that are retrieved based on Text-Based Image retrieval. The shortcoming of this approach is addressed in the learning-to-rank methodology [12], by relating the calculated score as the ranking feature of a query image. The proposed Iterative Ranking approach is one of the foremost fashionable learning to rank algorithms. This algorithmic rule is used repeatedly to handle the ranking problem. Following are the steps implemented to train the database.

Algorithm: **Iterative Learning methodology.** Iterative approach to train the images in the database and store them in a clustered layout.

Input: L set of input images from the image dataset collection.

Output: A set of k clusters with similar images grouped together and stored in the structured format

i. The input query image is searched in the initial data set in order to retrieve the similar images.

ii. The search is done using proposed multi-feature CBIR technique discussed in Section III.

iii. During this retrieval, each feature is assigned to a model weight. Thus images satisfying each feature will be assigned to a model weight W.

iv. Then L-Intermediate images are generated as a result of CBIR search and for each image L Meta rerankers are constructed.

v. The model weight 'W' is aggregated for each intermediate image separately to calculate the score vector $M(I_j)$. $M(I_j)$ is the score vector from the L meta rerankers for the image I_j ,

vi. Repeating the above steps iteratively helps to create the query log of these images. Representative queries are then sampled from the query log area to collect the training data.

vii. Then the re-ranking model is learned and stored as a trained image data set which is referred in the online part for Users input query.

D. Advantage of Proposed Algorithm

The assignment of Model weight for each feature is the challenging feature in the proposed approached. The model weights from query images are the key to ensure that the reranking model only needs to be learned once and can then be applied to any arbitrary query. Thus, the Iterative reranking method implemented along with CBIR search shows good performance and accuracy for a large input image data set when compared to existing ranking schemes [13].

E.Sample Model Weight Assignment

Table 2 shows the Model Weight Assignment for each image feature implemented in the proposed approach. The ranked image results for this assignment are discussed in the experimentation section of this document.

Table.2 Sample Model Weight Assignment

Feature	***Technique***	***Model Weight W***
Color Feature	Global Histogram	10
	Local Histogram	8
	Edge Histogram	6
	Color Histogram	4
Shape Feature	Geometric Moments	3
Texture Feature	GLCM	5

The model weights assigned to each feature can be changed dynamically during the simulation of the model. This enables the user to assign the weights logically based on the Input and the search criteria. The dynamic nature of the proposed approach empowers the search engine to effectively rank the images for a broad set of input queries.

V. CONSTRUCTING META RERANKERS

One of the key steps in the CBIR based image search reranking method is the construction of Meta rerankers. Given an image feature extraction P_i and a set of N images {Ij} where j=1 to N, ranking scores are generated for these images based on the number of features matched for an input image and the Model Weights assigned to each feature. The computed scores are then used as input for the reranking model to estimate the ultimate ranking scores to determine the rank position of the images in the reranked result. Based on the proposed Iterative approach, three types of rerankers are constructed.

1. Single-Image Set
2. Multiple-Image Set
3. Negative-Image Set

5.1. *Single-Image Set*

The basic method to generate the ranked images is to select the top images from the CBIR result, as illustrated in Fig.7. If this set of images are denoted as $\{G^S\}_,$ then the Meta rerankers for Single-Image Set M^S can be built directly based on the visual similarity of images S(.) between the Set G and the image I_j to be reranked:

$$M^S (I_j \mid G^S) = S(I_j \ _o \ G^S) \tag{6}$$

The Model Weight 'w' is calculated for each of the matching feature m. These weights are now aggregated to generate the score vector.

Score Vector $\mathbf{W} = \sum \mathbf{w_i}$ where i= 1 to 'm' matching features.

The score vector aggregating the values from all L meta rerankers is then used as input to the linear reranking model in order to compute the definitive ranking score R^S for image $I_{j.}$

$$R^S (I_j)= \sum (Wj * S (I_{j\,o}\, G^S)) \text{where } j = 1 \text{ to } N \tag{7}$$

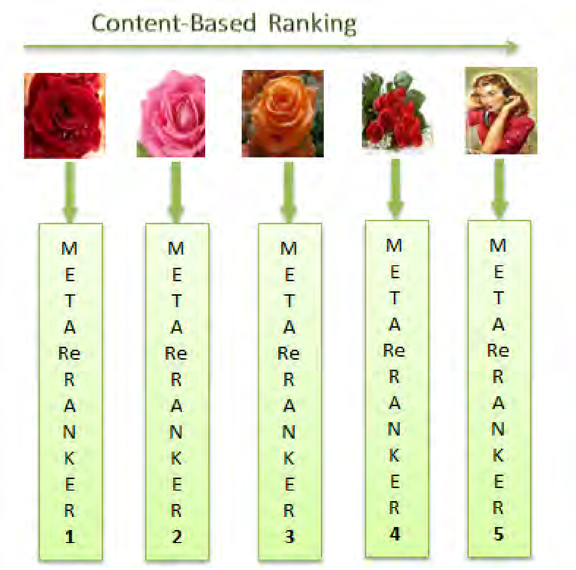


Fig 7. Meta Rerankers using Single-Image Set

Since this method uses only single image during the construction of Meta Rerankers, iteration cannot be performed effectively. Though the construction of Meta rerankers using this approach is simple and accurate, it can be leveraged only to limited number of queries. In this way, it does not jeopardize scalability.

5.2. *Multiple-Image Set*

As the name indicates, Multiple-Image Set uses the same intermediate images many times in order to construct the Meta Rerankers. Here the retrieved images are ranked from the intermediate CBIR search result and each image is compared with other images and based upon the visual information rank.

As shown in Fig 8, the image which has top rank will be ranked first and low rank images will be sent to the last of the result.

Scores are generated and it is applied to the reranking model.

Image Set for Multiple-Image Set can be defined as

$$G^M = 1/i \sum I_j \text{ where } j = 1 \text{ to } i. \tag{8}$$

The image set can be employed to compute the scores of individual Meta rerankers by again computing the visual similarity between the Set G^M and the image I_j to be reranked.

$$M^M (I_j \mid G^M) = S(I_j \ _o \ G^M)$$

$$M^M (I_j \mid G^M) = 1/i \ \sum(I_j \ _o \ I_{j+1}) \text{ where } j = 1 \text{ to } i. \tag{9}$$

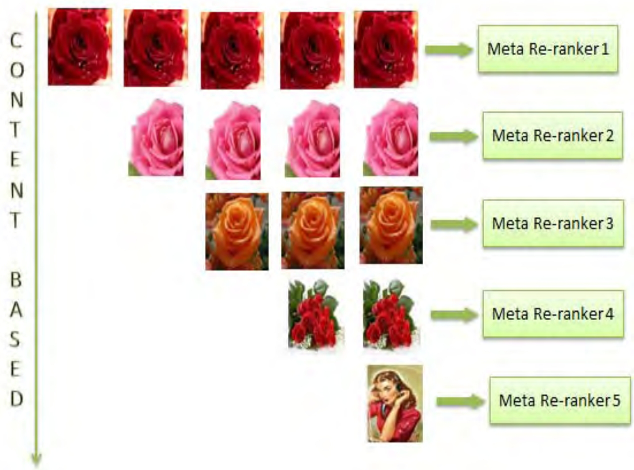


Fig 8 Meta Rerankers using Multiple-Image Set.

Here the rank positions of images are determined based on Bag of images. Thus comparison of two image, model the reranking technique and definitive Ranking Score is calculated based on the matching feature iteratively.

$$R^M(I_j) = \sum(W_i * S(I_j \circ G^M))$$
$$= \sum(W_i * 1/i \ \sum S(I_j \circ I_{j+1}) \text{ where } j = 1 \text{ to } i. \quad (10)$$

Replacing the constant value, Wi/i with α_i in the above equation, the final expression for this construction of Meta rerankers technique can be reduced to,

$$R^M(I_j) = \alpha_i * S(I_j \circ I_{j+1}) \text{ where } j = 1 \text{ to } i.$$

where, $$\alpha_i = \sum W_i * 1/i \ . \quad (11)$$

5.3. *Negative-Image Set*

The Multiple-Image average Set works in an Iterative manner for large number of input images. Thus, the above method is highly efficient and operates in a more scalable manner. But Multiple-Image Set has one drawback where the lower ranked images will not have much effective accuracy. Therefore to overcome this shortcoming, Negative-Image Set is implemented where the image database is trained with negative samples. As illustrated in Fig.9, the Negative-Image Set at rank *i* is defined as a bag of images ranked from the topmost position to the rank i, as in Fig.9.

Image Set for Negative-Image Set can be defined as

$$G^N = \{I_j\} \qquad \text{where } j = 1 \text{ to } i. \quad (12)$$

Fig 9. Meta Rerankers using Negative-Image Set

The Negative-Image Set is a more flexible representation satisfying Iterative functionality, which can support the development of more types of Meta rerankers.

Given a Negative-Image Set approach, visual classifier can be learnt by regarding all the images in as positive samples, which is then employed as Meta rerankers and the prediction score is used as the Meta reranking score.

Below two schemes are proposed to select the negative samples.

1. Background Images.
2. Random Images.

Background images: The advantage of selecting the background mages as negative samples is that they are very unlikely to be relevant to any query of interest. In this paper, negative samples are carefully chosen from the images which are ranked in the bottom for each query as the background.

Random images: The other strategy of selecting negative samples is to use the randomly sampled images from the entire database. The main benefit of selecting random images as negative samples is that multiple sets of negative trials can, so as to de-correlate different rerankers

The Meta reranker with a Negative-Image Set can be defined as follows:

$$M^N (I_j \mid G^N) = p(I_j \mid \theta^*) \qquad (13)$$

Where θ^* is the learned model and

$$\theta^* = \arg\max_\theta p (G^N \mid \theta) \qquad (14)$$

VI. EXPERIMENTS

In this section the experimental setup is first discussed followed by the result evaluation and performance of the proposed approach.

6.1. *Experimental Set Up*

Experiments are conducted using the set of images from the Web Image Dataset. The dataset we used for the experiments reported in this paper consists of 490 images of different categories of roses and other images as well. They are collected from three most popular commercial image search engines, i.e., Google[14], Live[15] ,Yahoo[16] as displayed in Fig.10

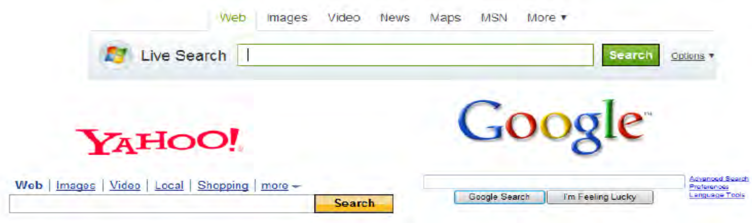


Fig 10. Image Search Engines

These images were grouped together into 5 datasets as shown in Table 3. In order to measure the performance of the proposed approach, images were clustered together based on the visual similarity for efficient retrieval.

Table 3 Input Dataset

Dataset	***Clustered Feature***
Dataset 1	Complete dataset
Dataset 2	Color Feature
Dataset 3	Shape Feature
Dataset 4	Texture Feature
Dataset 5	Negative Samples

Every input image in every dataset is retrieved using the proposed CBIR Multi-Feature Extraction. Each matching feature is assigned to a Model Weight as illustrated in Table1. Based on the matching features and the assigned model weights, intermediate images are retrieved from the input dataset. These images are further ranked using the relevant reranking score that are calculated from Meta Rerankers. This ranks the retrieved images more accurately and efficiently. The image retrieval and ranking is implemented using the proposed approach and tracked using the popular Web User activity tool – Infusionsoft. The results are calculated and displayed in the chart mentioned in Fig.11. The order of ranking will vary dynamically based on the initial Model Weight Assignment for each image feature extraction.

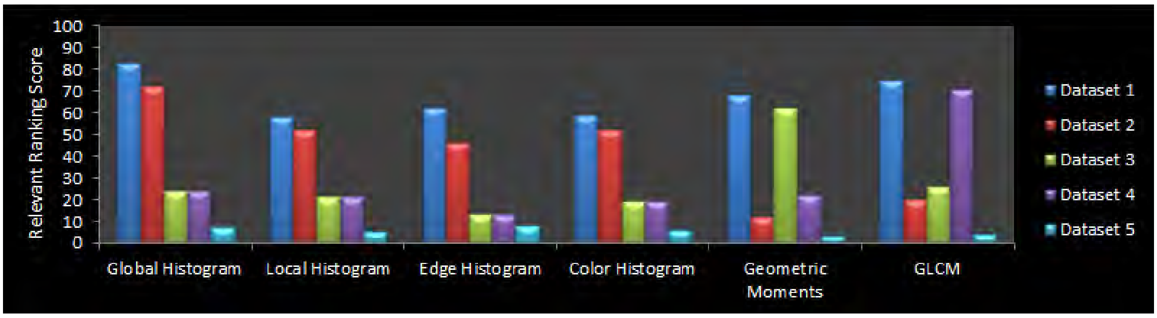


Fig.11 Results generated from set of 490 images using proposed approach.

6.2. *Performance Measure*

The performance of the proposed approach is measured using two Evaluation values.[17]

1. Recall
2. Precision
3. Error Rate

Recall: The measure of ability of system to present all relevant items.

$$\textit{Recall} = \frac{\textit{Number of Relevant Images Retrieved}}{\textit{Number of Relevant Images in Collection}} \quad (15)$$

Precision: The measure of ability of system to present only relevant items.

$$\textit{Precision} = \frac{\textit{Number of Relevant Images Retrieved}}{\textit{Total number of images retrieved}} \quad (16)$$

Error rate: The measure of ability of system to know whether the value is measured or not.

$$\textit{Error Rate} = \frac{\textit{Number of Non-relevant Images Retrieved}}{\textit{Total number of images retrieved}} \quad (17)$$

Precision and Recall are set-based measures. In the proposed approach, experiments were performed to evaluate the performance measure. To evaluate the ranked lists, precision can be plotted against recall after each retrieved documents. As shown in Fig,12, the actual precision values are plotted with circles (and connected by a solid line) and the interpolated precision is shown with the dashed line.

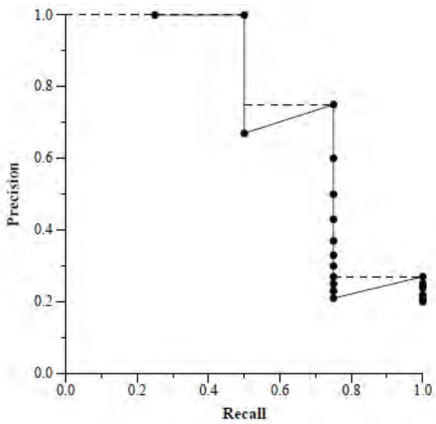


Fig.12. Plot between Precision and Recall

6.3. *Performance Comparison*

The Proposed CBIR Technique retrieves and ranks the images more effectively and efficiently. In order to compare the performance of the newly implemented technique with the existing approach, analysis is made with the same set of datasets. The performance comparison of both the approach is illustrated in Fig.13. The performance growth in the graph has increased more drastically. Since the approach is also iterative, it's more applicable to large number of input images. Thus the scalable nature of this approach helps the functionality in a more Query-Independent way.

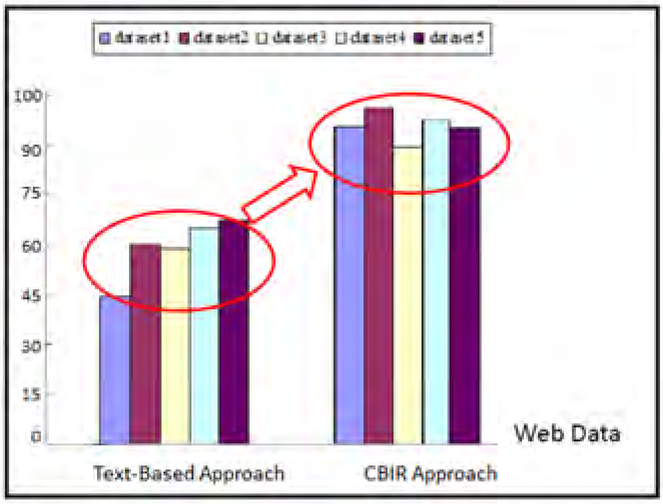


Fig.13 Performance Comparison

VII. CONCLUSION

This paper has presented a dynamic and active reranking framework for Web image search by using user interactions. The most promising Content-Based Image Retrieval Technique is used that is implemented based on Multi-Feature Extraction. This increases the accuracy of the retrieved images to a larger extent. To target the user's intention effectively and efficiently, unsupervised Learning methodology is performed which makes the proposed framework to be more query-independent. Also, the architecture is very much scalable with large set of input images with drastic performance upto 75% during Image Retrieval and Ranking. The experiments performed on the real Web image search dataset have demonstrated the effectiveness of the proposed Iterative reranking scheme and outperformed all the existing Text-Based approach. While our proposed methods have proved effective for reranking image search results, we could work on the future work to improve the proposed reranking model to make it more query-adaptive. Though this research works well for query-independent image datasets, extension of this approach to Query-adaptive framework will enable the system to work in a fully automatic manner. Another approach may be worked on making the Learning Process also to be iterative.

ACKNOWLEDGEMENT

I would particularly thank Asst. Prof. Augustian Isaac., who helped me constantly to get this research work successful .His inspiring guidance, valuable suggestions and numerous improvements assisted me to work on the thesis work and perform the experiments successfully. And a great thanks to the image search engines to provide the input datasets.

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