IJRSET April 2016 Volume 3, Issue 4 Pages: 1-11

ISSN 2394-739X

International Journal for Research in Science Engineering and Technology

VISUAL AND TEXTUAL FEATURES BASED IMAGE SEARCH RESULTS AND PREFERENCE LEARNING MODEL FOR QUALITY ASSESSMENT

[1] A. Umadevi, [2] R. Rangaraj,
[1] Research Scholar, [2] Associate & Head of the Department,
[1, 2] Pg & Research Department of Computer Science,
[1, 2] Hindusthan College of Arts and Science, Coimbatore.

Abstract:-

Retrieval of images from database plays a significant role in day to day life. Widespread investigation methods have been studied in recent work for retrieving images which is relevant to a user given query. Several factors are able to control of image search results. Concerning different settings in favor of these factors produce search result lists by means of varying levels of quality. On the other hand, no setting is able to constantly execute optimal results for all user given queries. So, known a set of search result lists produced through different settings, it is important to repeatedly decide which result list is the optimal in order to present it to users. At the same time to improve the efficiency of the system the major steps of image retrieval system such as feature extraction, similarity measurements and retrieval or matching is also discussed in this paper. Those steps extraction of the texture features and visual features increase the efficiency of retrieval system, so in this research work texture feature extraction is done using Grey Level Co-occurrence Matrix (GLCM). The major contribution of the paper consist of three major steps: at the initial stage of the work, a classification model based on user preference is formulated to find the most excellent image search result list classification problem. At the second step most important features such as visual and texture features are extracted from the returned images. Third, a query based preference classification model is created based on the user specified query. The results of third step have been tested on a diversity of applications such as the reranking capability evaluation, optimal search engine collection, and synonymous query proposition

Keywords: - Image retrieval, search results performance comparison, reranking ability assessment, texture feature extraction, Grey Level Co-occurrence Matrix (GLCM).

1. INTRODUCTION

Specified the explosive development of the web usage and the use of image sharing Web sites, image retrieval cooperate a gradually more significant role in the current days. Several investigations have been introduced in recent work toward recover images appropriate to a user specified query. Several numbers of factors is able to affect the image search results. In recent work aims to obtain correct retrieval results via the focus of their efforts on diverse aspects of the search development, such as efficient visual features [1-2] extraction methods, construction well-organized image indexes [3], introducing new ranking algorithms [4-5] and developing user-friendly interface [6]. These algorithms produces different results and their quality of retrieval results is varied based on their different settings. For example consider two real-time examples. In initial example match the image retrieval results produced by means of using two search engines, Bing and Google. Present 29 text queries in the direction of them, and together the images they returned. Google obtain best performance on regarding half the queries. For instance if the user given query is White House, the top most images returned through Google are more associated to the "White House" than those returned through Bing.

If an algorithm might repeatedly decide which search engine would create an improved result list designed for each query, one might obtain better retrieval results via the use of choosing the best search engine for user given query. By the using obtained Mean Average Precision (MAP) value is 60.71, concerning 16% comparative development over Bing and Google. In the second example compare the performance accuracy results of text-based image search and visual reranking. Many of the existing search engines are developed by using indexing and searching textual information connected by means of images, e.g., adjacent text, URLs. The text-based image investigate approach is well-organized designed for huge scale image databases. On the other hand, it suffers when the related text is not sufficiently expert of sufficiently relating the image. To solve this problem, visual reranking has been introduced to improve the text search results via integrating visual information from images. From the results it also shows that the retrieval results are increased by adding visual reranking especially for text-based image search [7-8]. On the other hand, it is not assured to promote every user given query. It is expansively observed with the intention of visual reranking be able to significantly enhance retrieval performance designed for some queries, at the same time as designed for others reranking be able to even decrease the performance of the first text-based search.

From the literature two popular reranking methods, BR [9] and PRF [10], are valuable on a public image search dataset (Web353). This dataset is collected from Krapac et al [11], which consists of 71,478 images returned by means of a Web search engine designed for 353 wide-ranging textual queries. The beyond two examples increase the equivalent problem: in favor of a user given query, known a set of result lists, which one provides best performance which result list must exist obtainable to users. The major objective of the work is to solve above mentioned problem: known a set of search result lists come back by means of multiple search executions of a user given query, how be able to design a new algorithm in the direction of repeatedly compare the value of those retrieval result lists in order toward discover the result list by means of the highest retrieval performance. In order to overcome this problem in this paper creates a new learning model based on the user preference query to enhance the quality of retrieval search results. In machine learning methods consists of two major stages: offline training and online testing. In the training stage, the visual division distinctiveness of good and bad investigate outcome lists are discovered and a set of light-weight features is resultant toward confine their distinction. Then, by means of structure the search result lists of training queries addicted to preference pairs, obtain a preference learning model (PLM) by means of training through RankSVM [12]. As a final testing stage, the introduced PLM is useful to calculate the user preference score designed for search retrieval result lists of every testing query.

The major contribution of the paper consist of three major steps: at the initial stage of the work, a classification model based on user preference is formulated to find the most excellent image search result list classification problem. At the second step most important features such as visual and texture features are extracted from the returned images. The proposed preference based learning model extract a valuable visual and texture features to repeatedly evaluate the quality of retrieved image search result lists. Third, a query based preference classification model is created based on the user specified query.

2. RELATED WORK

Retrieval of images from database plays a significant role in day to day life. Widespread investigation methods have been studied in recent work for retrieving images which is relevant to a user given query. Several number of research work have been proposed to improve the image retrieval results by using various image retrieval steps such as image annotation [2] and visual reranking [7-8]. Each and every one these investigate efforts have the similar objective of persistent image retrieval search results for user given query. Diverse of results found and returned from different image search methods and their accuracy on each query varies significantly. Each method has shows different performance based on their working procedure. But single method mightn't provide best results for all users and their queries. So developing effective image retrieval method for all user given queries becomes very difficult and challenging task. All the way through this section discuss the existing methods for better image search results. In the first work query difficulty forecast in document retrieval has been discovered for several years [13-14]. The major aim of this work is to predict whether a user given query determination produces high retrieval performance or not for document collection. It consists of two major steps, pre-retrieval and post-retrieval prediction. In pre-retrieval, the major aim is to measure the retrieval performance earlier than the retrieval step [13-14]. It mostly depends on statistics of query terms over document collections. In post-retrieval, the major aim is to measure the retrieval performance after the completion of retrieval step. It mostly depends on retrieval results over document collections.

Hauff et al [13] developed a new retrieval schema by measuring the clarity score which increases the sensitivity results in image retrieval system. The results of the clarity score methods are compared to various traditional query prediction algorithms, in both post-retrieval and pre-retrieval stages. All of the methods measure the sensitivity values towards the retrieval algorithm. Evaluation of these methods is experimented to three datasets documents and their query sets .It shows that the proposed clarity score based schema produces best retrieval results when compare to various traditional query prediction algorithms those perform extensively worse results on collected web documents dataset.

Imran and Sharan [14] developed a new retrieval schema with two pre-retrieval query difficulty predictors relying on their extracted texture features co-occurrence information between query terms. They implicit with the purpose of elevated co-occurrence of query terms with huge information is suggested, which direct towards a simple query or a lower query complexity level. In post-retrieval stage, the retrieval step is carried out at initially and query complexity prediction measure the retrieval results performance for user given query. These two pre-retrieval query difficulty predictors are most related to earlier [12-13] works. Query expansion (QE) has turn into a well known technique with the intention of has been shown toward increase average retrieval performance.

He and Ounis [15] compare the retrieval results of various pre-retrieval predictors through taking into consideration the basic statistical features of queries which consists of query length, standard deviation of the Inverse Document Frequency (IDF) for user given query, query capacity, and a Simplified Clarity Score (SCS). This study consists of different set of query predictors and their performance, which is able to be generated earlier than the retrieval process. Here we majorly focus on the linear and non-parametric correlations based query predictors and evaluated on TREC disk4 and disk5 document collections. From the results it shows that the proposed linear and non-parametric correlations based query predictors have achieves significant retrieval performance when compare to other predictors [13-14] performance in practical applications.

Kwok et al. [16] developed a Support Vector Regression (SVR) query difficulty prediction model for image retrieval to train a query by means of log document and query term frequency respectively. Elad Yom-Tov et al [17] measure the retrieval search results by considering top most results which is returned based on the user given query and its sub-queries. This proposed a learning schema is designed for the estimation of QoS returned by means of a search engine in answer to a user given query. Assessment is performed based on the measuring the result of top results for user given query and the top results of its sub-queries. Show the effectiveness of quality estimation designed for various applications, all of them the development of retrieval, detecting queries designed for which have no relevant substance exists in the document collection, and distributed information retrieval. Experiments on TREC data show the strength and the effectiveness of learning algorithms.

Jensen et al [18] solves query prediction difficulty problem via the use of extracted features from documents characterized in the search result list toward train a regression model. In image retrieval, recent work several methods have been studied in the literature to solve query difficulty estimation problem. Here introduces a new precision-oriented learning model used for predicting query difficulty problem in web search task. The precision-oriented learning model extract visual features from document with their different representations such as titles, snippets toward calculate retrieval efficiency for a user given query. By means of training a supervised machine learning schema through physically evaluated queries, visual clues investigative of relevance are discovered. It shows that precision-oriented learning model is reasonable correlation of 0.57 by means of precision next to 10 scores beginning manual relevance result of the top ten web search engines more than 896 queries.

Xing et al. [19] developed a new model by the extraction of textual features toward predict whether a user given query is complex or not. However this work doesn't measure the performance of image retrieval search results, it classifies the user given queries into two classes "easy" or "hard" namely. The schema is performed based on the machine learning methods to solve query prediction problem depending on their unique characteristics of the query words and their context. More purposely, the major aim of this works it to consider the queries based on noun word/phrase and extract four features along with their different assumptions. The experimentation results of machine learning model are compared with several machine learning methods on the query prediction task. It shows that the new machine learning model provides high performance and less execution time. Based on the above mentioned query prediction model and feature extraction methods, in this work is extended to new prediction model with extracted visual and texture features with their similarity also measured for retrieval search results.

3. PROPOSED METHODOLOGY

The major contribution of the paper consist of three major steps: at the initial stage of the work, a classification model based on user preference is formulated to find the most excellent image search result list classification problem. At the second step most important features such as visual and texture features are extracted from the returned images. The proposed preference based learning model extract a valuable visual and texture features to repeatedly evaluate the quality of retrieved image search result lists. Third, a query based preference classification model is created based on the user specified query.

Let us consider user given query as q for different image collection$\{x_1, .., x_N\}$, their results is determined by using different search algorithms. For each retrieved search results ranking or permutation operation is performed to find top most results .Here ranking is performed in descending order depending on their ranking scores, which are determined by means of the search algorithm. Make use of ranking list variable l toward represent a search result list. Make assume that there are n_q ranking lists created for user given query q, they comprise a set of explore result lists $L^q = \{l_1, \dots l_{n_q}\}$. The major aim is to routinely find which $l \, in \, L^q$ might attain high precision performance,

$$l^* = \mathrm{argmax}_{l \in L^q} \, y(l) \qquad (1)$$

where y(l) is represented as the achieved precision performance results for l. y(l) is determined by using the performance metric measures, such as precision, recall, Average Precision and Normalized Discounted Cumulated Gain (NDCG). On the other hand, in real applications, the ground truth relevance labels designed for images are not presented sometimes .To overcome and solve this problem in this research work uses a machine learning based model is considered as user preference model $f(l) = w^T \psi(l)$ from training samples, where w is denoted as the weight value for SVM and $\psi(l)$ is a vector which replicate the distinctiveness of l. This model must assure the subsequent restriction on the training set. Designed for two ranking lists l_i and l_j in training samples, if the performance of $y(l_i)$ is better than $y(l_j)$ and similarly $f(l_i)$ must be larger than $f(l_j)$. Define the machine learning method model function as $f(.)$ by RankSVM [14] algorithm. It reduces the prediction errors on a training queries $Q = (q^1, \dots q^m)$

$$\min \frac{1}{2} w^T w + C \sum \xi_{ijk} \ \mathrm{s.t.} \ \forall k = 1, .. m \ \forall (l_i, l_j) \in S^{q(k)} \ w^T \psi(l_j) + 1 - \xi_{ijk}, \xi_{ijk} \geq 0 \qquad (2)$$

Where ξ is considered as the slack parameter of SVM and $C > 0$ controls the tradeoff among learning method complexity and decrease training error. $S^{(q)}$ is denoted as the set of preference ranking list pairs for user specified query q determined from the ranking list set $L^q = \{l_1, \dots l_{n_q}\}$

$$S^q = \{(l_i, l_j) | y(l_i); i, j = 1, \dots n_q\} \qquad (3)$$

The preference learning model $f(.)$ is able to be resulting by means of solving problem (3). Subsequently, this model is able to be useful to every testing query q' designed for which ground truth relevance labels are not presented. Presume there are nq0 ranking lists created used for this user given query, $L^{q'} = \{l_1, \dots l_{n_{q'}}\}$ be able to predict a value designed for each list. In favor of any two ranking lists li and lj, if $f(l_i) > f(l_j)$, know with the intention of li performs better than lj, and vice versa.

From the motivation of the earlier work [20], in this research work introduces a new query based preference learning models designed for different queries. Distinctively, obtain the query-dependent PLM through creating a query-dependent training query set designed for each user given query. This is a simple way which classifies the query results into various classes (landmark, people, object, etc.), and then train a PLM model for each training samples. In the testing stage, user given test query is verified using PLM model. This PLM model to obtain classification performance depending on their user given query is very difficult. So in this research work discover K closet queries from Q_{train} as training set for PLM. Here extract a popular bag of visual word (BOVW) image representation [21], for visual feature extraction to text retrieval. In BOVW, an image is able to be treated as a document and represented by means of a set of visual words. By means of examining the visual features of images in the training set, propose a set of lightweight features by means of two basic assumptions:

Density Assumption: The major objective of this step is to determine a density values to relevant and irrelevant images. To validate whether this statement is true or not, compute the density to N images in user given query q and then evaluate their value characteristics. The density p_{xi} is determined via the use of Kernel Density Estimation (KDE). To find the density difference among relevant and irrelevant images, here we need to determine average density $AvgDense_+$ and $AvgDense_-$ for relevant and irrelevant images respectively for user given query. They are calculated as

$$\mathrm{AvgDense}_+ = \frac{1}{|X^+|} \sum_{x^i \in X^+} p_{x_i} \quad (4)$$

$$\mathrm{AvgDense}_- = \frac{1}{|X^-|} \sum_{x^i \in X^-} p_{x_i} \quad (5)$$

where X^+ and X^- is denoted as the set of relevant and irrelevant images . $Ratio_{dense}$ is defined as, $Ratio_{dense} = AvgDense_+ - AvgDense_-$.

Visual similarity assumption: To confirm the visual similarity statement computes several average similarity pair between relevant-relevant, relevant-irrelevant, and irrelevant-irrelevant for user specified query in the Web353 dataset. These similarity pairs is denoted as $AvgSim_{++}$, $AvgSim_{+-}$, and $AvgSim_{--}$ respectively .It is sorted using two ratio function $Ratio_{sim1}=AvgSim_{++}/AvgSim_{+-}$ and $Ratio_{sim2}=AvgSim_{++}/AvgSim_{--}$. In addition this research work also extract texture features using statistical feature extraction by using the GLCM feature extraction methods to increase the efficiency of retrieval system.

Statistical Feature Extraction: In statistical texture assessment [22] texture features are determined from the statistical distribution of investigational combinations of intensities at particular positions proportional to every other in the image. Based on the number of intensity points (pixels) in every grouping, statistics are classified into first-order, second-order and higher-order statistics.

First Order Statistics: First Order Statistical [22] feature compute the probability of examine a gray value at a randomly selected location in the image. FOS is able to be calculated beginning the histogram of pixel intensities in the image. But in FOS feature extraction methods simply few of the features such as mean, energy, variance, kurtosis and Skewness, which are directly calculated from the images ,it is not sufficient to differentiate the various classes ,this problem is solved by using the second order statistics feature extraction method.

Second Order Statistics: The features generated from the FOS offer information associated with the gray-level distribution of the image. On the other hand, they do not provide any information regarding the relative positions of the several gray levels inside the image. These characteristics will not be capable of measuring whether the entire low-value gray levels are positioned mutually, or they are interchanged with the high-value gray levels. As a result, SOS feature extraction approaches are exploited to consider the relative positions of the several gray levels within the images. The information can be extracted from the co-occurrence matrix that measures Second-order image statistics [23] where the pixels are considered in pairs. The GLCM method is a method of extracting SOS texture features. The GLCM gives information concerning the division of gray level intensities. A GLCM is a matrix in which the number of rows and columns is equal to the number of gray levels G. The matrix element $P(i, j|\Delta x, \Delta y)$is the comparative frequency through which two pixels, separated through a pixel distance $(\Delta x, \Delta y)$, occur surrounded by a known neighborhood, one through intensity i and the other with intensity j. One may also say that the matrix element contains the SOS probability values designed for changes among gray levels and at a specific displacement distance d and at a particular angle θ.

Feature extraction using GLCM: Co-occurrence features are a well-liked and efficient texture descriptor by means of statistical approach. Provided an image of n gray levels, features are strong-minded beginning the SOS features through taking the spatial association of pixels into account through sub-bands beginning WT. This process is usually employed in texture examination because it gives designed for every sample an enormous set of features and it is able to be presumed that in any case one of these features imitates the small discrimination of texture amongst classes. GLCM of an 4×4 each sub-image sub-band size, includes pixels with gray levels $(0, 1, \ldots, G-1)$ indicates a two dimensional matrix. A GLCM element $P(i,j)$ of the matrix point towards the probability of joint occurrence of intensity levels k and l at a certain distance d and an angle $\theta = \{0^0, 45^0, 95^0, 135^0, 180^0, 215^0, 270^0\}$.

Each sub-divided sub-band block is a self-determining Region of interest (ROI). Multi-distance and multi-direction know how to be employed to get an enormous number of features. In this approach, derive GLCM features by means of one distance $d = \{2\}$, and four direction θ which bring about 120 i.e. $(2 \times 4 \times 15)$ features derived for every block. GLCM is derived by indicating a matrix of relative frequencies P_{ij}, through two neighboring resolution cells divided through distance 'd' taking place on the image, one through gray tone i and the further with gray tone j. The co-occurrence matrix 15 features of texture are able to then be computed.

Contrast (CON): Contrast is the primary crosswise close to the second of inertia, which establish how the values of the matrix are allocated and number of images of local transformations reflecting the image clarity and texture of shadow intensity. Large contrast indicates deeper texture.

$$CON = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1,|i-j|=n}^{N_g} \sum_{j=1}^{N_g} p(i,j) \right\} \quad (6)$$

gray level value of the image $n = 0 \; to \; N_g - 1$, $p(i,j)$ be the probability value of the image.

Correlation (CORR): Correlation is an amount of gray level linear dependence amongst the pixels at the exacting positions balanced to each other, and it is given as,

$$CORR = \frac{\left[\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i,j) p(i,j)\right] - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (7)$$

$$\mu_x = \sum_{i=1}^{N_g} \left[i \sum_{j=1}^{N_g} p(i,j) \right] \quad (8)$$

$$\mu_y = \sum_{j=1}^{N_g} \left[j \sum_{i=1}^{N_g} p(i,j) \right] \quad (9)$$

$$\sigma_x = \sum_{i=1}^{N_g} \left[(i-\mu_x)^2 j \sum_{j=1}^{N_g} p(i,j) \right] \quad (10)$$

$$\sigma_y = \sum_{i=1}^{N_g} \left[(j-\mu_x)^2 i \sum_{i=1}^{N_g} p(i,j) \right] \quad (11)$$

Where μ_x, μ_y represent the mean values and σ_x, σ_y indicates the standard deviations of P_x and P_y, correspondingly.

Energy (ENER): This value is also well-known as Uniformity. It decides the textural uniformity through the purpose of pixel pair repetitions. It recognizes disorders in textures. Energy reaches a maximum value equivalent to one. The GLCM of lower homogeneous image determination have enormous number of small entries,

$$ENER = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P(i,j)^2 \quad (12)$$

$p(i,j)$ be the probability value of the image.

Entropy (ENT): Entropy is a difficult term to describe. The idea comes beginning thermo dynamics; it point toward to the compute of energy that is entirely lost to heat every time a feedback. Entropy cannot be improved to do constructive task. Owing to this, the term is able to be implicit as quantity of irremediable chaos or mess.

$$ENT = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}[P(i,j)log\,(P(i,j))] \quad (13)$$

$p(i,j)$ be the probability value of the image.

Inverse Difference Moment (IDM): IDM is typically called homogeneity with the intention of calculate the local homogeneity of an image. IDM feature obtain the amounts of the nearness of the division of the GLCM constituents to the GLCM diagonal. IDM weight value is the dissimilar of the Contrast weight, through weights declining exponentially away from the diagonal.

$$IDM = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\left[\frac{1}{1+(i-j)^2}P(i,j)\right] \quad (14)$$

$p(i,j)$ be the probability value of the image, i,j be the row and column coordinates in the pixel of the image, N_g be the pixel range N_g=255

Sum of Squares (SOS): Sum of squared deviates of the images is indicate as the approximated variance of the source population and it is specified as,

$$SOS = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i-\mu)^2 p(i,j) \quad (15)$$

$p(i,j)$ be the probability value of the image, μ means value of the image pixel, i,j be the row and column coordinates in the pixel of the image, N_g be the pixel range N_g=255.

Sum Average (SA): Sum average indicates the normal of normalized gray tone image in the spatial domain, correspondingly, and it is specified as follows,

$$SA = \sum_{i=2}^{2N_g}[iP_{x+y}(i)] \quad (16)$$

$P_{x+y}(i)$ be the probability value of the image in (x,y) coordinates.

Sum Variance (SV): This element puts comparatively high weights on the elements that fluctuate from the average value of $P(i,j)$ and it is given as

$$SV = \sum_{i=2}^{2N_g}[(i-SA)^2 P_{x+y}(i)] \quad (17)$$

$P_{x+y}(i)$ be the probability value of the image in (x,y) coordinates.

Sum Entropy (SE): The sum entropy is a quantity of uncertainty inside an image

$$SE = -\sum_{i=2}^{2N_g}[P_{x+y}(i)\,log[P_{x+y}(i)]] \quad (18)$$

$P_{x+y}(i)$ be the probability value of the image in (x,y) coordinates.

Difference variance (DV): It is an image variation in a normalized co-occurrence matrix.

$$DV = -\sum_{i=0}^{N_g-1}[(i - f']P_{x-y}(i)], \text{ where } \quad f' = \sum_{i=0}^{N_g-1}[iP_{x-y}(i)] \quad (19)$$

$P_{x+y}(i)$ be the probability value of the image in (x,y) coordinates.

Difference Entropy (DE): It is also a sign of the amount of uncertainty in an image.

$$DE = -\sum_{i=0}^{N_g-1}[P_{x-y}(i)]log\,[P_{x-y}(i)]] \quad (20)$$

Auto Correlation (Ac): The autocorrelation function, which is calculated along the horizontal and vertical axes of the analysis window I of an image in accordance with the following equation:

$$R_{(x,y)}^{I(\alpha,\beta)} = \sum_{\alpha\in\Omega}\sum_{\beta\in\Omega}\frac{I(x,y)}{I(x+\alpha,y+\beta)} \quad (21)$$

where $I(x+\alpha, y+\beta)$ represents the translation of the analysis window of an image $I(x,y)$ by α and β pixels along the horizontal and vertical axes correspondingly, described on the plane Ω.

Homogeneity (H): This assess estimates the homogeneity accurateness in terms of matching areas among the ground truth and result areas

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \qquad (22)$$

Information Measures of Correlation (1) (IMC_ (1))

Extract Information Measure of Correlation 1 property of the input GLCM.

$$IMC\_(1) = \frac{H(X,Y) - HXY1}{max\{HX, HY\}} \qquad (23)$$

$$\text{Where } p_x(i) = \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) \qquad (24)$$

$$p_y(j) = \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) \qquad (25)$$

$$HX = -\sum_{i=0}^{N_g-1} p_y(i) log\,(p_x(i)) \qquad (26)$$

$$HY = -\sum_{i=0}^{N_g-1} p_y(i) log\,(p_y(i)) \qquad (27)$$

$$HXY = -\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)\, log\,(p_{d,\theta}(i,j \qquad (28)$$

$$HXY1 = -\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)\, log(p_x(i)p_y(\qquad (29)$$

where HX be the entropy value X coordinates of the image , HY be the entropy value Y coordinates of the image, HX be the entropy value XY coordinates of the image, HX 1 be the entropy value XY coordinates of the image with information measure of correlation 1.

Information measures of correlation (2)(Imc(2))

$$Imc(2) = \sqrt{(1 - exp\,[-2.0(HXY2 - HXY)} \qquad (30)$$

HX 2 be the entropy value XY coordinates of the image with information measure of correlation 2.

4. EXPERIMENTATION RESULTS

In this section measure the performance accuracy results of the proposed preference learning model by experimenting it to Web353 dataset samples.

Dataset: In order to measure the results of PLM and PLM-GLCM designed for reranking ability evaluation, we perform experiments on a large scale publicly available search dataset "Web353", collected by means of Krapac et al. [13]. This Web353dataset contains of 71,478 images revisit by means of the French search engine Exalead1 designed for 353 search queries, which were sampled beginning the a large amount frequent terms investigated by means of Exalead users. These 353 queries are extremely various and cover a wide range of topics, together with landmark, painting, map, logo, flag, movie, sports, singer star, vehicle, instrument, building, sports tool, etc.,. Queries are rather consistently dispersed across these topics. Designed for each user given query, there are regarding 200 images returned by Exalead.

Prediction accuracy (AC):

AC = #Correctly predicted queries/ #Total queries In addition to this overall accuracy, also determine the prediction accuracy P_+, P_ for user given positive and negative queries. P_+= #Correctly predicted positive queries/ #Total positive queries P_=#Correctly predicted negative queries/ #Total negative queries

Samples	Methods	AC (%)	P+ (%)	P- (%)
20	SVR	73.63	93.21	17.24
	PLM	75.93	96.27	39.08

	PLM-GLCM	82.51	96.81	41.25
40	SVR	75.63	78.63	18.39
	PLM	79.81	94.28	43.20
	PLM-GLCM	83.86	95.25	45.83
60	SVR	77.96	91.98	28.58
	PLM	82.58	92.15	48.81
	PLM-GLCM	83.94	93.62	51.63
80	SVR	73.52	86.51	28.57
	PLM	82.91	91.87	50.68
	PLM-GLCM	86.83	92.43	52.81
100	SVR	73.94	83.21	40.51
	PLM	84.25	92.46	52.53
	PLM-GLCM	89.81	93.56	53.97

Table 1: Correlation Coefficients and Accuracy in Reranking Ability Assessment

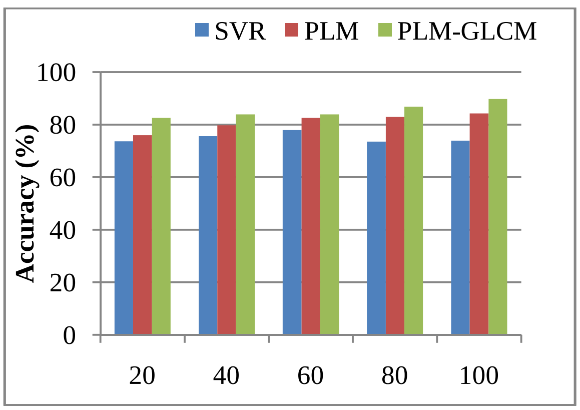

Figure 1: Prediction accuracy comparison

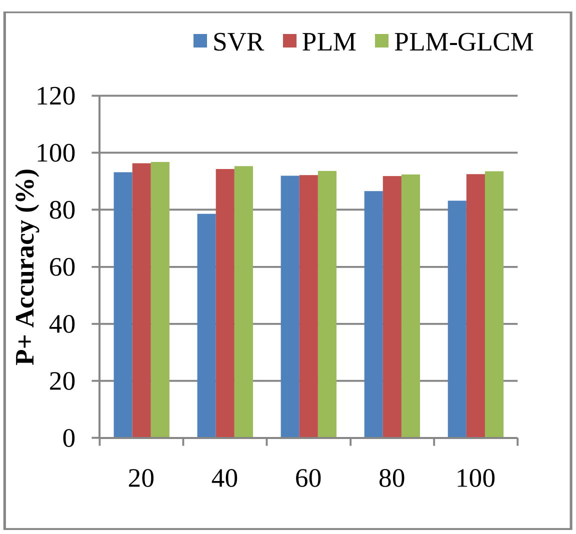

Figure 2: Prediction accuracy for positive queries comparison

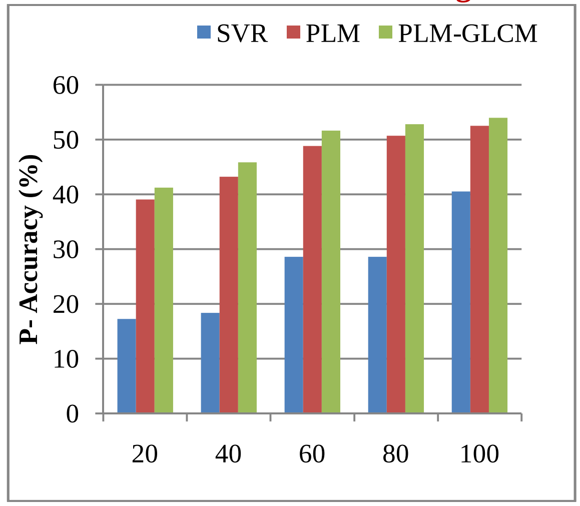

Figure 3: Prediction accuracy for negative queries comparison

The results of the above mentioned parameter is discussed in table 1 and illustrated in Figure 1, 2 and 3 , it shows that the proposed PLM-GLCM performs best when compare to existing methods.

CONCLUSION

Specified the explosive development of the web usage and the use of image sharing Web sites, image retrieval cooperate a gradually more significant role in the current days. Several investigations have been introduced in recent work toward recover images appropriate to a user specified query. The major contribution of the paper consist of three major steps: at the initial stage of the work, a classification model based on user preference is formulated to find the most excellent image search result list classification problem. At the second step most important features such as visual and texture features are extracted from the returned images. The proposed preference based learning model extract a valuable visual and texture features to repeatedly evaluate the quality of retrieved image search result lists. Third, a query based preference classification model is created based on the user specified query. Experimental results demonstrated that the proposed model have achieves high retrieval results and its capable applications on reranking feature, texture features and model collection, merging of image search results, as well as query submission. The scope of the future work is to apply the present model to other potential applications, e.g., query suggestion, query recommendation, query language selection and so on.

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