AN AUTOMATIC PERSONALIZED PHOTO RECOMMENDATION SYSYTEM BASED ON IMAGE VISUAL QUALITY AND USER PREFERENCES

A Dissertation submitted in partial fulfilment of Credit of Dissertation

Requirement for the award of the degree

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By

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DECLARATION

I declare that the work presented in this dissertation with title, "**An Automatic Personalized Photo Recommendation System Based on Image Visual Quality and User Preferences**", towards the fulfillment of the requirements for award of the degree of **Master of Technology** in **Computer Science & Engineering**, submitted to the **Department of Computer Science and Engineering, Indian Institute of Technology-Roorkee**, India, is an authentic record of my own work carried out during the period from June 2015 to May 2016 under the guidance of **Dr. Balasubramanian Raman** , Associate Professor, Department of Computer Science and Engineering, Indian Institute of Technology, Roorkee.

The matter presented in this dissertation has not been submitted by me for the award of any other degree of this or any other institute.

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CERTIFICATE

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Abstract

This paper presents an automatic personalized photo recommender system which recommends photos from a large collection. Our proposed system recommends photos based on user-preferences about aesthetics and visual quality features of the photo. A large dataset has been put together, which has been used to collect user-preferences. A random forest based learning system has been invoked to learn the user preferences about different image features including aesthetic features. The system is validated using a part of the collected user preferences as ground truth and it has been compared to a random selection of photographs. Our automatic system significantly outperforms the random selection, which shows the usefulness of our proposal, especially when the collection of photos is manually unmanageable.

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Dedication

To my family, for supporting and believing me always

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CHAPTER 1

INTRODUCTION

1.1 Overview

In Today's internet world, there is a large amount of digital data. Searching data from such a large database is a very time-consuming task. Recommender system is one of the solutions to this problem. The recommender system suggests items to users from a large storage of items, reducing searching time for users, and increases the performances of several businesses like e-commerce sites like Amazon, Flipkart etc. and social networking sites like Facebook, Twitter. There are various applications of recommender system in day to day life like restaurant, tourist, movies, music, and photo recommender system.

1.2 Motivation

With an increasing availability of digital cameras, there is an explosion in the generation of personal photographs and their collections. Generally, a photo collection contains hundreds to thousands of photographs. There are several digital photo management systems available commercially, which allow various ways to organize, browse and search photographs. Shoebox [6] is an example software package which provides a range of browsing and searching facilities.

As the social media is growing rapidly with more and more people connecting through it, flooding of digital data happens on these social networking sites. People nowadays like to share each and every moment of life with their friends and relatives. This gives a motivation to perform research and develop techniques which can recommend user on what to share on these social networking sites according to their interests and preferences.

Although research has been done in managing and browsing personal photographs [6], hardly any attention has been given on selection of photographs taken on various events for sharing it with friends and relatives on social media. Given the large number of photographs taken in an event, it is imperative that an automatic recommendation system is present that can suggest photographs to user from an event like wedding, trip, etc., according to user's choice, for sharing.

1.3 Problem statement

☐ To propose a novel personalized photo recommender system that suggests photographs from a large number of photographs. Recommendation is based on user-preferences about visual features of the photo.

☐ To improve the performance of the proposed system.

☐ Proposed system is also compared with a baseline system, i.e. Random system that selects recommend images selected randomly to users. Our Proposed system outperforms the Random system.

1.4 Contribution

☐ This system provides personalized recommendations to users based on learning user-preferences about visual features and aesthetics. This system would be very helpful for next-level of personalized recommender system.

☐ The proposed system is compared with a random system, shows significant improvement over it.

☐ The performance of the proposed system is improved by taking user-feedback and incorporating a system based on aesthetic with the system. This helps recommender system in providing a more personalized list of recommendations.

1.5 Organization

The dissertation comprises of five chapters:

☐ Chapter 1 introduces the overview of recommender system and their applications. We briefly formulate the problem and summarize the contributions made in this dissertation.

☐ Chapter 2 reviews the work related to recommender system based on image features and give a brief description about their advantages and limitations.

- Chapter 3 proposed an automatic personalized photo recommender system based on image visual quality and user preferences.In this chapter, components of the proposed system like user-input, feature extraction, training described one by one.

- Chapter 4 compares the performance of Proposed system with Random system. Results are taken on twenty different users and it is shown that the proposed system outperforms Random system for all users. Furthermore, the proposed system is enhanced by implementing some observations, observed through few experiments. The result shows the accuracy of the proposed system with enhancement perform better than proposed system without enhancement.

- Chapter 5 summarizes the dissertation and provides some open problems in this area for future extensions of this work.

CHAPTER 2

RELATED WORK

Our proposed system is a novel system. So there are no systems which are exactly similar to the proposed system. But, we have a few systems in literature that suggest items to the users based on photograph similarity as our system does . In this chapter ,such systems are described briefly.

2.1 Image based shoe recommendation system

This recommendation system [2] suggests images of shoes that are similar to user-query.User-query can consist either an image of shoe or keyword to describe shoe.This system recommends shoes using the generic property like color,shape ,and texture of shoe image. This system consist a huge dataset of shoe images,collected from Zappos.com. In the beginning of algorithm, shape similarity is computed.It is calculated using k-mean clustering approach. Some top images from previous phase is undergone to texture similarity phase,it is calculated by comparing local binary pattern(LBP) histograms of sub-divisions of query image and another image in the dataset. Some top images from the previous phase undergoes to color similarity phase, it is also determined using clustering approach.Experimental results shows that,this system has good accuracy.

Basically,this system uses the content of shoe image to recommend similar kind of images to user-query. This system is based on unsupervised learning.It is not taking user–preferences into account, not providing a personalized list of recommendations.It is just a image retrieval system similar to user-query.

2.2 Image content in location based shopping recommender system for mobile-users

This system [3] is a mobile based recommender system.It provides similar kind of shopping items with their GPS(global positioning system) locations in respond to the user-query.User-query consists of image with smart phone GPS coordinates.System provides a list of recommended items with their GPS coordinates based on generic content of images with an additional feature like GPS.

This system searches the items with respect to image given as user query, thus reducing text and spelling errors. It is also not providing a personalized list of items because it is not learning user-preferences.It is more or less similar to shoe recommender system [2] except it uses GPS for recommending items.Personalized list of items can be provided by taking user feedback into account.

2.3 Tourist recommender system

This system[5] recommends tourist places based on visual quality of images in respond to user-query.User query consists either an image of a location or keyword that describe location of image.System have large collection of geo-tagged photographs,grouped by locations.It finds the representative image from each geotagged clusters using clustering approach.Query image is compared with representative images to provide final recommendations.It is also based on unsupervised learning.It does not take user-feedback into account to refine recommendation list.

2.4 Context-aware photo recommendation system

This system [7] is mobile based photo recommender system that used context of user ,means location of user and the context of the photo like date,time and location at which picture is created. This system works on the metadata annotated with images available on photo sharing sites like Flickr® and Picasa® web .Location of the user is captured using GPS. User ask some images by giving keyword that describes the image, then the system capture location of the user (GPS coordinates) and recommend those images which are visually similar and taken into similar context as the query context.

This system is also based on keywords associated with image .It is difficult to associate keyword to each photograph in your personal collection of photographs and automatic annotations of keywords to image is an open research problem [manage].It is impossible for the system to provide personalized recommendations for collection of photographs which do not have keywords associated to them.This system[7] is not personalized as two or more users who are having same query and share same context, then system recommend the same thing to the users.

These system are like content based information retrieval system, that gives results similar to the user query. Obviously, such image similarity based system discussed above are not applicable for the purpose of recommending photographs for sharing in social media,especially when it is targeted to be a personalized one. If information provided to the users are not personalized one, a user may have to search through large collection of data to get the desirable results, requiring considerable amount of time and effort .

To provide personalized recommendation,user-profile need to build based on user-preferences. A very close system to our proposed system is Image based travel recommender system [19] provides personalized travel destinations based on user profile .User-profile is created based on socio-demographical data like age, gender etc. ,duration of visit,way of visit and preferences.These data is collected beforehand from user. Few preferences are drawn from set of photographs related to destination with explicit information related to users .Our proposed system is different than this system in the way of developing user-profile.In our system,user-profile built based on user-preferences collected through some set of image provided to user.

In this thesis, we would propose a novel personalized photo recommender system that recommends images after learning user’s interests about features in the image.Dataset of this system consists of photographs with no keywords associated with them, overcoming the limitations of the above described system.

CHAPTER 3

PROPOSED WORK

3.1 Overview of proposed work

In this work, an automatic personalized photo recommender system based user preferences about image visual quality is proposed. The architecture of the proposed photo recommendation system is shown in Fig. 3.1. The system suggests photos to users based on their preference about features such as color, texture and aesthetic features like low depth of field etc..Our system is based on supervised learning which takes input from users in the form of preferred images, extract elementary features and aesthetic features from these images and train the system to learn users' basic and aesthetic interests in images.

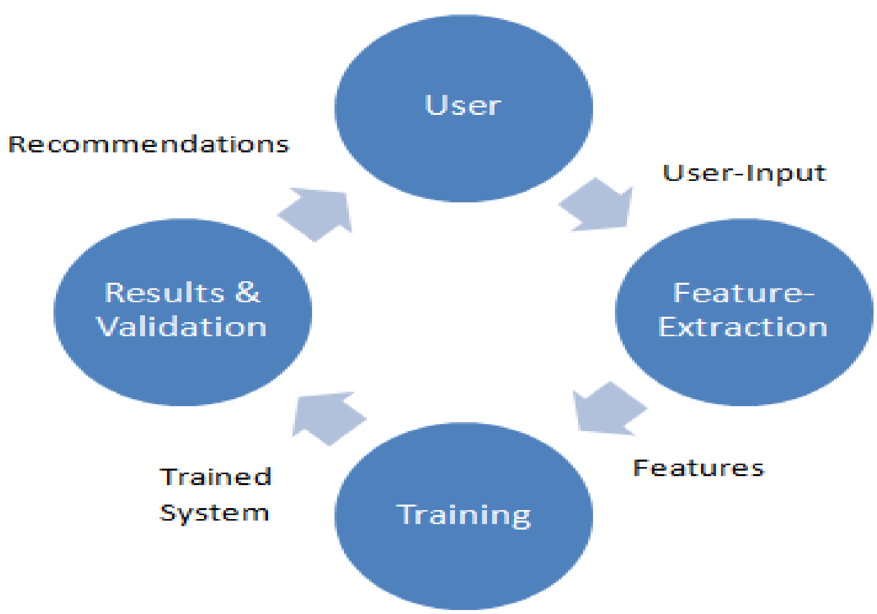

Fig.3.1 - Architecture of our proposed model.

The system is trained considering images from a few sample categories of them that come with the system. A sample category is formed by selecting two hundred images collectively having highest entropy (more dissimilar) from a thousand top images obtained through a Google® image search. The supervised learning approach used is the random decision forest, which grows a multitude of decision trees to train the system.

This trained system is used to provide the results for various users taking into account their interests. System performance is evaluated by its accuracy. Accuracy of system is frequently used for classification problem [17].Accuracy is fraction of correct results to the total results produced by system. The correct results are checked against the ground truth data (preference of user on a dataset other than training dataset) collected from the user.

Here, recommendation is provided to users based on learning user-preferences. Further improvement will be done by implementing some observations observed through performing some experiments.

3.2 User Input

In order to assist users for selecting photographs of their preference from large dataset of photos, we propose an automatic recommendation system which selects a small (user-defined) number of images as representatives of the large dataset.

The system is accompanied with ten different sets of two hundred images (total two thousand images) representing ten categories. The two hundred images in each category are selected from the top thousand retrieved through a Google® image search. This selection was based on the computation of an entropy value which gives the overall dissimilarity within the set of two hundred images considered. The two hundred images which yield the maximum entropy value were selected.

To calculate the entropy value, color and edge histogram of each photograph is calculated, and the histograms for all selected two hundred photographs are summed up. Edge histogram is computed based on Canny's edge operator. Entropy of a summed up histogram is computed using the formula

$$H = -\Sigma(p_i.* log(p_i)) \quad (1)$$

Where, p_i is a probability obtained by normalizing the histogram.

This way we get two hundred images of each category, which is accompanied with the system. When a system is to be used by a user, these ten categories of selected photographs are given to the users and they are asked to select twenty images from them according to their preference. So, from the ten categories a total of two hundred images are preferred and selected by the user. The system then automatically chooses two hundred more images from dataset that user did not like.

Then these four hundred photographs, with two hundred each marked as preferred and not preferred, are given as input to the next phase where feature extraction takes place. Fig. 3.2 depicts this whole procedure described above.

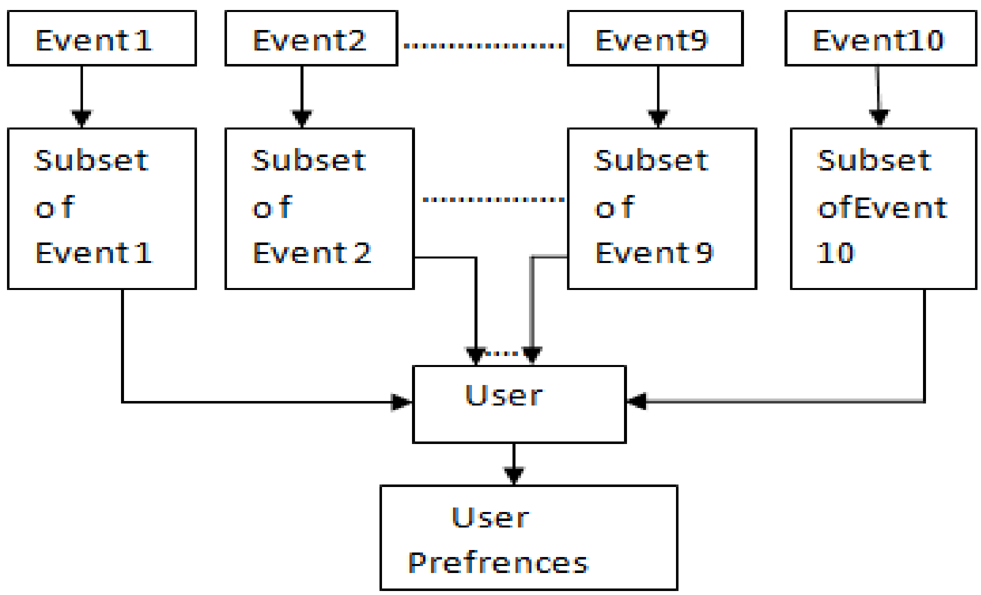

Fig .3.2 - User-Input phase of Proposed Photo Recommender System

3.3 Feature Extraction

Features required for the recommendation process of the system are shown in Fig. 3.3. Features that are used to classify objects are categorized into two categories. One category contains the basic features of image. Basic feature of image mainly consist of color and texture of image. Both these features found important in classification process.Second category is based on aesthetics. Aesthetics are basically appreciation of beauty and it is very subjective. We relate user-preferences to basic content and aesthetic of photos.

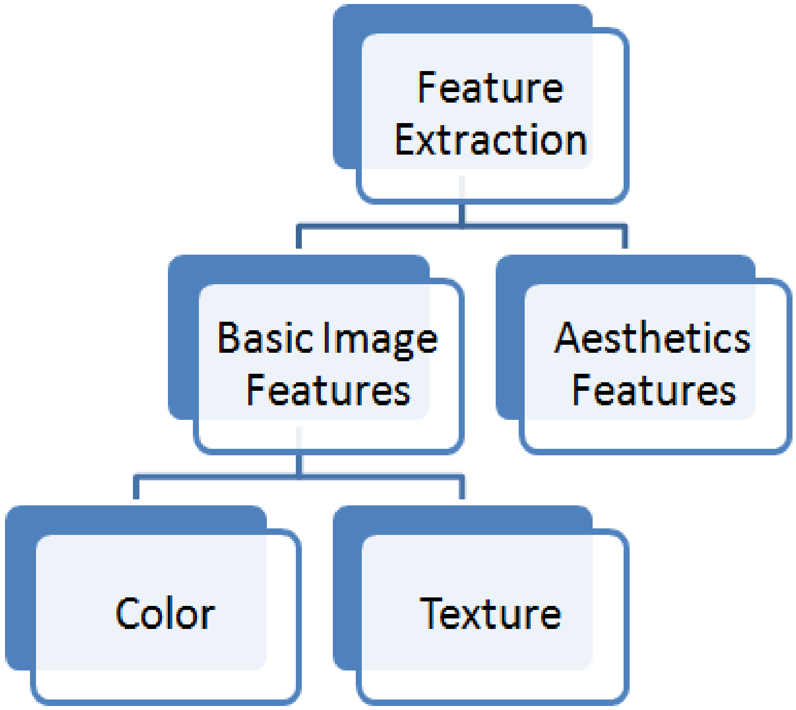

Fig. 3.3 Feature-Extraction phase of photo recommender system

Color of photo is computed using two approach,one is based on the RGB values of image ,will be explained later and another is based on CIE L*U*V color space. We computed color value for an image is computed by taking average of values along L,U and V field in the CIE L*U*V colorspace of image.

$$\text{Color} = (L + U + V)/3 \tag{2}$$

Texture of image is computed using haralick's texture features and local binary pattern. Haralick's features are computed using equations explained in Table 1.

Table 1: Haralicks Texture Features based on gray-scale co-occurrence matrix

Texture Features	**Equations**
Angular second Moment	$\sum_i \sum_j \{s(i,j)\}^2$
Contrast	$\sum_{n=0}^{t_{g-1}} n^2 \{\sum_{i=1}^{t_g} \sum_{\substack{j=1 \\ \lvert i-j \rvert = n}}^{t_g} s(i,j)\}$
Correlation	$\frac{\sum_i \sum_j (i,j)\, s(i,j) - \mu_x\, \mu_y}{\sigma_x\ \sigma_y}$
Variance	$\sum_i \sum_j ((i - \square)^2) s(i,j)$
Inverse difference moment	$\sum_i \sum_j \frac{s(i,j)}{(1 + (i-j)^2)}$
Sum Average	$\sum_{i=2}^{2t_g} i s_{x+y}(i)$
Sum Variance	$\sum_{i=2}^{2t_g} (i - f8)^2 s_{x+y}(i)$
Sum Entropy	$-\sum_{i=2}^{2t_g} s_{x+y}(i) \log\{s_{x+y}(i)\}$
Entropy	$-\sum_i \sum_j (s(i,j)) \log(s(i,j))$
Difference Variance	variance of s_{x-y}
Difference Entropy	$-\sum_{i=0}^{t_{g-1}} s_{x-y}(i) \log\{s_{x-y}(i)\}$
Information measures of correlation	(P2–P3)/max(P,P1)
F13	(1-exp[-2[P4-P2]])^ (1/2)
Maximal correlation Coefficient	(second largest eigen value of Q)^(1/2)

Notations required to understand equations in Table 1.

s(i,j) - (i,j)th entry in a normalized gray-tone spatial dependence matrix.

$s_x\ (i)$ - ith entry in a marginal probability matrix.

t_g - number of distinct gray-levels in quantized image.

P,P1 - are entropies of s_x and s_y.

P2= $-\sum_i \sum_j (s(i,j))\log(s(i,j))$

P3= $-\sum_i \sum_j (s(i,j))\log(s_x\ (i)\ s_y\ (j))$

P4 $= -\sum_i \sum_j (s_x\ (i) s_y\ (j))\log(s_x\ (i)\ s_y\ (j))$

Easily computable texture feature has general applicability for a wide variety of image classification application [4]. Haralick's texture features are based on gray-tone spatial dependencies which uses 14 texture features for image classification.Local binary pattern operator has also emerged as powerful tool for texture classification since its development[11]. It is a rotation invariant and computationally inexpensive technique to compute texture of image[8][9].

Algorithms for computing LBP feature vector is based on the use of local windows of size 3x3 as shown in Fig. 3.4. The examined window is divided into cells. Feature vector of a pixel in a cell is calculated, by thresholding the pixel values in the neighborhood of a pixel. The value of the pixel is greater than the value of central pixel is threshold to 1 and smaller than value of central pixel threshold to 0.Thus ,value of central pixel is given by 8-digit binary number by taking the values in a clockwise or anticlockwise manner. For convince, this value is converted into decimal numbers. Fig.3.4 to Fig.3.6 explains the whole procedure illustrated above.

100	45	80
59	50	115
201	185	30

Fig .3.4- A sample of 3*3 pattern of image

1	0	1
1	50	1
1	1	0

Fig .3.5- A sample of 3*3 pattern of Image after thresholding pixel values

If center pixel coordinate is (i,j), starting from p(i-1,j) in clockwise direction. we have 8 digit binary pattern 01101111.So local binary pattern of this pixel is 111 for the above central pixel in the image as shown in Fig.3.6.

	111	

Fig.3.6 -Local binary pattern value of central pixel in the given sample of 3*3 pattern of image

Then normalized histogram of each cell is computed. Feature vector of the entire window is calculated by concatenating feature vector of the normalized histogram of each cell. Various studies have suggested that the local binary pattern is very helpful in the classification process [8][9][10].

Aesthetic features of photographs are closely related to human emotions. Human emotions can play an important factor in getting good recommendation results. So, incorporating aesthetic features in recommendation process should definitely improve recommendation.

We can calculate aesthetic features computationally [1].Aesthetics of images can be measured using visual features of the image like brightness, colorfulness, average saturation, average hue, rule of third along hue, saturation and value, aspect ratio and size, wavelet texture along all levels 1st, 2nd and 3rd of hue, saturation and value, low depth of field indicator along hue, saturation and value.

3.3.1 Brightness

It is characterized using an exposure of light. Over exposure of light to photograph increase brightness and make the photograph blur and under exposure of a light turn a photograph content into black or gray shape, resulting in low quality image. So, there should be proper exposure of light to capture good photograph. As given in [1], we consider

$$Brightness = \frac{1}{XY}\sum_{x=0}^{X-1}\sum_{y=0}^{Y-1} I_V(x,y) \tag{3}$$

Where,

X – Height of Image in pixels.

Y – Width of Image in pixels

I_V (x ,y) – value of pixel along the value field of HSV plane.

3.3.2 Colorfulness

Color of photo has great impact on user mind. It is seen that colorful thing attract to users more in comparison of "monochromatic image". Colorfulness of the whole image is computed using RGB color space. As given in section 7 of [8], we consider,

$$\mathrm{rg} = \mathrm{R} - \mathrm{G} \tag{4}$$

$$\mathrm{yb} = 1/2(\mathrm{R} + \mathrm{G}) - \mathrm{B} \tag{5}$$

$$Colorfulness = \sigma_{rgyb} + 0.3*(\mu_{rgyb}) \tag{6}$$

$$\sigma_{rgyb} = \sqrt{\sigma_{rg}^2 + \sigma_{yb}^2} \tag{7}$$

$$\mu_{rgyb} = \sqrt{\mu_{rg}^2 + \mu_{yb}^2} \tag{8}$$

3.3.3 Saturation and Hue

" Saturation indicates chromatic purity. Pure colors in a photo tend to be more appealing than dull or impure ones." As given in [1], we consider

$$\mathrm{Saturation} = \frac{1}{\mathrm{XY}}\sum_{\mathrm{x}=0}^{\mathrm{X}-1}\sum_{\mathrm{y}=0}^{\mathrm{Y}-1} \mathrm{I_S}(\mathrm{x},\mathrm{y}) \tag{9}$$

$$\mathrm{Hue} = \frac{1}{\mathrm{XY}}\sum_{\mathrm{x}=0}^{\mathrm{X}-1}\sum_{\mathrm{y}=0}^{\mathrm{Y}-1} \mathrm{I_h}(\mathrm{x},\mathrm{y}) \tag{10}$$

Where,

X – Height of Image in pixels.

Y - Width of Image in pixels

I_S (x, y)- Value of pixel along the saturation field of HSV plane.

I_h (x, y)- Value of pixel along the hue field of HSV plane.

In the same manner, we can compute hue of the image using value of pixels along the hue field of HSV plane.

3.3.4 Rule of Third

A very popular rule of thumb in photography is the Rule of Thirds. Generally, photograph taken using the rule of the third is more appealing than other photographs. It specifies that, main element or the center of interest, in a photograph should lie on one of the four intersections. We compute average hue, saturation and value of this region. As given in [1], we consider

$$\text{Average Hue} = \frac{9}{XY}\sum_{x=X/3}^{2X/3}\sum_{y=Y/3}^{2Y/3} I_H\,(x, y) \tag{11}$$

$$\text{Average Saturation} = \frac{9}{XY}\sum_{x=X/3}^{2X/3}\sum_{y=Y/3}^{2Y/3} I_s\,(x, y) \tag{12}$$

$$\text{Average Value} = \frac{9}{XY}\sum_{x=X/3}^{2X/3}\sum_{y=Y/3}^{2Y/3} I_v\,(x, y) \tag{13}$$

Where,

X – Height of Image in pixels.

Y - Width of Image in pixels.

I_H (x, y) – Value of pixel along the Hue field of HSV plane.

I_s (x, y) – Value of pixel along the saturation field of HSV plane.

I_v (x, y) – Value of pixel along the value field of HSV plane.

3.3.5 Wavelet Texture

" One way to identify texture is to use Daubechies wavelet transform[1]". On all three color bands hue, saturation and value, we apply three-level wavelet transform. There are four coefficients

LH,LL,HL and HH at each level. Wavelet feature for hue image at all three levels are computed as given in [1]

$$F_i = \frac{1}{S_i} \{ \sum_x \sum_y w_i^{hh} + \sum_x \sum_y w_i^{hl} (x,y) + \sum_x \sum_y w_i^{lh} (x,y) \} \quad (14)$$

Where, For all $S_i = |w_i^{hh}| + |w_i^{hl}| + |w_i^{lh}|$, i={1,2,3} and w_i^{hh}, w_i^{hl}, w_i^{lh} are the wavelet coefficients of hue image at ith level.In the similar manner, we can compute three level wavelet feature for saturation and hue image.

3.3.6 Low depth of field indicator

By decreasing depth of field, the photographer can focus more on a single region of interest, and blurring the background of a photo. "Computation of low depth of field indicator (LDFI) along the hue field of image is done by partitioning hue image into sixteen equal rectangular blocks and numbered the blocks $\{M_1, M_2 \dots \dots M_{16}\}$ in row major order.We computed set of wavelet coefficients at third level decomposition of hue image $w_3 = \{w_3^{hh}, w_3^{hl}, w_3^{lh}\}$." As given in [1],we consider

$$A = \sum_{i=1}^{16} \sum_{(x,y) \in M_i} w_3 (x,y) \quad (15)$$

$$B = \sum_{(x,y) \in M_6 \cup M_7 \cup M_{10} \cup M_{11}} w_3 (x,y) \quad (16)$$

By using (15) and (16) , we have

$$\text{LDFI} = A/B \quad (17)$$

In this way , we computed LDFI along hue field of image and similarly we can compute low depth of field indicator along saturation and value fields also.

3.3.7 Size & aspect ratio

The size and aspect ratio of an image has a good chance of affecting the photo ratings. As given in [1], we consider

$$\text{Size} = X + Y \quad (18)$$

$$\text{Aspect ratio} = \frac{X}{Y} \quad (19)$$

Where,

X – Height of Image in pixels.

Y - Width of Image in pixels.

3.3.8 Blur

Generally, a blur image tends to be of bad quality image. Blurness of image is calculated using proposed model given in [18].

Now, we have feature vector consist value of various features that would be helpful in the classification process. This feature vector obtained at this step would be the input to the next phase of system i.e. training phase of proposed system.

3.4 Training

The proposed recommendation system uses a random forest classification algorithm for improved results, as it is an ensemble classification technique that consists of many classification trees [12][13]. Random Forest's model performance is better than single classification tree as it is less sensitive to noise in the training set. It reduces the error by averaging all errors produced by the classification trees in random forest.

This model is based on bagging as it randomly selects a sample of data from the training set to create classification trees. It is also based on the random subspace method as best attribute is selected from randomly selected attributes for each split at node of decision tree[15]. Gini index is used to find best attribute from the set of random attributes for the split. "Typically for a classification problem with p features, $\sqrt{p}$ (rounded down) features are used in each split" [14].Output classes would be leaves of the tree and it does not prune the trees.

To evaluate efficiency of our proposed system over random system, we perform an experiment for 20 different users. In experiment, for each user we have training dataset based on their choice. The proposed system is trained using random forest model.

Algorithm of Random forest model to train the system–

Input- Training dataset, number of classification trees.

- It randomly selects a sample of data point called as bootstrap sample from the training set, that would be used to create classification trees. This process is repeated for creating all classification trees in forest and it is also known as bagging.

- For growing classification tree, it randomly selects a number of features at each node of the tree. Best attribute is selected using gini-index from the list of attributes selected randomly.

- In this way, classification tree grows and leaves of tree would be labeled as classification class. There are two labels for classification class in our system. Label from one of them is ‘y’, means preference of user and other label is ‘n’, not the preference of user.

There are only two parameters that can affect the performace of system based on random forest model. One is the number of classification trees and other is randomly selected attributes for the split at node. To find appropriate number of classification trees to train the system using random forest model is tedious. Suppose, we have a large value of classification trees,let’s say it c to train the system. Such system is giving x% accuracy and using y% computational cost. Now, we trained the same system with a value of classification trees less than c. This system is accuracy is close to x% and its computational cost to train the system is very less than y%. Performance of system trained using random forest model can be calculated with oob (out of bag) error estimates. As, random forest model is based on bagging. So, in each bootstrap sample some data points from training dataset left over each time, treated as test dataset to calculate out-of bag error of predictions. For oob error estimates for a particular number of trees in random forest, we aggregate the values of oob predictions obtained through many runs of bootstrap iteration[26]. So, high value of oob error estimates means weak performance of system, and vice-versa.

So, if we see accuracy of system as criteria to judge performance of system, then system trained with large value of classification trees is good and if we see computational cost as only criteria to judge performance of the system, then system trained with small value of classification tree would be great. To get good performance of system, we need a value of classification trees which can maintain the balance between accuracy of system and computational cost to train the system.

Choosing a number of classification trees in random forest for all users is difficult. As performance of system for a particular number of trees could be different for different users. We evaluate performance of the system using oob(out of bag) error estimates, less value of oob error estimates means the high prediction accuracy of system.oob is an error estimates on the training dataset as in each bootstrap sample some data points left over. So, the system can be easily tested on these left over data points. For oob error estimates for a particular number of trees in random forest, we aggregate the values of oob predictions obtained through many runs of bootstrap iteration[19].

We calculated aggregate oob error on the training dataset by taking different values of classification trees like 5, 10, 20, 40, 60, 80, and 100 in random forest model to train the system.Table 2 and Table 3 shows the aggregate oob error for various values of classification trees in random forest model for user 1 and user 2 respectively. Difference in calculated aggregate out of bag error estimates for these values of classification trees is very small, as we can see in Table 2 and Table 3. So, Instead of choosing one appropriate value of classification tree in a random forest model, we train the system using all these values of classification tree and predict results for unseen objects. We have an array score containing percentage of positive class of predicted results. The score array is sorted in descending order. Total number of images asked by user is recommended in the order of their decreasing scores.

Table 2 . Aggregate out of bag error results for different values of classification trees in random forest of user 1

Classification Tree	**Aggregate out of bag error**
5	0.1525
10	0.1350
20	0.1050
40	0.1050
60	0.1
80	0.0975
100	0.1025

Table 3 Aggregate out of bag error results for different values of classification trees in random forest of user 2

Classification Tree	**Aggregate out of bag error**
5	0.1875
10	0.1650
20	0.1450
40	0.1375
60	0.1400
80	0.1300
100	0.1250

Each tree gives a classification, that is, it votes for an unseen object from input vector to be in a class. The classification class which is having highest vote is selected as class for that object. If two classification classes have the same number of votes, then tie is broken by selecting any classification class randomly.

Using the random forest model to train our proposed system has various advantages over other classification system. Performance of random forest's model is better than single classification tree as it is less sensitive to noise in the training set. It reduces the error by averaging all errors produced by the classification trees in random forest. It is matchless in correctness among current algorithms [15]. It can handle thousands of attributes easily. It is very fast and efficient method for training large data.

CHAPTER

4

EXPERIMENTAL SETUP AND RESULTS

4.1 Dataset Collection

We have collected photos for 10 different types of category which are vehicles, events, food and culture, architecture, fashions, fruits, nature, tourist, wedding, and wildlife. Each category contains thousand images. So, we have 10,000 photos in our dataset of different variety. Training dataset consists of user-preference from sample of photos which are extracted using entropy based technique and user-dislikes. In our training dataset, we have 400 photos in which 200 photos are as per user-preference and another 200 are due to user-dislikes.

To validate system performance, we retrieved 200 photos through a Google® image search known as test dataset. So, for testing purpose, we collected top 20 photos of user preference from test data set, known as ground truth data. Correctness of recommendations provided by the system will be computed by comparing the results with the ground truth data.

4.2 Experimental Results

Fig.4.1 (a) . Preferences of user 1

Fig. 4.1(b). Results(one sample) produced by our proposed algorithm for user 1

Fig. 4.1 (c). Results (one sample) produced by a random algorithm for user1

Fig .4.1 Recommendations for user 1 (a) Preferences of user 1, (b) shows results(one sample) produced by our proposed algorithm for user 1 and (c) shows results(one sample) produced by random algorithm for user 1

Fig.4.2 (a) . Preferences of user 2

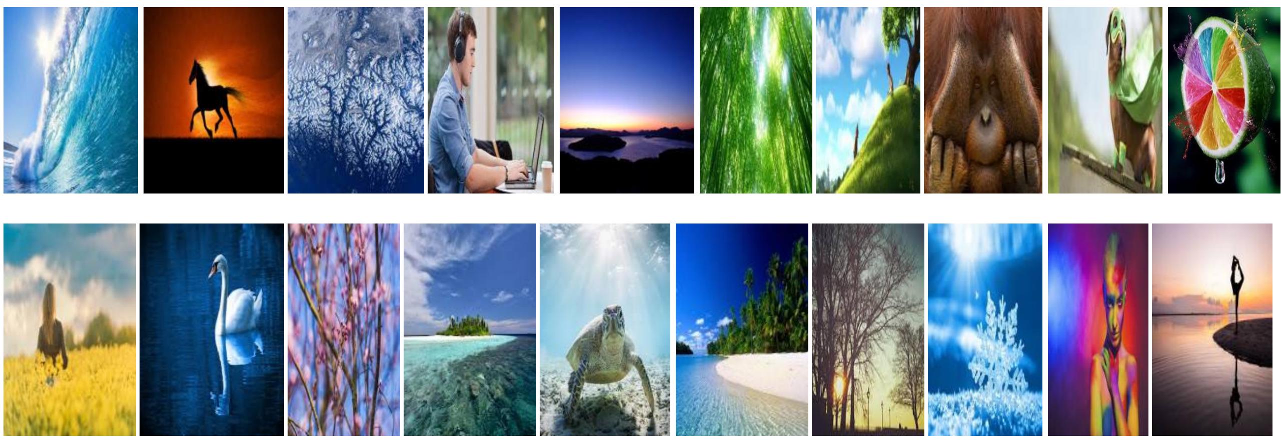

Fig. 4.2 (b). Results(one sample) produced by our proposed algorithm for user 2

Fig. 4.3 (c). Results (one sample) produced by a random algorithm for user 2

Fig .4.2 Recommendations for user 2 (a)   Preferences of user 2, (b) shows results(one sample) produced by our proposed algorithm for user 2 and (c) shows results(one sample) produced by random algorithm for user 2.

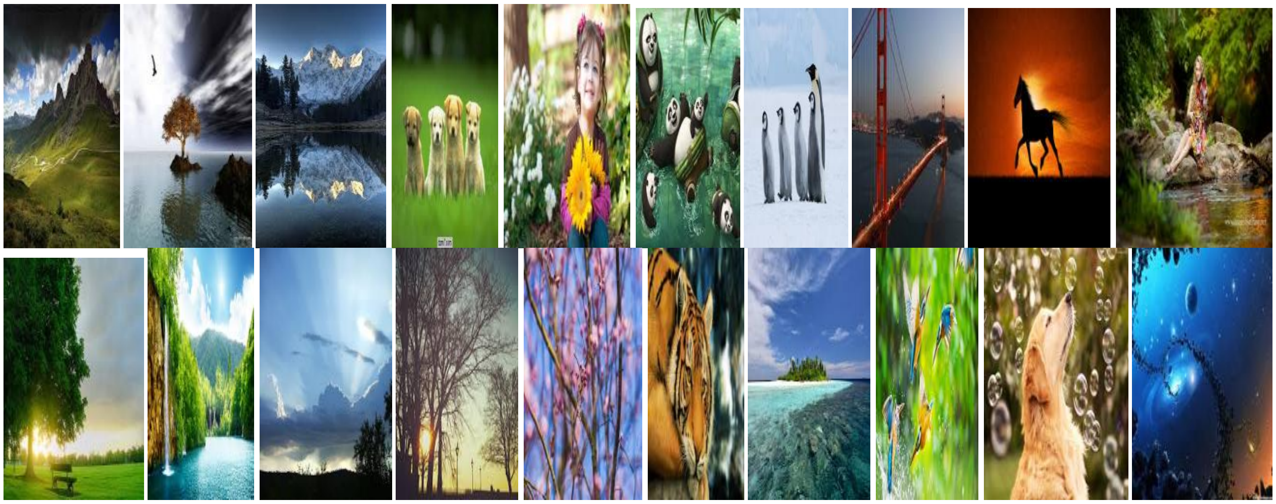

Fig.4.3 (a) . Preferences of user 3

Fig. 4.3(b). Results(one sample) produced by our proposed algorithm for user 3

Fig. 4.3 (c). Results (one sample) produced by a random algorithm for user 3

Fig .4.3 Recommendations for user 3 (a) Preferences of user 3, (b) shows results(one sample) produced by our proposed algorithm for user 3 and (c) shows results(one sample) produced by random algorithm for user 3.

Fig.4.4 (a) . Preferences of user 4

Fig. 4.4(b). Results(one sample) produced by our proposed algorithm for user 4

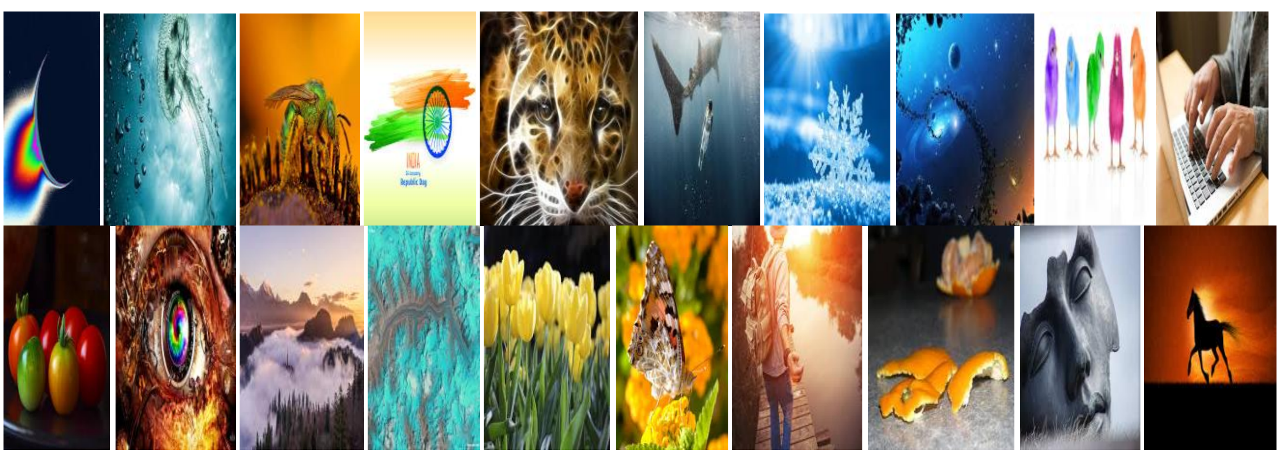

Fig. 4.4 (c). Results (one sample) produced by a random algorithm for user 4

Fig .4.4 Recommendations for user 4 (a)   Preferences of user 4, (b) shows results(one sample) produced by our proposed algorithm for user 4 and (c) shows results(one sample) produced by random algorithm for user 4.

Fig.4.5 (a) . Preferences of user 5

Fig. 4.5(b). Results(one sample) produced by our proposed algorithm for user 5

Fig. 4.5 (c). Results (one sample) produced by a random algorithm for user 5

Fig .4.5 Recommendations for user 5 (a) Preferences of user 5, (b) shows results(one sample) produced by our proposed algorithm for user 5 and (c) shows results(one sample) produced by random algorithm for user 5.

4.2.1 Experiment 1

The aim of this experiment is to evaluate the accuracy of the proposed system with training dataset. We train the proposed system using training dataset . We take some data from the training dataset as test dataset to check accuracy of the proposed system.We computed the accuracy of the system using (20).Tp + Tn are the correct results provided by system. It is calculated, by comparing results provided by system to the ground truth data.p+n are the total results provided by system.As given in [17],the accuracy of the system is,

$$\text{Accuracy} = (Tp + Tn) / (p+n) \tag{20}$$

Where,

Tp = true positive,

Tn = true negative,

p = true positive + false negative,

n = false positive + true negative

We perform this experiment with 20 users.Accuracy of the proposed system on a part of training dataset is shown in Table 4 for 10 users. Accuracy of the proposed system is very high for different users. It has found from this experiment that the system is trained accurately as it is giving results with less errors. It means system has learned user-choices correctly, so it lays the foundation for the promising results on unseen dataset by our proposed system.

Table 4. Accuracy of proposed system on training dataset

User	Accuracy of proposed system (in percentage)
1	100%
2	100 %
3	99.5 %
4	100 %
5	99 %
6	100%
7	99%
8	99.5%
9	99%
10	100%

4.2.2 Experiment 2

The aim of the experiment is to find the performance of our system on unseen data. We perform this experiment with 20 users.The accuracy of the system is shown in Table 5 for ten different users.

Table 5. Accuracy of proposed system on unseen dataset

User_Number	Accuracy of Proposed System
1	46%
2	42%
3	36%
4	40%
5	33%
6	40 %
7	50%
8	35%
9	45%
10	60%

Fig. 4.1 to 4.5 shows the results for five different users. Fig 4.1-4.5(a) shows the preferences of users ,Fig 4.1-4.5(b) shows results provided by our system, and Fig.4.1-4.5(c) shows results provided by random system.

We compare our proposed algorithm to ‘Random algorithm’ for recommending photos. ‘Random algorithm’ randomly selects photos and recommends photos to the user.

Fig.4.1 shows the recommendations provided to user 1.Fig.4.2 shows recommendations provided to user 2.Fig.4.3 shows recommendations provided to user 3. Fig.4.4 shows recommendations provided to user 4. Fig.4.5 shows recommendations provided to user 5. Our proposed algorithm is giving more accurate results in comparison to random algorithm.In Fig.4.1 (b) , user finds 10 images useful out of 20 images recommended to user in one sample,thus giving accuracy of 50%.while, accuracy of random system is 15 % in Fig.4.1(c).One can see from Fig.4.1 to 4.5 that our proposed system outperform random system as accuracy of our proposed system is more than accuracy of random system.Fig.4.1 to 4.5 shows one sample of results for both the algorithm.Overall accuracy of proposed system for user 1 is 46 % and accuracy for random system is 25 %. Fig .4.2 (b) shows one sample of results provided by our proposed system for user 2 and accuracy of it is 45,while accuracy of one sample of results provided by random system is 15%. Fig .4.3 (b) shows one sample of results provided by our proposed system for user 3 and accuracy of it is 40%, while accuracy of one sample of results provided by random system is 15%. Fig.4.4 (b) shows one sample of results provided by our proposed system for user 4 and accuracy of it is 45% ,while accuracy of one sample of results provided by random system is 20%. Fig.4.5 (b) shows one sample of results provided by our proposed system for user 5 and accuracy of it is 30% ,while accuracy of one sample of results provided by random system is 20%.

Our proposed system is considering various aspects like texture, aesthetics of photos and user-preferences. These aspects are helpful in predicting results more accurately than the random method.

4.2.3 Experiment 3

The aim of this experiment is to improve performance of our proposed system. “Certain features in photographic images are believed, by many, to please humans more than certain others” [1]. Using this observation, we incorporate a system based on aesthetic features of image with our system to determine recommendations. Our modified proposed system is defined by-

$$P = (\alpha * A + \beta * B)/2 \tag{21}$$

Where,

α - Weightage given to a system based on aesthetic features only.
β - Weightage given to a system based on user-preferences only.
A - A system based on aesthetic features .
B - A system based on user-preferences.

The proposed system is combined with two systems,one of them is based on aesthetic features and other one is based on user-preferences about image visual features and aesthetics. We evaluated the performance of the system by giving different weightage to both the system.

Table 6. Accuracy of system for user 6

α	**β**	**Accuracy of proposed system (in percentage)**
0	1	40%
1	0	50 %
0.5	0.5	60 %
0.75	0.25	60 %
0.25	0.75	60 %

Accuracy of our proposed system for user 6 as shown in Table 6 is 40 % based on the preferences of user.But the performance of our proposed system can be increased by assigning different weightage to both the component systems.Performance of our system is increased to 60 %,when 50 % weightage is given to both the component systems , shown in Table 6.

Table 7. Accuracy of system for user 12

α	**β**	**Accuracy of proposed system (in percentage)**
0	1	55 %
1	0	50 %
0.5	0.5	60 %
0.75	0.25	70 %
0.25	0.75	65 %

Table 8. Accuracy of system for user 11

α	**β**	**Accuracy of proposed system (in percentage)**
0	1	60 %
1	0	70 %
0.5	0.5	70 %
0.75	0.25	65 %
0.25	0.75	70 %

The performance of such system (combination of aesthetic system and system based on user-preferences) for user 12 is very high i.e. 70% at α=0.75 and β =0.25(by giving 75 % weightage to system based on aesthetic and 25 % weightage given to other component system), shown in Table7.Sometimes, performance of system based on the preferences of user can be decreased also shown in Table 9,but we can use the best combination of weightage value to improve performance of such weighted system.

Table 9. Accuracy of system for user 16

α	**β**	**Accuracy of proposed system (in percentage)**
0	1	35 %
1	0	25 %
0.5	0.5	20 %
0.75	0.25	15 %
0.25	0.75	20 %

In the above shown Table 6-8, performance of system based on preferences is improved by assigning weightage to system based on aesthetic and preferences of user.Performance of the system based on preferences can be improved by incorporating it with system based on user-preferences and vice-versa.As shown in Table 7,10-11, performance of aesthetic system is also increased by combining it with system based on preferences at certain weightage.

Table 10. Accuracy of system for user 13

α	**β**	**Accuracy of proposed system (in percentage)**
0	1	35%
1	0	25%
0.5	0.5	30 %
0.75	0.25	35 %
0.25	0.75	30 %

Table 11 Accuracy of system for user 15

α	**β**	**Accuracy of proposed system (in percentage)**
0	1	55%
1	0	25 %
0.5	0.5	40 %
0.75	0.25	40 %
0.25	0.75	45 %

To achieve better performance ,we modify our proposed system incorporating it with other system based on aesthetics.

4.2.4 Experiment 4

The system provides recommendations based on preferences of user about the image visual features.But, object in the image has great impact on user-choice. If objects in the images is favourite of user or somehow attached to her ,then user is definitely going to like it. We did this experiment, to know the importance of weightage given to the features in the system and how it can improve performance of system.Table 12 shows performance of system for user 6 ,who prefer object of their interest in the image.

Table 12. Accuracy of system for user 6

α	**β**	**Accuracy of proposed system (in percentage)**
0	1	40%
1	0	50 %
0.5	0.5	60 %
0.75	0.25	60 %
0.25	0.75	60 %

We add HOG (histogram of Gradients) feature, that determine a local object and shape information in the photo by intensity gradients or edge directions. We trained our system with an additional feature i.e. HOG . The results for user 6 shown in Table 13 significantly improved over the previous system shown in Table 12.

Table 13. Accuracy of system for user 6 with HOG

α	**β**	**Accuracy of proposed system (in percentage)**
0	1	70%
1	0	75 %
0.5	0.5	65 %
0.75	0.25	65 %
0.25	0.75	65 %

For other user for e.g. user 10 ,who prefer color combination and other features over object in the image. Performance of the system with HOG shows very poor results for user 10, shown in Table 14.

Table 14. Accuracy of system for user 10 with HOG

α	**β**	**Accuracy of proposed system (in percentage)**
0	1	16.68%
1	0	30%
0.5	0.5	30 %
0.75	0.25	25 %
0.25	0.75	20 %

But, without including HOG in our system, the performance of system for user 10 is quite good as shown in Table 15.It was very high compared to the results shown in the Table 14.

Table 15. Accuracy of system for user 10

α	**β**	**Accuracy of proposed system (in percentage)**
0	1	60%
1	0	35%
0.5	0.5	40 %
0.75	0.25	40 %
0.25	0.75	35%

It is obvious that every user do not like all image features equally. For a user, some features may be more important than other features in the image. From above experiment we can see that ,if weightage were given to features of image according to user- preference in the system, then performance of system would increase significantly .

4.2.5 Experiment 5

The Performance of system can also be improved, by incorporating changing interests of users. Dynamic interests of user can be captured by user-feedback. User-feedback can be explicit or implicit. Explicit feedback is collected from the user.Implicit feedback is captured by the system without involving user. To perform this experiment, feedback of user collected explicitly in the form of relevant/non-relevant about the items recommended. For user1, the performance of the system at alpha=0 and beta=1 is 46 % and with one time user-feedback, performance of the system is increased to 55% which is a significant improvement. With the above observations, our proposed system is modified to the new system shown in Fig.4.6.

Here, we got a combined system with two approaches, one is based on aesthetic and other is based on the preferences of the user.The performance of our proposed system is improved by combining aesthetics.Fig.4.6 shows the architecture of our proposed system with improvements.

4.3 Proposed system with improvements

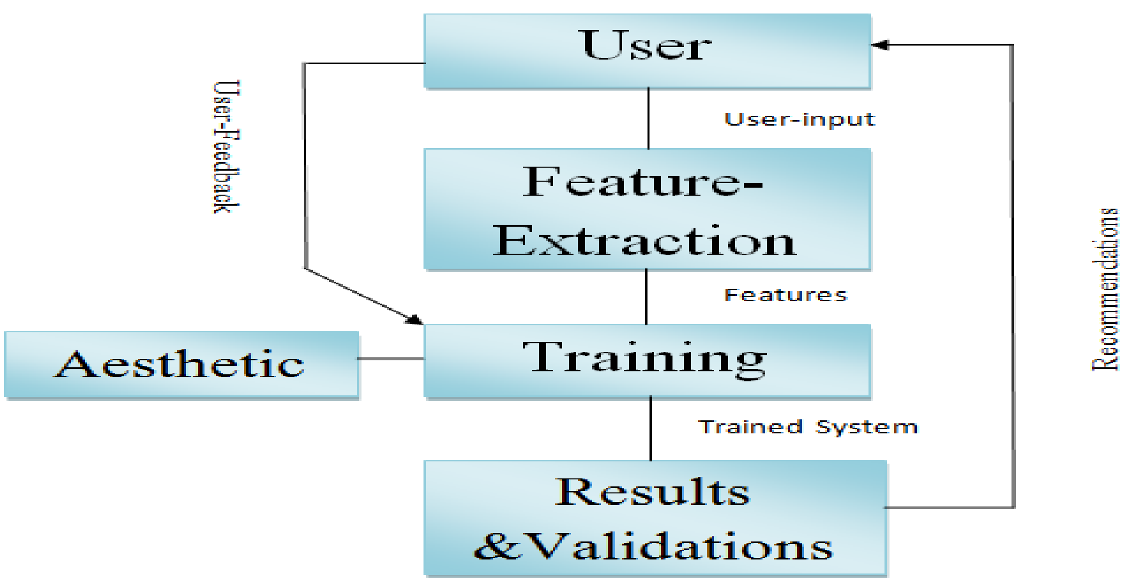

Fig .4.6 Architecture of proposed system with improvements

We observed a few things that can help in improving the recommendations given by our system. The proposed system performance is improved by incorporating it with a system based on aesthetics, giving weightage to both of the system in certain ratios. Experiment 3 shows that if we combine both the system with certain weightages, then performance of such composite system may improve.Such composite system performance depends upon the value of the weightage given to both the system. Sometime joining both the system may decrease the performance of others.But we can use the best combinations of weightages given to both the system in order to obtain best performance of composite systems.Every user has different taste about features.Some user may like features for instance color combination of image and prefer images with good color combination and other user may prefer image according to other features. So, giving weightage to different features by our system according to user-interest may increase the performance of the overall system.Experiment 4 proved that, if the system is trained with weighted feature values according to user-interest, then the accuracy of the system will improve. User- interests change over the time. The system must know the new user –interest to provide better recommendations. User-feedback is incorporated in the system to accommodate dynamic interest of user. Experiment 5 shows that including user-feedback improved the performance of the system. It helps the system in updating their knowledge about user-interests and improved its accuracy. We implemented all these observations and included them into our proposed system to improve the performance of our system. Fig. 4.6 shows our final proposed system i.e. the proposed system with improvements.It have some new features over the previous proposed system to increase performance of it.

4.4 Factors affecting performance of Proposed System

Accuracy of recommendation system depends upon the preferences given by users to create the training data set.The Recommendations provided by the system depend upon honesty of user about their choices.Suppose, user is not upright about her choices and selected her preferences randomly for creating training dataset, then recommendations provided by the system would be random,showing degradation in the performance of recommender system. For e.g. user x selects its training dataset randomly.Accuracy of system trained on such training dataset is very poor, as shown in Table 16 .It is important for the users to be fair to their preferences for creating the training dataset. User honesty and effort plays a major role in the performance of recommendation system.

Table 16. Accuracy of system for user x

α	β	Accuracy of proposed system (in percentage)
0	1	20%
1	0	25 %
0.5	0.5	20 %
0.75	0.25	15%
0.25	0.75	20 %

4.5 Comparison of Proposed System with Random System

Our system is novel, so there does not exist any system to be compared with our system. We implemented a baseline system which selects images randomly from a large collection of photos to recommend to users.Accuracy of both the system for four different users are compared, shown in Table 17-20. One can see that our proposed system outperforms a random system. Infact, in some cases difference between performances of both the system is very high.

TABLE 17. COMPARISON OF PROPOSED SYSTEM WITH RANDOM SYSTEM FOR USER 1.

α	β	Accuracy of proposed system (in percentage)	Accuracy of Random System
0	1	46 %	25%
1	0	50 %	25 %
0.5	0.5	50 %	15 %
0.75	0.25	55 %	20 %
0.25	0.75	45 %	25%

TABLE 18. COMPARISON OF PROPOSED SYSTEM WITH RANDOM SYSTEM FOR USER 2.

α	β	Accuracy of proposed system (in percentage)	Accuracy of Random System
0	1	50%	20%
1	0	35 %	25 %
0.5	0.5	40%	25 %
0.75	0.25	35 %	20 %
0.25	0.75	45 %	25%

TABLE 19. COMPARISON OF PROPOSED SYSTEM WITH RANDOM SYSTEM FOR USER 3.

α	β	Accuracy of proposed system (in percentage)	Accuracy of Random System
0	1	35%	23%
1	0	30 %	25 %
0.5	0.5	33%	15 %
0.75	0.25	30 %	20 %
0.25	0.75	33 %	25%

Table 20. Comparison of proposed system with random system for user 4.

α	β	Accuracy of proposed system (in percentage)	Accuracy of Random System
0	1	32%	25%
1	0	25 %	20 %
0.5	0.5	35%	15 %
0.75	0.25	29 %	5 %
0.25	0.75	30 %	25%

Our proposed system is considering various aspects like texture, aesthetics of photos and user-preferences. These aspects are helpful in predicting results more accurately than the random method.

We have run both algorithm for test dataset and comparison of both algorithms on 20 different users. For each user, accuracy of random system is less than accuracy of our proposed system as shown in Fig.4.7.In some case proposed algorithm performance is very good compared to random system. Random algorithm is giving results haphazardly, but our proposed system is more reliable than random algorithm due to its consistent accurate result.

This work gives an indication that such systems are useful indeed.Results show that our proposed system has significant improvement over random system.But, our system performance can be improved by incorporating more features in the system that are closely related to user-interests.To evaluate system performance at large scale,we can perform the experiment over big dataset of images with large number of users.

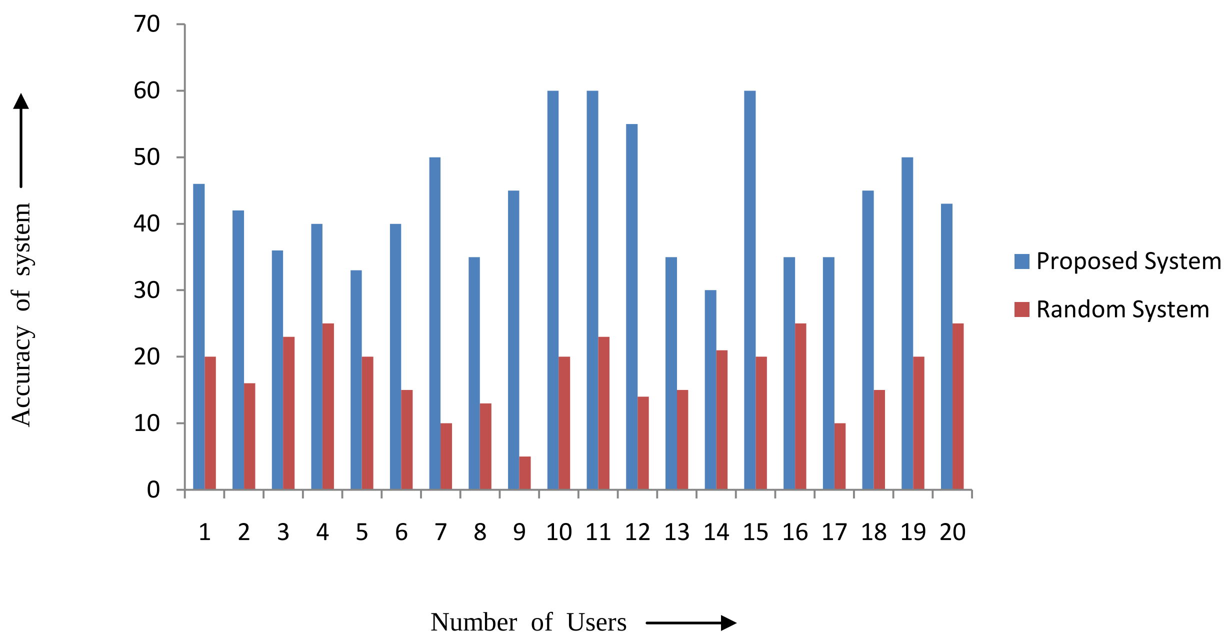

Fig.4.7 – Comparison of Proposed System with Random System at α =0 and β = 1

CHAPTER 5

CONCLUSION AND FUTURE WORK

In this thesis, a personalized photo recommender system has been presented. A large dataset has been created for this purpose.Dataset associated with this experiment contains ten different categories and each category contains thousand images. We found representative images for each category in the dataset.We collected images/data on user-preference from these representative images of each category.

Using random forest, the system learns user preferences about aesthetics and image features.Random forest model is an ensembling technique, consist of various classification trees. It is the best approach for training large dataset ,with large number of features. Its accuracy is high in comparison to single classification tree.

The System is validated by two approaches. In the first approach, a part of training dataset is kept as a test dataset to measure accuracy of system on training dataset. Accuracy of system on training dataset is very high.In the second approach , we tested the accuracy of the system on unseen data.We collected images for unseen data through Google® image search,termed it as a test dataset to validate the system.We collected images of user-preferences from the test dataset reserved as ground truth data and compared with the results produced by the proposed system to validate the system performance.

To improve performance of the system further, we observed some observations by performing few experiments and include them into the system. User preferences in the system are dynamically updated with the user-feedback. Accuracy of proposed system has increased from 45% to 60% for user1 at alpha= 0 and beta=1. It shows that, adding user-feedbacks in the system have significant effect on the performance of the system.

The performance of the system is measured using the accuracy measure. The performance of the proposed system is compared with a baseline system that selects images randomly.

The proposed system has been found to produce significantly better performance than random selection, which emphasizes the importance of such as systems in an era when huge amounts of digital image data is being produced and collected. More studies on features for accurately capturing of user preference would be useful in further improving the performance of the system. In future, we intend to enhance the system by combining its user-specific knowledge with general image characteristics and features that signify better visual quality in order to recommend images.We would like to include diversity and serendipity in the recommendations so that user may get something that can surprise them and improves the effectiveness of the recommendations.

‘

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