Efficient CBIRS Using Fusion and Machine Learning

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***Abstract*: Nowadays digital imaging has become an essential segment in many applications such as medical imaging, remote sensing, crime prevention, education, multimedia, data mining etc. These applications require digital images as a source for various processes like segmentation, object recognition, tracking and others. To index and search suitable images from the rapidly increasing digital image collections, an image retrieval system is used. An image is retrieved in CBIRS system by adopt numerous techniques all together such as integrating Pixel Cluster Indexing and Histogram Intersection. In this thesis work, we propose to design and implement a technique of CBIRS to be less complex and highly accurate retrieval system. Here score level fusion is used with machine learning to improve precision in CBIRS. The proposed framework initially selects pertinent images from a large databases using color moment information. Color information can be extracted from the image by both global and local techniques. consequently local binary pattern(LBP) and edges detection methods are used to extract the texture and edge features respectively from the query and resultant images of initial stage of this framework .The texture information is often estimated locally from the gray-level representation of an image and ELM for machine learning classifier is designed for unfussiness and speed.**

Index Terms: Image retrieval, machine learning, image extraction, Histogram intersection, CBIRS technique.

Introduction

Image retrieval is a method of browsing , searching and retrieving images from a large database of digital images . Image reclamation has been a very dynamic research area since 1970s. Image retrieval methods can be classified into two categories, Text- based image retrieval (TBIR) and Content-based image retrieval(CBIR). CBIRS also signifies as query by image content (QBIC) and content based visual information retrieval (CBVIR) . In CBIRS , the word "content" describes about the context that states about the features such as color , shape and texture . We can examine content with the help of images. CBIR maintains the extracted features for both the dataset images and query images. Content – based image retrieval is a technique uses visual contents such as (color, texture and shape) to search images from large scale image databases according to users interest . In CBIR , every image in the dataset extracts its features and compares with the query image . In recent years, combined feature based image retrieval is an active research area in CBIR. Because of issues that exist in finding suitable feature extraction methods and their combinations, precision of the retrieval system is still scanty. The proposed framework mainly concentrates on improving the retrieval accuracy of the CBIR system by integrating the low- level features such as color, texture and edge of an image in a multilevel fashion [1].

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1.1 Need of CBIR

Today technological advances in digital imaging, broadband networking, and data storage have motivated people to communicate and express by sharing images, video, graphics and other forms of media which has resulted into an explosion in the amount and complexity of digital data being generated, stored, transmitted, analyzed and accessed . Much of this information is multimedia in nature, generated from diversity of sources like digital camera, scanner, internet etc. which has caused technical challenges for computer systems to acquire, store or transmit and manage image data effectively to make such large collections easily accessible [2].

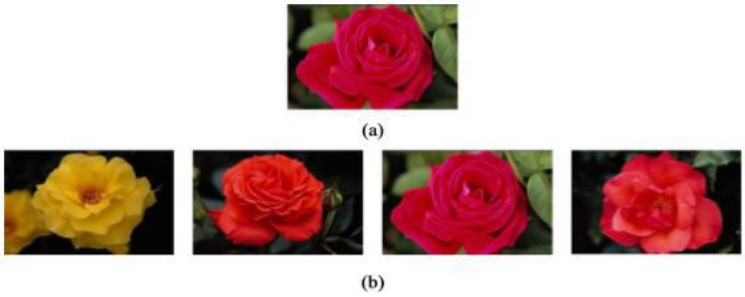


Fig 1.1 Representation of CBIR

A Content Based Image Retrieval (CBIR) is an interface between a high level system and a low level system [3].The human brain is capable of performing complex visual perception, but is limited in speed while a computer is capable of restricted visual

capabilities at much higher speeds [14]. In a CBIR, visual image content is represented in the form of image features, which are extracted automatically and there is no manual intervention, thus eliminating the dependency on humans in the feature extraction stage. These automated feature extraction approaches are computationally expensive, difficult and tend to be domain specific. So lot of scope for minimizing computational complexity, simplification and generic attempts do exist for research in CBIR. The feature vector is generated by this set of low-level feature which is used to represent the content of each image in the images database and then retrieval of image is based on the similarities in their contents. According to the similarity between the query and target image the ordered list of the matched images is displayed [4].

1.2 Process and Block diagram of CBIR

Initialization process is the first step where it collects the images and considers all the images, and it determines the size of the image. Then, the feature extraction such as color and location information is carried, and then, the extracted information is stored. Based on the information stored, the indexes are created and stored in the index table. The image database is processed off-line in order to save query-processing time. Feature extraction component is available for querying and retrieval only for the images that have been processed. In query process, user gives sample query image, and this query image goes through initialization, feature extraction, and indexing process [5].

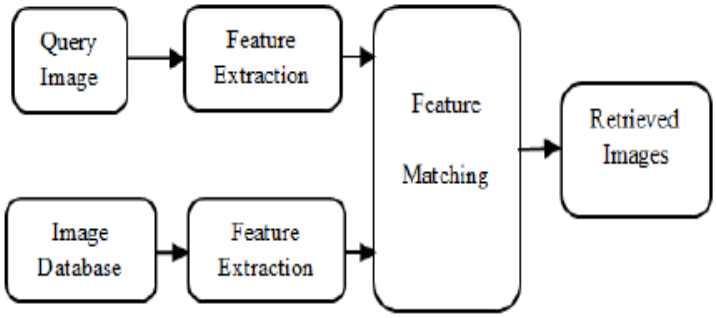


Fig 1.2 Block Diagram of CBIR

II. RELATED WORK

W.M. Smeulders et al. 2000 [6] introduced the paper starts with discussing the working conditions of content-based retrieval: patterns of use, types of pictures, the role of semantics, and the sensory gap. Consequent sections converse computational steps for image retrieval systems. Step one of the review is image processing for retrieval sort by texture, color and local geometry. Features for retrieval are discussed subsequently, sorted by: accumulative and global features, salient points, object and shape, signs, features and structural combinations. Similarity of pictures and items in pictures is reviewed for each of the quality types, in close connection to the types and means of feedback the user of the systems is capable of giving by interaction. We briefly discuss aspects of system engineering: databases, system architecture, and evaluation.

S. Mangijao Singh et al. 2012[7] introduced an efficient image retrieval method based on color moments and Gabor texture features. To improve the discriminating power of color indexing techniques, encode a minimal amount of spatial information in the index by extracting features from the regions of the image divided horizontally into three equal non overlapping regions. In this approach, from each region in the image, we extract from each color channel the first three moments of the color distribution and store the 27 floating point numbers, each region being represented by a vector of 9 floating point numbers) of the image in the index. As its texture feature, Gabor texture descriptors are adopted.

T. Karthikeyan et al. in 2014[8] introduced text based and content based image retrieval. Text- based image retrieval has some limitations such as task of determining image content is highly perspectives. So overcomes this problem, we will discuss the CBIR system. CBIR is a fast developing technology with significant potential. Research in CBIR has been focused on image processing, low level feature extraction and so on. It has been believed that CBIR provide utmost support in bridging „semantic gap‟ between low level feature and affluence of human semantics. Feature extraction is the process of extracting image features to a distinguishable extent. CBIR system distinguishes the different regions present in an image based on their similarity in color, texture and shape. CBIR technology has been used in numerous function areas such as fingerprint biodiversity, identification, crime prevention, digital libraries, medicine, and historical research. Similarity measures are used to determine how similar or dissimilar in the given query image and image database collections.

L. Ramteke et al. in 2015 [9] introduced image mining techniques is discovering significant correlations and formulations from previously collected image data. Many different application areas operate image mining as a means to accomplish effective practice of semantic information about images. Image mining is appropriate increasingly more widespread in both the private and public sectors. Sector such as biomedical, space research organization, remote sensing, fashion, crime prevention, publishing, medicine, architecture, commonly use image mining to reduce costs, enhance research, and increase sales.

K. Chauhan et al. in 2016 [10] introduced CBIR system that evaluates the comparison of query image with each of the images of image dataset in terms of color, texture and shape characteristics and returns the query image class for determining the system accuracy. For texture analysis Gabor and GLCM features are extracted, for shape analysis, Hu-7 Moment feature is extracted and lastly for color analysis, color moment, Histogram of Oriented Gradient (HOG) and Edge Oriented Histogram (EOH) are used. In the absence of Genetic Algorithm, Neural Network provides the accuracy of 72 % and Nearest Neighbor Classifier provides the accuracy of 34 %. In the presence of Genetic Algorithm, Neural Network provides the accuracy in the range of 85–95 % and the Nearest Neighbor Classifier provides the accuracy in the range of 70–90 %.

P. Chandana et al. in 2017 [11] introduced a new mechanism for CBIR systems, which is mainly based on two phases. The first phase is to convert the query image and the test image to gray-level images. The second phase is based on the feature extraction which includes texture features. These two processes will be undergone at both the side of training and testing images of the proposed system. At last, the similarity-based matching will be done where the distance of each observation is computed using the Euclidean distance measure and KL divergence approach. Finally, the normalized results were obtained by the proposed methodology. The experimental results show that the proposed technique of CBIR using GLCM retrieves the exactly matched images with the distances calculated. The distance ranges between 0 and 1 are the exactly matched images, whereas the distance range more than 1 is mismatched images.

Y. Zheng et al. in 2018 [12] introduced with the development of digital pathology, histological sections can be scanned by pathologists using micro-scanners during their rest time and stored as digital whole slide images (WSIs).The time between scanning and diagnosis is a valuable resource for computer-aided diagnosis (CAD). After or during35 the scanning period, the WSIs can be analyzed using a reliable artificial intelligent algorithm, which can support the diagnostic exactness and relieve the workload of the pathologists.

L.K. Pavitra et al. 2018 [13] Presented hybrid framework for Content-Based Image Retrieval (CBIR) system to address the accuracy issues connected with the traditional image retrieval systems. The proposed framework initially selects pertinent images from a large database using colour moment information. Consequently Local Binary Pattern (LBP) and Canny edge detection method are used to take out the texture and edge explanation respectively, from the query and ensuing images of the initial stage of this framework. Then, the Manhattan remoteness information about these two features corresponding to the query and selected images are calculated and combined, and then sort using bubble sort algorithm. Wang's, Corel-5K and Corel-10K are the three databases used for evaluate the performance of the proposed hybrid framework using exactitude and recall measures.

III.PROPOSED APPROACH

The typical feature descriptors used in the proposed work to extract the local features like color, texture and edge are illustrated in this section. The generalized architecture of the proposed framework is shown in Fig. 1.3.

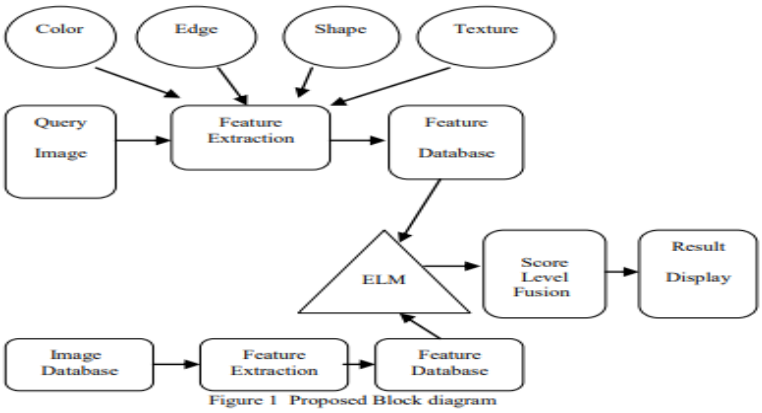


Fig 1.3 Block Diagram of Color, Texture and Edge Based CBIR

3.1 Color descriptor

In the proposed work, for minimizing the complexity and improving the effectiveness of the CBIR, the global color descriptor is used in the first level of retrieval. The review of these color descriptors claims an extensive use in many applications due to their consistent behavior. Additionally, they have a fast response for a specific request, which is comparatively higher than the local color extraction techniques used in the image. Hence, color moments (statistical measure) are chosen to represent the color details of the image. It gives the pixel distribution information of the image in two compact forms [15]. The first order moment gives average information about the pixel distribution of a given image and the closeness of the pixel distribution about mean color is estimated by second order moment. Moreover, the usage of color feature in the proposed work is different from the conventional CBIR system although both employ color moments. In the first stage of the retrieval process, average color information (mean) and the quantity

of the amount of pixels that differs from the mean (standard deviation) of the query image are estimated globally from the three color channels (Red, Green, and Blue) of the RGB color space using Eq. (1) and (2). If the pixels present in the image are close to the average value, it decreases value of standard deviation. A high standard deviation indicates that the huge amount of color pixel is not close to mean value.

$$Mean\ (Ic) = 1\ M \times N\ M\ \_\ i = 1\ N\ \_\ j = 1\ P\ cij\ ,\ c = \{\ R, G, B\ \} \qquad \text{Eq..(1)}$$

$$Std(Ic) = \_\ 1\ M \times N\ M\ \_\ i = 1\ N\ \_\ j = 1\ \_P\ cij - Mean\ (Ic)\ \_2\ \_\ 1\ 2\ ,\ c = \{\ R, G, B\ \} \qquad \text{Eq..(2)}$$

Where *Ic* holds the color channel information of an image. *M* and *N* are the row and column size of an image. *P cij* indicates the value of image pixel in the *i*th row and *j*th column of the particular color channel. Only the mean value of R, G and B color channels is required for the database images to obtain the reduced search space. It is not confirmed that the mean value is one of the pixel information of the given particular image. Meanwhile, standard deviation of the image is also important to give details about the distribution of image pixel around the average information. This information acts as a lower and upper bound for the mean value and allows taking values between them. Hence, standard deviation details are added and subtracted with the mean. The results of these operations give two threshold values for each channel. They are represented as Low-Threshold (LT) and High-Threshold (HT) which is given as follows:

$$LT\ (\ Ic\ ) = Mean\ (Ic) - Std(Ic)\ ,\ c = \{\ R, G, B\ \} \qquad \text{eq..(3)}$$

$$(HT\ (Ic) = Mean\ (Ic) + Std(Ic)\ ,\ c = \{\ R, G, B\ \} \qquad \text{eq..(4)}$$

If the first order color moment of each channel (R, G and B) of the database images lies in between the two thresholds (including two threshold values) then those images are selected for the next stage of feature extraction process. The threshold values of the R, G and B color channels are combined by the logical AND (&&) operator. Here, first stage of the proposed work behaves as a filter that takes all images from the database and passes the images which satisfy the well-defined rule in this level. At the end of this first stage, selected images collectively form a subset from the original database. Subsequent level of the retrieval system uses this subset of images instead of using the original database for image retrieval.

3.2 Texture descriptor

Texture is another leading descriptor in a CBIR system. Due to its implementation, simplicity and energetic performance in the field of texture analysis nowadays LBP based texture extraction is extensively used in various application domains like face recognition, biometric application, etc. The proposed system also makes use of a simple LBP to extract the texture of the image. This extraction algorithm is performed over the subset of images selected from the first level of the retrieval process. Before exploring LBP on the selected images, RGB to gray scale transformation is carried out as a pre-processing step on these images. For iteration it takes 3 ×3 overlapping gray scale image as input. The pixel value available in the Center Position (CP) of the 3 ×3 sub block acts as a threshold value for its neighboring pixels. Using this threshold value, binary representation of that sub block is created. Then, the LBP value of the 3 ×3 sub block is evaluated in the counter clockwise direction. Finally, the LBP value is updated in the center pixel position of that block in the image. First iteration of the LBP is illustrated in fig 3.2 and Eq. (5) shows the estimation of LBP for a 3 ×3 block representation:

$$LBP\ N = N-1\ \_\ i = 0\ f(\ P\ i - CP\ )\ 2\ i\ ;f(p) = \_1\ ;P \geq 0\ 0\ ;P < 0 \qquad \text{Eq..(5)}$$

where *N* denotes the total number of neighboring pixels for the center pixel in the 3 ×3 sub block, here *N* = 8. *P i* holds the value of neighboring pixels, *i* = {0, 1, 2,..., 7}. *CP* is the center pixel value of the sub block. In fig 3.2(a) the first 3 ×3 sub block is taken from the simple 5 ×5 size gray image. In this, the center pixel value 21 is the threshold value for its 8 neighbors. The difference between the value of every neighbor pixel and the center pixel value is calculated. If the difference value is greater than or equal to 0 then that particular pixel value is turned into 1, otherwise 0 is updated in its place. Subsequently, these 8 bit binary values are converted to decimal values and rehabilitated in the place of the center pixel. After obtaining the LBP for the whole image, histogram of LBP values are computed which gives the representation of texture feature of an image.

3.3 Edge descriptor

Normally, edges are formed by the abrupt change in the intensity value of the image which is captured by the edge detection algorithms and it holds the boundary representation of the objects present in Fig. 1.4.

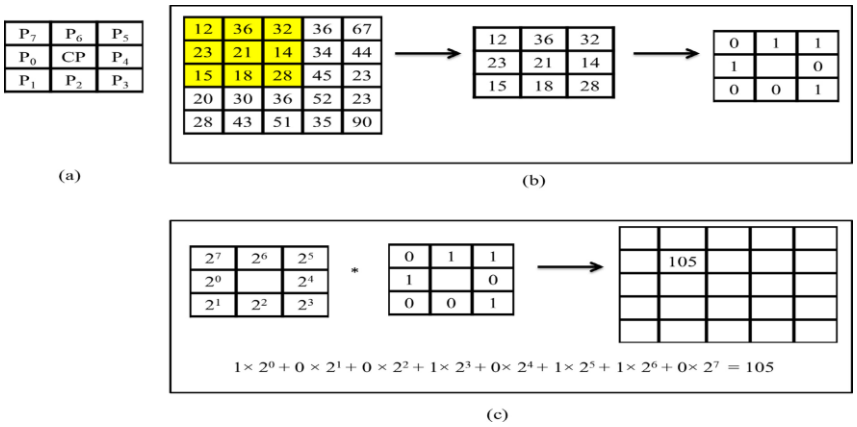


Fig 1.4 First iteration of LBP: (a) Pixel position of 3 ×3 block image (b) Binary value creation using threshold value (c) LBP value generation through the obtained binary values.

Low -level visual content of an image can also be expressed and preserved in the form of edges. Human perception is highly sensitive to edges [11]. Since canny edge detection is used to represent the shape of the object, the proposed work uses Canny edge extraction on the selected images at the end of the first stage. In RGB color space, each color channel is highly correlated with other**.** Color channels such that the splitting of chrominance and luminance information is impossible and is perceptually non-uniform to human perception. Gray scale information is enough to mark edges in images but gray to RGB conversion is not possible to produce color image. Hence, color space transformation has to be performed to obtain the edge details from the intensity plane of an image. This is the first step in edge feature extraction process. RGB to HSV conversion [20] takes place as per Eq.(6)–(8).

$H = 60 \times\_(G - B)\ \delta,\ R = \max(R, G, B)\ 60 \times\_2 + \_B - R\ \delta,\ G = \max(R, G, B)\ 60 \times\_4 + \_R - G\ \delta,\ B = \max(R, G, B)$ Eq..(6)

Where $\delta = \max(R, G, B) - \min(R, G, B)$ Eq..(7)

$S = \delta \max(R, G, B)$ (7) $V = \max(R, G, B)$ Eq..(8)

where H and S carry the chrominance details of the given image. V channel holds the intensity distribution of that image. Canny edge detection algorithm is run over the V channel. Then, the edge extracted V channel is combined with un-modified H and S channel and transformed back to RGB color space. After that, these color edge features are estimated through the histogram of R, G and B channels separately. Over all processing procedure of the proposed work is depicted in the following algorithm.

IV.EXPERIMENTAL RESULTS

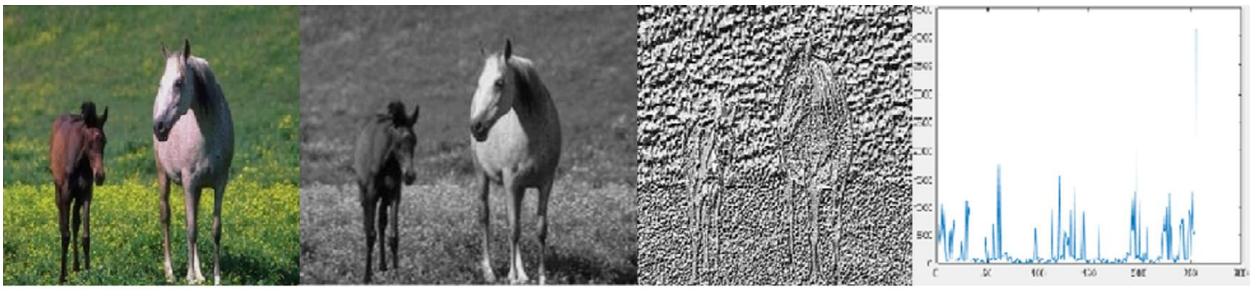
For the purpose of experimentation and verification, experiments are conducted over the Wang's [22], Corel-5K [23] and Corel-10K [23] databases. Each database contains 1000 images respectively of size 256 ×384 or 384 ×256(Wang's). In Wang's database, 1000 images are divided into 10 groups and a sample image from each class (African tribes, Food, Sea, Buildings, Bus, Dinosaurs, Elephants, Flowers, Horse and Mountains) is shown in Fig. 1.5. Wang's database images are also divided into 50 and 100 classes and each class has 100 images into it. Here, the experiments are executed in the MATLAB R2013a, an environment along with the dual core processor, 2 GB memory and 64 bit windows operating system and the experiment is performed over the three databases.

4.1. Stage 1: Image selection

Retrieval accuracy and similar image search space of this hybrid system is highly dependent on the result of global visual content descriptor. Color is the easily assessable, more powerful and widely used visual content in image and video based retrieval systems. Beyond that, here it plays an additional role as a filter to restrict the set of images which do not fall within the limits defined in Eq. (3) and (4).

4.2. Stage 2: Texture and edge feature extraction

The feature extraction process is carried out with images from the new database and query image. For texture feature extraction, each image in the subset is converted to it corresponding gray scale form and then LBP extraction is applied over those images which serve texture information in 256 values. LBP creation of an image is shown in Fig.1.5



(a) (b) (c) (d)

Fig 1.5 LBP texture and edge feature extraction

Efficiency of the proposed system's image selection process is tabulated in Table 1 which is evaluated by measuring the average number of images involved in second level feature extraction process and their retrieval time. The experimental results of this work show that it approximately takes 490, 1850 and 3500 number of images from the Wang's, Corel-5K and Corel-10K database for the subsequent process. Size of the image is also responsible for the feature extraction time and retrieval efficiency. Here, feature calculation time of the Corel-5K and Corel-10K database image is less than the Wang's database image since image size of the Corel database is less. Moreover, Corel-5K is a subset of the Corel-10K database so that the average time taken for feature extraction is same in both databases but the retrieval time of these databases is different as it depends on the size of the database.

The average precision has been calculated for all matrices and categories this and precision is averaged after getting average outcomes from all categories shown in fig. 1.6 and Fig.1.7. Here the comparison between LBP precision and ELM precision technique clearly shown that there is an improvement in performance of CBIR.

catname	**Category**	**Base-Precision**	**Proposed-Precision**
African Tribes	1	90	95
Sea	2	85	100
Building	3	65	90
Bus	4	100	100
Dinosaurs	5	100	100
Elephants	6	80	95
Flowers	7	100	100
Horse	8	97.5	97.5
Mountain	9	55	100
Food	10	82.5	95
	Avg. Precision	**85.5**	**97.25**
	Avg. ExeTime.	0.246156	0.182674

Fig.1.6 feature extraction process and their retrieval time

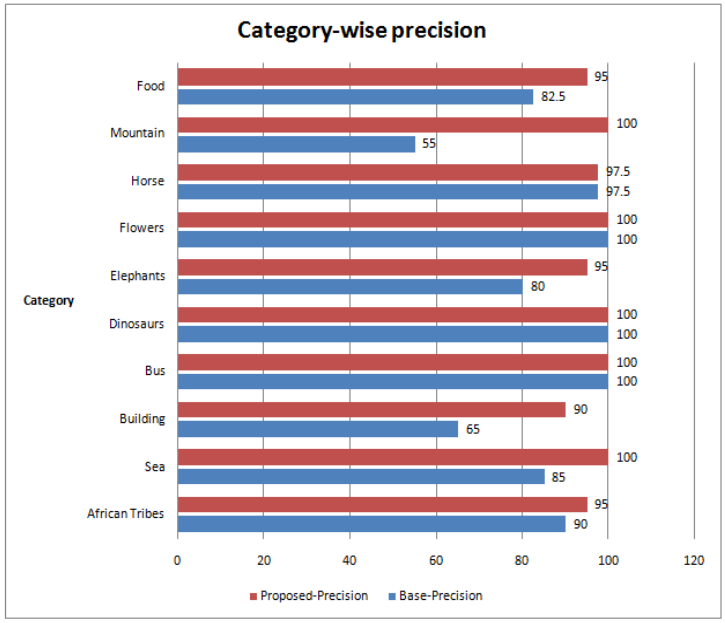


Fig.1.7 category-wise precision comparison

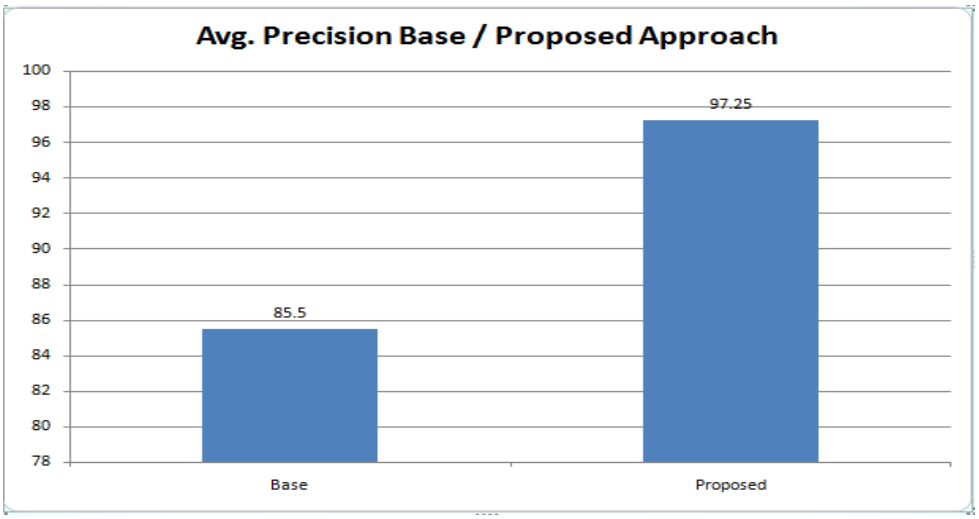


Fig.1.8 comparison between base LBP precision and proposed ELM precision

V. CONCLUSION

A new hybrid feature scheme is proposed for efficient CBIR in this thesis based on color and texture with various distance metrics. The main benefaction of this work is to construct an efficient (well organized) and effective (productive) CBIR system using fusion and machine learning that tends to be workable for massive datasets. Therefore, this proposed work has presented an efficient image indexing and search system based on color and texture features. The color features are described by the edge extracted V channel is combined with un-modified H and S channel and transformed back to RGB color space. A group of experiments was executed to select the optimum vocabulary size that obtains the best retrieval performance. All considered retrieval procedures are analyzed on Wang datasets in RGB color spaces. The proposed approach is effective in image retrieval. LBP technique gives texture features extraction obtained 85.5% average precision, where proposed ELM which is used to extract color features obtained 97.25% average precision.

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