Effectiveness of Unsupervised CBIR Systems by fusing Multiple Traits of an Image

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Abstract- An image retrieval system is a process of finding the relevant images in the image database. Mainly there are two types of image retrieval processes; text-based and content-based retrieval of images. The content-based method of image retrieval utilizes the visual traits of an image such as color, texture, shape, and spatial design. A content-based method, on the other hand, is used for representing and indexing the images. A cluster-based graph partitioning algorithm is used for retrieving the images in an unsupervised mode. In this work, the performance of various CBIR systems is compared by the fusion of multiple characteristics of an image. The performance is evaluated at different precision levels. The accuracy is compared with a few existing CBIR systems of the same semantic. The accuracy of the mentioned CBIR systems is found to be better than the existing systems. The methods are tested on a COREL standard database of 1000 images of the same resolution.

Keywords –Unsupervised CBIR, Multi-Traits of an Image, Graph Partitioning Method, Accuracy Rate

I. INTRODUCTION

Content-based image retrieval (CBIR) is any development that on a fundamental level helps to establish digital image databases by their visual content. By this description, whatever fluctuating from an image likeness task to a healthy image explanation system comes under the interpretation of CBIR. This depiction of CBIR as a field of study places it at an exceptional junction inside the scholarly organizations. While the strength in resolving the ultimate problem of healthy image understanding, observe the people from distinct backgrounds, such as information retrieval, information theory, computer vision, human-computer interaction, machine learning, Web and data mining, database systems, and statistics assisting and attaching with the CBIR organization[5, 8 and 19].

The three most broadly used visual features are: color, texture, and shape. Details of each given as (1) Color: Perceiving the pictures based on the colors they cover is one of the most widely used techniques because it does not hang on the image orientation or dimension. (2) Texture: Measure of textures seems for visual arrangements in pictures and how they are mostly defined. Textures are personified by texels which are then placed into several sets, depending on how many textures are identified in the image. (3) Shape: Shape doesn't give to the state of a picture yet to the state of a particular locale that is being searched out. Shapes will frequently be resolved first applying edge detection or segmentation to an image. A CBIR system extracts images by accomplishing three central tasks i.e. (a) Image segmentation, (b) Feature Extraction, and (c) Computation of similarity measures [9, 16, and 23].

Image Segmentation is the technique for parting an image into areas with the end goal that each segment is indistinguishable as for some feature reported in [20]. Various audits endeavor to group diverse segmentation procedures. Segmentation techniques can be grouped into the following forms: Thresholding of Histogram, Feature Space Clustering, Edge Detection Approaches, Region-Based Approaches, Graph-theoretical Approaches, Fuzzy Approaches, and Neural network Approaches [12, 18, and 28].

The rest of the paper is arranged as follows: A CBIR method to be valuable in the reality, various issues should be dealt with. Hence, the image retrieval methods, counting different basic parts of their plan, are elaborated in Section 2. Some important methods and approaches of the implementation are discussed in Section 3. The implementation of the recommended CBIR system and corresponding results are presented in Section 4. The work is concluded in Section 5.

II.CBIR SYSTEMS IN REAL WORLD

In the real-world, the existing CBIR structures can be assembled into two classes: a full-image recuperation system and a region-based picture recuperation structure. A segment of the current CBIR systems may in like manner have a spot with the two characterizations. In full-image recuperation structures, features are eliminated for the entire image without segment it into areas. Full-image recuperation structures use the overall composition of images. In this system, the images in the database are segmented at this point the request image isn't administered. In region-based structures, the image is administered into regions going before the extraction of the features. By then, the features are removed for each area. Here, neighborhood features are used for both the query image and the image in the database. Region-based structures can be moreover divided into three sorts: In the essential kind, the query image isn't segmented anyway the images in the database are divided and the system looks for images that hold the request picture as their part, this is called sub-image recuperation. In the second kind, both the request and the images in the database are partitioned at this point simply a solitary bit of the query image is used for the looking. In the third kind, both the query image and images in the database are divided and all the regions of the request picture will be used for the connection [10, 21, and 22].

A large portion of the current CBIR frameworks is area-based frameworks since locale-based frameworks are more advantageous than full-picture recovery frameworks. Locale based frameworks utilize distinctive division strategies to separate pictures into subparts. A portion of the current frameworks is (i) Blobworld, which has been created by UC Berkeley Computer Vision Group [1]. It sections the picture into blobs (areas) utilizing an (Expectation-Maximization) EM-calculation dependent on the shading and surface highlights of the pixels. (ii) The Earth Mover's Distance, Multi-Dimensional Scaling, and Color-Based Image Retrieval, in this recovery framework, pictures are regarded as focuses in a measurement space in which they are moved generally to find picture neighborhoods of interest, because of shading data. This separation work is known as the Earth Mover's Distance (EMD) [14]. The framework additionally utilizes multi-dimensional scaling (MDS) strategies to embed a gathering of pictures as focuses on a few-dimensional Euclidean space so their separations are saved as much as attainable. It is a full picture based recovery framework [15]. (iii) PicSOM is created by the Laboratory of Computer and Information Science, Helsinki University of Technology. The picture is isolated into five districts. For every area, shape and texture properties are utilized. Also, edge and shape properties are utilized as features. Highlights are put away in a tree course of action that utilizes a self-organizing map (SOM) [11]. (iv) SIMPLIcity (Semantics-sensitive Integrated Matching for Picture LIbraries) is created by J. Z. Wang, et.al., at Stanford University [24]. It portions the picture into 4 x 4-pixel squares and concentrates an element vector for each square. Utilize the k-mean grouping way to deal with a portion of the picture into districts. (v) UFM (Unified Feature Matching) was created by Chen and Wang in 2002 [2]. UFM conspire portrays the closeness between pictures by consolidating properties of all areas in the pictures. The likeness of two pictures is then characterized as the general similitude between two groups of fluffy highlights and evaluated by a comparable measure, the UFM measure, which joins properties of the apparent multitude of areas in the pictures. It is a region-based picture recovery framework. (vi) CLUE (CLUster based rEtrieval of pictures) is created by Chen et al. in 2006 [4]. It is known as bunch based recovery of pictures by unsupervised learning (CLUE), for improving client relations with picture recovery frameworks by building up the closeness data. Sign recovers picture groups by applying a chart hypothetical bunching calculation to an assortment of pictures in the encompassing region of the query. Specifically, groups made rely upon which pictures are recovered in reply to the query [3].

In this work, three CBIR systems have been developed by fusing the two visual traits of an image. The visual contents are combined in the form of color and shape, color and texture, and shape and texture. The accuracy at different precision levels is evaluated. After that, the results are compared with two existing CBIR systems of the same semantic known as UFM and CLUE.

III. RESEARCH METHODS AND IMPLEMENTATIONS

In this paper, A CBIR strategy is built up that joins the three visual features color, shape, and textures together. It depends on the joining of visual traits and an unsupervised learning strategy. For any color model, the color instant can be determined. There are 3 color instants are calculated per channel, in the case of RGB nine instants are possible and 12 instants are possible in the case of CMYK [6and 26].

The source color instant can be taken as the typical color in the image, and it might be controlled by the following mean (Mi) balance:

$$M_i = \sum_{j=1}^{j=N} \frac{Probij}{N} \qquad (1)$$

Here, *N* decides the total amount of possible pixels in the image and Prob*ij* indicates the value ith color channel and jth pixel of the image.

The Standard deviation (SD) is the second color instant. It is done by calculating the square root of the variance of the distribution of color.

$$\mathrm{SD} = \sqrt{(\frac{1}{N}\sum_{j=1}^{j=N} 1 * |Mi - Probij|^2} \qquad (2)$$

Here, $M_i$is the mean of the image ith color channel

The *skewness* (Skewi) is the third color instant. It evaluates how unstable color spreading is, and in this way, it provides facts regarding the color spreading outline. It can be computed by the following relation:

$$Skewi = \sqrt[\frac{2}{3}]{\sqrt{\left(\frac{1}{N}\sum_{j=1}^{j=N}(Probij - Mi)^3\right)}} \qquad (3)$$

Shape traits are measured using Gradient Vector Flow (GVF) fields. In this, the images are partitioned into segments. GVF is frequently used in image processing for examining the number of chunks in the image. By this, it retrieves the shape trait of an image. It is presented by Xu and Prince, reported in[25].
The GVF is given by Vector [(x, y) = [a(x, y), b[x, y)] that shrinks the functional of energy:

$$S(GVF) = \iint_{R^2} |\Delta f|^2\, |Vector - \nabla f|^2 + \mu(ax^2 + ay^2 + bx^2 + by^2)dxdy \qquad (4)$$

Here, f is a two-dimensional image function f(x, y) known as an edge map characterized on the image range.
Texture features (T) are evaluated by statistical Tamura feature and multi-resolution filtering methods. Multi-resolution filtering methods comprise Gabor and Wavelet transform depicts texture by the statistical scattering of the image intensity [7]. The texture measure is given by the following equation [13]:

$$T(i,j) = \frac{1}{W^2}\sum_{m=-w}^{m=w}\sum_{n=-w}^{n=w} Edge(i+m, j+n) \qquad (5)$$

Here, $w = 2w + 1$, it shows observation window size.

The CBIR system fuses the values of color, shape, and texture traits by using the above equations. Then these trait values are stored in the feature database. A restriction of 0.7 (says a threshold value of 70%) is allotted for the texture, color and shape features values. The mathematical model of the recommended CBIR system is given by the following relations.

$$(ColorShape) = Skewi + S(GVF) \qquad (6)$$

$$(ColorTexture) = Skewi + T(i,j) \qquad (7)$$

$$(ShapeTexture) = S(GVF) + T(i,j) \qquad (8)$$

The same restriction is also fixed for the query image as 70% of the color, shape, and texture traits values of the query image. If the color, shape, and texture visual traits values of a target image are above the threshold value for the color, shape, and texture visual traits respectively, the color, shape, and texture traits values of the target images are combined and save in the stored features database. If not, discard the target image as a significant image The structure of the CBIR system which is based on a combination of visual traits is shown in Figure 1.

This approach combines the values of color, shape, and texture traits of each image and put away that feature values in the database of features. At that point look at the color, shape, and texture features estimations of the target image with joined of two visual contents color & shape, color & texture, shape & texture traits values of each image. If the feature values of color and shape, color and texture, and the shape and texture of a target image are larger than the 70% value for the color, shape, and texture visual contents values respectively, add up the color & shape, color & texture, and shape & texture values of the object images and save them in the stored features database. If not, the images are discarded as the relevant image [17 and 27].

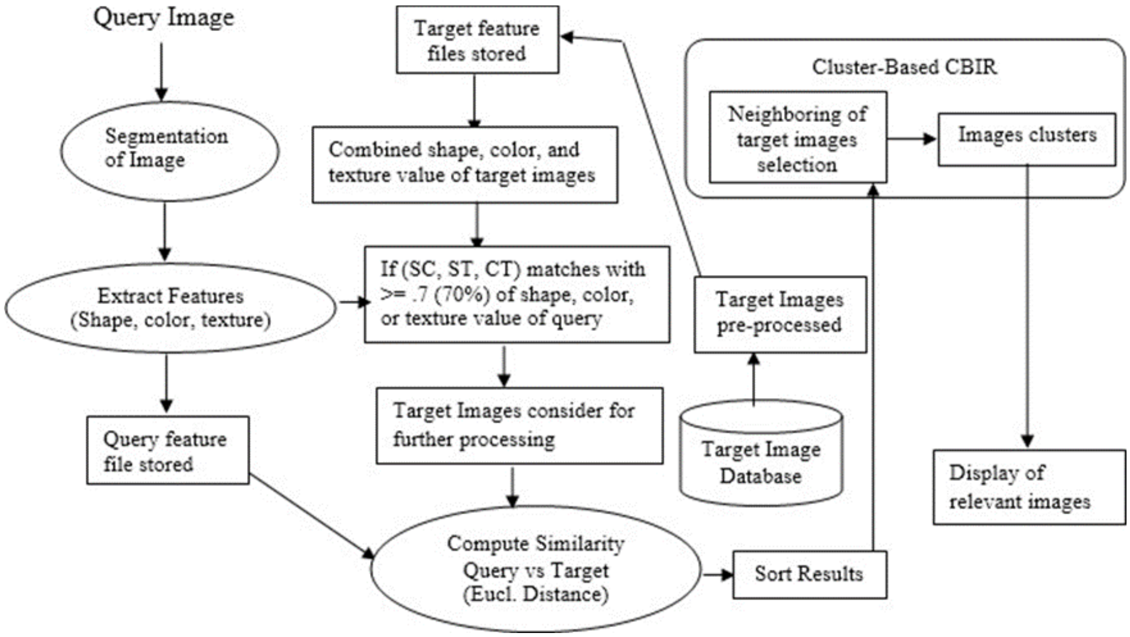

Figure 1. The CBIR system based on a combination of visual features

IV. RESULT AND DISCUSSION

The exploratory outcomes have been performed with a generally helpful COREL image database, which contained 10 distinct classes of pictures, each class has 100 pictures of dimension 256 X 384, and absolute around contained 1,000 pictures appeared in Table 1. The Euclidean distance as the similarity measure is used for evaluating the similarity between the query and target images in the database.

$$Distance(x, y) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \qquad (9)$$

Precision reflects all extracted images into account. Precision is evaluated at a given cut-off rank of 0.7.

$$Precision = \frac{|Relevant\ \ Images\ \ upto\ \ k|}{|Total\ \ Images\ \ Retrieved\ \ upto\ \ k|} \qquad (10)$$

$$P\ (atk = 100) = \frac{|P_1 + P_2 + \ldots + P_{100}|}{|k=100|} \qquad (11)$$

Once a query image is received, the system displays a list of computed similarity measure values for the distinct images in the database. After that, it shows a list of images in a decreasing manner of their similarity with the query image. Presently, just the main 25 outputs are shown because of space restriction, for the one arbitrarily selected query image with distinct semantics from each model of the combination of two visual traits, from the flower category shown in Figure 2 (a-c).

Table 1:Image Database with Index Values: COREL [29]

Class No.	Class Name	Class No.	Class Name	Class No.	Class Name
1 (0-99)	People and village	5 (400-499)	Dinosaurs	9 (800-899)	Mountains and glaciers
2 (100-199)	Beach	6 (500-599)	Elephants	10 (900-999)	Food
3 (200-299)	Buildings	7 (600-699)	Flowers		
4 (300-399)	Buses	8 (700-799)	Horses		

CBIR system Results for flower category with same query image, the first image is the query image, at the top of each image given image ID (Class number) and similarity measure.

The consequences of CBIR approaches are broken down those likewise dependent on unsupervised learning. The top k results have been chosen from the CBIR methods to calculate precision,i.e. precision at k. The average precision values have taken at varying precision levels of k of each CBIR model and reported in corresponding tables Table 2, Table 3, and Table 4 respectively. The performance of five CBIR systems at an average precision of 100 for each class of image database is reported in Table 5. The five CBIR systems are UFM, CLUE, CS, ST, and CT. It is experimentally found that the CBIR models in the combination of two visual features produce better results in comparison to the other existing methods. The performance of these CBIR systems is pictorially shown in Figure 3 and Figure 4 respectively. Overall it is also observed that the CBIR model in the combination of color and texture is outperformed.

Figure 2(a). CBIR system results in a combination of color & shape feature: There are 21 similar images out of the top 25 results.

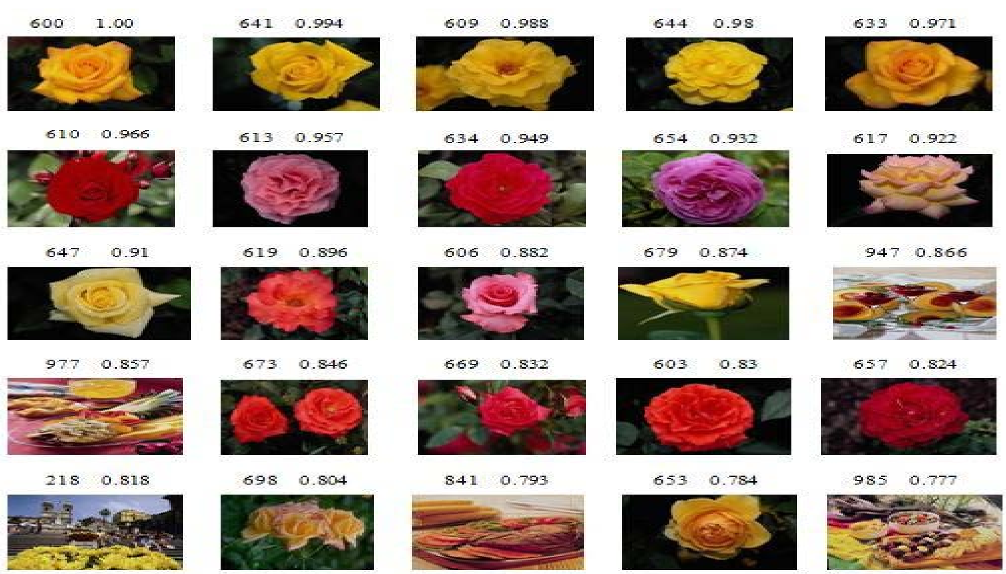

Figure 2(b). CBIR system results in a combination of shape & texture feature: There are 20 similar images out of the top 25 results.

Figure 2(c). CBIR system results in a combination of color & texture feature: There are 23 similar images out of the top 25 results.

Table 2: Performance of CBIR system in combination of color & shape features at varying precision levels of k with a threshold of 0.7 for each class of image database

ID	Name	10	20	30	40	50	60	70	80	90	100
1	People	0.70	0.685	0.667	0.636	0.615	0.595	0.59	0.585	0.58	0.57
2	Beach	0.68	0.645	0.617	0.586	0.554	0.535	0.505	0.475	0.446	0.42
3	Buildings	0.60	0.565	0.537	0.506	0.485	0.454	0.433	0.415	0.395	0.39
4	Buses	0.84	0.775	0.767	0.746	0.725	0.71	0.705	0.697	0.688	0.68
5	Dinosaurs	1.00	0.995	0.987	0.980	0.978	0.975	0.973	0.972	0.971	0.97
6	Elephants	0.58	0.535	0.487	0.436	0.395	0.386	0.38	0.375	0.369	0.36
7	Flowers	0.86	0.855	0.847	0.838	0.829	0.825	0.82	0.818	0.815	0.81
8	Horses	0.86	0.855	0.845	0.842	0.841	0.84	0.839	0.838	0.836	0.83
9	Mountains	0.54	0.525	0.517	0.492	0.475	0.442	0.415	0.398	0.387	0.37
10	Food	0.78	0.765	0.742	0.727	0.713	0.702	0.7	0.697	0.695	0.69
Avg	**All Categories**	**0.744**	**0.72**	**0.701**	**0.678**	**0.661**	**0.646**	**0.636**	**0.627**	**0.618**	**0.609**

Table 3: Performance of CBIR system in combination of shape & texture features at varying precision levels of k with a threshold of 0.7 for each class of image database

ID	Category Name	10	20	30	40	50	60	70	80	90	100
1	People	0.73	0.693	0.671	0.653	0.642	0.632	0.615	0.593	0.586	0.581
2	Beach	0.70	0.649	0.621	0.616	0.601	0.595	0.577	0.563	0.496	0.452
3	Buildings	0.64	0.572	0.559	0.536	0.523	0.511	0.486	0.471	0.423	0.413
4	Buses	0.83	0.779	0.771	0.763	0.753	0.742	0.737	0.727	0.713	0.712
5	Dinosaurs	1.00	0.996	0.992	0.987	0.981	0.976	0.975	0.974	0.973	0.971
6	Elephants	0.59	0.546	0.491	0.474	0.442	0.428	0.412	0.408	0.396	0.372
7	Flowers	0.88	0.858	0.853	0.842	0.831	0.828	0.823	0.820	0.817	0.813
8	Horses	0.87	0.858	0.851	0.853	0.848	0.844	0.841	0.840	0.838	0.832
9	Mountains	0.57	0.531	0.527	0.517	0.502	0.476	0.463	0.427	0.415	0.39
10	Food	0.80	0.769	0.761	0.732	0.723	0.712	0.709	0.701	0.699	0.69
Avg	**All Categories**	**0.761**	**0.725**	**0.709**	**0.697**	**0.684**	**0.674**	**0.664**	**0.652**	**0.635**	**0.623**

Table 4: Performance of CBIR system in combination of color & texture features at varying precision levels of k with a threshold of 0.7 for each class of image database

ID	Category Name	10	20	30	40	50	60	70	80	90	100
1	People	0.70	0.685	0.676	0.646	0.625	0.615	0.598	0.587	0.582	0.57
2	Beach	0.68	0.645	0.628	0.605	0.575	0.555	0.525	0.485	0.476	0.46
3	Buildings	0.64	0.595	0.567	0.546	0.525	0.494	0.483	0.475	0.462	0.45
4	Buses	0.88	0.845	0.817	0.786	0.775	0.768	0.755	0.734	0.721	0.71
5	Dinosaurs	1.00	0.995	0.979	0.977	0.974	0.973	0.973	0.972	0.971	0.97
6	Elephants	0.58	0.565	0.556	0.526	0.495	0.487	0.477	0.454	0.444	0.43
7	Flowers	0.86	0.86	0.858	0.854	0.85	0.849	0.847	0.844	0.843	0.84
8	Horses	0.90	0.894	0.89	0.888	0.88	0.879	0.874	0.873	0.872	0.87
9	Mountains	0.55	0.53	0.513	0.505	0.492	0.471	0.465	0.454	0.442	0.43
10	Food	0.78	0.77	0.769	0.767	0.761	0.754	0.75	0.749	0.742	0.74
Avg	**All Categories**	**0.757**	**0.738**	**0.725**	**0.71**	**0.695**	**0.684**	**0.674**	**0.662**	**0.655**	**0.647**

Table 5: Performance of five CBIR systems at an average precision of 100 for each category of the image database

ID	Category Name	UFM [3]	CLUE [6]	CS [46]	ST	CT [50]
1	People	0.38	0.49	0.57	0.581	0.57
2	Beach	0.31	0.34	0.42	0.452	0.46
3	Buildings	0.34	0.35	0.39	0.413	0.45
4	Buses	0.61	0.63	0.68	0.712	0.71
5	Dinosaurs	0.92	0.96	0.97	0.971	0.97
6	Elephants	0.24	0.28	0.36	0.372	0.43
7	Flowers	0.66	0.75	0.81	0.813	0.84
8	Horses	0.63	0.70	0.83	0.832	0.87
9	Mountains	0.27	0.28	0.37	0.39	0.43
10	Food	0.48	0.60	0.69	0.69	0.74
Avg	**All Categories**	**0.484**	**0.538**	**0.609**	**0.623**	**0.647**

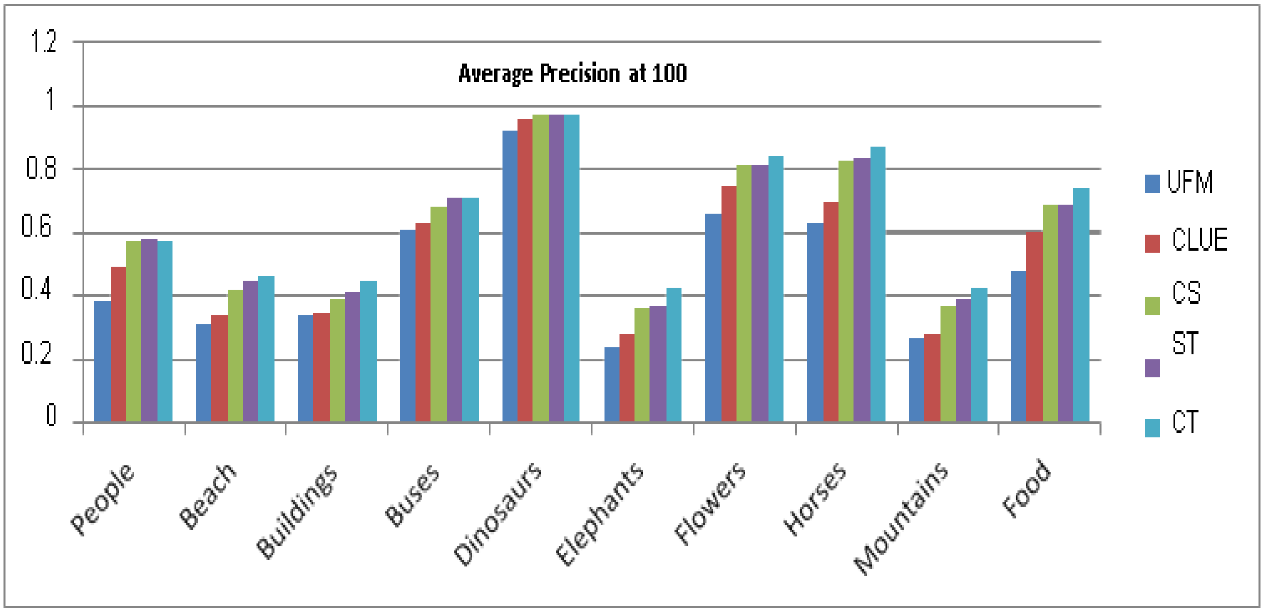

Figure 3. Comparison graph of five CBIR systems at Average Precision 100 for each class of image database

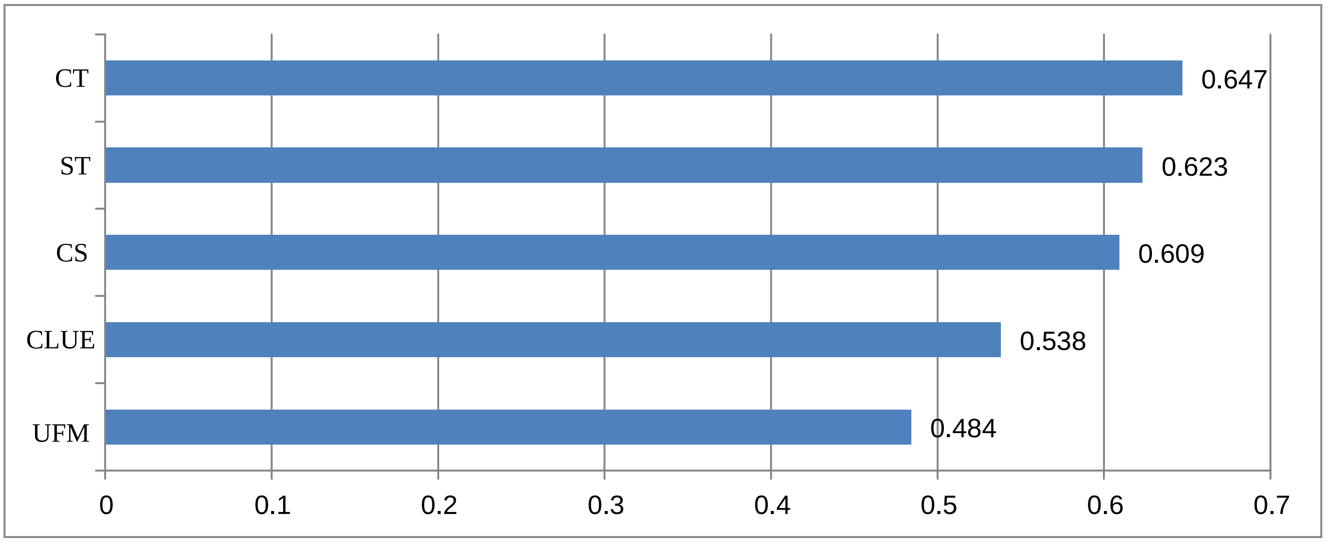

Figure 4. Five CBIR systems at an average of each category

V. CONCLUSION

In this work, the performance of five unsupervised CBIR systems has been analyzed at varying precision levels. The two well-known systems, UFM & CLUE, and three proposed CS, CT, and ST are considered for analysis. All these approaches are based on graph-clustering (unsupervised learning) the algorithm, where, two visual trait values are clubbed together. The CS system is based on a combination of color and shape, SC on shape & texture, and CT on color & texture. A weight is allocated to various images (as the target images) in the image repository with 70% features store of each visual trait. A bench-mark image database containing 1000 images is used. The Euclidean distance is used as the similarity metric for identifying the resemblance of images in the image database with a test image. It is observed that the CBIR models based on a combination of two visual features produce better performance in comparison to the other two mentioned models. The average precision value at varying levels of k has been taken by all three models viz. CS, ST, and CT. It is also found that the CT system, in particular, outperforms the CS and ST systems. Other clustering algorithms as well as systems based on a combination of more than two traits may also be developed and tested for accuracy improvement.

REFERENCES

[1] C. Carson, et.al,, “Blobworld: Image Segmentation Using Expectation-Maximization and its Application to Image Querying”, *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 24, no. 8, pp. 1026–1038, 2002.

[2] Y. Chen and J. Z. Wang, “A Region-Based Fuzzy Feature Matching Approach to Content- Based Image Retrieval”, IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 24, no. 9, pp. 1252-1267, September 2002.

[3] Y. Chen, J. Z. Wang, and R. Krovetz, “An unsupervised learning approach to content-based image retrieval”, Proceedings - 7th International Symposium on Signal Processing and Its Applications, ISSPA 2003, IEEE Computer Society, pp. 197 – 200, 2003.

[4] Y. Chen, J. Z. Wang, and R. Krovetz, “CLUE: Cluster-Based Retrieval of Images by Unsupervised learning”, IEEE Transaction on Image Processing, Vol. 14, No. 8, pp. 1187-1201, (August 2005).

[5] R. Datta, D. Joshi, J. Li, and J. Z. Wang, “Image retrieval: Ideas, influences, and trends of the new age”, ACM Comput. Surv., Vol. 40, no. 2, Article 5, 60 pages, April 2008.

[6] J. Han, and K. Kuang, “Fuzzy color histogram and its use in color image retrieval”, IEEE Trans. Image Process. Vol. 11, No. 8., pp.944-952 (August 2000).

[7] M. R. Haralick, et.al., "Textural Features for Image Classification", IEEE Transactions on Systems, Man, and Cybernetics, SMC-3 (6), pp. 610–621, 1973.

[8] J. K. Hawkins, “Textual Properties for Pattern Recognition”, in Picture Processing and Psychopictorics, B. C. Lipkin and Rosenfeld, Editions, Academic Press, New York, pp. 347 – 370, 1970.

[9] P. S. Hiremath and Jagadeesh Pujari, “Content Based Image Retrieval Using Color, Texture and Shape Features”, Proceedings of the 15th International Conference on Advanced Computing and Communications, pp.780-784, 2007.

[10] S. Jabeen, et.al., “An effective content-based image retrieval technique for image visuals representation based on the bag-of-visual-words model”, PLoS ONE,13(4), 2018.

[11] J. Laaksonen, et.al., “Picsom - Content-based image retrieval with Self-Organizing Maps”,Pattern Recognition Letters, vol. 21, pp.1199–1207, June 2000.

[12] J. Li and J. Z. Wang, “Real-time computerized annotation of pictures”, IEEE Trans. Pattern Analysis Machine Intelligence, Vol. 30, no. 6, pp. 985 – 1002, 2008.

[13] A. Rosenfeld and E. B. Troy, “Visual Texture Analysis”, Proc. UMR-Mervin J. Kelly Communications Conference, University of Missouri-Rolla, MO, pp. 1 – 10, October 1970.

[14] Y. Rubner, L. J. Guibas, and C. Tomasi, “The Earth Mover’s Distance Multi- Dimensional Scaling, and Color-Based Image Retrieval”, Proceeding DARPA Image Understanding workshop, pp. 661-668, May 1997.

[15] Y. Rubner, C. Tomasi, and L. J. Guibas, “The Earth Mover's Distance as a Metric for Image Retrieval”, International Journal of Computer Vision, vol. 40, pp. 99–121, 2000.

[16] P. Shamna, V.K. Govindan and K. A. Abdul Nazeer, "Content-based medical image retrieval by spatial matching of visualwords", Journal of King Saud University –Computer and Information Sciences, pp. 1 - 14, 2018.

[17] J. Shi and J. Malik, “Normalized Cuts and Image Segmentation”, *IEEE Transaction on Pattern Analysis and Machine Intelligence*, Vol. 22, No. 8, pp. 888- 905 (August 2000).

[18] A. Smeulders, et.al., “Content-based image retrieval at the end of the early years”, *IEEE Transaction Pattern Analysis Machine Intell.*, vol. 22, No. 12, pp. 1349–1380, December 2000.

[19] Town, Christopher, and David Sinclair, “Content based image retrieval using semantic visual categories”, Society of Manufacturing Engineers, pp. 1 – 15, 2000.

[20] K. V. Trambitskiy, et.al., "Out-of-focus region segmentation of 2D surface images with the use of texture features", Scientific and Technical Journal of Information Technologies, Mechanics and Optics, 15 (5): pp. 796–802, 2015.

[21] A. Vailaya, et.al., “Image classification for content-based indexing”, IEEE Trans. Image Process. Vol. 10, no.1, pp. 117 – 130, 2001.

[22] Y. Velazco-Paredes, et.al., "Region-based image retrieval using color and texture features on irregular regions of interest", IEEE Colombian Conference on Communication and Computing (IEEE COLCOM 2015), Popayan, pp. 1 – 6, 2015.

[23] J. Z. Wang, et.al., “Unsupervised multiresolution segmentation for images with low depth of field”, IEEE Trans. Pattern Analysis Machine Intelligence, Vol. 23, no. 1, pp. 85 – 90, 2001.

[24] J. Z. Wang, J. Li, and G. Wiederhold, “SIMPLIcity: Semantics-Sensitive Integrated Matching for Picture Libraries”, IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 23, no. 9, pp. 947-963, September 2001.

[25] C. Xu, and J. L. Prince, "Snakes, Shapes, and Gradient Vector Flow", IEEE Transactions on Image Processing, 7 (3): 359–369, 1998.

[26] D. Xiaoyin, "Image Retrieval Using Color Moment Invariant", Seventh International Conference on Information Technology, pp. 200-203, 2010.

[27] S. M. Zakariya and Nadeem Akhtar, “Analysis of Unsupervised Content-based Image Retrieval by Fusing the Image Features”, Proc. of Int. Conf. on Recent Trends in Information, Telecommunication and Computing, ITC, Association of Computer Electronics and Electrical Engineers, pp. 328 – 337, December 2014.

[28] John Eakins and Margaret Graham, “Content-based Image Retrieval”, University of Northumbria at Newcastle, http://www.leeds.ac.uk/educol/documents/00001240.htm

[29] COREL Image Database is Obtained from: http://wang.ist.psu.edu/docs/related/