Design of an Effective Content-Based Image Retrieval System Using Colour and Texture Features

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CANDIDATE DECLARATION

I hereby certify that the work, being presented in the report, entitled "**Design of an Effective Content-Based Image Retrieval System Using Colour and Texture Features"**, in fulfilment of the requirement for the *summer training*, and submitted to the institution is an authentic record of my own work carried out during the *period June-2017 to July- 2017* under the supervision of Prof**. Rajeev Srivastava,** Indian Institute of Technology (Banaras Hindu University), Varanasi**.** I have also cited the references about the texts, figures, tables from where they have been taken.

Date: Signature of the candidate

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Date: Signature of the Mentor

ACKNOWLEDGEMENTS

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ABSTRACT

In this project, an efficient CBIR system is designed and implemented using various colour and texture features. Colour features such as Colour Moments and HSV Histogram and Texture Features like Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) are used. Various distance metrics are analysed for retrieval and their performance is compared to get the best distance metric for better retrieval performance. From the experimental analyses on benchmark (WANG) database, it is observed that the city block distance performs consistently encouraging from other measures. Further, this project has introduced the combination of HSV Histogram and LBP feature whose retrieval performance are significantly encouraging than other variants of colour and texture features.

Keywords. *CBIR; Colour Moments; HSV Histogram; Gray Level Co-occurrence Matrix; Local Binary Pattern; Distance Metrics*

1. INTRODUCTION

The use of images in human communication is not new, our cave-dwelling ancestors painted pictures on the walls of their caves, and the use of maps and building plans to convey information almost certainly dates back to pre-Roman times. But in the current twentieth century has paralleled growth in the number, availability and importance of images in all area of life. Images play a crucial role in fields as diverse as medicine, journalism, advertising, design, education and entertainment. Technology, in the form of inventions such as photography and television, has played a major role in facilitating the capture and communication of image data.

In today's world, various works and research are dependent on the image mining in which desired information are derived from the image and video databases. Many search engines that exist in the today's world can retrieve the text in machine-readable form but fail to retrieve the intensity and colour of images quickly. The traditional approaches to search and retrieve and indexing images are slow and expensive. Thus, there is a continuous need for the development of efficient algorithms in the field of image mining and also the content-based image retrieval (CBIR). In this, the retrieval of images is fast with the minimum no. of computational steps. Thus, CBIR is the most efficient method of image retrieval. Retrieving the semantic information of the image using similarity relation in low-level image features such as colour, texture and shape is done in CBIR. In this, we identify the manual correspondence between two images in a set of database images by processing a query image and assigning this unknown image to the closest possible image available in the database using similarity relations of the low-level image feature.

Mining of image data is a challenging problem due to the traditional data mining techniques that are suitable for structured data types that do not belong to the image type of data. Image mining is a challenging area of study based on the human visual system which remains a mystery how the human brain naturally and effortlessly processes semantic content of the images and thus, it is still a research challenge. The research and development of mining image data are relatively new and emerging field of today's study. The image retrieval systems are broadly divided into following two categories on the basis of types of search:-

1). Description-Based /Text-Based Image Retrieval: - In this, images are indexed and retrieved on the basis of user-defined textual descriptions of the image features and these are typed manually for each image in the database, which is a very labour-intensive and impractical in today's age. Since the descriptions are very much subjective, the automatic generation of keywords for image indexing could be very inaccurate and incomplete without incorporation of visual information and feature extraction. Thus, this system is not suitable for today's age.

2) Content-based image retrieval (CBIR) means that the search examines the visual content of the image, such as colour, texture etc. rather than the text data such as tags and keywords. Content-based image retrieval algorithm uses the visual content of the image for retrieval which removes the disadvantages of text-based retrieval systems. Some approaches have been proposed as an attempt to retrieve similar image among the large collection. Swain et al. [1] implemented the method of the colour histogram which has proved to be effective, efficient and easy to implement. Daisy et al. [2] propose the use of shapes and texture features which are extracted from the query images and are compared by means of Euclidean distance metric. Vatamanu et al. [3] used Local Binary Pattern Operator and Data Mining Techniques for the retrieval process. Block-Based Methods for Image Retrieval Using Local Binary Patterns was proposed by Valtteri et al. [4]. Kekre et al. [5] used DCT on Row mean, Column mean and Combination for Grayscale Image Retrieval. Similarly, row mean and column mean of images using 2D DWT was proposed by Sai and Patil [6]. Mistry et al. [7] used combination of spatial, frequency, CEDD and BSIF features to develop a hybrid CBIR algorithm. Goyal and Walia [8] used local binary pattern (LBP), local directional pattern (LDP) and their variations. Priya and David [9] proposed the use of multiple feature fusion and matching to retrieve images from the database. Many other features such as colour correlogram [10], colour moments [11] and MPEG-7 colour descriptors [12] have been used too.

In this, three fundamental parts are present for image retrieval and these are:-

i) Feature Extraction: - The images from the image database are processed and features like colour, texture, pattern, image topology, shape, layouts and locations, etc. are extracted from each image in the database and stored in the form of metadata information of the image in the database.

ii) Multi-dimensional Indexing: - The features extracted are used to index the images to provide the basis for search and are represented in the form of multidimensional vector or feature vector, which acts as the signature of the image. This feature vector can be assumed to be associated with a point in the multidimensional space. An image represented by say an N-dimensional feature vector whose let first n1 components represent colour, next n2 components may represent shape, next n3 components may represent image topology and next n4 components let represent texture and so on then N=n1+n2+n3+n4 +….. components, and these feature vectors for each image are stored in the metadata database along with the images.

iii) Retrieval: - An example or sample image according to which we have to perform the search related to the similarity in visual content-based indexing is called a query image. The query image is analysed to extract the features and compared with the indices of the images stored in the database. The indices of those images are found whose feature vectors in the N-dimensional space lie within the close proximity of that of query image for retrieval of similar images to the given query image. That is, often the similarity of two images is measured by computing the distance between the feature vectors of those two images. In this way, the system retrieves similar images to a query image and returns the let say k images, whose distance from the query image is below some defined threshold.

2. Feature Extraction

Feature is defined as "point of interest" for image description. Basically feature is the property of an object, which can discriminate the one object from other. Properties of a good feature include consistent over several images of the same scene, invariant towards certain transformations, insensitive to noise. Here we reviewed some important feature related to our work.

2.1 COLOUR

One of the most important features that make possible the recognition of images by humans is colour. Colour is a property that depends on the reflection of light to the eye and the processing of that information in the brain. We use colour every day to tell the difference between objects, places, and the time of day. Usually colours are defined in three dimensional colour spaces. These could either be *RGB* (Red, Green, and Blue), *HSV* (Hue, Saturation, and Value) or *HSB* (Hue, Saturation, and Brightness). The last two are dependent on the human perception of hue, saturation, and brightness. Most image formats such as *JPEG*, *BMP*, *GIF*, use the RGB colour space to store information. The RGB colour space is defined as a unit cube with red, green, and blue axes. Thus, a vector with three co-ordinates represents the colour in this space. When all three coordinates are set to zero the colour perceived is black. When all three coordinates are set to 1 the colour perceived is white. Some important colour descriptors are given below.

2.1.1. Colour Histogram

The main method of representing colour information of images in CBIR systems is through colour histograms. Colour histogram is one of the most important descriptor used in content-based image retrieval. It's efficient to compute and effective in searching results. A colour histogram is a type of bar graph, where each bar represents a particular colour of the colour space being used. It is used for image characterization based on the global distribution of colors in image. In this, first we quantize the color spaces into a fixed no. of discrete levels according to our need and then compute the no. of pixels corresponding to the discrete levels which acts as bins in the histogram. Thus, Histograms are the graphical representation of pixels corresponding to each bin. Histograms represent the global distribution of color pixels in the image. Histograms are less efficient in terms of the discrimination of various parts of the images due to not having the ability of distinguishing color pixels of two different images in terms of spatial distribution of colors.

HSV (hue, saturation, value), HLS(hue, lightness, saturation) and CIE color spaces (such as CIELAB, CIELUV) produce better results as compared to the RGB color space. We find the similarity between two images in terms of color distribution by computing the minimum possible distance between two histograms.

In MATLAB, for example we can get a colour histogram of an image in the RGB or HSV colour space. An example of a colour histogram in the RGB colour space can be seen with the following image:

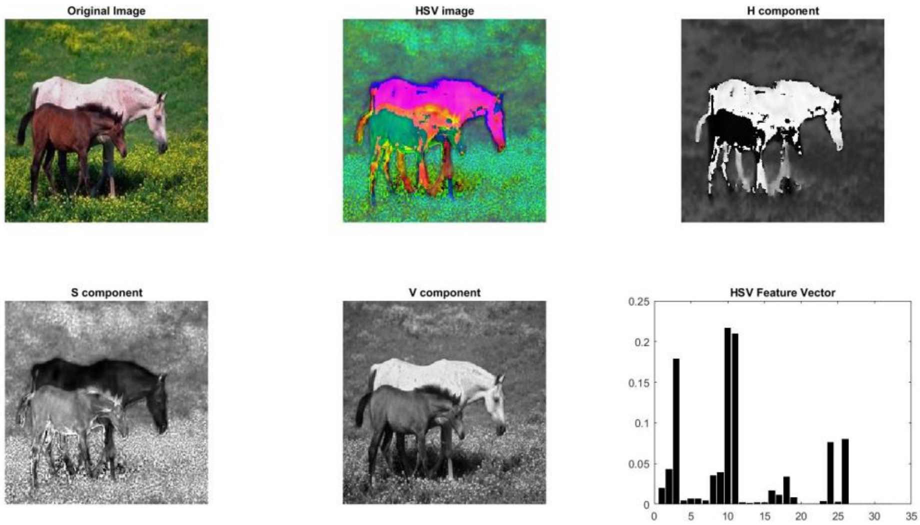


Figure 1. Various components of the HSV image along with the feature vector

Feature extraction using HSV histogram includes three steps and they are colour space conversion, colour quantization, and histogram computation. The first step is to convert RGB image into HSV colour space. In the HSV colour space, h stands for hue, s stands for saturation which is the percentage of white light added to a pure colour and v stands for value which refers to the perceived light intensity [13]. These are calculated from the RGB components of the image using the formula:

$$H = cos^{-1}\left[\frac{\frac{1}{2[(R-G)+(R-B)]}}{\sqrt{(R-G)2+(R-B)(G-B)}}\right] \qquad (1)$$

$$S = 1 - \left[\frac{3[\min(R,G,B)]}{R+G+B}\right] \qquad (2)$$

$$V = \frac{[R+G+B]}{3} \qquad (3)$$

The second step is to minimize the complexity and to reduce the feature vector size. Third and the last step is to obtain a histogram for each image which shows the frequency distribution of quantized HSV values of each pixel in the given image. In this method various intervals are used such as for H 8 bins are used; for S 2 bins are used and for V 2 bins are used. A 32-D feature vector is obtained. Fig.1 shows various components of the HSV image along with the feature vector.

2.1.2. Colour Moments

Colour moments are measures that can be used differentiate images based on their features of Colour. Once calculated, these moments provide a measurement for colour similarity images. These values of similarity can then be compared to the values of images indexed in a database for tasks like image retrieval. The basis of colour moments lays in the assumption that the distribution of colour in an image can be interpreted as a probability distribution. Probability distributions are characterized by a number of unique moments (e.g. Normal distributions are differentiated by their mean and variance). It therefore follows that if the colour in an image follows a certain probability distribution, the moments of that distribution can then be used as features to identify that image based on colour. Stricker and Orengo use three central moments of an image's colour distribution. They are Mean, Standard deviation and Skewness.

2.2 TEXTURE FEATURES

The texture is a very interesting image feature that has been used for characterization of images, with application in content-based image retrieval. There is no single formal definition of texture in the literature. However, a major characteristic of texture is the repetition of a pattern or patterns over a region in an image. The elements of patterns are sometimes called textons. The size, shape, colour, and orientation of the textons can vary over the region. The difference between two textures can be in the degree of variation of the textons. It can also be due to the spatial statistical distribution of the textons in the image. The texture is an innate property of virtually all surfaces, such as bricks, fabrics, woods, papers, carpets, clouds, trees, lands, skin, etc. It contains important information regarding the underlying structural arrangement of the surfaces in an image. When a small area in an image has a wide variation of discrete tonal features, the dominant property of that area is texture. On the other hand, the grey tone is a dominant property when a small area in the image has a very small variation of discrete tonal features. Texture analysis has been an active area of research in pattern recognition since the 1970s.

LBP (Local Binary Pattern) Feature

The LBP feature vectors created in the following step. The first step is to divide the examined window into cells. Each pixel in a cell is compared to each of its 8 neighbours. The set of neighbours is selected from a circularly symmetric pattern around each pixel. The number of neighbours (P) is increased to encode greater detail around each pixel. The radius of circular pattern (R) is to capture detail over the spatial scale. To capture detail over a larger spatial scale, the radius is increased. When the centre pixel's value is greater than the neighbour's value, 0 is stored. Otherwise, 1 is stored. The second step is to set the rotation invariance flag which can be set as either not to encode rotation information or to encode the rotationally invariant features. The third step is to compute the histogram using the LBP feature vector, returned as a 1-by-*N* vector of length *N* which depends on the rotation invariance flag.

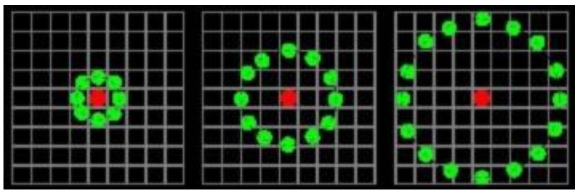


Figure 2. LBP computation with the values of P as 8, 12 and 16 and R as 1, 2.5 and 4 respectively.

The value of N, if the rotation information is not encoded then is [(P) (*P*–1) +3] and if the rotation information is encoded then is [*P*+2]. Here P is the number of neighbours.

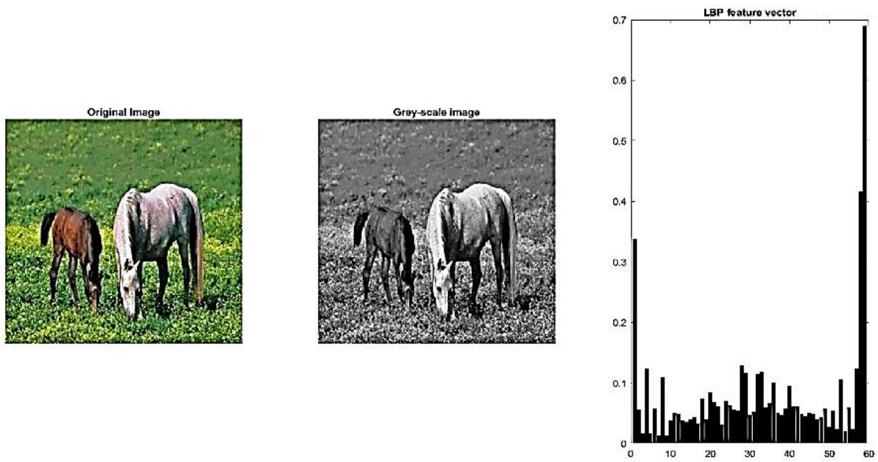


Figure 3. LBP feature vector for the respective image

3. Distance metrics

Description of various distance metrics are given in Table 1.

Table 1: Distance metrics

Distance Metrics	Mathematical Equation	Description
Euclidean Distance	$D^2=(x-y)(x-y)'$	The Euclidean distance is the L2-norm of the difference. It is the square root of the sum of the square of the difference of respective element in two vectors. It is the natural distance in a geometric interpretation.
City Block Distance	$D=\sum_{j=1}^{n}\lvert x_{sj}-y_{tj}\rvert$	The City Block distance is the L1-norm of the difference and is equivalent to the sum of absolute difference.
Chebyshev Distance	$D=\max_j\{x_{sj}-y_{tj}\}$	The Chebyshev distance is the L∞-norm of the difference. It is equal to Minkowski distance where p tends to infinity.
Minkowski Distance	$D=\sqrt[p]{\sum_{j=1}^{n}\lvert x_{sj}-y_{tj}\rvert^p}$	The Minkowski distance is the generalized Lp-norm of the difference. In this project, the value of p is taken as 3.
Cosine Distance	$D=1-\frac{xy'}{\sqrt{(xx')(yy')}}$	The cosine distance contains the dot product scaled by the product of the Euclidean distances of each vector from the origin. It represents the

		angular distance between two vectors.
Correlation Distance	$D = 1 - \frac{(x - \bar{xs})(y - \bar{yt})'}{\sqrt{(x - \bar{xs})(x - \bar{xs})'}\sqrt{(y - \bar{yt})(y - \bar{yt})'}}$ Where, $\bar{xs} = \frac{1}{n}\sum_j x_{sj}$ $\bar{yt} = \frac{1}{n}\sum_j y_{tj}$	Distance correlation is a measure of statistical dependence between two random variables or two random vectors of arbitrary, not necessarily equal, dimension. The distance correlation of two random variables is obtained by dividing their distance covariance by the product of their distance standard deviations.
Spearman Distance	$D = 1 - \frac{(rs - \bar{rs})(rt - \bar{rt})'}{\sqrt{(rs - \bar{rs})(rs - \bar{rs})'}\sqrt{(rt - \bar{rt})(rt - \bar{rt})'}}$ Where, rs is the rank of xs taken over x_1, x_2, ...$x_{mx,}$ rt is the rank of ys taken over y_1, y_2, ...y_{myj} rs and rt are the coordinate-wise rank vectors of xs and yt $\bar{rs} = \frac{1}{n}\sum_j rs_j$ $\bar{rt} = \frac{1}{n}\sum_j rt_j$	Spearman Rank Correlation measures the correlation between two sequences of values. The two sequences are ranked separately and the differences in rank are calculated at each position.

4. METHODOLOGY & IMPLEMENTATIONS

General CBIR Model

The architecture for a possible content-based image retrieval system is shown in Figure 4.1. The CBIR systems architecture is divided into two parts. In the first part, feature vector is extracted from each image in the database and next these features are used to index the image, and they are stored into the metadata database along with the images. And in second part as a query time, a feature vector is extracted from the query image and it is matched against the feature vectors in the database and assigns this unknown image to the closest possible image available in the database.

Here rather than directly comparing two images, similarity of the visual features of the query image is measured with the features of each image stored in the metadata database as their descriptors. Often the similarity of two images is measured by computing the distance between the feature vectors of the two images. The retrieval systems return the first *n* images, whose distance from the query image is below some defined threshold. Several image features have been used to index images for content-based image retrieval systems. Most popular among them are colour, texture, shape, image topology, colour layout, region of interest, etc.

Four different techniques are used here for image retrieval namely colour moments, HSV histogram, GLCM, and LBP. In the first technique, an RGB image is separated into R, G and B component images and then the mean, standard deviation and skewness of each of the component is computed. Colour moments create a 9-D feature vector as shown in equation 4. In the second technique, a 32-D vector of HSV histogram is generated using the methods discussed in previous section 2 as shown in equation 5. In the third technique, GLCM matrix for an image is generated. Features like Contrast, Correlation, Energy, and Homogeneity were extracted from the matrix and a 4-D feature vector was formed as shown in equation 6. In the last technique, LBP feature vector was generated using the approach mentioned in previous section 2 and a 59-D feature vector was generated as shown in equation 7.

$$F_{\text{colour moments}} = \{F_{c1}, F_{c2}, \ldots\ldots, F_{c9}\} \tag{4}$$

$$F_{\text{HSV Histogram}} = \{F_{h1}, F_{h2}, \ldots\ldots, F_{h32}\} \tag{5}$$

$$F_{GLCM} = \{F_{g1}, F_{g2}, F_{g3}, F_{g4}\} \tag{6}$$

$$F_{LBP} = \{F_{L1}, F_{L2}, \ldots\ldots, F_{L59}\} \tag{7}$$

For image retrieval, feature vectors of HSV histogram and LBP are combined. Final Feature vector is represented as

$$F = \{F_{\text{HSV Histogram}} \cup F_{LBP}\} = \{F_1, F_2, \ldots.., F_{91}\} \tag{8}$$

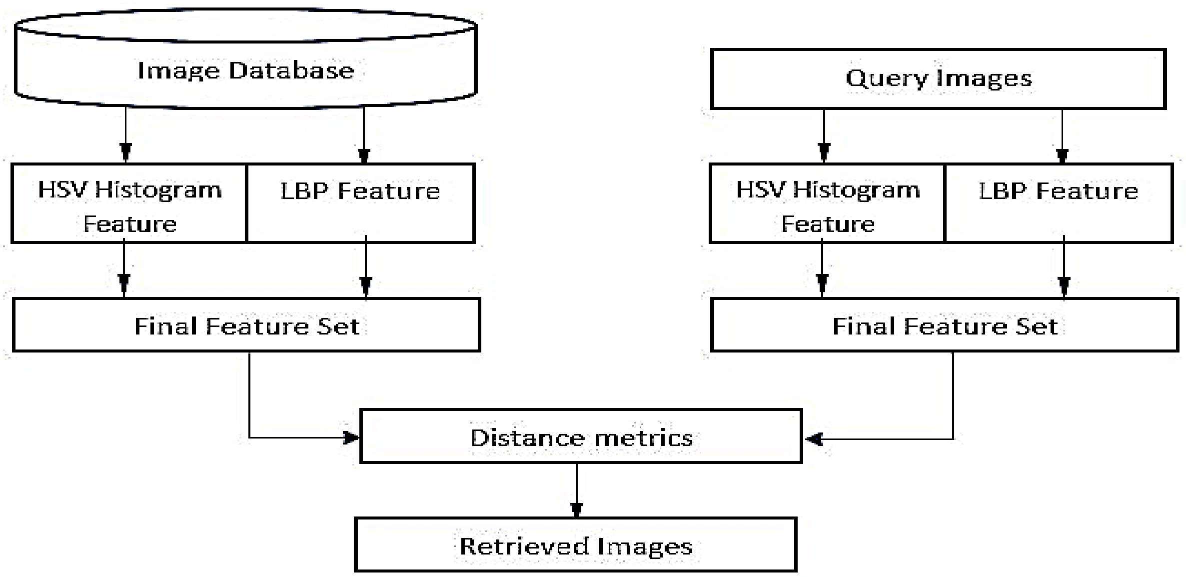


Figure 4. Block diagram of CBIR system.

The feature vector of both query images and image database is compared using the various distance metrics.

4. SIMULATION & DISCUSSION

4.1. Various Performance Measure

Following Performance measure have been used to calculate the retrieval performance

Recall

Recall is measure of the ability of the system to retreive all the models that are relevant. It can be defined by using the following equation:

$$Recall = \frac{Number\ of\ Relevant\ Images\ retrieved}{Total\ number\ of\ relevant\ images} \tag{9}$$

Its value ranges between 0 and 1, where 0 and 1, respectively, mean worst and best for retrieval.

Precision

Precision is a measure of the ability of the system to retrieve only the relevant models. Its value ranges between 0 and 1, where 0 and 1, respectively, mean worst and best for retrieval.

$$Precision = \frac{Number\ of\ Relevant\ Images\ retrieved}{Total\ number\ of\ images\ retrieved} \tag{10}$$

4.2. Database used for Analysis

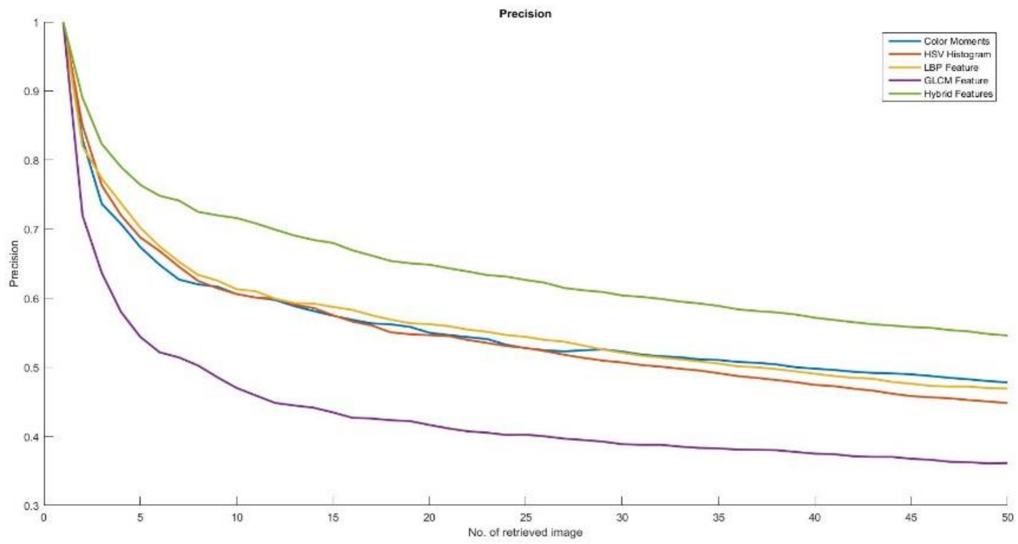
To evaluate the performance of proposed framework, the experiments have been performed on Wang (Corel-1000 image) database [14, 15], widely used for analysing the performance of retrieval system. The corel-1000 database contains, 10 different categories of images, each category contains 100 images of African, Beach, Building, Buses, Dinosaurs, Elephants, Flowers, Horses, Mountains and Foods with resolution of 256*384 or 384*256 pixels. Sample images are shown in Figure 5.

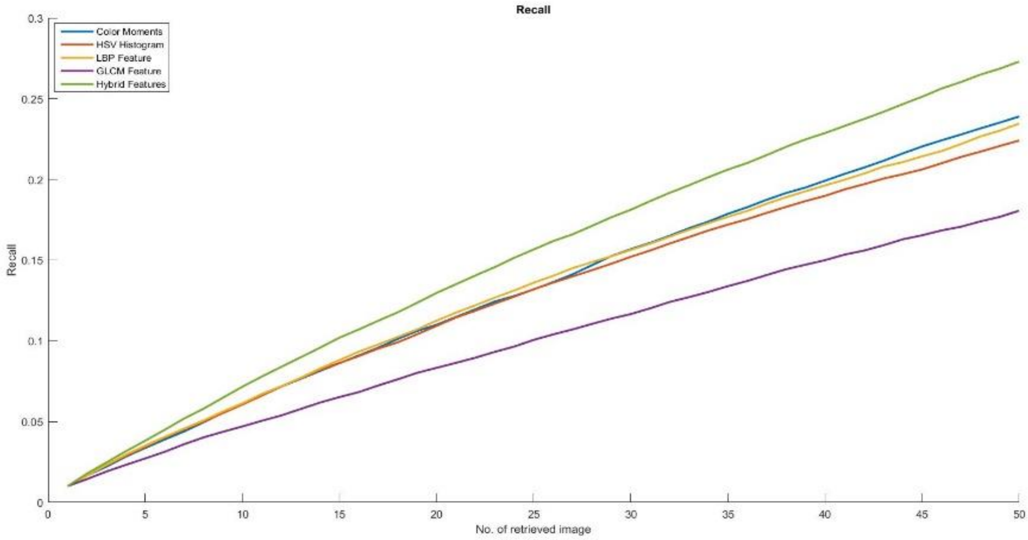
Figure 5. Sample images from each class

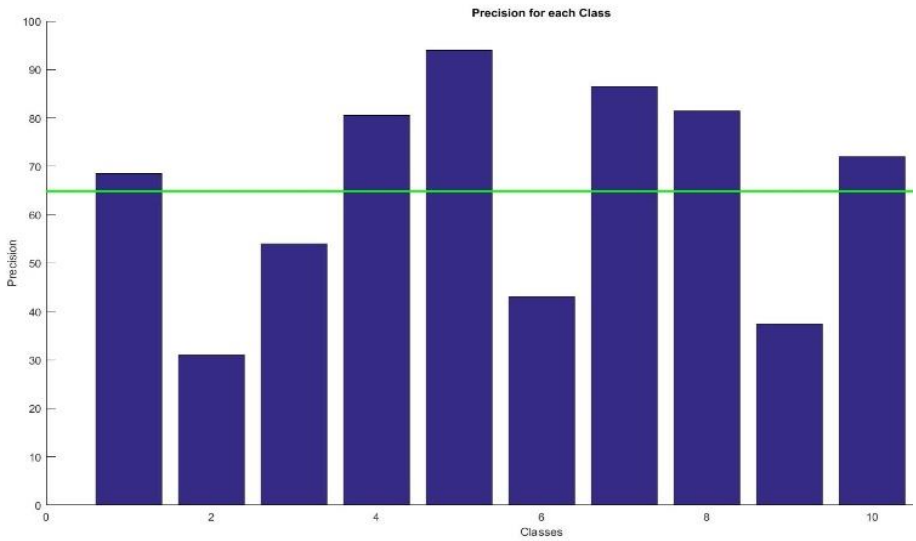
4.3. Result Analysis

In all the figures from figure 6 to 11, the first figure shows the graph of precision vs no. of images retrieved while the second figure dhows the plot of recall vs no. of images retrieved. The last figure shows the performance of the hybrid feature for the respective distance metric for each class. The bins of the bar graph in figures depict the classes of Africa, Beach, Monument, Bus, Dinosaur, Elephant, Flower, Horse, Mountain and Cuisine respectively.

In figure 6 and 7, precision by using the Euclidean distance and City Block distance was evaluated and was plotted against the no. of images. It's evident from the graph that the Hybrid feature performs better compared to other feature in both the cases. The average precision if 20 images were retrieved was found to be around 65% for Euclidean and 71% for City Block. In figure 8 and 9, precision by using the Chebyshev distance and Minkowski distance was evaluated. For Minkowski distance, hybrid feature performs much better compared to others but for Chebyshev distance performance of colour moments surpasses that of the hybrid feature when more than 25 images are retrieved. The average precision if 20 images were retrieved was found to be around 62% for Minkowski and 55% for Chebyshev. In figure 10 and 11, precision by using the Cosine distance and Correlation Distance was evaluated. It's evident from the graph that the Hybrid feature performs better compared to other feature in both the cases. The average precision if 20 images were retrieved was found to be around 65% for both cases. A comparative analysis has been done in figure 12 where it is clearly depicted that the best result is obtained using the City Block distance for the proposed algorithm. It is evident from the Figures shown that the hybrid features formed from the union of the feature vectors of HSV histogram and LBP perform better than other features such as colour moments and GLCM. The precision obtained is also better than the two features (HSV Histogram and LBP) used individually.



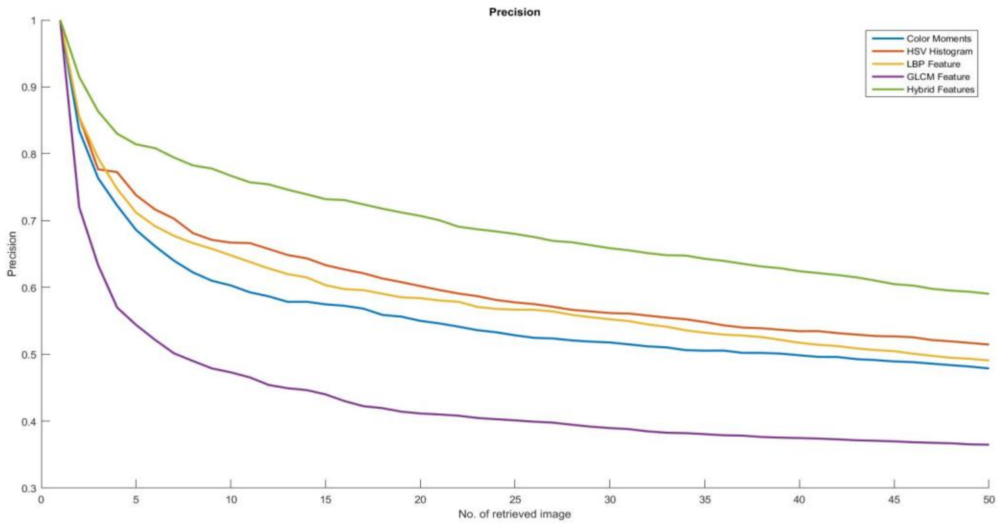


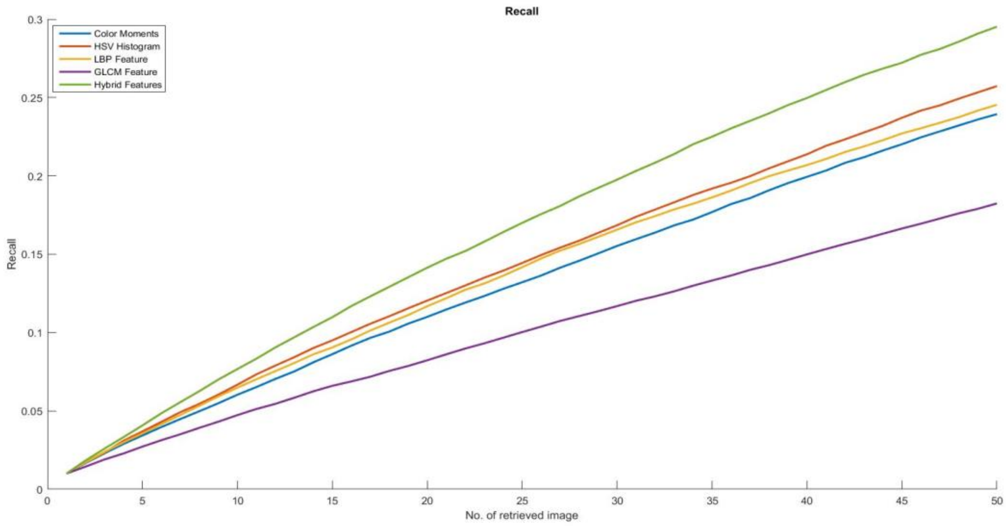


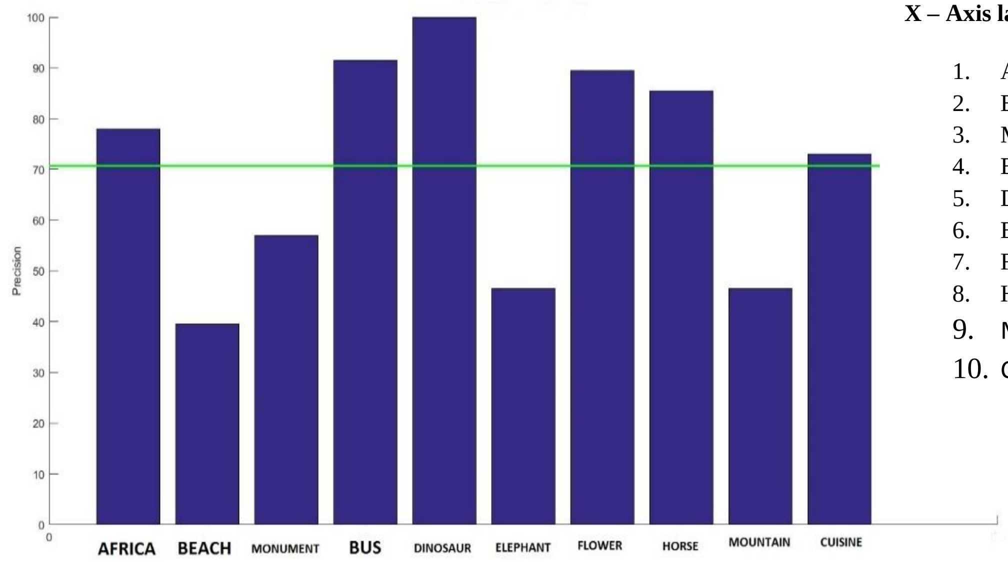
X – Axis labels:

1. Africa
2. Beach
3. Monument
4. Bus
5. Dinosaur
6. Elephant
7. Flower
8. Horse
9. Mountain
10. Cuisine

Figure 6. Performance for Euclidean distance



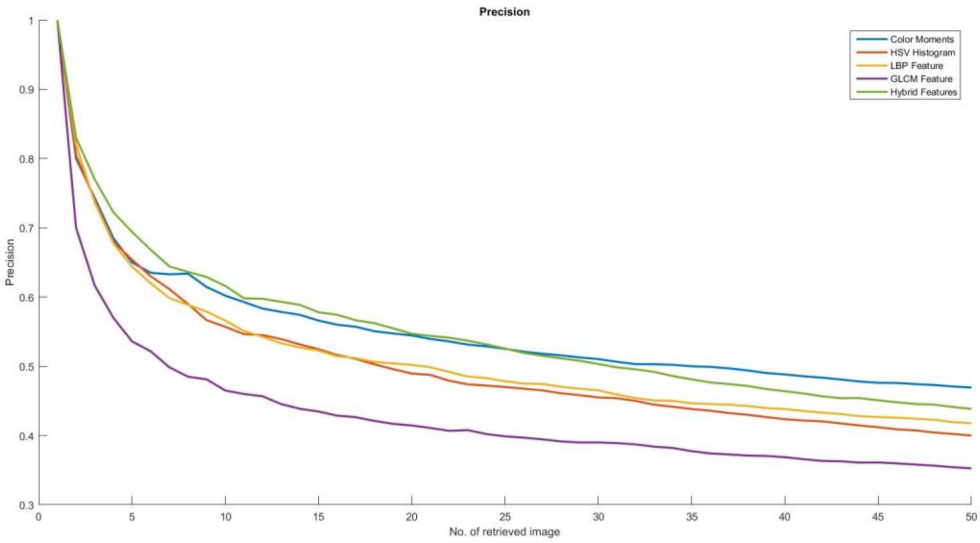


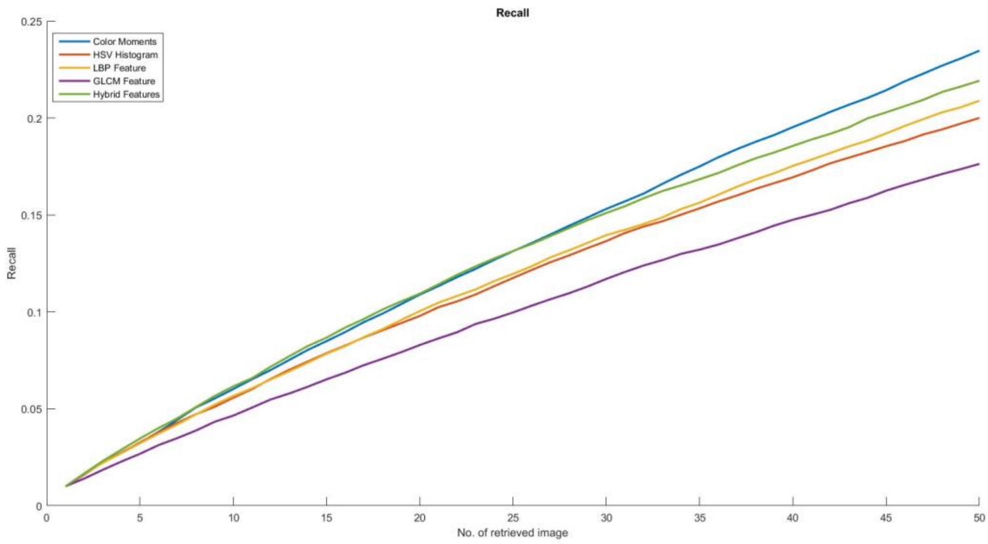


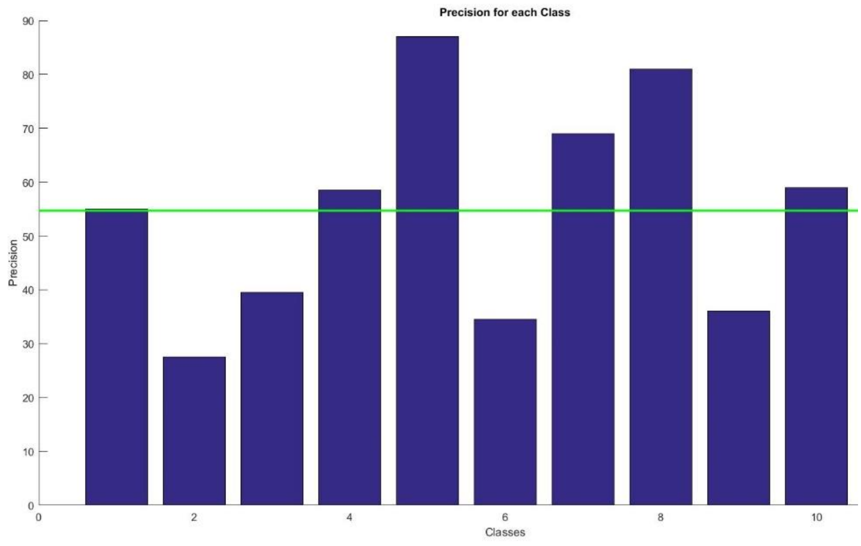
X – Axis labels:

1. Africa
2. Beach
3. Monument
4. Bus
5. Dinosaur
6. Elephant
7. Flower
8. Horse
9. Mountain
10. Cuisine

Figure 7. Performance for City Block distance



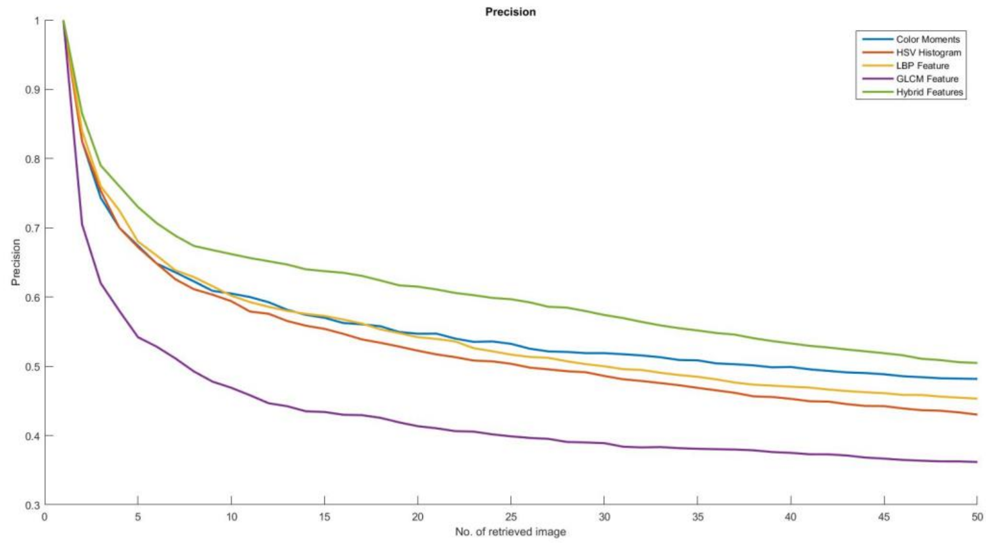


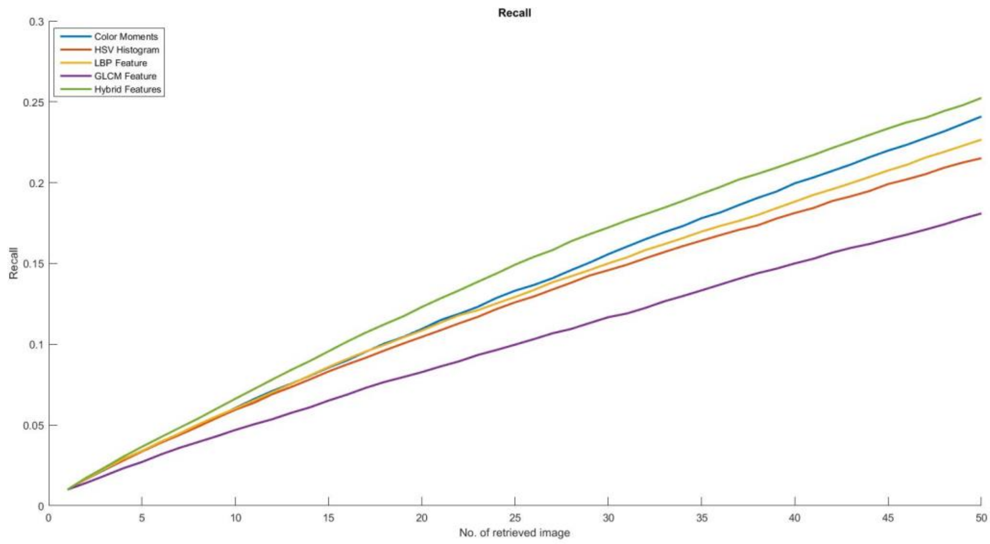


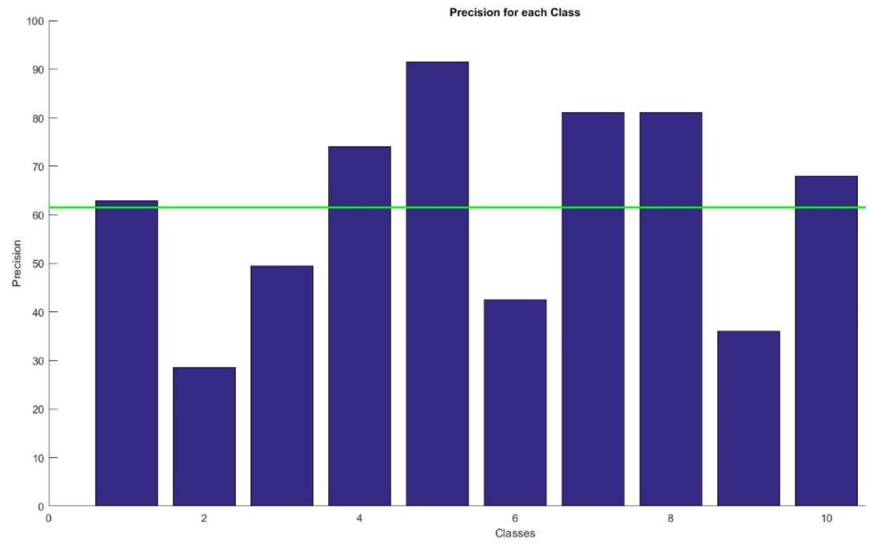
X – Axis labels:

1. Africa
2. Beach
3. Monument
4. Bus
5. Dinosaur
6. Elephant
7. Flower
8. Horse
9. Mountain
10. Cuisine

Figure 8. Performance for Chebyshev distance



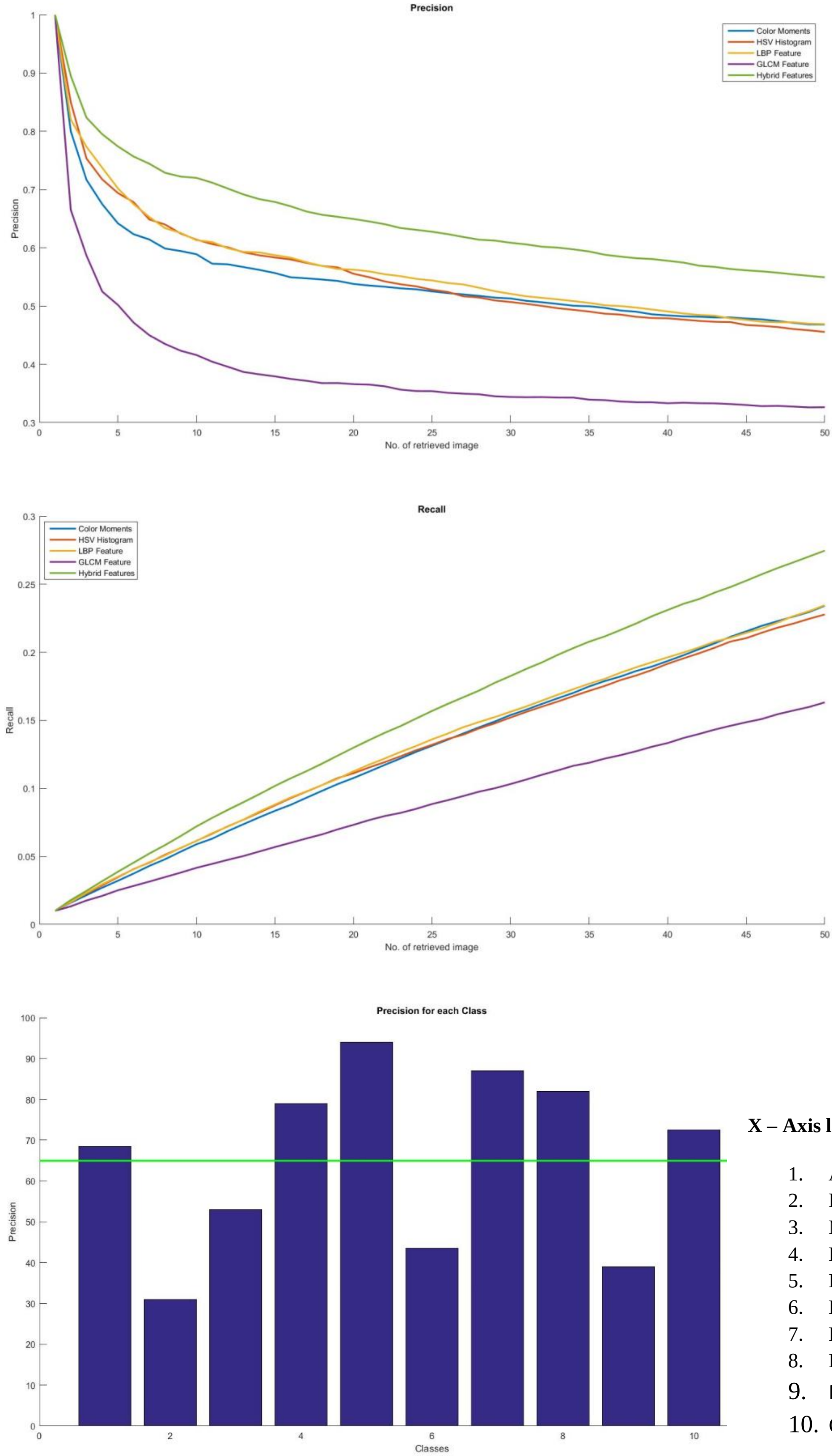




X – Axis labels:

1. Africa
2. Beach
3. Monument
4. Bus
5. Dinosaur
6. Elephant
7. Flower
8. Horse
9. Mountain
10. Cuisine

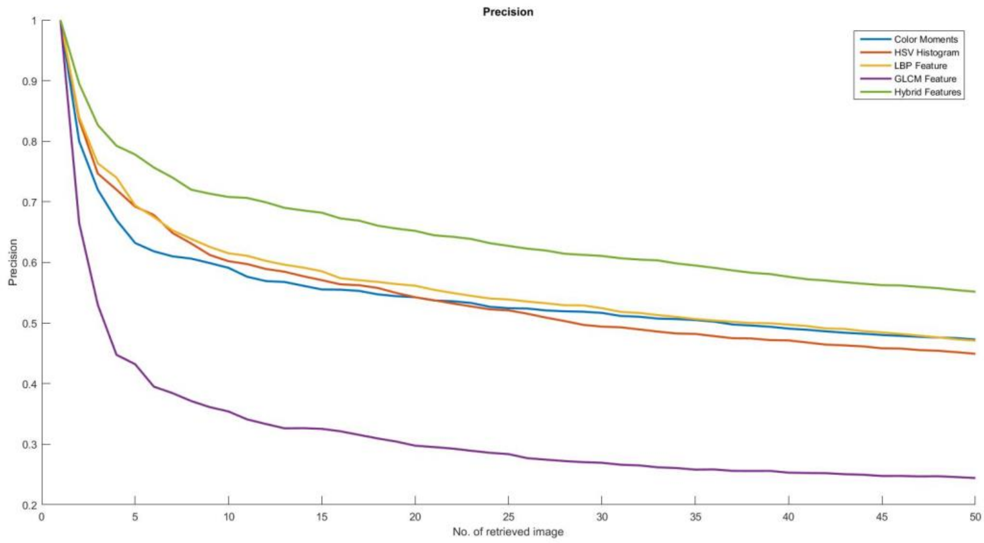
Figure 9. Performance for Minkowski distance

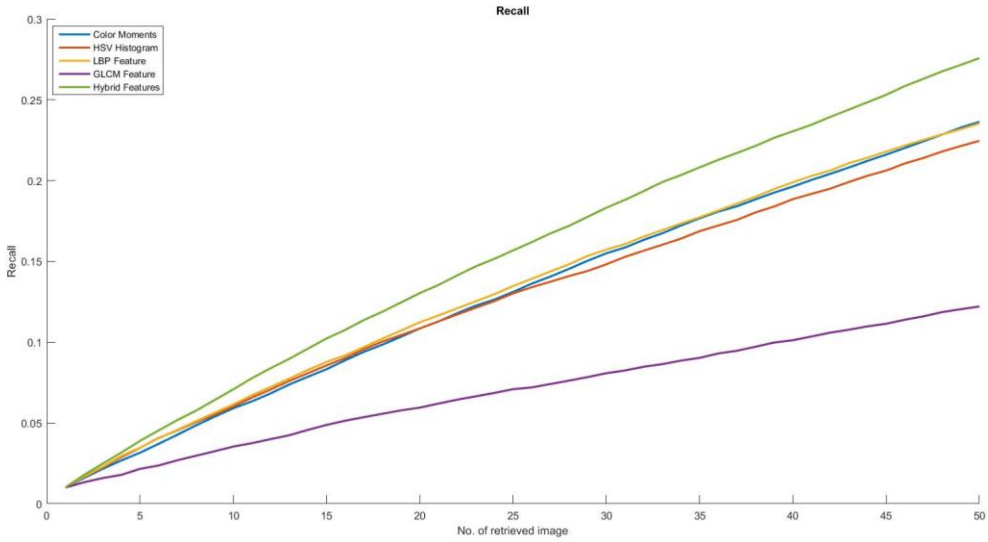


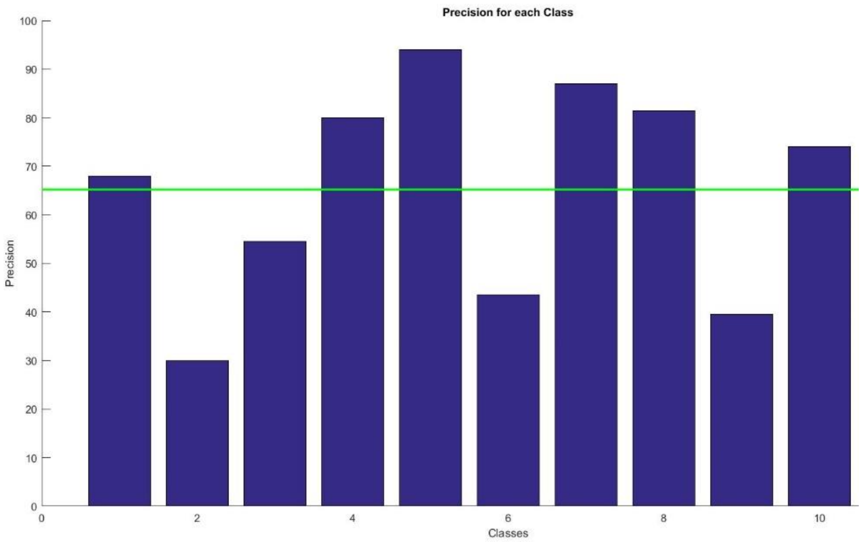
X – Axis labels:

1. Africa
2. Beach
3. Monument
4. Bus
5. Dinosaur
6. Elephant
7. Flower
8. Horse
9. Mountain
10. Cuisine

Figure 10. Performance for Cosine distance







X – Axis labels:

1. Africa
2. Beach
3. Monument
4. Bus
5. Dinosaur
6. Elephant
7. Flower
8. Horse
9. Mountain
10. Cuisine

Figure 11. Performance for Correlation distance

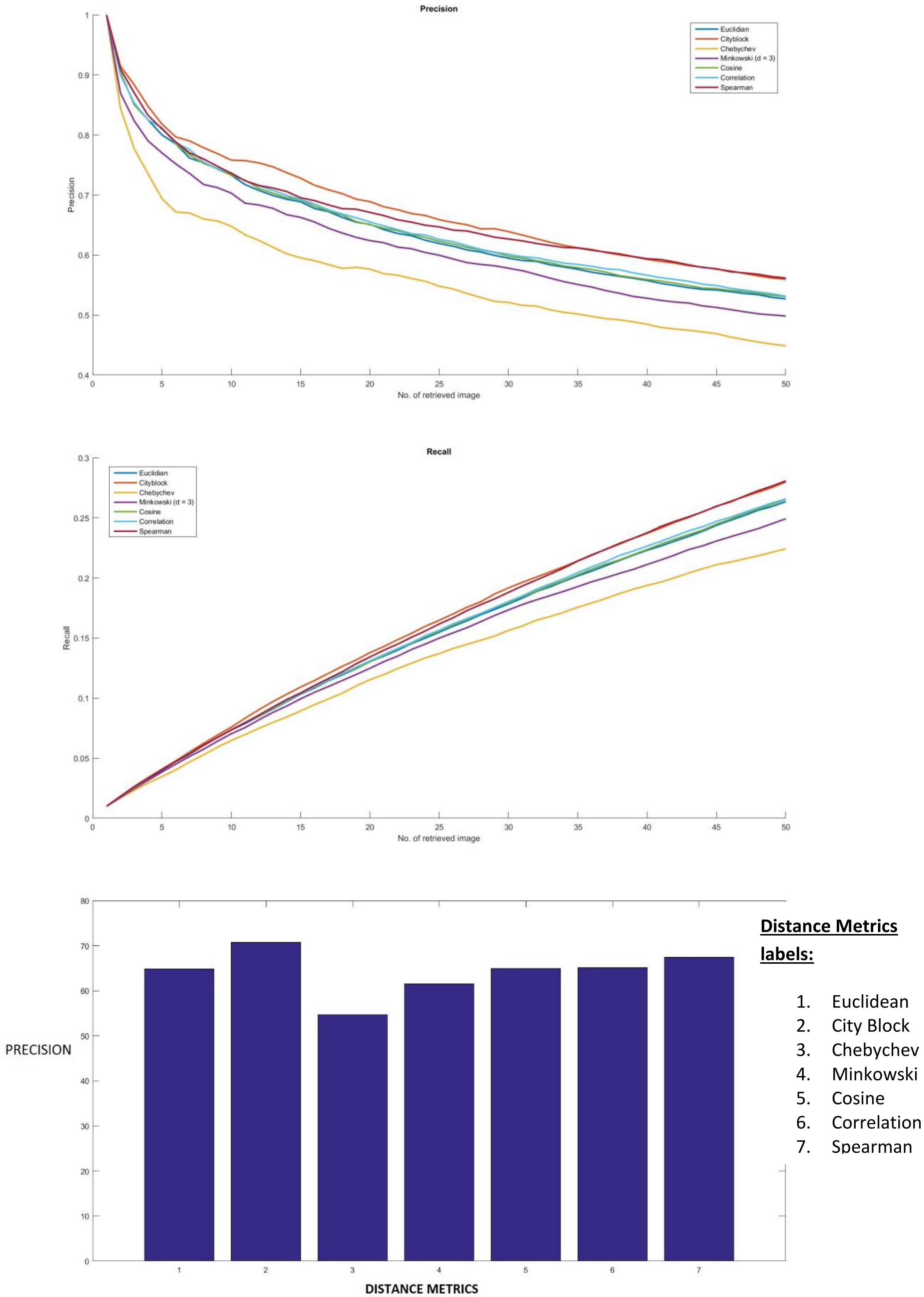


Figure 12. Performance for all distance metrics

In distance metrics, the best result is obtained for the City Block distance. Further using City Block distance for the retrieval process, in figure 13 and 14, image retrieval using the algorithm for City Block Distance is shown. The top left image is the query image for the retrieval process. In Table 2 the analysis of each class with respect to each distance metric is shown and it is evident that City Block distance metric give better results for all the classes except Beach, Elephant and Mountains where the Spearman distance performs better. However, the overall performance of City Block is much better than the Spearman as shown in the table 2.

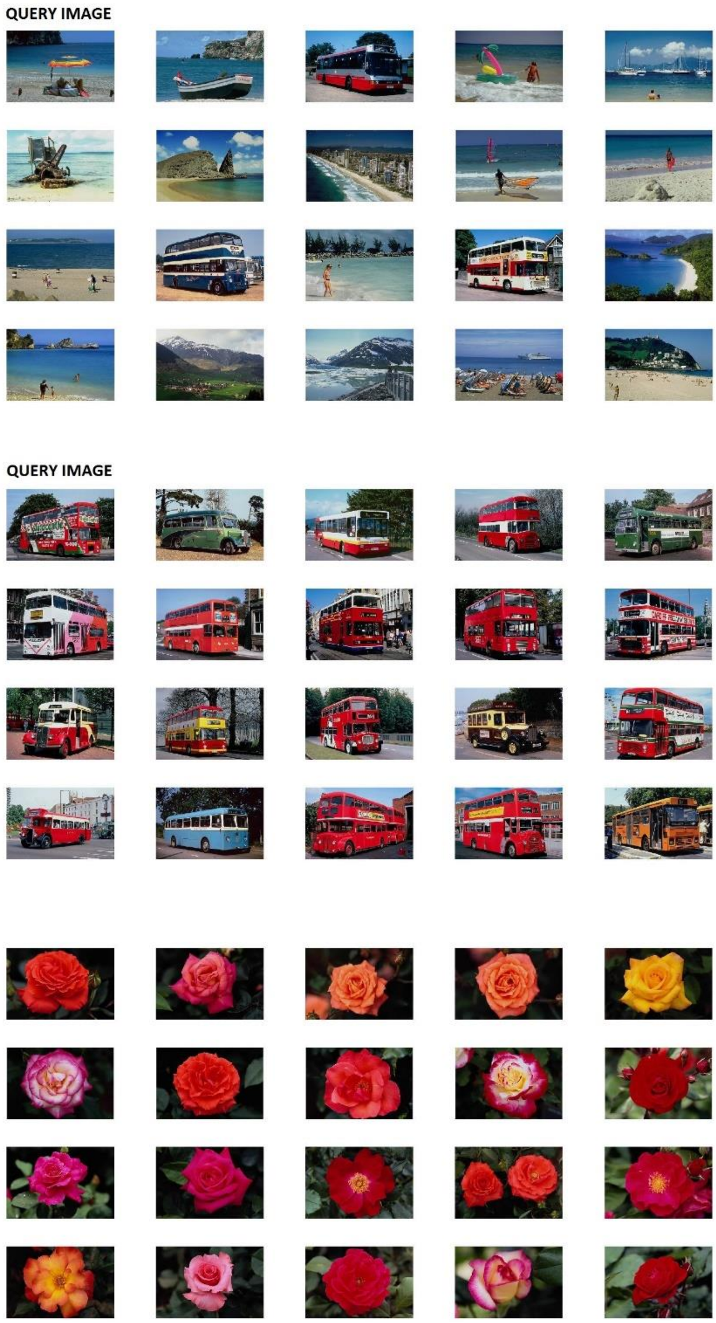


Figure 13. Image retrieval performance

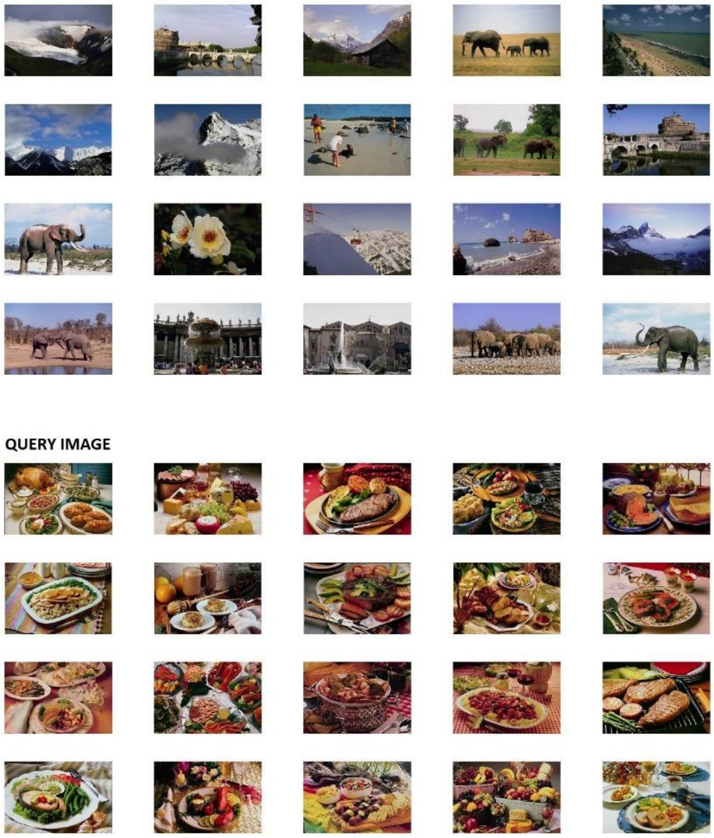


Figure 13. Image retrieval performance

Table 2. CLASS vs DISTANCE METRIC PRECISION

	Africa	Beach	Monument	Bus	Dinosaur	Elephant	Flower	Horse	Mountain	Cuisine	Average
Euclidean	68.5	31	54	80.5	94	43	86.5	81.5	37.5	72	64.85
City Block	**78**	39.5	**57**	**91.5**	**100**	46.5	**89.5**	**85.5**	46.5	**73**	**70.7**
Chebyshev	55	27.5	39.5	58.5	87	34.5	69	81	36	59	54.7
Minkowski	63	28.5	49.5	74	91.5	42.5	81	81	36	68	61.5
Cosine	68.5	31	53	79	94	43.5	82	82	39	72.5	64.45
Correlation	68	30	54.5	80	94	43.5	81.5	81.5	39.5	74	64.65
Spearman	70.5	**46.5**	49.5	66	87.5	**57**	87.5	49	**49**	75	63.75
Average	67.36	33.43	51	75.64	92.57	44.36	82.43	77.36	40.5	70.5	63.52

5. CONCLUSION

A new hybrid feature approach is proposed for efficient CBIR in this project based on colour and texture feature. Using colour and texture features individually, low retrieval performance was obtained for the retrieval process. Colour feature that is HSV histogram feature and texture feature that is LBP feature are concatenated to increase retrieval performance of the presented algorithm. It was evident from the experiment that the distance metric best suitable for this method was City Block Distance as compared to other distance metrics. Currently, I am working on techniques for reducing the feature vector size which will further reduce the execution time and increase the precision value.

References

1. Swain, Michael J., and Dana H. Ballard. "Color indexing." *International journal of computer vision* 7, no. 1 (1991): 11-32.
2. Daisy, M. Mary Helta, S. TamilSelvi, and L. Prinza. "Gray scale morphological operations for image retrieval." In *Computing, Electronics and Electrical Technologies (ICCEET), 2012 International Conference on*, pp. 571-575. IEEE, 2012.
3. Vatamanu, Oana Astrid, Mirela Frandes, Diana Lungeanu, and Gheorghe-Ioan Mihalas. "Content based image retrieval using local binary pattern operator and data mining techniques." In *MIE*, pp. 75-79. 2015.
4. Takala, Valtteri, Timo Ahonen, and Matti Pietikäinen. "Block-based methods for image retrieval using local binary patterns." *Image analysis* (2005): 13-181.
5. Kekre, H. B., Sudeep Thepade, Archana Athawale, A. Shah, Prathmesh Verlekar, and Suraj Shirke. "Grayscale Image Retrieval using DCT on Row mean, Column mean and Combination." *Journal of Sci., Engg. & Tech. Mgt* 2, no. 1 (2010).
6. Sai, N. S. T., and R. C. Patil. "Image retrieval using 2d dual-tree discrete wavelet transform." *International Journal of Computer Applications (0975–8887)* 14, no. 6 (2011).
7. Mistry, Yogita, D. T. Ingole, and M. D. Ingole. "Content based image retrieval using hybrid features and various distance metric." *Journal of Electrical Systems and Information Technology* (2017).
8. Goyal, Anjali, and Ekta Walia. "Variants of dense descriptors and Zernike moments as features for accurate shape-based image retrieval." *Signal, Image and Video Processing* (2014): 1-17.
9. Priya, R., and Vasantha Kalyani David. "Optimized content based image retrieval system based on multiple feature fusion algorithm." (2011).
10. Huang, Jing, S. Ravi Kumar, Mandar Mitra, Wei-Jing Zhu, and Ramin Zabih. "Image indexing using color correlograms." In *Computer Vision and Pattern Recognition, 1997. Proceedings, 1997 IEEE Computer Society Conference on*, pp. 762-768. IEEE, 1997.
11. Stricker, Markus A., and Markus Orengo. "Similarity of Color Images." In *Storage and Retrieval for Image and Video Databases (SPIE)*, vol. 2420, pp. 381-392. 1995.
12. Manjunath, Bangalore S., J-R. Ohm, Vinod V. Vasudevan, and Akio Yamada. "Color and texture descriptors." *IEEE Transactions on circuits and systems for video technology* 11, no. 6 (2001): 703-715.
13. Hua, CAO Li, L. I. U. Wei, and LI Guo Hui. "Research and implementation of an image retrieval algorithm based on multiple dominant colors [j]." *Journal of computer research and development* 1 (1999).
14. Li, Jia, and James Ze Wang. "Automatic linguistic indexing of pictures by a statistical modeling approach." *IEEE Transactions on pattern analysis and machine intelligence* 25, no. 9 (2003): 1075-1088.
15. Wang, James Ze, Jia Li, and Gio Wiederhold. "SIMPLIcity: Semantics-sensitive integrated matching for picture libraries." *IEEE Transactions on pattern analysis and machine intelligence* 23, no. 9 (2001): 947-963.