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Content-based Image Retrieval Based on Color Layout Descriptor (CLD) and Image Segments Extraction with k-Means Technique

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Abstract

The increasing need for computer-like capabilities is a key concern in computer vision, with content-based image retrieval (CBIR) being a crucial area in this field. In this paper, CBIR is proposed and achieved based on the feature extraction stage which prepares feature vectors from query and dataset images, where two types of features are considered: color feature and image segment features. The color features are extracted using Color Layout Descriptor (CLD), where the image segment is determined based on texture features and detected interested pixel intensity, and then k-means is applied to extract these interested image parts. Precision and mean average precision (mAP) are utilized to measure the proposed CBIR performance based on different distance measures for matching similarity. The result is achieved using mAP with 0.841.

Keywords: image retrieval, CLD, image object, k-means, local standard deviation

الملخص:

وتحقيقه بناءً على مرحلة استخراج الميزات التي تقوم CBIR استرجاع الصور المستندة إلى المحتوى في هذا البحث، تم اقتراح بإعداد متجهات الميزات من صور الاستعلام ومجموعة البيانات، حيث يتم أخذ نوعين من الميزات في الاعتبار: ميزة اللون ، و حيث يتم تحديد مقطع Color Layout Descriptor (CLD) وميزات مقطع الصورة. يتم استخراج ميزات اللون باستخدام لاستخراج أجزاء الصورة المعنية. يتم k-means الصورة بناءً على ميزات النسيج وتحديد كثافة البكسل المعنية، ثم يتم تطبيق المقترح بناءً على مقاييس مسافة مختلفة لمطابقة التشابه CBIRاداء لقياس (mAP) استخدام الدقة ومتوسط الدقة

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1. Introduction

Great multimedia repositories have been established due to the rising use of digital computers and storage technologies. These repositories are used in industries in a variety of, including video, satellite data, digital forensics, electronic games, archaeology, still image repositories, and medical treatment. As a result, there is a constant need for large-scale image retrieval systems [1]. This retrieval of the image methodology from large databases is achieved by applying text-based or content-based approaches. In a text-based procedure, utilizing the keywords consumes a high cost. While visual content is similar to key points, colors, and textures are utilized for retrieving similar images [2]. Large databases cannot be manually annotated; the user must annotate the database, subjecting the approach to human observation and limited to one language. content-based image retrieval (CBIR) avoids these problems by exploring an image database to find comparable visual content images to a specified query image [3].

CIBR is considered a significant area of image processing with applications ranging from digital libraries and entertainment to multimedia, internet, and criminal prevention [4]. For utilizing these images in a certain area or application, they must be retrieved from several sources, which accounts for the significant and quick development in the size of the digital content of images. One of the most advanced and efficient approaches for retrieving images from different image and web repositories is the content-based image retrieval (CBIR) approach [5]. The CBIR technique is considered an advanced image search and retrieval procedure that utilizes features at low levels, for instance, texture, color, and shape to invent and retrieve images from great data collections. That results in creating a feature vector, that designates the image content that exists in the database. The retrieval of the image depends on the similarity measure between the query and the dataset features vectors, sorting the list of matching images [6]. A feature is demarcated as taking a specific visual image characteristic. An image may be compared and matched to other images by encoding it with a description. Global or local feature descriptions are often possible for images. The entire image's visual content can be described as global feature descriptors. In contrast, local features define an area within an image that means (a small group of pixels) of the content of the image [7]. The main drawback of the CBIR method is that, in terms of the user's perception of semantics, images with comparable low level attributes may differ from the query image [8].

Many researchers worked in this field and proposed different algorithms to retrieve images as in [9], where the images are retrieved based on their contents by employing the networks and the internet for the tourism industry. Several techniques were chosen and implemented as well including Edge Histogram Descriptor (EHD), Color Layout Descriptor (CLD), and recommends a CBIR algorithm for enhanced retrieval performance.

Also in [7], the researchers employed the BoVW model and local feature descriptors to implement the retrieval operation of images that are similar to standard databases effectively. The introduced method utilized SURF and SIFT procedures for invariant image signatures, the method for visual vocabulary is K-Means, and the SVM algorithm for further related images.

In the same field, the work [2] presented the retrieval of relevant images between query images and database images. it is using the proximity space theory. The color histogram is used to determine the colors that rank highest, and an enhanced dominance granule structure similarity approach is used to determine the similarity.

within [10] this work represents the image contents depending on color and texture features, precisely the color layout descriptor (CLD) and gray-level co-occurrence matrix (GLCM). For localized dominating areas, CLD and GLCM are effective methods. City block distance is used to match the features of the source image with the features of the query image.

In [11] the researchers in this work suggested a set of color and texture characteristics were employed for both approaches of fusion strategies. First, a single vector representation is formed by combining twelve texture features and eighteen color features at an early stage, second, the late fusion stage is considered with the fusion implementation of three of the more common distance measures.

where in [12] the suggested CBIR methods employ RGB color with neutrosophic clustering procedure and utilize a Canny edge scheme to achieve an extraction operation of shape features, also texture features are prepared based on a co-occurrence matrix, and then YCbCr color with a discrete wavelet transform and Canny edge histogram for color features.
Also in [13], this work produced a local structural descriptor (LSD) based on edge orientation similarity intended for color image retrieval. The associations of color, texture, and shape for image retrieval have been implemented in LSD, taking part in statistical and structural texture explanation approaches. With its low dimensionality and high indexing ability, it is a promising choice for image retrieval.
While authors in [6] suggested a method for CBIR based on combining color and texture features, where information of color is extracted utilizing Color Histogram (CH), while Edge Histogram Descriptor (EDH) with Discrete Wavelet Transform (DWT) is employed for extracting texture features.
In [14] the study concentrates on finding color features depending on color histograms and color moments, and the similarity was measured in library images based on employing the Euclidean distance process and manipulating the closest distance.
The author in [15] provided a procedure for retrieving images based on SURF and ORB characteristics from a great collection. The extraction from the query image was achieved to SURF and ORB characteristics, where the use of the K-means technique for analyzing it and employing LPP for achieving dimensionality reduction for improving the performance of the system.
Where some proposed works used deep learning as [16] The production of hybrid deep learning and machine learning was implemented for the CBIR method, applying transfer learning procedures to achieve the extraction of features from images. The two pre-trained models of deep learning are applied which are, ResNet50 and VGG16, and one machine learning model, KNN, to estimate image similarity and Euclidean distance.
and the authors in [17] extracted the features in CBIR utilizing produced a framework through a deep-learning by employing convolutional-neural networks (CNN), the goal of this suggestion is to achieve the reduction of the semantic gap between features in low and high levels, determine the distance between the query and database image features has been determined by utilizing the measurements of similarity.
This proposed work produces a suggestion for retrieving relevant images based on image color feature extraction using the CLD method and image object extraction, where the object of the image is extracted depending on the set of different features and the extraction operation achieved using the K-means technique. The remainder of this paper is arranged in the following sequence, including illustrations of the retrieval methodology in section 2, where the results of the experiments and its discussion are explained in section 3, and the conclusion is displayed in section 4.

2. Retrieval methodology

In this paper, a method for image retrieval based on its content has been proposed, where the images are retrieved based on their color feature vectors using the CLD technique and feature vectors extracted based on interest parts detection using a proposed method depending on a combination of features and k-means clustering technique. The similarity matching is achieved by utilizing different similarity measurements like Euclidean distance, City block, and Minkowski distance. the steps of this proposed retrieval are illustrated in Figure 1, and the details are as follows:

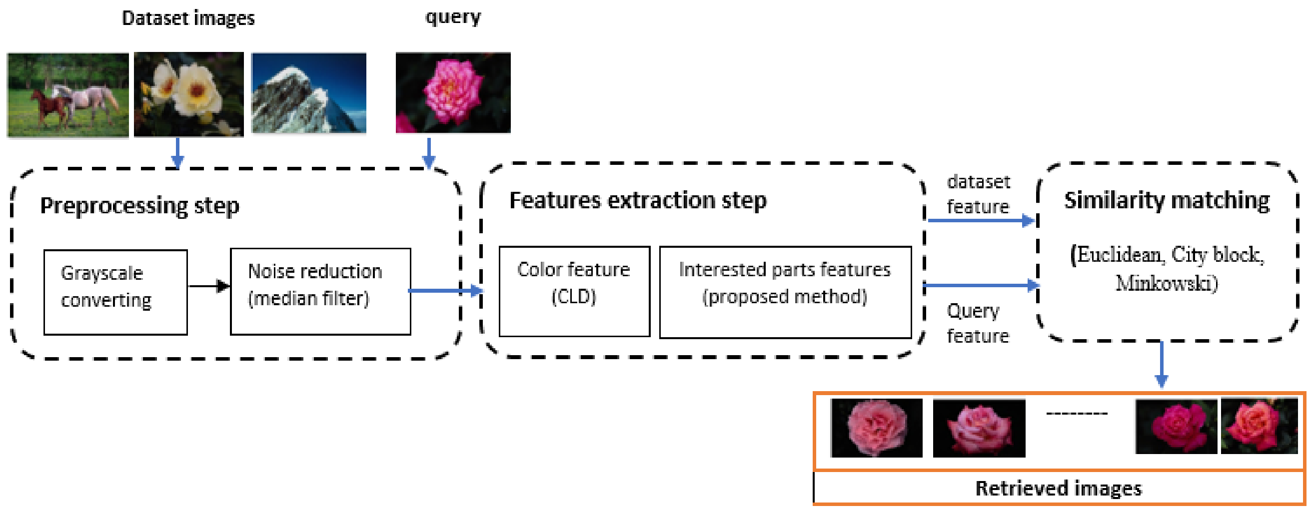


Figure 1. Flowchart of the proposed CBIR

2.1 preprocessing input image

The image firstly is read and then converted to a grayscale image, and the noise is reduced as a preprocessing step with median filtering in a 3*3 neighborhood around the corresponding pixel. The median filter is considered effective for computational and its ability for noise-suppressing, for this reason, it is a widely employed filter for eliminating impulse noise. In recent years, various exciting study directions have been emphasized by median filters, which are nonlinear filters of rank filters [18].

2.2 Image retrieval features and matching

Color features are considered the more regularly employed low-level characteristics for image retrieval due to their simplicity. People utilize them for visual recognition [19]. Two types of feature vectors are created in this stage, the first type is a color feature extracted using the CLD method, and another type of feature vector is extracted from image segments (objects) based on the proposed method, where The feature vectors are formed in this stage from testing and training images. This paper examines Color Layout Descriptor (CLD) which displays the color distribution in an image spatially. It finds that this depiction is both compact and invariant of an image's resolution. That is mainly a benefit for image retrieval in fast [20]. A color descriptor is found as a numerical value in which a description has been given of the color feature of an image [19]. The CLD [10] has been calculated with three diverse steps.

In this stage the image is divided into several blocks (8×8 blocks) with block sizes (32*48) or (48 *32), finding the dominant color for each block using the average color method then resizing this resulting image to block size (8*8) and block numbers (4*6), then converting the averaging image color space to YCbCr color space and applying discrete cosine transformation (DCT) to each of these color space components. Three 4x6 matrices were formed into three arrays, each gaging 1 x 24 to simplify feature matching. Upon successively combining the three arrays, the obtaining of a 1×72 color layout descriptor is achieved. Then the query and training color image differences cld_{dis} as showed in (1) [19] using Euclidian distance.

$$cld_{dis} = \sqrt{\sum_i w_{yi}\,(dYi - dYi')^2} + \sqrt{\sum_i w_{cbi}\,(dCbi - dCbi')^2} + \sqrt{\sum_i w_{cri}\,(dCri - dCri')^2} \qquad (1)$$

where w_{yi}, w_{cbi}, and w_{cri} are the weighting values for the ith coefficient, and dYi, dCbi, and dCri indicate the ith coefficients of the Y, Cb, and Cr color components, respectively. The more similarity between the database images and the query image is shown by a lower value of cld_{dis}.

The second type of the features vector has been created based on the proposed method for segmenting the input image to obtain the interested parts of the image which means detecting the interested pixels convey image information, then take the features of these parts (objects). Figures 2 and 3 explain the steps of implementing this proposed image segmentation that was realized in this stage.

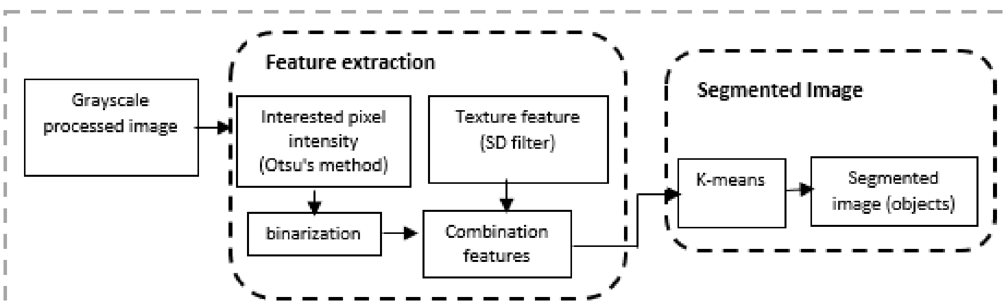


Figure 2. Steps of the proposed method for detecting interested parts by segmented image

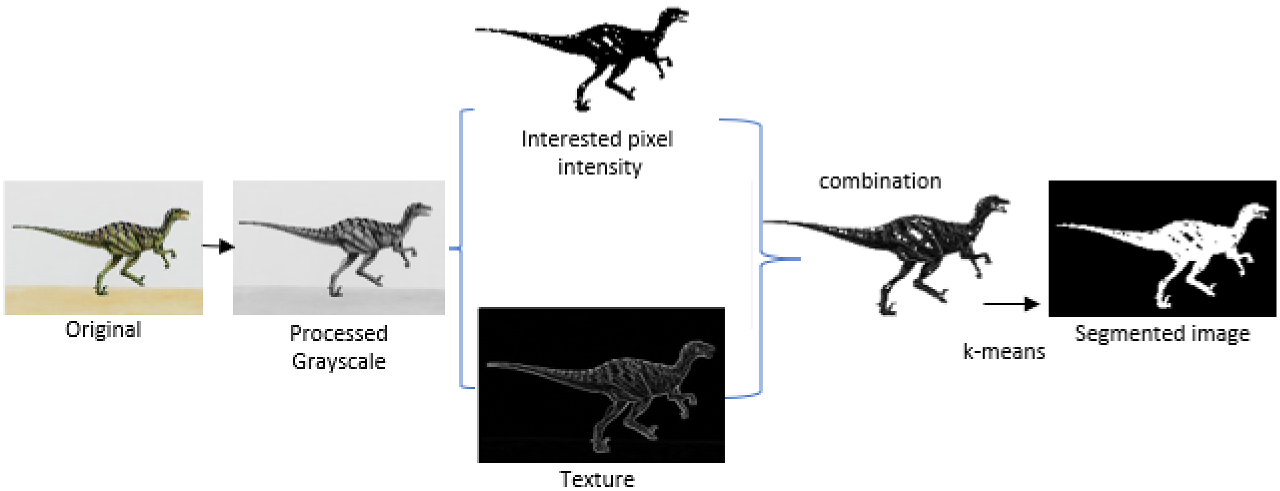


Figure 3. Example of applying the proposed image segmented for interested parts

As can be seen in these figures, this proposed method for detecting interested parts of the image by segmentation consists of combining two types of feature matrices that are extracted from the processed grayscale image: texture feature and detecting the intensity of interested pixels of an image. a key element of natural images is texture [19], the texture feature is extracted using the local standard deviation filter (SD) [21] of the 3-by-3 neighborhood around the consistent pixel that describes the regions of the image by its texture contents, the texture region provides local variability of the pixel's intensity values information and calculated as follows [22]:

$$\mu_j = \frac{1}{N}\sum_{i=1}^{N} x_{ji} \qquad (2)$$

$$\sigma_j = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_{ji} - \mu_j)^2} \qquad (3)$$

Where μ_j represents the mean value, σ_j is considered as the standard deviation

The interested pixels are determined depending on a threshold value established based on Otsu's method, where Otsu's mechanism utilizes image pixel intensity to find the finest threshold value. This is achieved after all potential values have been iterated and the mechanism estimates the space of the pixel levels scale on the threshold side, precisely background and foreground pixels, to minimize background spread and foreground summation [23]. Then these interested image pixels are binarized. Finally, the interested image parts (object) are recognized by applying this combination features matrix to the k-mean technique, K-means is a widely used method for clustering data due to its ease of use and quick calculation, consisting of two stages: initializing the centroid and determining the cluster based on the distance to the closest centroid, so, it is used in this stage [24].

The similarity matching between the training and query image segments is achieved when the training and testing image segments are divided into 8*8 blocks, and each block's mean absolute deviation (MAD) is calculated. From these 8*8 mean absolute deviation values for each block, a feature vector with size 1*64 is created for similarity matching. This process creates the matching feature vectors to the second type of feature (interested parts) that is used in this proposed CBIR as illustrated in Figure 4.

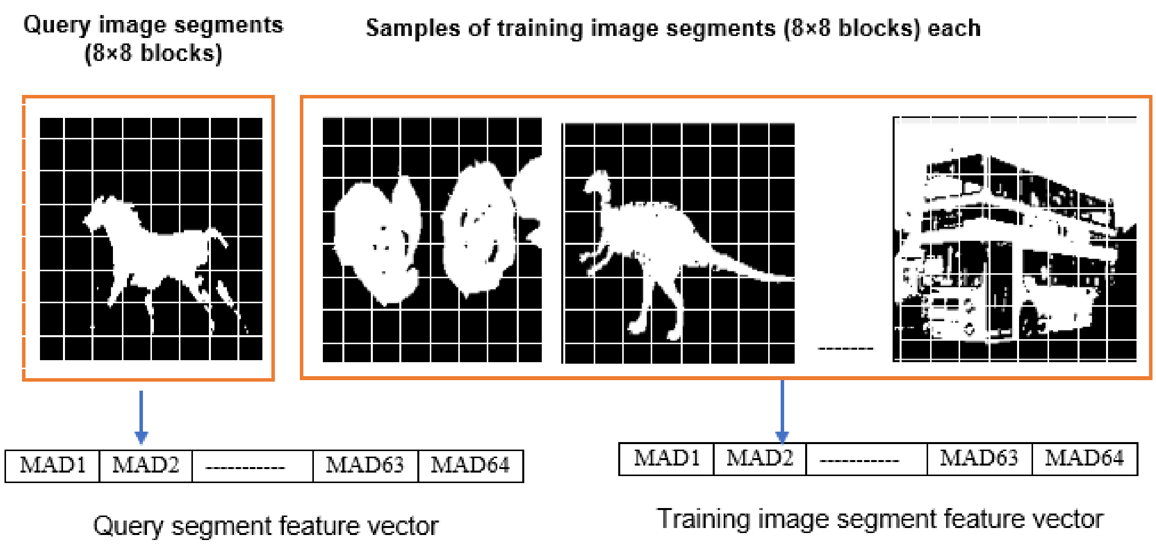


Figure 4. Generate second-type feature vectors

Next, using similarity distance measurements (Euclidian distance, city Block, and Minkowski distance), for example, when using Euclidian distance, the query and training images object differences are as in (4) [25].

$$dis_{obj} = \sqrt{\sum_{i}(obji - obji')^2} \qquad (4)$$

Where $obji$, $obji'$ are the pixels of query and training respectively.

3. Experimental Results and Discussion

3.1 Input images

In this study, the Corel 1K dataset is utilized to conduct the performance of the proposed CBIR scheme, this database contains 1,000 JPEG images in 10 categories with 100 images each, including Africa, horses, flowers, beaches, buses, buildings, mountains, dinosaurs, elephants, flowers, and food, as shown in Figure 5 with resolutions of 256*384 or 384*256 pixels.

Figure 5. Image sample of Corel-1K dataset

3.2 CBIR Features vectors

In this study, the experiments were conducted based on fusion features vectors extracted dependent on color descriptor using CLD and interested segments extraction with a proposed method using the k-means technique.

In generating the second feature vector, the number of k-means clusters for this suggested segments-recognizing approach is determined based on evaluating the object segmenting accuracy using the homogeneity measure that is provided in (5) that used in [26,27], Image segmentation is regarded as a technique for breaking up an image into homogeneous areas, and object-based analysis has emerged as a powerful tool for interpreting high spatial resolution images [28]. K-means with 2 clusters give more homogeneous regions (objects). Some examples of images from the dataset to evaluate this method of object recognition are shown in Table 1 and Figure 6, as can be seen in this table better evaluation results were achieved in 2-cluster k-means. That means k-means with 2-cluster create regions (objects) with more homogeneity than 3-clusters.

$$homogenity(I) = \sum_{i=0}^{w-1}\sum_{j=0}^{h-1}\frac{I(i,j)}{1+(i-j)} \qquad (5)$$

where I with the size of w×h.

Table 1. Object extraction evaluation-based cluster number using Homogeneity

class	Image No.	Homogeneity measure	
		2-cluster	3-cluster
Bus	331	303772.568	176127.026
Building	238	407167.486	353702.309
Africa	15	388887.520	340441.7643
Flower	622	246390.534	142214.452
Food	991	200790.087	154471.762
Horse	701	275360.383	156981.736
Elephant	553	148497.896	107912.516

(a) (b) (c)

Figure 6. Example applying k-means, (a) horses class (sample 701), (b) 2-cluster, (c) 3-cluster

3.3 CBIR Performance evaluation and matching similarity

The performance of the suggested CBIR was evaluated by employing precision and mean average precision (mAP). Precision is determined by dividing the total number of retrieved images by the total number of relevant images as illustrated in (6), Which reflects the scheme's capability only to return the relevant images. mAP represents the mean average precision for all classes, AP is described in (7) and the computing of mAP is shown in (8) [17].

$$p = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ images\ retrived} \quad (6)$$

$$AP = \frac{1}{n}\sum\nolimits_{i=1}^{n} p_i \quad (7)$$

$$mAP = \frac{1}{m}\sum\nolimits_{k=1}^{m} AP_k \quad (8)$$

Where P denotes the precision, and n signifies the image number. AP_k symbolizes the AP of class K, and m designates the class's numbers.

The retrieval performance was evaluated using precision to the N retrieval image with top 10 and top 20 as achieved in many related works, indicating higher precision in returning relevant images. Ten randomly selected images from each category were used in each experiment as query images. Table 2 and Figures 7,8 show the retrieval performance by considering the effect of distance measures. different distance measures were used such as Euclidean distance, City block as in (9)[11], and Minkowski distance in (10) [29], as explained in this table to measure the similarity between the query image and images in the dataset and from the results that showed, CBIR with Euclidean distance gives a higher performance than others with Top 10. Figure 9 explains samples of query and retrieved images.

$$cityblock = \sum\nolimits_{i}^{n} |x_i - y_i| \quad (9)$$

Where x and y denote vectors with n dimensions.

$$d_M(i,j) = \sum_{k=1}^{p} (\left|(x_i^k - x_j^k)\right|^M)^{\frac{1}{M}} \qquad (10)$$

Where x_i^k , x_j^k are vectors with dimension p.

Table 2. CBIR performance by precision and mAP based on distance measures

Measures	**Euclidean distance**		**City block**		**Minkowski distance**	
N / class	**Top 10**	**Top 20**	**Top 10**	**Top 20**	**Top 10**	**Top 20**
Africa	0.73	0.65	0.7	0.66	0.69	0.59
Beaches	0.76	0.665	0.75	0.66	0.8	0.665
Building	0.62	0.44	0.7	0.505	0.54	0.4
Bus	0.83	0.745	0.83	0.73	0.79	0.69
Dinosaurs	1	1	1	1	1	0.99
Elephant	0.83	0.77	0.82	0.74	0.85	0.79
Flowers	0.98	0.905	0.99	0.91	0.97	0.855
Horses	0.97	0.895	0.95	0.93	0.96	0.905
Mountains	0.86	0.665	0.81	0.645	0.77	0.595
Food	0.83	0.69	0.83	0.69	0.8	0.7
mAP	**0.841**	0.742	0.838	0.747	0.817	0.718

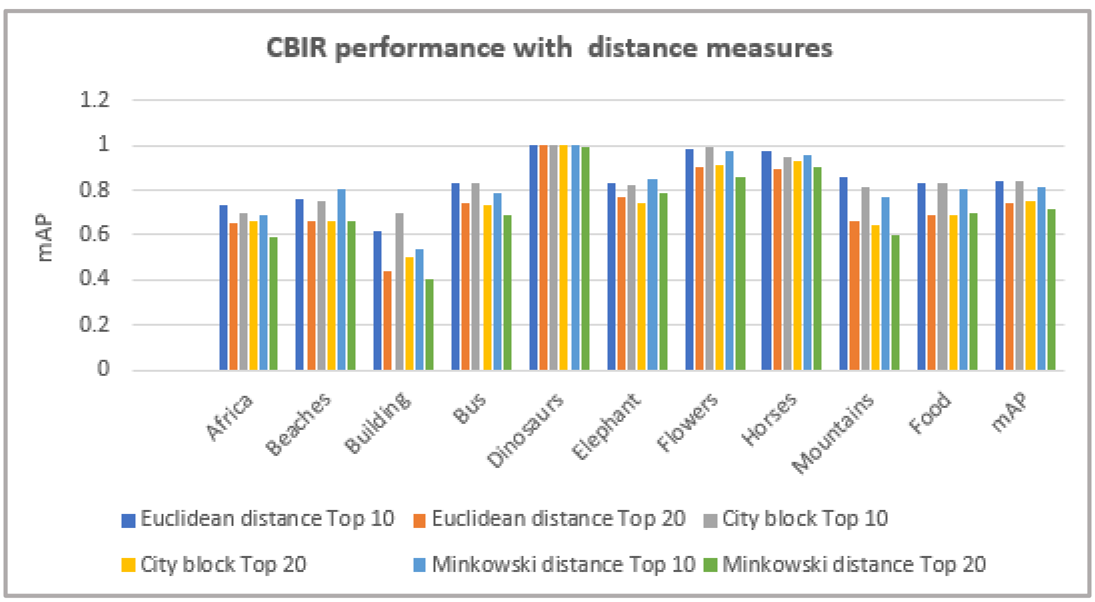


Figure 7. CBIR performance with different distance measures

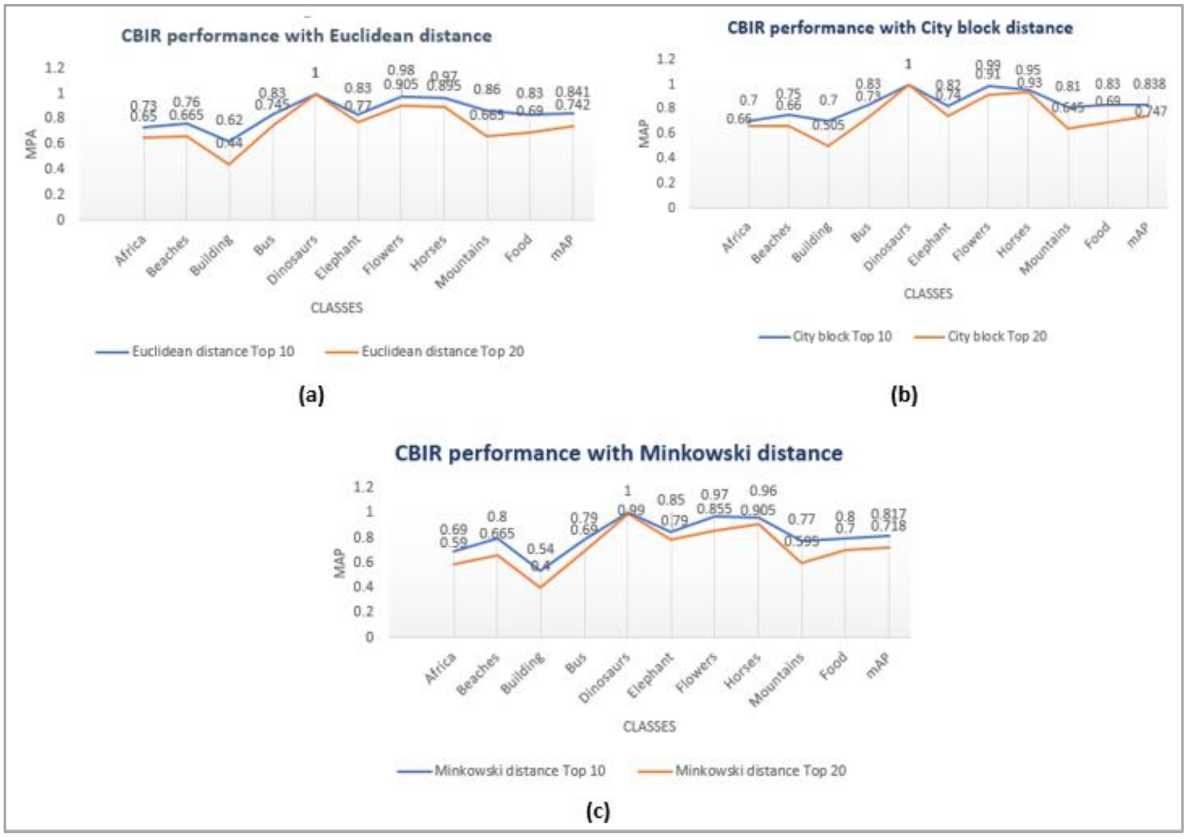
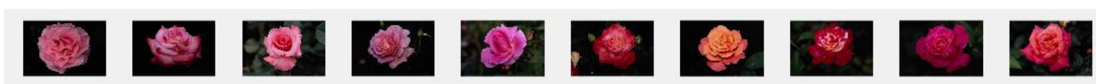
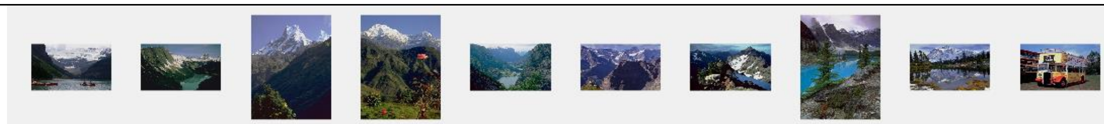


Figure 8. CBIR performance by precision and mAP, (a) based on Eucleadin distance, (b) based on City block distance, (c) Minkowski distance

Figure 9 Samples of query and retrieved image

The nature of the images affects the results. Some certain classes have clear, basic colors that make it easy to differentiate objects apart from their background. The challenge is when the classes have similar colors, making it difficult to recognize. The fusion of different types of features attempts to reduce this challenge. Dinosaurs, Flowers, and Horses achieved higher performance in retrieving images with three types of similarity distance measures Eucleadin distance, City block distance, and Minkowski distance, while the Building class made less performance for retrieving images. Among these three types of distance similarity measures, the Euclidian distance measure performs in the top 10 better than others for image retrieval with a mean average precision (mAP) of 0.841.

Future work suggestion: The suggestion for future work may be to combine the study with another feature type because using different features gives more precision in the description of image contents.

Query	Retrieved images
	
	
	
	
	
	

3.4 Comparison with other works

The result of this work compared with other works that used the Corel 1K dataset as seen in Table 3 with Top 10 image retrieval. Ahmed, A., & Mohamed, S [11] used texture and color attributes for both fusion strategy approaches. Initially the integration of twelve textures and eighteen colors characteristics a unified vector representation is created in an early stage. Subsequently, the late fusion stage is examined using the integration of three frequently used distance measures. Rasha et al. [17] used convolutional neural networks (CNN) through a suggested deep learning basis to implement the extraction of features in CBIR. The proposed work used color and interested pixels features, where the color features extracted by the CLD method, interested pixels detected by the proposed method, and similarity matching implemented with different similarity measures.

Table 3. Comparison of proposed work with other works

Classes	**Performance in [11]**	**Performance in [17]**	**proposed method**
Africa	0.412	0.91	0.73
Beaches	0.338	0,65	0.76
Building	0.575	0.95	0.62
Bus	0.825	0.9	0.83
Dinosaurs	1	1	1
Elephant	0.438	0.75	0.83
Flowers	0.912	1	0.98

Horses	0.825	0.99	0.97
Mountains	0.362	1	0.86
Food	0.375	0.65	0.83
mAP	**0.6060**	**0.88**	**0.841**

4. Conclusion

This paper proposes a content-based image retrieval method. Using the CLD technique, images are retrieved based on their color feature vectors, and the proposed method extracts feature vectors based on the detection of interest segments. The retrieval performance was evaluated using precision to the N retrieval image with the top 10 and top 20, and different distance measures were used such as Euclidean distance, City block measure, and Minkowski distance, to calculate the similarity between the query image and images in the dataset. The nature of the images affects the results. The CBIR performance achieved more accuracy with mAP based on Euclidean distance than others.

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