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Content-Based Image Retrieval System using Color Moment and Bag of Visual Words with Local Binary Pattern

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Researchers have recently focused their attention on Content-Based Image Retrieval (CBIR). It has emerged as one of the most fascinating areas in image processing and computer vision. With CBIR, the most comparable pictures that match the query image are pulled from an image database. As a result, it necessitates feature extraction (Local / Global) and similarity calculation. This paper uses a CBIR technique to determine the images that best match the image query by utilizing both global and local image features. A color moment is used for global features to describe the complete image. Local Binary Pattern (LBP) as a local feature, on the other hand, extracts interest points by building a Bag of Visual Words (BoVW). The distance between the query and database image features is computed using the Euclidean distance. Precision and recall are computed on the Corel-1K dataset to assess the retrieval performance.

Keywords

Content-based image retrieval, Color Moment, Local Binary Pattern, Bag of Visual Words.

RESEARCH PAPER

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Abstract

Researchers have recently focused their attention on Content-Based Image Retrieval (CBIR). It has emerged as one of the most fascinating areas in image processing and computer vision. With CBIR, the most comparable pictures that match the query image are pulled from an image database. As a result, it necessitates feature extraction (Local/Global) and similarity calculation. This paper uses a CBIR technique to determine the images that best match the image query by utilizing both global and local image features. A color moment is used for global features to describe the complete image. Local Binary Pattern (LBP) as a local feature, on the other hand, extracts interest points by building a Bag of Visual Words (BoVW). The distance between the query and database image features is computed using the Euclidean distance. Precision and recall are computed on the Corel-1K dataset to assess the retrieval performance.

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1. Introduction

Technology advancements have enabled widespread usage of devices capable of quickly collecting, storing, and sharing vast volumes of photographs. This scenario necessitates the creation of effective and efficient ways of performing image retrieval tasks based on the visual content of the image, a technique known as content-based image retrieval (CBIR) [1]. CBIR has been a popular topic of community multimedia research since the early 1990s [2]. Such a technique, CBIR, is the most important technique for image processing and computer vision. It is also employed in various disciplines, including medical applications where CBIR is used for medical image datasets. For this study [3], can evaluate photos by extracting features utilizing global, local, or integrating global and local features. The result of this facilitates the process of classification or retrieval of images. CBIR is a well-defined image retrieval and search technique. That uses the visual content of images to find and retrieve images from extensive data collections [4]. Fig. (1) shows the basic block diagram for CBIR. Low-level elements such as shape, color, and texture are utilized to characterize the contents of an image. This set of low-level features generates a feature vector, which describes the content of every image in the image database. Subsequently, image retrieval is based on similarities in their contents. The similarity measurement between the dataset feature vector and the query is used to sort the list of matching images [5]. Features are separated into local and global groups based on feature extraction methods [6]. Global features such as spatial information, texture [7], color [8], and shape [9] create a representation of the complete image. Local features are key points or specific areas of a picture, such as blobs, edges, and corners. Local features resist scaling, rotation, translation, and background

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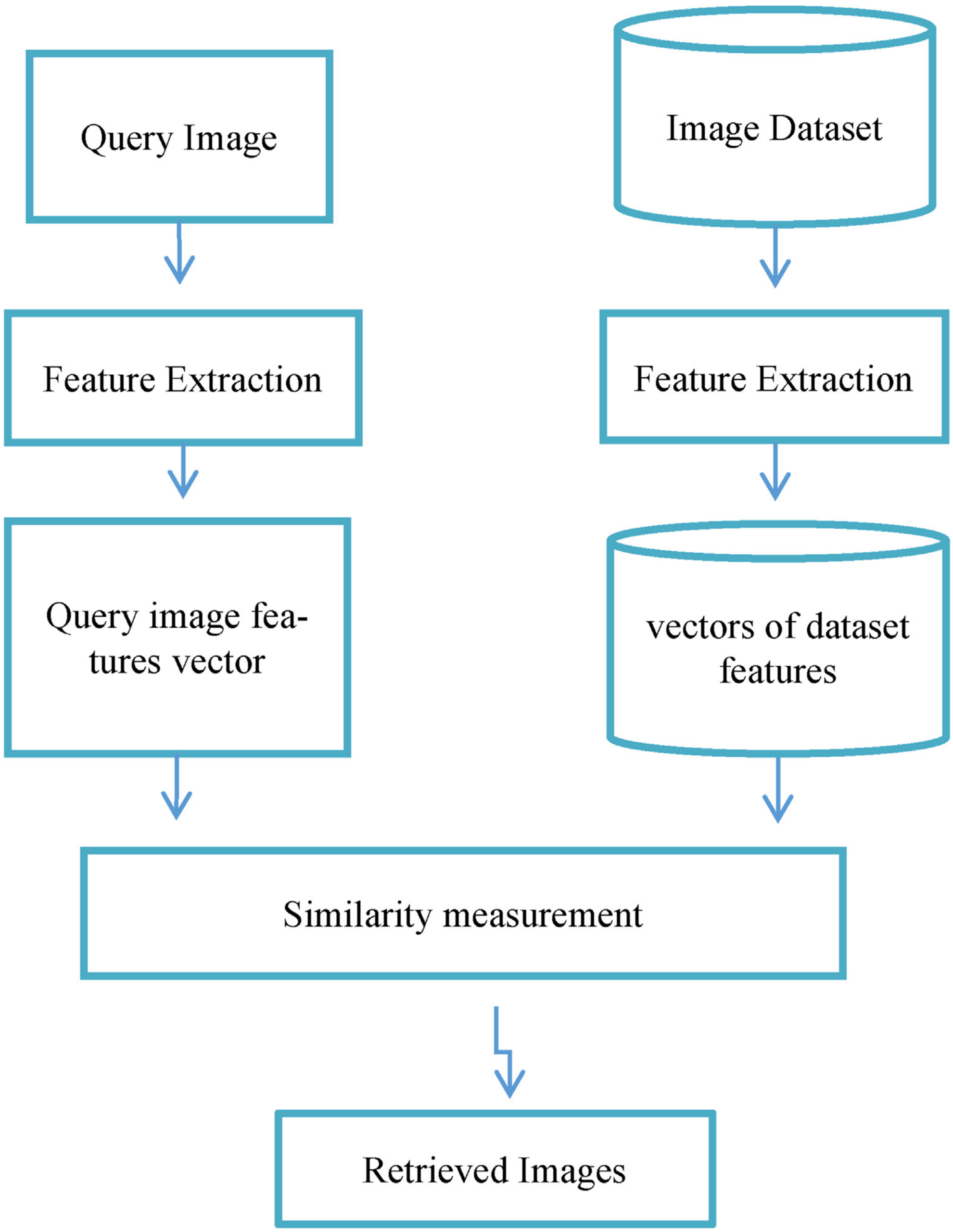


Fig. 1. A basic block diagram for CBIR.

alterations [10]. Histogram of oriented gradient (HOG) [11], local binary pattern (LBP) [12], oriented fast and rotated BRIEF (ORB) [13], Scale-invariant feature transform (SIFT) [14], and speeded-up robust feature (SURF) [15], are examples of local features [16]. The bag-of-visual words (BoVW) method is well-known for local aggregating characteristics into a fixed-length vector. One of the most often used methods for representing image features is BoVW. For the first time, the BoVW framework for text document analysis was proposed in the text retrieval area. Following that, it was applied to computer vision applications. Visual words are quantized from feature vectors to create a dictionary or codebook. By clustering local features, visual words can be created [17]. In this paper, two features are utilized:

- LBP as a local feature used to build the BoVW (LBP-BoVW),

- The color moment (CM) as a global feature is employed to discover more images that match the query image.

Outline of Paper:

Related works are discussed in Section 2. Section 3 provides an illustration of the paper's methodology. Similarity evaluation is defined in Section 4. The results and discussion are displayed in Section 5. Finally, Section 6 presents the conclusions of this paper.

2. Related works

Researchers have proposed many ways to improve CBIR, which has become a popular study area.

For CBIR, the authors in Ref. [18] suggest two block-based texturing approaches. In both cases, the texture feature LBP is used to describe the image. The average precision for the Corel Gallery database was 0.23.

Authors in Ref. [19] utilized a wide range of features for content-based image retrieval and then quantitatively compared them on four distinct tasks: stock image retrieval, retrieval from a personal image collection; retrieval from a building; and retrieval of medical images. In the experiments, five free image databases are used, and the features are tested to see how well they help find images.

The authors in Ref. [20] presented a method for retrieving images based on moments. Using the moment-based approach, the image is split into blocks of varying sizes, and the geometric moment of each block is calculated. The retrieval is then based on the threshold after the technique calculates the distance between blocks of database images and the query. Recall and precision metrics were utilized to assess the method's effectiveness. The presented technique outperformed some of the other image retrieval techniques. The average precision for the Corel database was 0.3594.

The authors in Ref. [21] presented a technique for CBIR that combines global and local features. Geometric moments extract global features, while SIFT descriptors extract local features. SIFT and moments are combined to find visually similar images. The Corel-1k has an average precision of 0.3981.

The authors in Ref. [22] propose a CBIR technique based on overlapping blocks. After converting images to the Hue, Saturation, and Intensity (HIS) color space, they are separated into blocks, with the primary block chosen. Histogram projection is used to determine color characteristics, while texture properties are determined using Roberts Edge detection. As a similarity metric, the authors utilized a weighted Euclidean distance, with the weights chosen experimentally, to obtain similar images.

The proposed approach has poor accuracy values for texture rotation and color change when compared to other techniques.

Authors in Ref. [23] presented a CBIR technique based on combining SIFT visual words with binary robust invariant scalable key points (BRISK). BRISK was utilized to overcome SIFT's drawbacks in low-light conditions and when important points are poorly localized. The average precision for the Corel-1K, Caltech-256, Corel-1.5k, and Corel-5K datasets was 0.8439, 0.475, 0.7814, and 0.5737. For image retrieval, the authors in Ref. [24] proposed a weighted feature merging of n-ary Thepade's Sorted Block Truncation Coding (TSBTC)-based color features and gray level co-occurrence matrix (GLCM)-based texture features. Using a Mean Squared Error (MSE), the similarity between the dataset's image and the query was calculated. The efficacy of proposed techniques is evaluated using average retrieval accuracy (ARA).

Outcomes of the experiment indicate that, for the augmented Wang dataset, the weighted merging of GLCM features and TSBTC 8-ary with weights of 0.3 and 0.7, respectively, gives an ARA of 0.4474. For the modified COIL, the weighted merging of TSBTC 4-ary and GLCM features with weights of 0.6 and 0.4, respectively, gives an ARA of 0.7436.

The author in Ref. [25] presents a combination of n-ary TSBTC and Haralick features (GLCM) for picture retrieval. To evaluate the presented approach, modified COIL and augmented Wang datasets are employed. MSE is used to measure how similar an image dataset and a query image are related. ARA is used to evaluate the effectiveness of the present method. When 8-ary TSBTC features and Haralick features are combined, the ARA for the augmented Wang dataset is 0.4420, while for the modified COIL dataset, the ARA is 0.7408 when the feature fusion of 4-ary TSBTC and Haralick feature. Table 1 summarizes the related work above.

3. Proposed methodology

The CM and LBP approaches are utilized to find the most relevant image. LBP is employed in this paper because it effectively thresholds the neighborhood for each pixel. BoVW is built using LBP as a local feature called LB- BoVW. CM is important for indexing images in image retrieval systems because it makes it possible to find images based on their color index.

Table 1. Summary Table of Related work.

Reference	Feature	Feature Extraction	Similarity measurement	Dataset	Results
[18]	texture	LBP	L1 dissimilarity Based on Minkowski	Corel Gallery	AP = 0.23
[19]	Global texture Local	Gabor Vector SIFT global search		Wang UW	MAP = 0.237 MAP = 0.383
[20]	Geometric moments	moments	Euclidean	Corel 1k	AP = 0. 3594
[21]	local global shape	SIFT moments	Euclidean	Corel 1k	AP = 0.3981
[22]	Global color Global texture	histogram projection Roberts Edge detection	weighted Euclidean		
[23] combine two features	Local	SIFT BRISK		Caltech-256 Corel-1.5K Corel-1K Corel-5K	0.4752 0.7814 0.8439 0.5737
[24] fusion two feature	Global color Global texture	n-ary TSBTC GLCM	MSE	Wang COIL	ARA = 0.4474 ARA = 0.7436
[25] fusion two feature	Global color Global texture	n-ary TSBTC Haralick features	MSE	Wang COIL	ARA = 0.442 ARA = 0.7408

The Corel database was utilized to validate the results. It is a 1000-image database collection. Ten categories with 100 images each have been created from these images. Fig. (2) displays the proposed methodology block diagram.

3.1. Local binary pattern

Ojala et al. [26] created LBP as an attractive texture pattern descriptor to describe the local texture pattern of an image. LBP operates on a 3×3 block size, where the center pixel is used as a threshold for the neighboring pixel. The histogram feature is extracted for the obtained LBP code. Hence, a 256-feature vector length is obtained [27]. The LBP algorithm is described in the following points.

1. If the neighbor is bigger than or equal to the center, a binary 1 is returned.
2. If the neighbor is smaller than the center, a binary 0 is returned.

An 8-bit value represents the center's eight neighbors. Fig. (3) illustrates the calculation of LBP using an example. The transformed image to the LBP image is seen in Fig. (4). LBP's properties are simple and quick techniques to describe textures on a local scale. The numbers 0 and 1 reflect the relationship between the gray values of the surrounding pixels and the center pixel. It makes it simpler to extract local information from a picture [28]. The LBP radius in this paper is 1.

3.2. Bag of visual words

The LBP feature vector is extracted and clustered from the training set of images using the k-means technique. The cluster centroids were used as visual words. A vector represents each training image called BoVW, which has dimensions equal to the number of visual words, in this case, k. The ith element of BoVW represents the frequency of appearance of the ith visual word in an image. The query image's BoVW representation is discovered in the same way as the training images. The step of the BoVW process.

1. Extract the local feature vector for each image. This paper uses a LBP for local feature extraction to generate a feature vector.
2. Send LBP features vector to the K-means cluster. This paper uses 50, 100, 200, 400, and 600 for the number of clusters (K). Obtain the center for each cluster. These centers are the visual words. The visual word vector's size equals the number of K.
3. Create histograms for each image in the test and training datasets by extracting local features as explained in step 1 and comparing them to the visual word vectors extracted in step 2. Fig. (5) illustrates the process of creating a BoVW representation for an image. The most similar image is retrieved by computing the minimum Euclidean distance between the BoVW for the training images and the query image.

3.3. Color moment

CM is a popular color feature representation approach in image processing because it is simple and effective. The lower-order moments are primarily where image color information is distributed. The image's color distribution can be fully described by the color information mean, variance, and

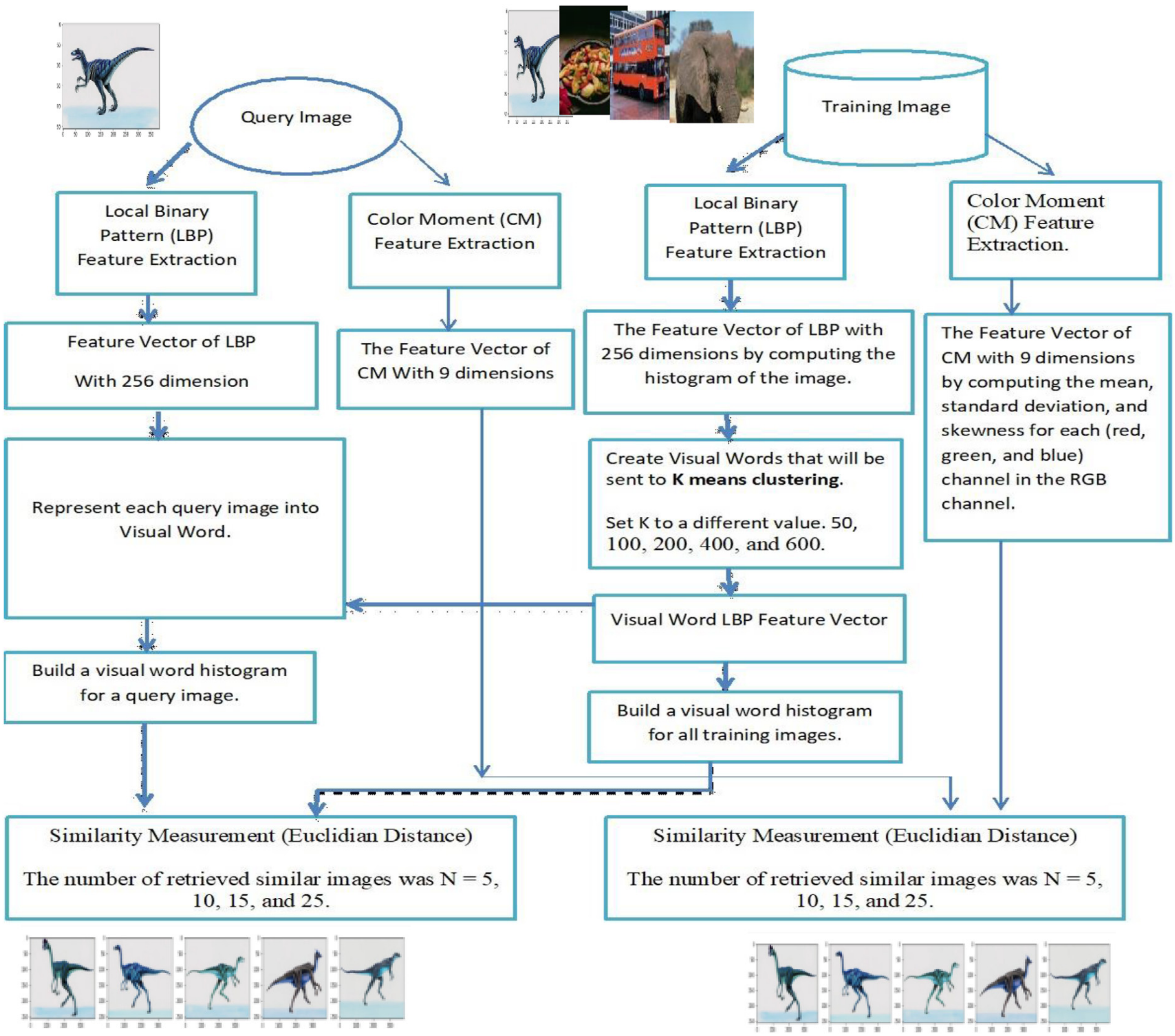


Fig. 2. Proposed methodology.

skewness. Color features are represented by color moments [29]. The CM algorithm [30] is described in the following points.

Step 1. Read the image file and for each of the (blue, green, and red) color channels:

Step 2. Find the mean value using Eq. (1).

$$E = \frac{1}{N*M} \sum_{i=1}^{N} \sum_{j=1}^{M} P_{ij} \tag{1}$$

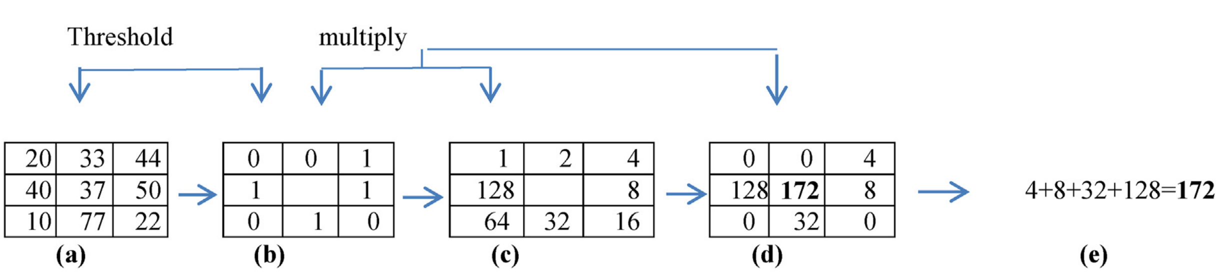


*Fig. 3. LBP Calculation. Consider (a) a 3*3 window, (b) a threshold with a center, (c) power of 8 bits per neighbor, (d) multiplication of (b) and (c), and (e) converting binary to decimal and placing it in the center (d).*

(a) (b)

Fig. 4. The LBP conversion; (a) the original image, (b) the LBP image.

E denotes the mean, Pij denotes the pixels, and the number of pixels is denoted by N and M.

Step 3. Find the standard deviation value using Eq. (2):

$$\sigma = \sqrt{\frac{1}{\mathrm{N}^*\mathrm{M}}\left(\sum_{\mathrm{i}=1}^{\mathrm{N}}\sum_{\mathrm{j}=1}^{\mathrm{M}}(\mathrm{P_{ij}} - E)\right)} \tag{2}$$

E denotes the mean, Pij denotes the pixels, σ denotes the standard deviation, and the number of pixels is denoted by N and M.

Step 4. Find the skewness value using Eq. (3).

$$\mathrm{S} = \sqrt[3]{\left(\frac{1}{\mathrm{N}^*\mathrm{M}}\sum_{i=1}^{N}\sum_{j=1}^{M}(P_{ij} - E)^3\right)} \tag{3}$$

E denotes the mean, Pij pixels, N and M denote the number of pixels, and S denotes the skewness.

Step 5. Finally, store the mean, standard deviation values, and skewness in a 1D array.

Step 6. For each image in the database, repeat steps 1-5.

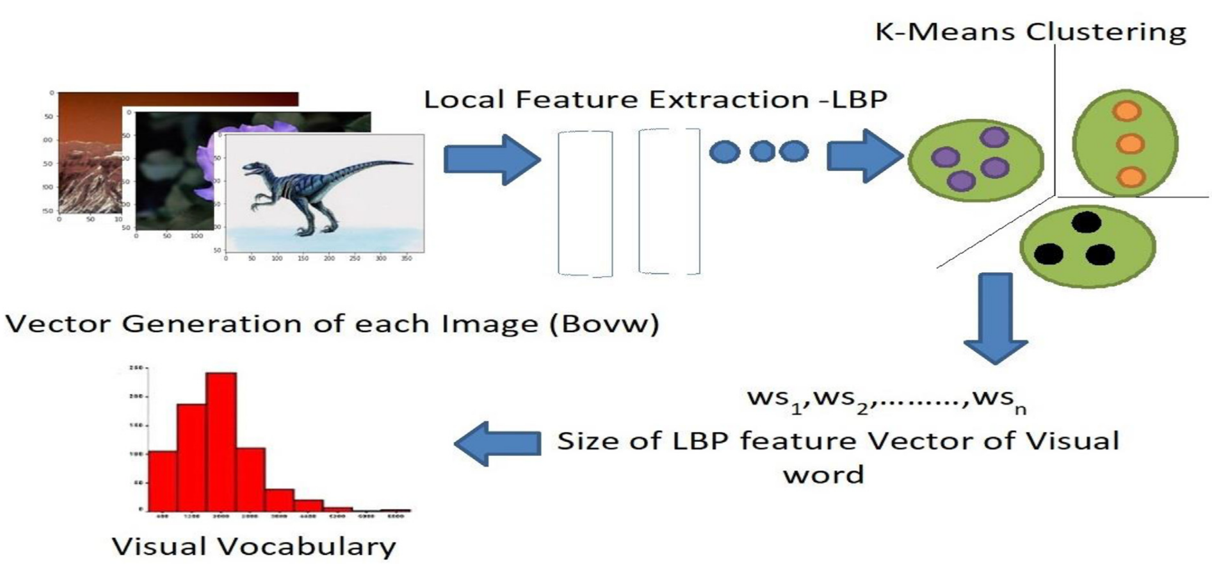


Fig. 5. The BoVW process.

Fig. 6. A sample of the Corel dataset.

4. Similarity measurement

A similarity metric is necessary when comparing images based on their feature vectors. The performance evaluation process of CBIR systems can use various similarity metrics. The authors in Ref. [31] performed similarity matching on texture and color information independently using the Canberra distance. This paper evaluates how similar the dataset images and the query feature vectors are to one another using the Euclidean distance. If there is little space between the two vectors, the generated image and the query are similar.

$$D(Q, DB) = \sqrt{\sum_{i=1}^{M} \left(Fv_{DB}(i) - Fv_{Q}(i)\right)^2} \tag{4}$$

The feature vector size is M. $Fv_{DB,}$ and Fv_Q are feature vectors for dataset and query images.

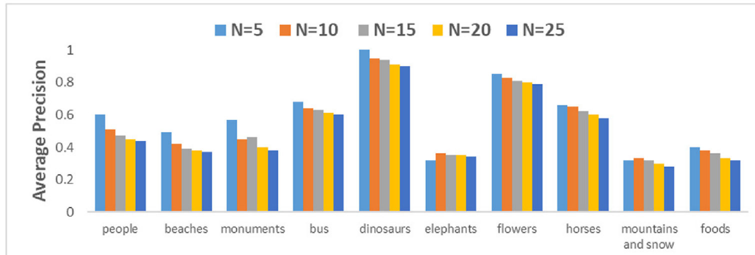
Table 2. The average precision for each class using color moment extraction with N retrievable images.

Class	N				
	5	10	15	20	25
People	0.55	0.47	0.47	0.44	0.43
Beaches	0.18	0.21	0.21	0.22	0.22
Monuments	0.2	0.25	0.26	0.25	0.25
Bus	0.58	0.52	0.51	0.49	0.41
Dinosaurs	0.52	0.49	0.46	0.45	0.43
Elephants	0.42	0.38	0.36	0.36	0.35
Flowers	0.78	0.77	0.72	0.72	0.69
Horses	0.68	0.66	0.61	0.6	0.59
Mountains and snow	0.27	0.27	0.24	0.23	0.23
foods	0.38	0.37	0.37	0.35	0.34
Avg. of classes	0.456	0.439	0.421	0.411	0.394

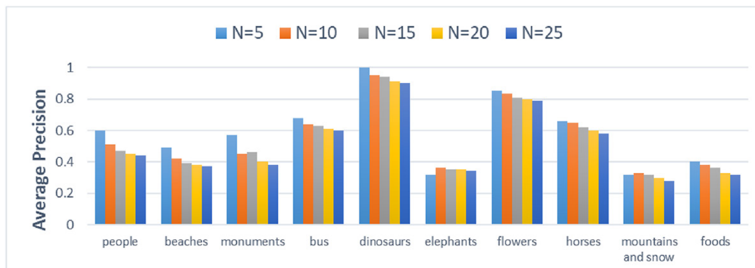
5. Result and discussion

5.1. Dataset

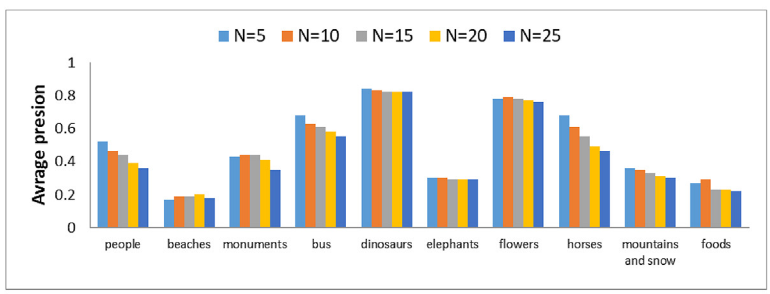
The Corel dataset [32] contains 1000 JPEG images with dimensions of 256 by 384 or 384 by 256 pixels. These images are organized into ten categories;



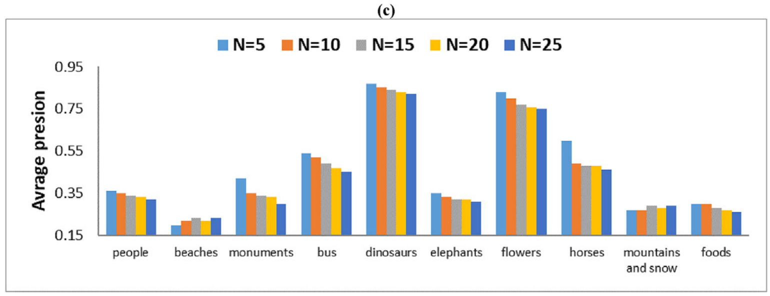
(a)



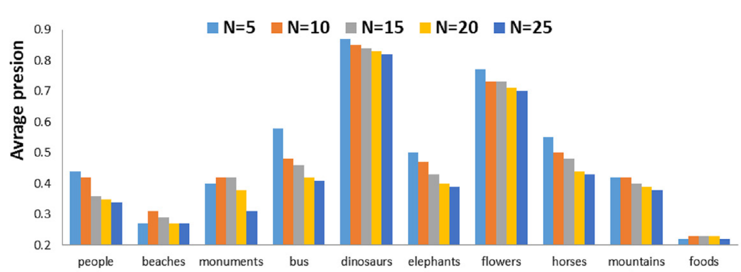
(b)



(c)



(d)



(e)

Fig. 7. The average precision for each class using LBP-BoVW with N retrieved images and K visual words K is equal to (a) 50; (b) 100; (c) 200; (d) 400; and (e) 600.

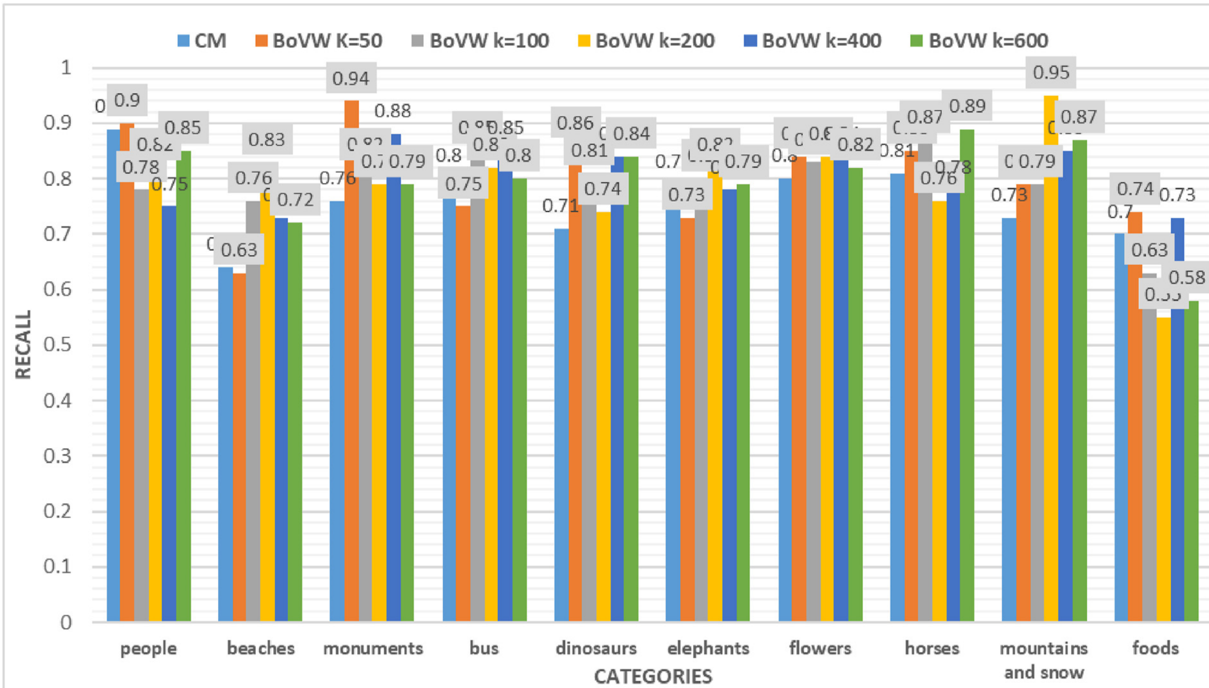


Fig. 8. Recall for CM and LBP-BoVW for all categories with different sizes of visual words (K), and N = 20.

there are 100 images in each of them. The categories include people, elephants, dinosaurs, beaches, food, mountains, horses, buses, flowers, and buildings. Fig. (6) displays a sample from each class. In this paper, all training images were combined and stored in one folder and all testing images in another, making retrieval more challenging and complicated. That means a training folder with 900 images and a test folder with 100 images, each of which is a query image.

5.2. Evaluation measurement

Recall, and precision metrics are used to evaluate performance in the CBIR. To obtain precision, the total number of photos obtained is divided by the number of relevant images retrieved. It demonstrates a system's capacity to return only relevant images, as shown in Eq. (5). The recall measures how well the system can find all relevant photos. It is calculated by dividing the number of relevant photos found by the total number of photos in the database, as shown in Eq. (6).

$$\text{Precision} = \frac{\text{The number of relevant images retrieved}}{\text{Total number of images retrieved}} \quad (5)$$

$$\text{Recall} = \frac{\text{The number of relevant images retrieved}}{\text{Total number of relevant images}} \quad (6)$$

Table 3. The proposed method's precision value compared to the precision values of existing approaches.

Reference no.	Approaches	Precision
[18]	LBP Block Based	0.23
[19]	Gabor Vector	0.237
[20]	moment	0.3594
[19]	LF SIFT global search	0.383
[21]	SIFT as a local feature, and geometric moments as a global feature.	0.3981
Proposed Method	**CM**	**0.41**
Proposed Method	**LBP-BoVW k = 50, and N = 20**	**0.51**

5.3. Experiment results

The extracted features were used to find images in the database that looked like the query image. Retrieval performance has been assessed using recall and precision. Higher precision indicates that the system retrieves images that are more relevant than irrelevant ones. However, high recall implies that the system retrieves the most relevant images. In this paper, 100 query images were used. The precision of each query in all categories was calculated, along with the average calculated precision. Results depend on the nature of the images, the

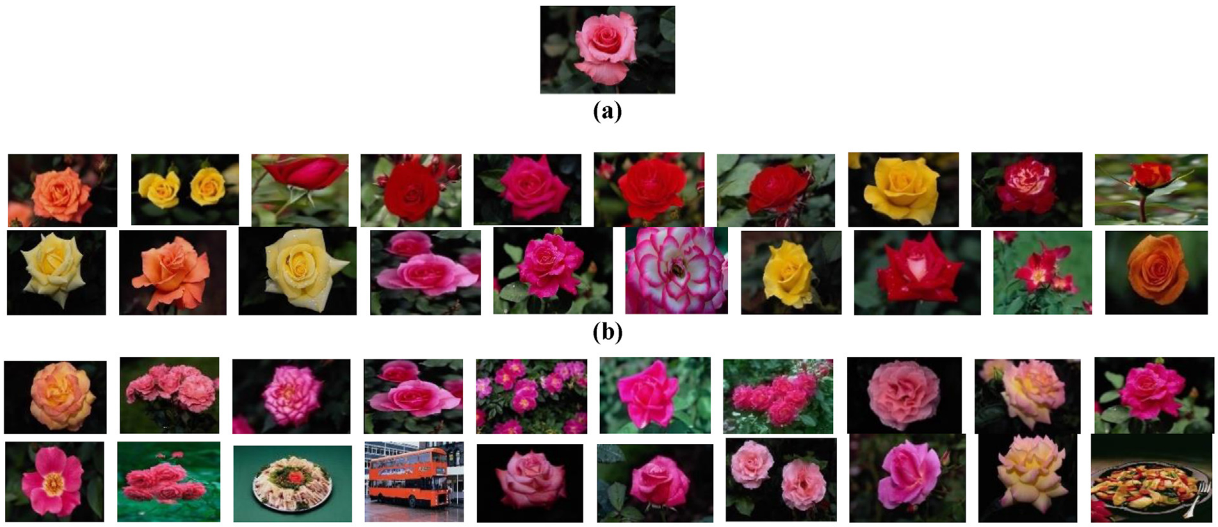


Fig. 9. Retrieved Images N = 20 for a flower image; (a). Query Image; (b) CM Results; (c) LBP-BoVW results.

lighting, the purity of colors, and the number of objects. Table 2 shows the flower and horse classes got the highest precision in the color moment because the images contained a few objects with different colors. In addition, the objects and background are easily distinguishable compared to the rest of the classes. The flower and horse classes had the best average precision. The average precision for the flower class was 0.78, and for the horse, the precision was 0.68 when the number of retrieved images N was 5. When N = 10, the flower class had an average precision of 0.77, while the horse class had an average precision of 0.66. When N = 15, the flower class had an average precision of 0.72, and the horse class had an average precision of 0.61. When N = 20, the flower class had an average precision of 0.72, and the horse class had an average of 0.6. Fig. (7) shows the average precision result of the LBP-BoVW for all testing images, with a different size of K for the visual word and a different size of N for the retrieval image. The dinosaur and flower classes got the highest precision compared to the rest of the classes. Based on the texture image, the "Dinosaur" class images are easily found because they have the same background with one object and the LBP. When the size of visual words K = 50, the average precision for the dinosaur and flower classes when the number of retrieved images

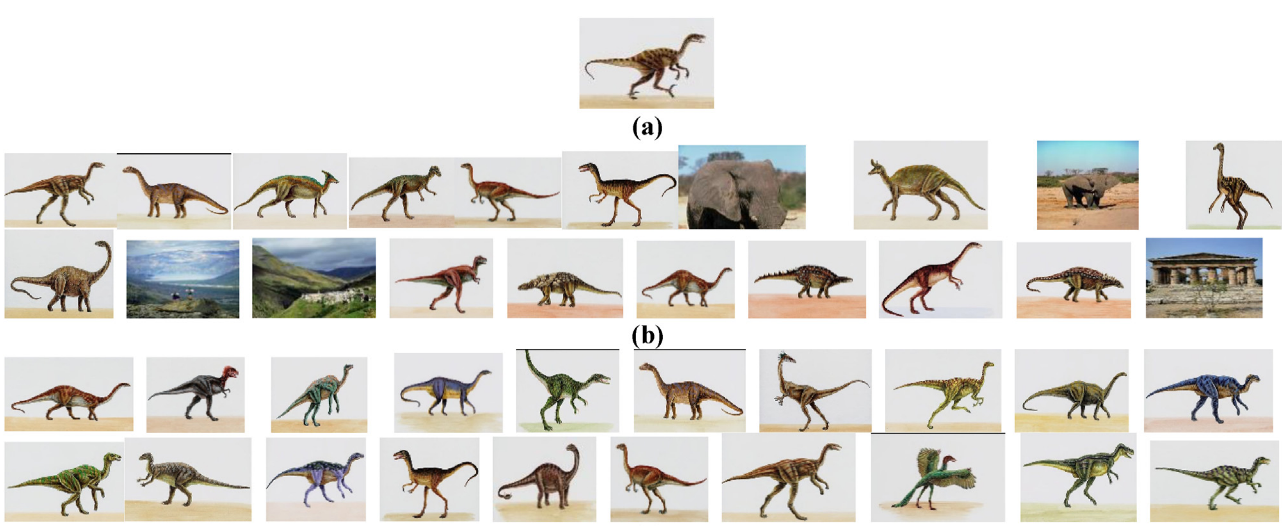


Fig. 10. Retrieved Images N = 20 for a Dinosaur image: (a). Query Image, (b) CM Results; (c) LBP-BoVW Results.

was N = 5 was 1 and 0.85, respectively. In the case of N = 10, the dinosaur and flower classes had an average precision of 0.95 and 0.83, respectively. When N = 15, the dinosaur class had an average precision of 0.94, and the flower class had an average precision of 0.81. When N = 20, the dinosaur class had an average precision of 0.91, and the flower class had an average precision of 0.81. Recall for CM and LBP-BoVW are shown in Fig. (8). The proposed method's precision value was compared to the precision values of existing approaches. As shown in Table 3, the suggested methodology outperforms other techniques. The retrieved images, according to a query image using LBP-BoVW and CM, are illustrated in Figs. (9) and (10).

6. Conclusion

This paper extracted local and global features using Local Binary Pattern (LBP) descriptors, which are utilized to construct BoVW (LBP-BoVW), and global features using Color moment. The effectiveness of the proposed method is evaluated using recall and precision. In the LBP-BoVW approach, performance increases with decreasing N, the number of retrieved images. Regarding the K feature vector length of visual words, the 50-length produced the best results. The experimental data shows that the proposed LBP-BoVW method with K = 50 and N = 20 are more precise than the proposed global feature using color moment and some existing state-of-the-art methods. In future work, researchers will provide filtering approaches to enable the CBIR to return better and more accurate results and combine the local and global feature vectors and high-level visual features that can be used to achieve further improvement.

References

[1] J.M. dos Santos, E.S. de Moura, A.S. da Silva, R. da Silva Torres, Color and texture applied to a signature-based bag of visual words method for image retrieval, Multimed. Tool Appl. 76 (2017) 16855–16872, https://doi.org/10.1007/s11042-016-3955-4.

[2] M.K. Alsmadi, An efficient similarity measure for content based image retrieval using memetic algorithm, Egypt J. Basic Appl. Sci. 4 (2017) 112–122, https://doi.org/10.1016/j.ejbas.2017.02.004.

[3] M.F. Alsaffar, Studying of certain immunological parameters in the Province of Babylon for systemic lupus erythematosus, Drug Invent. Today 12 (2019) 2835–2839.

[4] M. Garg, G. Dhiman, A novel content-based image retrieval approach for classification using GLCM features and texture fused LBP variants, Neural. Comput. Appl. 33 (2021) 1311–1328, https://doi.org/10.1007/s00521-020-05017-z.

[5] J.M. Patel, N.C. Gamit, A review on feature extraction techniques in content based image retrieval, in: International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), IEEE. 2016, pp. 2259–2263, https://doi.org/10.1109/WiSPNET.2016.7566544.

[6] A. Suharjito, D.D. Santika, Content based image retrieval using Bag of Visual Words and multiclass support vector machine, ICIC Expr. Lett. 11 (2017) 1479–1488, https://doi.org/10.24507/icicel.11.10.1479.

[7] S.P. Rana, M. Dey, P. Siarry, Boosting content based image retrieval performance through integration of parametric & nonparametric approaches, J. Vis. Commun. Image Represent. 58 (2019) 205–219, https://doi.org/10.1016/j.jvcir.2018.11.015.

[8] M. Sajjad, A. Ullah, J. Ahmad, N. Abbas, S. Rho, S.W. Baik, Integrating salient colors with rotational invariant texture features for image representation in retrieval systems, Multimed. Tool Appl. 77 (2018) 4769–4789, https://doi.org/10.1007/s11042-017-5010-5.

[9] R. Ashraf, M. Ahmed, S. Jabbar, S. Khalid, A. Ahmed, S. Din, G. Jeon, Content based image retrieval by using color descriptor and discrete wavelet transform, J. Med. Syst. 42 (2018) 1–12, https://doi.org/10.1007/s10916-017-0880-7.

[10] I.M. Hameed, S.H. Abdulhussain, B.M. Mahmmod, Content-based image retrieval: a review of recent trends, Cogent Eng. 8 (2021) 1927469, https://doi.org/10.1080/23311916.2021.1927469.

[11] V.N. Degaonkar, P. Gadakh, P. Saha, A.V. Kulkarni, Retrieve content images using color histogram, LBP and HOG, in: 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA), IEEE. 2020, pp. 896–899, https://doi.org/10.1109/ICECA49313.2020.9297608.

[12] P. Liu, J.M. Guo, K. Chamnongthai, H. Prasetyo, Fusion of color histogram and LBP-based features for texture image retrieval and classification, Inf. Sci. 390 (2017) 95–111, https://doi.org/10.1016/j.ins.2017.01.025.

[13] P. Chhabra, N.K. Garg, M. Kumar, Content-based image retrieval system using ORB and SIFT features, Neural. Comput. Appl. 32 (2020) 2725–2733, https://doi.org/10.1007/s00521-018-3677-9.

[14] D. Giveki, M.A. Soltanshahi, G.A. Montazer, A new image feature descriptor for content based image retrieval using scale invariant feature transform and local derivative pattern, Optik 131 (2017) 242–254, https://doi.org/10.1016/j.ijleo.2016.11.046.

[15] F. Baig, Z. Mehmood, M. Rashid, M.A. Javid, A. Rehman, T. Saba, A. Adnan, Boosting the performance of the BoVW model using SURF–CoHOG-based sparse features with relevance feedback for CBIR, Iran J. Sci. Technol. Trans. Elec. Eng. 44 (2020) 99–118, https://doi.org/10.1007/s40998-019-00237-z.

[16] Z.N. Sultani, B.N. Dhannoon, Modified bag of visual words model for image classification, Al-Nahrain J Sci 24 (2021) 78–86, https://doi.org/10.22401/ANJS.24.2.11.

[17] M. Alkhawlani, M. Elmogy, H. Elbakry, Content-based image retrieval using local features descriptors and bag-of-visual words, Int J. Adv. Comput. Sci. Appl. 6 (2015) 212–219, https://doi.org/10.14569/IJACSA.2015.060929.

[18] V. Takala, T. Ahonen, M. Pietikainen, Block-based methods for image retrieval using local binary patterns, in: Scandinavian Conference on Image Analysis, Springer. 2005, pp. 882–891, https://doi.org/10.1007/11499145_89.

[19] T. Deselaers, D. Keysers, H. Ney, Features for image retrieval: an experimental comparison, Inf. Retr. 11 (2008) 77–107, https://doi.org/10.1007/s10791-007-9039-3.

[20] P. Srivastava, N.T. Binh, A. Khare, Content-based image retrieval using moments, in: International Conference on Context-Aware Systems and Applications, Springer. 2013, pp. 228–237, https://doi.org/10.1007/978-3-319-05939-6_23, 128.

[21] P. Srivastava, A. Khare, Content-based image retrieval using scale invariant feature transform and moments, in: IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics Engineering (UPCON), IEEE.

2016, pp. 162–166, https://doi.org/10.1109/UPCON.2016.7894645.
[22] X. Zheng, B. Tang, Z. Gao, E. Liu, W. Luo, Study on image retrieval based on image texture and color statistical projection, Neurocomputing 215 (2016) 217–224, https://doi.org/10.1016/j.neucom.2015.07.157.
[23] U. Sharif, Z. Mehmood, T. Mahmood, M.A. Javid, A. Rehman, T. Saba, Scene analysis and search using local features and support vector machine for effective content-based image retrieval, Artif. Intell. Rev. 52 (2019) 901–925, https://doi.org/10.1007/s10462-018-9636-0.
[24] J.H. Dewan, S.D. Thepade, Image retrieval using weighted fusion of GLCM and TSBTC features, in: 2021 6th International Conference for Convergence in Technology (I2CT), IEEE. 2021, pp. 1–7, https://doi.org/10.1109/I2CT51068.2021.9418131.
[25] J.H. Dewan, S.D. Thepade, Fusion Based Image Retrieval Using Haralick Moments and TSBTC Features International Conference on Emerging Smart Computing and Informatics (ESCI), IEEE. 2021, pp. 748–752, https://doi.org/10.1109/ESCI50559.2021.9396833.
[26] T. Ojala, M. Pietikainen, T. Maenpaa, Multiresolution gray-scale and rotation invariant texture classification with local binary patterns, IEEE Trans. Pattern Anal. Mach. Intell. 24 (2002) 971–987, https://doi.org/10.1109/TPAMI.2002.1017623.
[27] A.M. Salih, B.N. Dhannoon, Weighted k-nearest neighbour for image spam classification, Iraqi J. Sci. 62 (2021) 1036–1045, https://doi.org/10.24996/ijs.2021.62.3.32.
[28] P. Srivastava, A. Khare, Integration of wavelet transform, local binary patterns and moments for content-based image retrieval, J. Vis. Commun. Image Represent. 42 (2017) 78–103, https://doi.org/10.1016/j.jvcir.2016.11.008.
[29] X. Zenggang, T. Zhiwen, C. Xiaowen, Z. Xue-min, Z. Kaibin, Y. Conghuan, Research on image retrieval algorithm based on combination of color and shape features, J. Signal Process Syst. 93 (2021) 139–146, https://doi.org/10.1007/s11265-019-01508-y.
[30] A. Malakar, J. Mukherjee, Image clustering using color moments, histogram, edge and K-means clustering, Int. J. Sci. Res. 2 (2013) 532–537. https://www.ijsr.net/archive/v2i1/IJSRON2013308.pdf.
[31] N. Kayhan, S. Fekri-Ershad, Content based image retrieval based on weighted fusion of texture and color features derived from modified local binary patterns and local neighborhood difference patterns, Multimed. Tool Appl. 80 (2021) 32763–32790, https://doi.org/10.1007/s11042-021-11217-z.
[32] J. Li, J.Z. Wang, Automatic linguistic indexing of pictures by a statistical modeling approach, IEEE Trans. Pattern Anal. Mach. Intell. 25 (2003) 1075–1088, https://doi.org/10.1109/TPAMI.2003.1227984.