A Mighty Image Retrieval Descriptor Based on Machine Learning and Gaussian Derivative Filter

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Abstract *– The development of new image descriptor has always been an important topic to improve the efficiency of content-based image classification and retrieval. Improvements and developments in machine learning and deep learning algorithms as well as artificial intelligence algorithms are widely used by researchers to obtain effective CBIR descriptors. In our article, we will present a robust image descriptor, extended by machine learning and deep learning algorithms. The descriptor is provided through a Gaussian derivative filter scaffold named GDF-HOG with an enhanced convolutional neural network (CNN) AlexNet, to reduce the dimensions we used the principal component analysis algorithm. The experimental results were carried out on Oliva and Torralba, Caltech-101, Wang and Coil100 datasets. Experiments show that the accuracy of the proposed method is 98.23% for Coil-100%, 95.92% for Corel-1000, value 87.17 and 94.6% for Oliva and Torralba. In comparison our results with other descriptor image classifiers show that they achieved accuracy increases of 0.12% on average and up to 3.23%. These experimental results affirm the advantage of the proposed descriptor over existing systems based in terms of average accuracy. the proposed descriptor improves the precision, and also reduces the complexity of the calculation.*

Keywords: *Federated Learning, Machine Learning, Deep Learning, Privacy, Collaborative Machine Learning*

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1. INTRODUCTION

Nowadays, the amount of digital images in the form of personalized and corporate collections has increased enormously thanks to the widespread and easy use of the Internet and the enormous use of audiovisual data in digital format for communications. Hence, there is a increasing demand for powerful image indexing and retrieval in an automatic way. Nevertheless, with such use and availability of images, the solutions based on textual images (grace of keywords) become impassable and inappropriate for indexing and retrieving images. To overcome this problem content-based image retrieval (CBIR) has become a great research interest among research communities [1,2,3]. Content-based image indexing and search discriptors generate considerable image representations by considering the visual features of images, i.e. salient points ,texture and shape [4-14] , It brings similar images using distance as a semantic result. The audacious increase in image descriptors has been an active field of research and will help to increase the performance vast actions in computer vision. various systems such as cale-invariant feature transform (SIFT) [15], speeded up robust features (SURF) [16] ,co-occurrence matrix (GLCM) [45] , local binary patterns (LBP) [17] , GIST algorithms were used for CBIR systems [18]. Such hand-crafted feature generation algorithms are still used in Machine Learning [19–22]. Each of these descriptors has abnormalities, such as a large capacity of the feature vector , is that it cannot describe the characteristics of textures efficiently and distinctively and is mathematically weak and sensitive to noise. In this article we propose an efficient image descriptor to overcome these problems. This descriptor is created by combining Gaussian derivative filters named GDF-HOG more AlexNet CNN Enhanced. Also , for dimensional reduction . Principal Component Analysis (PCA) was applied. Detailed experimental analysis is performed using precision and recall on four datasets : Coil100, Corel1000, OT and FP datasets. The remainder of this article is put away as pursuant. Related works in the field of CBIR are presented in section 2. For section 3 we will present and discuss the proposed system. In section 4, the experimental results are reported, these results are compared to the experimental results existing systems in section 5. Finally, the conclusion and future perspectives are presented in section 6.

2. RELATED WORK

Simulation The deepening of automated CBIR systems has been an attractive field of study owing to its wide range of application in critical fields such as space imagery, bioinformatics, medical imaging, online surveillance and security. interior, etc.

There are many CBIR approaches described in the literature [23-28]. have been published until today to converge on the problem of image indexing and image retrieval descriptors in a more efficient and faster way. in general, the early work of CBIR applied to a single collection of features among the various features. Usually, it is difficult to obtain acceptable recovery results by applying only one characteristic. This is the reason why several scientists have employed a conjunction of systems to state new ones in order to speed up the performance and to consecrate it for astonishing cases [29]. Some of them are represented as follows:

In the work of [30] proposed a method in which uses Gaussian derivative filters named GDF-HOG a novel extension in which the local texture patterns are subjected to further treatment and then computed in Gaussian derivative filters way. In [31] showed a virtual solution for recovering semantically similar images from large image databases with respect to any solicitation image. to reduce discrepancy between low-level and high-level attributes. Genetic algorithms and support vector machines are used In [32], three image attribute s have been suggested for sovereign automatic overlay of images. To distill the color feature the color cooccurrence matrix (CCM) was used, while the difference between the scanning pattern pixels (DBPSP) is used for the texture features.

In the work of [33], a method based on the mixture of features extracted from two networks used for face discovery has been proposed. In works, the mixture of convolutional and system neural networks is used to realize a new image system. In [34], propose a system due to which the features of the image are compiled using SURF systems with HOG, the features of two descriptors are plenipotentiaries to convolutional spaces and feature vectors of measures 1×2016 and 1×1024 are created. The performances of these algorithms have exposed that they are efficient systems for the exploration of categories, the main problem found is the unequal dimension. In this paper, we propose a new algorithm to solve this unequal dimension problem.

3. PROPOSED METHOD

Our proposed method is graphically illustrated as Fig. 1. Overall, the proposed framework consists of four parts, in the first step the images are studied and scaled to $227 \times 227 \times 3$ using MATLAB's bicubic intercalation. Then all images are sent to an in-depth feature extractor (an enriched AlexNet CNN) and crafting systems such as HOG. First, the enriched CNN AlexNet hosted the images and explored its models, and finally suggested a feature vector of dimension 1×64 [33]. On the other hand, we use GDF-HOG an extension in which the local texture patterns are subjected to a complementary emolument then calculated in the manner of Gaussian derivative filters [30], thereafter, we use the PCA algorithm at the end to reduce the dimensions of the characteristics given by GDF -HOG Descriptor and also we use in order to match the dimension by GDF-HOG descriptor with deep feature vector . To finish, the deep aspect vector and the GDF-HOG-PCA descriptor essential vector are combined to have an efficient image system.

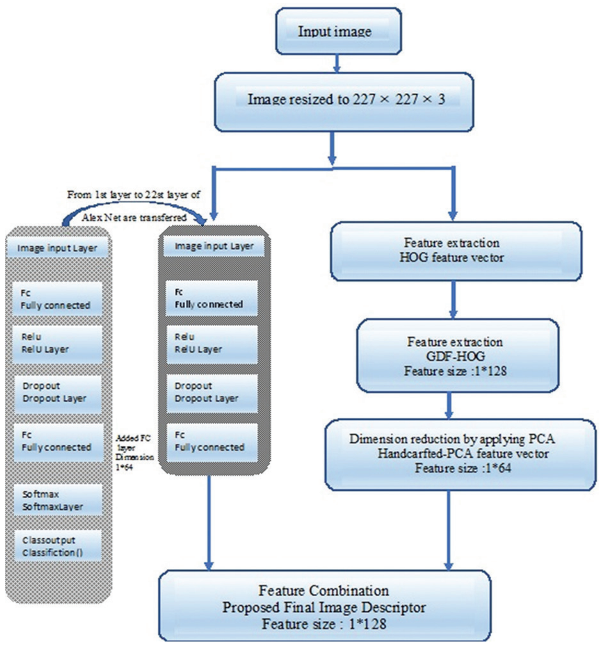

Fig. 1. Proposed Final Image Descriptor

The choice AlexNet CNN, HOG, GDF and PCA in this research due to some reasons. These reasons are described as follow:

The PCA algorithm is a means of vector downscaling that is commonly practiced to reduce the size of large data sets, by metamorphosing large sets of elements into sets with fewer elements without changing most of the information in the data set. data set. big set. we have exploited the PCA algorithm for different arguments, for example the reduction of the computation volume and the learning times, the simplification of the models, etc. [34].

The CNN Alexnet includes 25 layers, in order to create an Alexnet -improved, three last layers (23rd, 24th and 25th layers) of Alexnet CNN have been eliminated but other layers (22 layers - from the 1st to the 22nd) are transferred. Then, at the end of the Alexnet CNN diapers transferred, a fully connected layer (FC) from dimension1*64 was added [54].

The AlexNet CNN not only reduces the number of parameters and the proportion of full connection layer parameters, but also improves the automatic detection of interesting and super-scale features to the exclusion of human control [33].

The basic concepts of the Histogram of Oriented Gradients (HOG) are the regional characteristics and mode of the objects, which experience the marked by the assignment of local intensity gradients or edge administrations [35]. The orientations of the gradients are robust to all lighting variations, since the training histogram gives rotation invariance. the window-based HOG algorithm concerted locally to a stale point of interest. The advantage of this algorithm is that it ends up with local cells that are invariant to the geometric and photometric change, to the derogation of the orientation of the object [36,37].

The GDF algorithm yields amplification in which local texture patterns are kneed to additional processing after computed in the form of Gaussian derivative filters. He practiced the algorithm of Gaussian derivative filters to draw and catalog texture images, even if the dimensions of the image modify because the absolute state of the form does not modify. The first and second Gaussian derivative filters can be rotated at any angle by linear combination of two basis filters [38]. Gradient calculation which is calculated via Gaussian function and two-dimensional convolution gives more overwhelming texture and intensity factors than conventional gradient. Thus, Gaussian derivative filters are usually a suitable exemplar for extracting fundamental properties from texture pretexts.

4. EXPERIMENTAL RESULTS AND SIMULATION

In the experimental part the proposed system was implemented on the Anaconda software for an environment of Python, a computer system with 8 GB 1600 MHZ DDR RAM , Intl HD Graphics 5000 15366Mo graphics ,processor IntelCore i5,1.40 GHz central processor. accomplishment of exfiltration does not depend exclusively on a skilful description of the characteristics, but also on effective measures of similarity. In our experiments, we have used the measures of similarity mainly the overriding ones, including square chord distance for classification [39], extended Canberra distance [40], Euclidean distance has also been used [41,42] . In this paper, a detailed experimental analysis is performed using average mean precision (mAP) and recall criteria to quantify the proposed descriptor for archiving and CBIR [43] on four datasets: Coil100, Corel -1000, FP (Catech101) and OT. For our experiments, reducing image to size 227*227is grown by resizing the MATLAB load employing bicubic interpolation.

In this study, we estimate the achievements of the various basic steps and their absorption of functionalities, as appropriate in paragraph 4.2, on four most used datasets: COIL-100 [44], Corel-1000 (Wang) [48], FP (Catlech-101) [46] and OT [47]. The amounts of images on board these datasets are 7200, 10000, 380 and 2688 respectively. Each dataset contains color images that represent various features. These datasets are depicted in detail below:

COIL-100 is a database [44] of 100 uses of color images. Objects were placed on a motorized turntable against a dark background and images were taken at internal exposures of 5 degrees. This dataset was used in a real-time 100-use recognition system in which a sensor in the system could identify the object and display its angular pose. There are 7,200 images of 100 objects. Each object was rotated 360 degrees to vary the pose of the object against a stationary color camera. Images of the objects were taken at 5 degree exposure intervals. This corresponds to 72 exposures per object. These images were then normalized in size. Objects have a wide variety of complex geometric characteristics and reflectance.

Corel-1000 (Wang) is an image dataset containing 1000 of the Corel photo gallery [48] with ground truth. the images are collected in ten groups just like (Africa, beach, monuments, buses, dinosaurs, elephants, flowers, horses, mountains and food), there are 100 images of size 256x384 or 384x256 for each group. The images of the same group are admired as similar images. The images are subdivided into ten groups so that it is almost certain that a user will want to find the other images in a group if the query comes from one of these ten groups.

The FP(Caltech-101) [46] dataset is a widely used dataset for object identification missions, it includes almost 9,000 images of 101 classes of objects (e.g., "helicopter", " elephant" and "chair", etc.) and a background class that dominate images that are not part of the 101 object classes. For each category of objects, there are around 40 to 800 images, while most classes have around 50 images. images are 300×200 pixel dimensions.. The categories were chosen to reflect a variety of real-world objects, and the images themselves were carefully selected and annotated to provide a challenging benchmark for object recognition algorithms.

The Oliva & Torralba (OT) dataset globally includes 2,688 color images [47]. The dataset has eight classes, namely coast, forest, mountain, countryside, highway, inner city, high-rise building and street. These images are of JPG types with a dimension of 265 × 265 pixels.

4.1. EFFECT OF DISTANCE MEASUREMENTS ON THE SIMULATION AND EVALUATION OF THE PROPOSED SYSTEM FOR IMAGE RETRIEVAL

In this paragraph, we demonstrate that the performance of the proposed descriptor on the four datasets with six different measures of similarity has been evaluated and compared to the best existing similar methods. for image classification [43]. In these experiments, we randomly selected 10 images of any class as search images. Mean values of precision and recall are shown for N = 10. The value N = 10 is taken because later in Table 5 we will compare our results with other methods.

4.1.1. Proposed system performance on the COIL-100 dataset for the CBIR

The performance of the proposed descriptor on the COIL-100 dataset and for the six distance offerings for CBIR has been proven in Table 1. It is observed from Table 1, that the best mAP and the best average recall for recovery. Ten vertices are collected for the square chord distance which is 98.75%, followed by the extended Canberra distance measurement which gives a value of 98.26% for accuracy. The accuracy value achieved using Euclidean distance is 97.32%. The distance with a value of 92.53%. For all relative images, the best mAP and best average recall are achieved for the square chord distance which is 92.15%, followed by the extended Canberra distance measurement which gives a value of 91.71%, for the Euclidean distance measure which gives a value of 90.84. %.

Table1. Performance of proposed approach on Coil100 dataset on Mean Average Precision

Distance metrics	Proposed method	
	10-top (mAP)	All relative (mAP)
Square Chord	98.75	93.34
Euclidean Distance	97.32	91.84
Extended Canberra	98.26	92.71
L1	93.53	88.64
L2	92.53	87.39
X^2	96.8	90.18

4.1.2. Proposed system performance on the Wang dataset for the CBIR

The performance of the proposed descriptor on the Wang dataset and for the different distance measures are represented in Table 2. According to this table, the average mAP and recall using the square chord distance for the search of the top ten are 96.39% and for all similar images they are 92.15% for extended Canberra distance the mAP and mean Recall which is 96.16% for 10-top retrieval and 91.93% for all relative images. we observe for the euclidean distance that the mAP and mean Recall which is 95.9% for 10-top retrieval and 91.69% for all relative images. For the other distances the average mAP and Recall for the recovery of the top 10 relative images for the distance of X^2, L1 and L2 is 91.8%, 91.5% and 90.1% respectively, and for the recovery of all the relative images is 87% for X^2 , 85.5% for L2 and 86% for L1.

Table 2. Performance of proposed approach on Wang dataset on Mean Average Precision

Distance metrics	Proposed method	
	10-top (mAP)	All relative (mAP)
Square Chord	96.39	92.15
Euclidean Distance	95.9	91.69
Extended Canberra	96.16	91.93
L1	91.53	86.21
L2	90.1	85.48
X^2	91.80	87.14

4.1.3. Proposed system performance on the Caltech-101 dataset for the CBIR

For OT(Caltech-101) dataset the visual results of proposed system for the various similarity measures are depicted in Table 3. According to Table 3, it can be concluded for top ten image retrieval that, the best mean average precision (mAP) is provides for the square-chord distance which is 95.18%, followed by the euclidean distance measure which yields a value of 94.23% for precision. The precision value provides by using extended Canberra is 94.29%. followed by the L1 distance for which this values is 89.05% which is superior than the performance provides by L2 distance measure with a value the 88.53% ,which is slightly lower than the performance provides by X^2 which is 89.36%. When we look for the overall results, the square-chord distance measure provides best results which is 89.15%. The second best result for the euclidean distance measure which is 86.24%, The mean average precision (mAP) values for the extended Canberra distance , L1, L2 and for X^2 distance are 88.56% , 84.46% , 82.7% and 84.52%, respectively.

Table 3. Performance of proposed approach on FP (Caltech101) dataset on Mean Average Precision

Distance metrics	Proposed method	
	10-top (mAP)	All relative (mAP)
Square Chord	95.18	89.15
Euclidean Distance	94.23	86.24
Extended Canberra	94.29	88.56
L1	89.05	84.46
L2	88.53	82.7
X^2	89.36	84.52

4.1.4. Proposed system performance on the Oliva and Torralba (OT) dataset for the CBIR

The average mean precision (mAP) using the different methods on the Oliva and Torralba (OT) datasets are marked in Table 4. respectively. The qualitative propensity of these performances is similarly the same as that found for the COIL-100, Corel-1000 and FP (Caltech-101) datasets.

The proposed system produces an excellent collection balance for the square-chord distance for 10-top retrieval which is 90.3% and for all relative images are 85.92%, followed by the extended Canberra distance measure which yields a value of 88.37% for 10-top retrieval and 84.02% for all relative images , in third place the euclidean distance measure which yields a value of 87.56% for 10-top retrieval and which yields 87.56% for all relative images. The L1 distance measure and L2 distance measure provides mean average precision results which is 82.68% and 81.19% for 10-top retrieval which is slightly lower than the results acquired by X^2 distance measure which is 86.14% for 10-top retrieva. For all relative images the L1 distance measure, L2 distance measure and X^2 distance measure provides mean average precision results which is 79.48%, 78.47% and 80.26% respectively.

Table 4. Performance of proposed approach on Oliva and Torralba (OT) dataset on Mean Average Precision

Distance metrics	Proposed method	
	10-top (mAP)	All relative (mAP)
Square Chord	90.3	85.92
Euclidean Distance	87.56	83.62
Extended Canberra	88.37	84.02
L1	82.68	79.48
L2	81.19	78.47
X^2	86.14	80.26

4.2. THE PROPOSED APPROACH'S MAP-MEAN RECALL CURVES FOR SQUARE-CHORD DISTANCE

We will illustrate the proposed descriptor map averaged recall figures for square chord distance and for ten vertex retrieval across the four databases for CBIR Coil-100, Corel-1000, FP, and OT. In figure 2, the power of the proposed descriptor is noted on the Coil-100 dataset. In proportion to this figure, the average mAP and recall are 96.02%. The proposed descriptor power on the Corel-1000 dataset is expressed in Fig. 3. According to this figure, the average mAP and recall for the recovery of ten peaks is 93.91%. For the FP dataset, the power of the proposed descriptor is demonstrated in Fig. 4. Based on this figure, the mean mAP and recall are shown as 86.86%. In Fig. 5, the proposed descriptor power is shown on the OT dataset. According to this graph, the average mAP and recall is 96.02%. Considering the result of the four graphs. We can conclude that the proposed methodology perfectly recovers many relevant images with a very high rate on different image datasets. The proposed descriptor graph fruits for the CBIR on the four image datasets are shown in Figs. 6, 7, 8. For each dataset, an image is randomly named and content-based image trapping is performed. At the end, the ten images most similar to the requested image are collected and displayed.

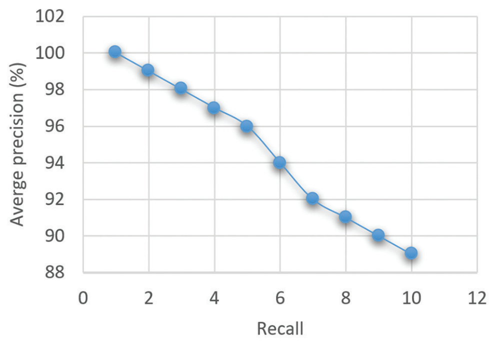

Fig. 2. Average Descriptor Accuracy Rate Curve on the Coil-100 Dataset

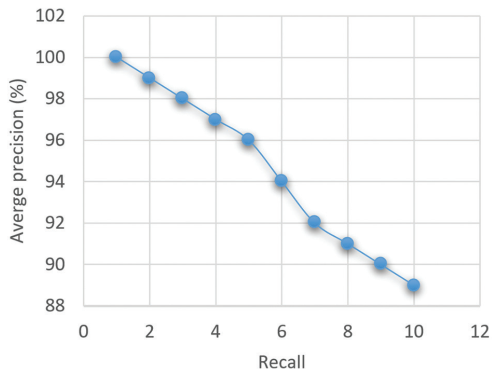

Fig. 3. Average Descriptor Accuracy Rate Curve on the Wang Dataset

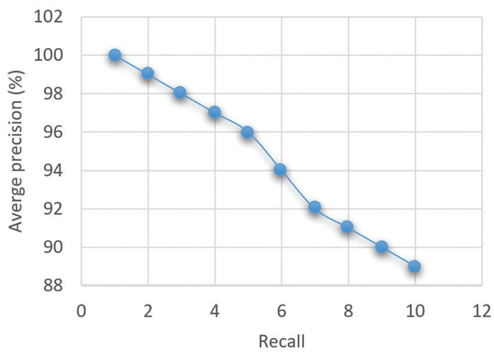

Fig. 4. Average Descriptor Accuracy Rate Curve on the Coil-100 Dataset method for FP (Caltech-101) dataset

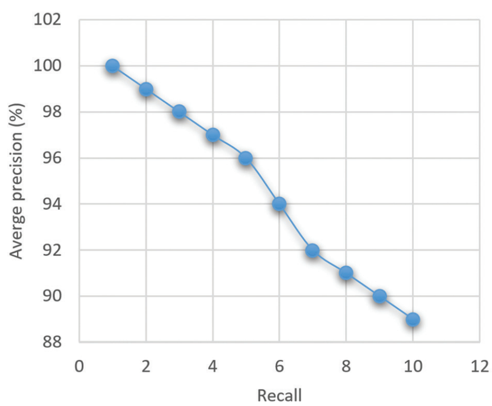

Fig. 5. Average Descriptor Accuracy Rate Curve on the Oliva and Torralba(OT) Dataset

According to Figs. 6, 7, 8, it can be said that in more cases, the images most similar to the query image were retrieved and placed in the first position, which is the goal of an effective CBIR system.

Fig. 6. Examples of the proposed descriptor visual results on the Wang dataset

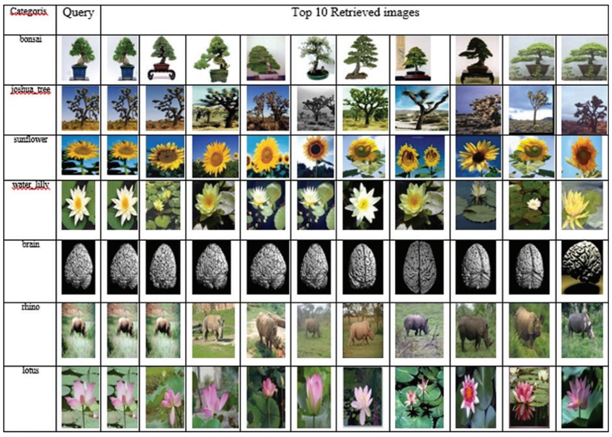

Fig. 7. Examples of the proposed descriptor visual results on the FP dataset

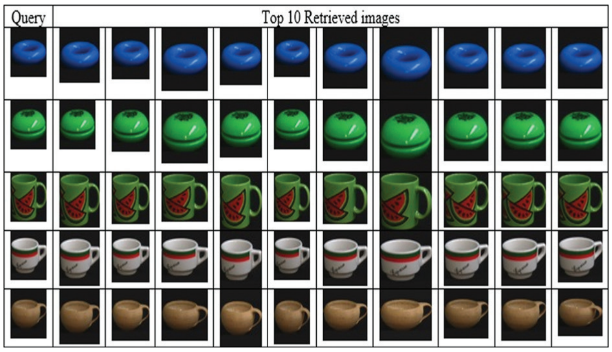

Fig. 8. Examples of the proposed descriptor visual results on the.Coil-100 dataset

4.3. COMPARISON RESULTS OF VARIOUS APPROACHES

In this part, the descriptor efficiencies proposed using the Coil100, Wang, OT and FP databases were estimated and evaluated with other descriptors for CBIR. In this regard, the technique is compared to [33, 49, 50, 51, 52, 53]. All the experiments below were carried out under the same conditions. the reason for our choice to compare with these discriptors is that these systems declare their balance sheets on the same databases and that they also use the Euclidean distance measure. The average mean precision values (mAP) are presented in Table 5. The performance of the proposed descriptor in terms of ranking compared to the other available descriptors is proven. From this table, it is concluded that the proposed descriptor has a higher accuracy compared to other existing descriptors.

For the Coil-100 dataset, our proposed method give higher recovery performance for which the average accuracy is 98.23%. The results obtained from the average precision for approach [53] and for approach [51] are respectively 81% and 95%.

For the Corel-1000 dataset, the results show that the proposed system is more efficient in terms of average precision than the other systems, with the average precision obtained being 95.92%. The mAP values obtained for the other approaches are 91.87% for the AlexNet CNN[49] approach, 80.61%, 95.80%, 66.5% and 73.27% respectively for the HOG + SURF approaches [50], [53], [51] and [03]. On the FP dataset (Caltech-101) also reflect a trend similar to that obtained for the Wang and Corel-1000 datasets. The average accuracies obtained by the different approaches in the FP dataset (Caltech-101) are respectively 87.17%, 81.80%, 86.86% and 76.39% for the proposed approach, [33], [49] and [52]. For the OT (Oliva and Torralba) dataset, again, the proposed method gives the best result with a value of 94.6%.

According to the results, one can easily monitor that the proposed method has the highest mAP-average rate. Therefore, it can be concluded that the proposed method is an operational method for image classification and retrieval.

Table 5. Comparison the proposed method with other standard retrieval systems in datasets for CBIR

	Coil-100	Corel-1000	Caltech-101	Oliva and Torralba
Proposed method	98.23	95.92	87.17	94.6
AlexNet CNN [49]	……….	91.87	81.80	92.30
HOG + SURF [50]	……….	80.61	……….	……….
AlexNet+ HOG [33]	……….	95.80	86.86	93.91
Co-occurance matrix[52]	……….	……….	76.39	78.83
H.Color + 2D.F.C.G [53]	81	66.5	………	…………
2-D histogram + S.M+ GLCM [51]	95	73.27	………	…………

5. CONCLUSION

In this study, we investigated the performance of a high-performance image overlay descriptor. The proposed descriptor was created using a combination of Gaussian derivative filters named GDF-HOG with an improved AlexNet convolutional neural network (CNN), principal component analysis (PCA) algorithm was used for dimension reduction. In the present analysis, it is observed that the proposed descriptor gives analog image retrieval results to current descriptors similar to the proposed one. we even analyzed different distances from the similarity measurements, which gives very high results for our descriptor and we also monitor that the square chord distance measurement gives excellent results on the Coil100 we obtained an average score of 98.23%, on Wang we obtained an average score of 95.92%, on Caltech-101 we obtained an average score of 87.17% and on Oliva and Torralba (OT) we obtained an average score of 94 .6%. which exceeds between 0.12% and 3.3% other descriptors . The design and explanation of computer-aided diagnosis (CAD) systems has currently become a priority that researchers have focused on. In these systems, data descriptors play an essential function. For our future research, we will study the extension of the proposed descriptor on the CAD system, and we can also use other new powerful convolutional neural networks.

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