Journal of Engineering Sciences
Vol 12, Issue 06, JUNE /2021
ISSN NO:0377-9254

Content BasedImage Retrieval Techniques- An Overview

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Abstract: The digital images are to be provided as input to some machine vision computer algorithms to make some useful conclusions, as the attributes in the images are not the type of information that can be read by the naked human eye. The images, those are produced using a different type of sophisticated several imaging devices are stored in a repository for future reference and usage. These repositories where the images are stored are vast. As the images are stored in these vast databases over a period, and not a common annotation method is being used to store the images, retrieval of any particular image from the database using name of a particular image is a herculean task. Here comes a technique that makes the process much simpler, in which a query image is provided as an input image that is used to retrieve an image or set of images having nearly the same or similar attributes. The main objective of the image retrieving technique is to bring out the maximum possible nearest image to that of the input query image based on some standard features. In this paper, the state-of-the-art technologies in the area of image processing are discussed.

Keywords: Image Processing, Retrieve, Machine Learning, Medical Image.

I. INTRODUCTION

Computer Vision and its associated areas have been extended manifold and possess a lot of avenues for carrying out research works exploring real-world applications and innovations. The domain of image recognition possesses challenges of developing appropriate models to detect and identify objects that appear in still digital images or frames of video sequences. In a real-world object classification problem, the supervised learning of the models is typically used in common image recognition tasks in the multiple images representing samples of a given class. The task is more challenging when the search is conducted inside a collection of images for occurrences of an object, for which only the picture of the object or parts is provided as input [6-7]. A set of relevant images are retrieved and returned by the system, regardless of their labels.

This process is similar to searching a collection of text documents using a combination of keywords or an entire sentence, to retrieve relevant documents. Analogous to the text retrieval by providing a keyword, an image or a group of similar images could be retrieved by providing an image which similar in content to that of an image or group of images that need to be retrieved from the image database.

Content-based image retrieval is defined as an image recognition and retrieval task, which facilitates the detection of key visual elements in a collection of pictures and returns a set of visually relevant images from the image database [8]. The current methodologies for text-based retrieval could be utilized on visual information, provided that a language is created to represent it. Written language is characterized by the set of characters representing vowels and consonants and the diacritical marks which indicate breathing and vocal shaping,

which all are considered as values for features of the spoken language. Equivalently, the visual features referring to color, texture, or shape form visual words describing the region of a picture that could be used in form a visual document for the whole picture retrieval [9-10]. A simplified step-by-step methodological solution to this problem would be: a) Extracting the proper visual features from an image. b) Creating a language that describes them completely. c) Indexing the collection of images analogous to the collection of text documents.

II. LITERATURE REVIEW

The field of content-based image retrieval (CBIR) is a hotbed of study. This paper provides a method for feature extraction of the colour image that uses a soft hypergraph paired with a weighted adjacent structure (WAS) to improve the performance of a CBIR system, particularly the retrieval accuracy. The correlations between images are computed and a similarity matrix is created using this method. In addition, a unique WAS and a soft hypergraph model are used to boost retrieval precision even more by utilizing neighboring picture data. An image's colour, edge orientation, and texture can all provide a lot of information. People are sensitive to the image's colour contrast and texture information. To better explain the link between pictures, a conjoined colour difference histogram and micro-structure descriptor technique is developed, other methods are contrasted to the one proposed. It approaches in a variety of datasets, the proposed method's performance [1] and robustness are demonstrated by experimental findings.

One of its most difficult and ambiguous jobs in content-based image retrieval (CBIR) is correctly understanding the person keyword intention and calculating its conceptual relation with the image database. Because of visual saliency's excellent ability to forecast human visual interest, which is strongly tied to query intent, using qualitative and quantitative tests, this research aims to determine the crucial effect of visual saliency in CBIR. To achieve this, we begin by creating image fixation density maps from a dataset. Using eye-tracking equipment, researchers examined the widely utilized CBIR dataset. These ground-truth saliency maps are then utilized to calculate the saliency of the data. The impact of visual saliency on the CBIR task by exploring several probable ways of incorporating such saliency cues into the retrieval process. Two-stream attentive convolutional neural networks (CNNs) with saliency integrated therein are discussed in this work for CBIR. There are two streams in the planned network. The primary stream is concerned with identifying visually discriminative traits that are closely related in terms of semantic qualities. Meanwhile, the auxiliary stream seeks to aid the mainstream by directing feature extraction to the most important image content that a human would notice. Photo likeness could be estimated as a person does through retaining salient data and eliminating unnecessary regions by integrating the two streams into the Main and Auxiliary CNNs [2]. Extensive tests on four available datasets showed that the suggested method fits admirably in picture retrieval.

The goal of this study is to develop a hybrid CBIR technique that employs descriptive statistics [3], Discrete Wavelet Transform-Entropy, plus Peak-oriented Octal Pattern-derived Majority Voting (POPMV)-based selected features to accurately obtain various colour images from a colour picture dataset (CBIR SWPOPMV). A novel texture descriptor, POPMV, which is an octal pattern based on histogram peak information, influences the proposed

method's ideology, resulting in a majority voting-based feature set and three histogram-based feature sets. The DWT-based Entropy feature extraction is performed and the stochastic set of features are also added to improve retrieval accuracy. Eventually, the Distance measure matching procedure returns more relevant photos that are more favorable in comparison to the search query. Using seven standard databases, including Corel-1k, USPTex, MIT-VisTex, KTH-TIPS, KTH-TIPS2a, Colored Brodatz, and a user-contributed database dubbed DB VEG, the suggested technique is empirically compared against the existing recent CBIR versions.

Machine Learning and Deep Learning algorithms are used to produce an efficient approach for image description in this study [4]. An upgraded AlexNet Convolutional Neural Network (CNN), Histogram of Oriented Gradients (HOG), and Local Binary Pattern (LBP) descriptors were used to build this approach. Dimension reduction was also accomplished using the Principle Component Analysis (PCA) technique. The testing results show that the proposed method outperforms existing approaches by the ability to progress, mean Average Precision (MAP), and reducing the complexity of computation. The PCA algorithm's feature selection methodology has been employed for a variety of purposes, including decreasing computing volume and training times, model simplification, and so on. The LBP descriptor is a useful tool for classifying textures. On some datasets, combining the LBP with the HOG descriptor enhances detection performance significantly. The HOG descriptor is computed on such a higher dimension of spaced evenly pixels as well as includes repeating local contrast normalization to improve accuracy. This descriptor has the advantage of running on cell is based, which are insensitive to architectural and photographic modifications apart from object-orientation. Without any human intervention, the upgraded AlexNet CNN recognizes significant and high-level features automatically. The tests were carried out on the Corel-1000, OT, and FP datasets.

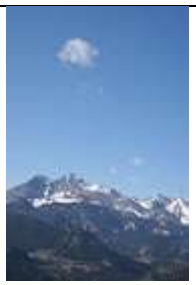
The Fourier transform and low-pass filtering are used in this study to offer a deep feature aggregation method for image retrieval that can adaptively compute the weights for each feature map with discrimination. By converting images to the frequency domain, low-pass filtering can maintain the semantic information in each feature map [5]. In addition, the three adaptive approaches were developed, namely Region of Interest selection, geographical weighting, and channel weighting, to improve the robustness of feature aggregation. For feature aggregation, adaptive Fourier transform and lowpass filter were designed. The image that the standard Fourier transform can analyze is a two-dimensional matrix, whereas the convolutional features derived from CNNs' convolutional or pooling layer are always three-dimensional. Under-five benchmark datasets, experimental results show that the proposed method outperforms previous state-of-the-art methods in terms of providing resilient and accurate object retrieval.

III. ANALYSIS OF DIFFERENT IMAGE RETRIEVING TECHNIQUES

Generally, the required images can be retrieved from the databases. This process depends on the features of the image, shapes involved in the image, color components of the image, size of the image, etc. retrieval of the necessary documentation is mandatory in many fields like forensic, security-based systems, etc. Figure 1 depicts a nature image as a query

and it is retrieved with five different algorithms. Even though the query image is the same, the results are in not a unique sequence.It means that the feature selection of an algorithm is different from others. It retrieves the best five images nearer to a query image. The retrieved images of different algorithms are similar, but the order is different.

Next figure, figure 2 showsa sequence of retrieved images for the given input query image. It is gray image retrieval. It shows the number of retrieved images is depending on the number the user-defined. It is from one to the database size. Figure 3 is the set of the top 10 retrieved images that is retrieved with the query image as an animal image. The database size, color combination of images, features of the imagesand size of the images show an impacton the processing time of the retrieving.Figure 4 illustrates a sample database of animals and Figure 5 illustrates a sample database of vehicles.

QUERY IMAGE					
Method 1					
Method 2					
Method 3					

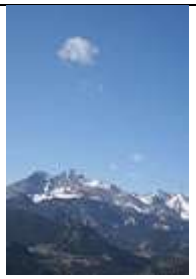
Method 4					
Method 5					

Figure 1: Query image and its topimage retrievals with different algorithms

Query image					
N = 1					
N = 2					
N = 3					

N = 4					
N = 5					

Figure 2: A queryimage and itstop retrieved images
(N= required number of retrieved outputs) (Top-1 to Top-5 image retrieval results)

		
Tiger Query Image	First Best Retrieved Image	Second Best Retrieved Image
		
Third Best Retrieved Image	Fourth Best Retrieved Image	Fifth Best Retrieved Image

		
Sixth BestRetrieved Image	Seventh BestRetrievedImage	Eighth BestRetrieved Image
		
Ninth BestRetrieved Image	Tenth BestRetrieved Image	

Figure 3: Tiger query image and its best 10 image retrieval outputs

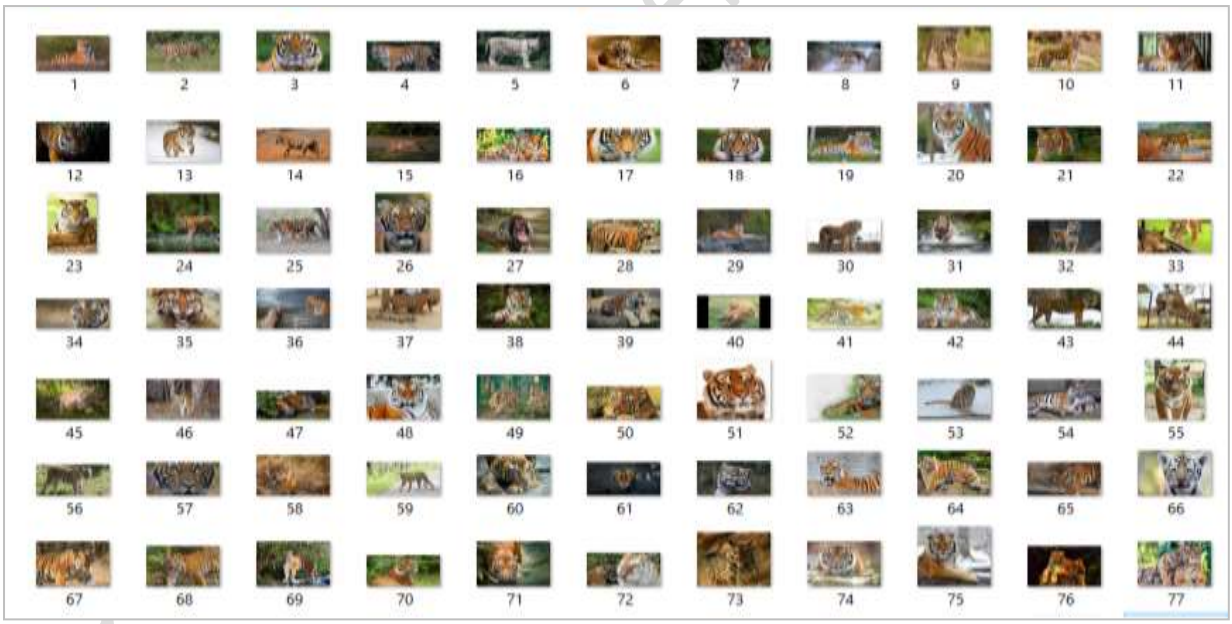


Figure 4: Animal Image Database

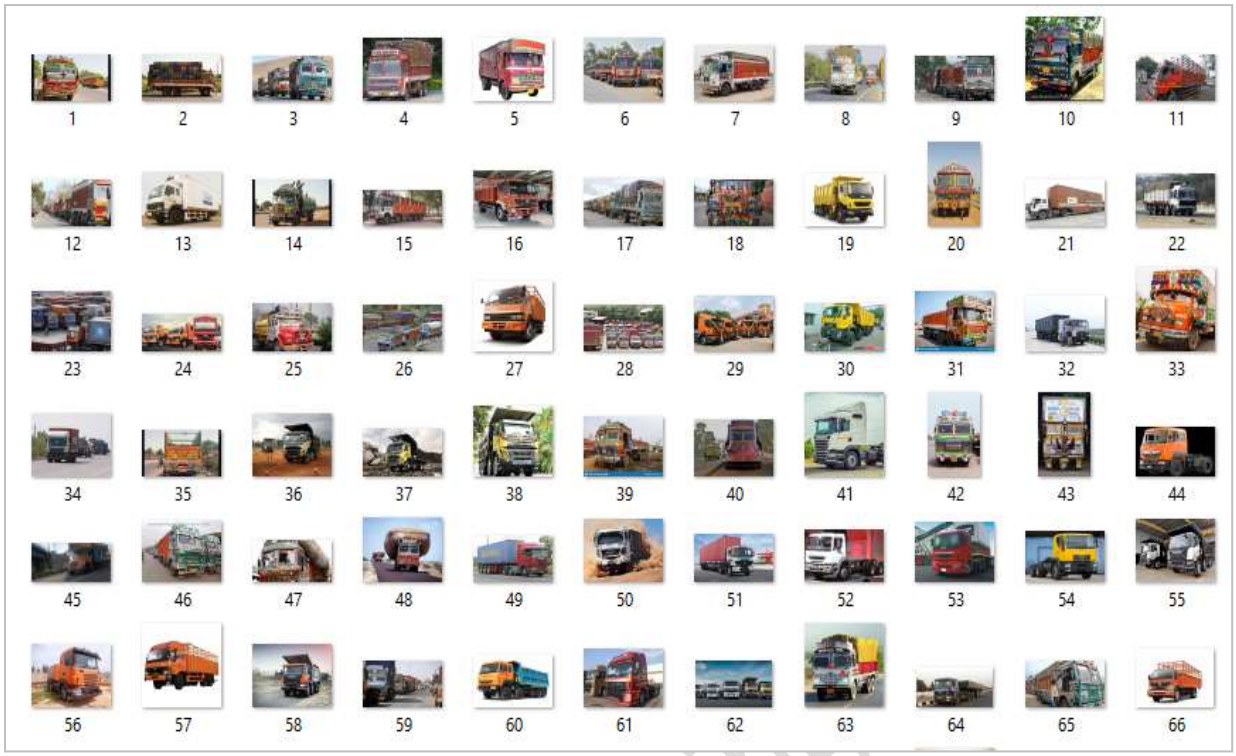


Figure 5: Vehicle Image Database

Similarity Measurement Techniques: Generally any retrieving process depends on the calculation of similarity between the given query image and each image of the selected database images. The percentage of similarity gives the order of retrieved position after the retrieving process. The topmost percentage of similarity images comes as the first fitted image and the lowest percentage of similarity images comes as the last fitted image in the retrieving process.

The popular and useful similarity operations that are being usedretrieving process are

a) Cosine Similarity
b) Squared Euclidian Distance
c) Manhattan Distance
d) Hybrid Graph
e) Minkowski distance
f) Latent Semantic Indexing
g) Chebyshev Distance
h) Euclidean Distance
i) Earth Mover's Distance

Retrieval Measures: Theoretical analysis can conclude the results in a better way. The statistical analysis of any process reveals the exact results. So, it is mandatory to analyze the process with mathematical equations and get statistical reports. The retrieved images may be ofrelevant or irrelevant. This relevance impacts a lot in the statistical reports. The following are some of the statistical parameters that are used generally in the image retrieval process.

a) Confusion Matrix
b) Mean Average Precision
c) Average Precision
d) Precision

e) Accuracy
f) F1-score
g) Recall
h) Total Processing Time
i) Precision-Recall Curve
j) Averaged Normalized Modified Retrieval Rank
k) Error Rate
l) Feature Extraction Time

IV. CONCLUSION

The image retrieval process is a common process in digging for the best-suited image in these days. Due to having many applications in the different areas, the research is going on high propriety. Digital technology is moving with faster speed and retrieving process is not moving the same. The retrieving process depends on the features of the image, shapes involved in the image, color components of the image, size of the image, etc. The retrieval of the necessary documentation or image is mandatory in many fields like forensic, security-based systems, etc. The efficiency of the retrieving method depends on feature selection, algorithm selection, distance measure, etc. In this paper, the state-of-art retrieving methods have been explained. The popular retrieving parameters and distance measure procedures have been listed.

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