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AN EXAMINATION OF MODERN APPROACHES TO VISUAL FEATURE EXTRACTION FOR CONTENT-BASED IMAGE RETRIEVAL

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Abstract— *Research in content-based image retrieval (CBIR) is currently a dynamic and expanding field with a wide scope. CBIR, a computer vision technique, addresses the challenge of searching for digital images within vast databases. This technique finds applications in various domains, including weather forecasting, data mining, remote sensing, medical imaging, education, crime prevention, and earth resource management, and is in high demand.*

Numerous studies have been conducted in recent years to enhance the process of visual similarity search and image retrieval in CBIR. Various methods and approaches have been developed to tackle this task. However, despite these advancements, there remain several unresolved issues in CBIR that warrant further attention.

This paper aims to delve into the contemporary practices employed in content-based image retrieval and assess their effectiveness. It seeks to explore the current state of the field and identify areas where improvements or innovative solutions are needed to advance the capabilities of CBIR systems.

Keywords— ***Content-Based Image Retrieval; Similarity Matching; Precision and Recall***

I. INTRODUCTION

Image retrieval systems serve the vital function of searching, browsing, and retrieving images from extensive image databases. These systems are typically categorized into two main types: concept-based and content-based image retrieval systems.

Concept-based image indexing relies on metadata such as keywords, annotations, captions, tags, or descriptions associated with each image [1]. This approach has been in use since the 1970s. However, manual annotation of images is a labor-intensive, tedious, and error-prone process. Image descriptions can vary from person to person, and it's not always possible to include every relevant description for each image. Consequently, using concept-based retrieval systems often results in the challenge of retrieving irrelevant or unsatisfactory search results.

The demand for digital images has been rapidly increasing, fueled by the exponential growth of digital image content on the internet. Professionals across various fields, including law enforcement, graphic design, fashion design, medicine, publishing, advertising, crime prevention, engineering, and architectural design, rely extensively on digital image databases for record-keeping and on-the-fly access.

This growing reliance on digital imagery has generated a need for systems that can swiftly and effectively retrieve images that are not only similar but also highly relevant to specific needs and contexts. Such systems are essential to enable professionals to efficiently access and utilize the vast reservoir of digital images available today.

Content-based image retrieval (CBIR) technique was adopted in the early 1990s to meet above demand. In this system, images are indexed based on their visual content, as opposed to relying on manual annotations. Content-Based Image Retrieval (CBIR) operates by analyzing the intrinsic characteristics of the images, which are derived directly from the images themselves. CBIR utilizes various image features, including color, shape, texture, and spatial location. The CBIR process involves feature extraction, feature matching, and semantic image retrieval [2]. The effectiveness of a CBIR system hinges largely on the techniques employed for extracting image features and the distance metric used to measure similarity between the query image and images within the database.

In recent years, there has been significant research interest in the application of relevance feedback to address image retrieval challenges, particularly because it involves human interaction. Relevance feedback aims to bridge the gap between human perception of images and computer-based retrieval by allowing users to assess retrieved results and provide feedback. This feedback is then used to enhance subsequent searches and the results generated by the system. Support Vector Machines (SVM) are commonly employed for learning from relevance feedback. This approach follows the nearest neighbor paradigm, where each image is ranked based on its proximity to the query image.

Researchers have developed both offline and online CBIR systems, often combining multiple image features. Some of these systems have achieved success in retrieving similar images with high precision and recall values. Commercial CBIR packages like VIR image engine by Virage Inc., IBM's QBIC, and Excalibur by Excalibur Technologies are available, while academic institutions and researchers have created experimental CBIR systems such as VisualSEEK, Surfimage, Photobook, Chabot, Netra, and MARS to demonstrate innovative techniques. Many of these systems have working demonstrations accessible online, and numerous research papers on CBIR have been published in prestigious journals. Dedicated issues focused solely on CBIR have also been recently released, underscoring the high demand and the need for further exploration in this research area.

The remainder of this paper is organised as follows: In section 2, we explore the general architecture of a CBIR system with a brief description of its components. In section 3, we review various image features and their extraction techniques. Section 4 gives an overview of the feature matching techniques to measure similarity between images.

Performance measurement parameters and techniques to compare various CBIR systems have been considered in section 5. Section 6 deals with the current practices in CBIR. Open issues as well as future directions have been discussed insection 7.

II. ARCHITECTURE

Figure 1 illustrates the block diagram of a Content-Based Image Retrieval (CBIR) system. In this system, various image features such as color, texture, and shape are extracted from the query image and compared with the corresponding features extracted from a database of images, which may include datasets like Wang, Caltech256, Indoor, Corel5000, and ImageCLEF. Both the query image and the database images are represented within a vector space.

Color information is typically represented using techniques such as Color Moment, Color Coherence Vector, Color Histogram, Color Correlogram, Dominant Color Descriptors, and Color Sets within specific color spaces. Texture features of an image are analyzed through structural, statistical, and spectral methods. Commonly used texture descriptors include Wavelet Transform, Gabor-Filter, Co-occurrence Matrices, Curvalet Transform, and Tamura features. Shape features are extracted using methods such as Fourier Descriptors, Grid Descriptors, Pseudo Zernike Moments, Moment Invariants, Canny Algorithm, Chain Code, B-splines, Eccentricity and Axis Orientation, Angular Radial Transform, and R-transform.

To effectively measure similarity among these extracted features, a distance formula is applied. Common distance metrics include Mahalanobis distance, Euclidean distance, Quadratic-Form Distance, and Minkowski-Form Distance. The result of this comparison process is a set of precision values, typically stored in a matrix format.

The images that are most similar to the query image are retrieved from the database in ascending order of the calculated precision values. It's important to note that this search is based on similarity rather than exact matches. The performance of the CBIR system is evaluated in terms of its recall and precision, which provide a measure of how effectively the system retrieves relevant images from the database.

III. IMAGE FEATURES

CBIR system extracts features like Color, Shape, Texture, Spatial Location and domain specific features such as human faces and fingerprints. Features are extracted based on the numeric pixel value of either the entire image or from a region obtained by image object's segmentation.

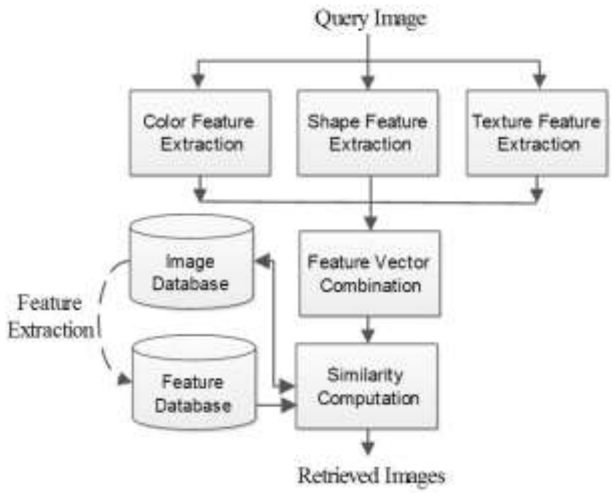

Fig. 1 Architecture of proposed CBIR system

A. Color

One of the spatial domain feature is color it is a best tool for understanding the insights of an image. The Color is a fundamental aspect of any digital image, and it plays a crucial role in the capabilities of a device or a digital image file. A color space is a three-dimensional model that encompasses all possible combinations of colors and establishes a numerical representation for actual colors. It provides a controlled and consistent framework for editing images, allowing for the determination of the range of colors that can be used. There are five major models of color spaces, which can be further subdivided to create other models. These five major color models are CIE, YUV, RGB, CMYK, and HSV/HSL.

Among the various visual features of an image, color is the most extensively studied and widely used feature [3]. Due to the vividness and perceptibility of color, it can be easily discerned on any surface or background. Moreover, color features are independent of an image's orientation and size. Numerous techniques have been developed for image retrieval based on color similarity, although many of them are variations of a common core concept.

One of the most widely employed techniques for color-based image retrieval is the Color Histogram. In this method, a histogram is computed for each image, illustrating the distribution of pixel colors within it. The Color Histogram is created by discretizing the image's colors into discrete levels and then counting the occurrences of each discrete color in the image [4]. It is worth noting that a three-dimensional object can be effectively represented using a few histograms, as the object's appearance changes gradually with variations in the viewing angle.

The Histogram Intersection method, introduced by Swain and Ballard, compares the model histogram with the image histogram to identify objects in the image. This comparison yields the number of pixels that are common between the model and the image histograms. This method is particularly suitable for object recognition, as it eliminates the need to distinguish objects from the background or from occluding foreground objects. The Histogram Intersection method is robust in the face of distractions in the object's background, changes in viewpoint, occlusions, and variations in image resolution. Swain and Ballard also devised an Incremental Histogram algorithm, which computes partial histogram values by comparing only the largest bins of the image and model histograms. This method is effective for indexing large databases of images [5].

Another approach to color-based image retrieval is the use of cumulative color histograms in combination with the $L\infty$-metric, proposed by Stricker and Orengo. This method is robust and yields superior retrieval results compared to traditional color histograms [6]. Additionally, Stricker and Orengo introduced the Color Moments method, where only a few dominant features of the color distribution are stored to characterize the color distribution by its moments, thereby reducing the quantization effect seen in the Color Histogram method [6].

The Color Sets method, developed by Smith and Chang, is employed for rapid searching in extensive image databases. This method first converts the image into the HSV color space, which closely aligns with human visual perception, and then applies a quantization process to the transformed color space to generate various color bins [7].

B. Texture

Texture refers to the visual pattern that conveys the structural arrangement of colors or intensities within an image. It possesses characteristics of periodicity and scalability, making it a valuable complement to color features in the process of finding visually similar images. Texture patterns can be found on nearly every surface, whether natural or artificial, including fabrics, tree leaves, brick walls, cloud formations, and wooden planks. However, defining texture precisely can be challenging due to its contradictory properties, such as randomness versus regularity and distortion versus uniformity.

To describe texture based on human visual perception, Tamura et al. developed a method that involves six parameters: directionality, regularity, coarseness, roughness, line-likeness, and contrast [8]. In segmentation and classification methods, two or more textured regions can be identified by selecting a set of properties defined for a particular region rather than a single point. Detecting texture boundaries between two adjacent regions becomes relatively straightforward when they differ in contrast, scale, orientation, or shape of elements. However, identifying texture boundaries in images with multiple textured regions can be more complex. Decomposing textural properties into contrast, coarseness, and directionality can help human observers specify these conditions more easily.

In the early 1970s, Harlick et al. developed the Co-occurrence Matrix method, which is based on the orientation and distance between image pixels. This method represents the distribution of various intensities and the relative positions of neighboring pixels, exploring gray-level spatial dependence in texture [9]. However, the entropy feature of the Co-occurrence Matrix is not as visually meaningful compared to Tamura features.

In 1994, Smith and Chang developed a method that used the energies of image subbands to classify and discriminate textures. This approach involves a comparison of extracted subband energy sets using image decompositions such as Discrete Cosine Transform (DCT), Uniform subband, Wavelet subband, and Spatial partitioning. The method achieved 90% accuracy in classifying texture images from the Brodatz collection using uniform and wavelet subband image decompositions. DCT and simple spatial block reported 80% and 34% accuracy, respectively. To simplify text-based searches in databases, Smith and Chang applied the Fisher Discrimination analysis method to reduce the discriminant space by compressing the features into uncorrelated linear discriminant functions [10].

Ma and Manjunath compared various wavelet transforms, including Gabor wavelet transform (GWT), Orthogonal wavelet transform (OWT), Bi-orthogonal wavelet transform (BOT), and tree-structured decompositions using orthogonal/bi-orthogonal filter banks. They assessed these methods in terms of texture classification, discrimination, image processing complexity, and suitability for developing indexing techniques [11]. Their findings indicated that algorithms using multi-resolution wavelet transforms performed better. Orthogonal and Bi-orthogonal wavelet transforms were efficient in multi-resolution storage with lower image processing complexity and lower feature dimensionality. In contrast, tree-structured decomposition led to high dimensionality, making indexing complex and not significantly improving pattern recognition performance and classification. Gabor wavelet transform, despite being computationally expensive, outperformed others due to its interpretability and ease of controlling orientation and scale information.

C. Shape

Shape refers to the external form, contour, or outline of an object, independent of its color, texture, or material composition. Human perception is highly capable of recognizing objects based solely on their shape, as the semantic features conveyed by shape are often more pronounced than those based on texture [12]. Effective shape representation should be invariant to common transformations like rotation, translation, and scaling [2]. Methods used for shape feature representation can be broadly categorized into boundary-based descriptors, which focus on the object's outer boundary, and region-based shape descriptors, which consider the entire object region [2].

One significant development in region-based shape descriptors was introduced by HU, who identified seven region-based moments that are invariant to transformations. HU combined absolute orthogonal moment invariants and similitude invariants in central moments, allowing for the identification of characters and visual patterns independent of size, orientation, and position. HU concluded that to achieve orientation independence, there could be multiple absolute moment invariants or infinitely many normalized moments along the principal axes [13].

Chuang and Kuo employed Wavelet Transform, known for its multiresolution representation, stability, spatial localization, and invariance properties, to describe object shapes [14]. They decomposed a curve into components at various scales, with the coarsest scale components carrying global approximation details and the finer scale components preserving local detailed information. Chuang and Kuo also introduced a deformable wavelet descriptor for character recognition and contour extraction from low signal-to-noise ratio (SNR) images. Experimental results demonstrated the effectiveness of the descriptor in representing local deformations within a group of deformable contours. Wallace and Wintz developed a method that efficiently represents 3D shapes while retaining all shape information, leveraging the interpolation property of Fourier descriptors [15].

Research on shape descriptors has revealed several insights. Zernike moment descriptors (ZMD) exhibit multiple representation capabilities, invariance to basic geometric transformations, and resilience to image noise, although they may lack perceptual meaning [16]. The Fourier Descriptor method utilizes the Fourier-transformed boundary of a query object as the shape feature. However, to account for image noise, Rui et al. developed a modified version of the Fourier descriptor that is not only robust to digitization noise but also invariant to geometric transformations [17].

Spatial Location information

Spatial Location information describes the position of the object in the image and is frequently used for region segmentation. Many times it happens that two objects have similar characteristics of color and texture and then it becomes difficult to distinguish among them, this is when spatial location is used. Sky and Sea both have similar color and texture characteristics but their spatial information is unlike, sky generally represents the topmost portion of an image and the sea generally occupies the lower portion of the image.

IV. SIMILARITY MEASURE

To find similar images to the query image from the database, the extracted feature of the query image needs to be compared with the extracted features of the images in the database. This can be done by using the distance equations such as Euclidean distance, City block metric, Minkowski distance, Mahalanobis distance and Quadratic Form distance. The system assigns an index value to rank the images according to the similarity level. Similar images are then retrieved according to their ranking value [18]. The selection of similarity measure is crucial as it can affect the performance of an image retrieval system.

A. Euclidean Distance

Euclidean distance generalizes our notion of physical distance in two or three dimensional space to multi dimensional space often referred as Pythagorean distance as well.

$$d_{st}^2 = (x_s - x_t)(x_s - x_t)' \quad (1)$$

Where x is an m-by-n data matrix, x_s and x_t are vectors. Minkowski form distance is the generalization of Euclidean distance [19].

B. City Block Distance

City block distance [19] is a special case of Minkowski distance when p=1.

$$d_{st} = \sum_{j=1}^{n} |x_{sj} - x_{tj}| \quad (2)$$

C. Minkowski-Form Distance

Minkowski-form distance is widely used when the dimensions of the image feature vectors are independent and when each dimension holds equal importance in image retrieval process.

$$d_{st} = \sqrt[p]{\sum_{j=1}^{n} |x_{sj} - x_{tj}|^p} \quad (3)$$

When p=1 Minkowski distance gives City block distance and when p=2 Minkowski distance gives Euclidean distance colors which retrieves more relevant images than the Histogram intersection and Euclidean distance method [19].

$$d_{st}^2 = (x_s - x_t)^T A (x_s - x_t)' \quad (5)$$

Where A is the similarity matrix $[a_{ij}]$ and a_{ij} represents the similarity between i and j bins.

V. PERFORMANCE MEASURE

Efficiency and effectiveness are the two parameters on which CBIR systems are evaluated. Efficiency relates with the speed of retrieval and effectiveness with the high accuracy of the retrieval. Performance comparison of image retrieval systems can be measured using many methods such as Precision and Recall, Average normalized modified retrieval rank (ANMRR), Sensitivity and Specificity. Precision and Recall is the most widely used evaluation measure among all the available methods [18].

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

$$\text{Recall} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images}} \quad (7)$$

There is a trade off between these two methods, improving the performance of one will result in lowering the performance of the other and vice-versa. ANMRR is a performance evaluation measure which is a combination of Precision and Recall. In this method evaluation of the system is made on the basis of increase in the effectiveness of the system to retrieve images from the database and the fundamental accuracy of the system is measured through user interaction.

Sensitivity and Specificity are the commonly used parameters for evaluating CBIR systems used in the medical field [20].

$$\text{Sensitivity} = \frac{\text{Positive items classified as positive}}{\text{All positive items}} \quad (8)$$

$$\text{Specificity} = \frac{\text{Negative items classified as negative}}{\text{All negative items}} \quad (9)$$

[19].

D. *Mahalanobis Distance*

In 1936 P.C.Mahalanobis developed the similarity/distance measure Mahalanobis distance using which different patterns can be identified and an analysis can be carried out based on the correlation between the variables [19].

$$d_{st}^2 = (x_s - x_t)C^{-1}(x_s - x_t)' \tag{4}$$

Where C is the covariance matrix

E. *Quadratic-Form Distance*

Quadratic form distance is used to measure similarity between images considering the cross similarity between

The systems that perform classifications of images use accuracy [20] as a measure to evaluate the system.

$$\text{Accuracy} = \frac{\text{Items classified correctly}}{\text{All items classified}} \tag{10}$$

VI. CURRENT CBIR SYSTEMS

Xiang-Yang Wang *et al*. developed an effective color image retrieval method combining the color, shape and texture features of the image. They used the modified version of Dominant color descriptors to extract the color feature. In this method some dominant colors and their percentages are obtained after predetermining the image using the Fast Color Quantization algorithm with clusters merging. Steerable Filters were used to extract the spatial texture feature of the image. In this method the filters having arbitrary orientations are synthesized. Then the image is split into orientation sub-bands to detect the edges located at various orientations in the image. Pseudo-Zernike Moments based shape descriptors were used to extract the shape feature as their magnitudes are invariant to the image rotation and are less sensitive to image-noise. Also, they have multilevel representation capabilities. The performance of the developed CBIR system was tested using the Corel image database and the results prove that the method has higher accuracy and efficiency levels compared to methods such as Color Histogram and Color Histogram of subblocks [12].

Nidhi Singh *et al*. developed a method in which firstly the image is segmented using the Fuzzy C-Mean algorithm to get the boundary of the object which is converted into signature. The Fast Fourier Transform of this signature gives the first feature vector. To extract the color feature HSI model is considered and Hue and Saturation component forms the second feature vector. The feature vector of query image and that of the images in the databases are compared. Feature vectors matching corresponding threshold are converted into text and the text is then passed to various web based search engines for image search in dynamic environment [16].

Tandon *et al*. developed a CBIR system called FISH- Fast Image Search in Huge Databases which learns the relevance of image features based on user feedback. Experimental results prove that the FISH system can seamlessly scale to huge image databases and maintain the interactive response time. Short and Long term learning of the intent of a user within a session is used to retrieve images with higher accuracy and efficiency. In this system the users provide the query image through the user interface, which is a web-front end. The query image is then processed and an appropriate index structure is used for a quick search of similar images. The retrieved images are then displayed to the user. User can give a feedback whether the retrieved images are similar to the query image. The feedback provided by the user is used for short term learning by the system to provide better results in the next iteration. This learned knowledge is stored in the long term memory to provide better retrieval results in the future queries [21].

Manimala Singha *et al*. developed a novel method called lifting wavelet-based colour histogram based on the combination of Haar Wavelet transform using lifting scheme and the color histogram method. Color features extracted by this method are rotation and translation invariant and as it extracts the local characteristics of the image along with the texture features, it has higher accuracy in the retrieval process [22].

PATSEEK: A CBIR system for US based patent database was developed by Tiwari *et al*. as a patent always consists of an image along with textual information. The user has to provide keywords along with the query image that might appear in the text of patents whose images would be searched for similarity. The image grabber searches the patent database on a certain criteria and provides a page image which consists of more than one image. Connected components or blocks are identified using horizontal scans and the vertical scans. Feature vectors are then calculated from these separated images using Edge Orientation Autocorrelogram (EOAC). Magnitude and gradient of the edges are found using the canny edge operator. The gradient of edges is then quantized and the edge orientation autocorrelogram is stored in the database along with the patent number and the page number where the image was found. These feature vectors stored in RDBMS table are then computed for similarity using the L1 and L2 distance measures. Experimentally, PATSEEK obtained 100% recall rate on 61% of query images [23].

Ganar *et al*. used colour, shape and texture fused features to retrieve desired image from huge image databases. Color Histogram and texture features are first obtained by quantifying the HSV color space. The feature matrix consisting of these features is then mapped to the Global and Local Color Histogram. Gradient method is used to extract shape feature [4].

In 2011, Buch *et al*. performed a comparative analysis of CBIR systems representing color feature using Color Moments and the texture feature using the Wavelet and Gabor Texture features. Euclidean distance and Chi-Square distance were used to measure similarity between images [24]. Each method was compared in terms of the precision value of the retrieved images and average precision for each class was computed. The comparison results proved that the maximum precision value in each class of images and in terms of average precision in all was obtained from Color Moments and Gabor texture using Euclidean distance.

A CBIR based on color was developed by Krishnan *et al*. based on the dominant colors in the foreground image which gives only the semantics of the image. Dominant color identification by using foreground objects alone is able to retrieve number of similar images considering the foreground color irrespective of size. Higher average precision and recall rates compared to the traditional Dominant Color method wereobtained successfully [25].

VII. Research Challenges

The paper suggests several promising research directions and areas for further improvement in the field of content-based image retrieval (CBIR):

Optimizing Existing Methods: Many CBIR systems have achieved good Precision and Recall values. Future research can focus on reanalyzing these methods and making enhancements to further optimize system performance, striving for even higher Precision and Recall values.

User-Centric Approaches: While efforts have been made to develop fully automated CBIR systems, they often fall short because human input and feedback are essential. Researchers should explore ways to leverage user feedback and provide rich context to CBIR systems, reducing the semantic gap between visual features and human perception. Developing techniques for image annotation that bridge this gap could be a valuable research avenue.

Integration of Multiple Features: No single image feature can consistently deliver satisfactory retrieval results. Future CBIR systems should explore the integration of various methods for extracting multiple image features, such as color, texture, shape, and spatial location, to enhance overall effectiveness.

Domain-Specific CBIR: Tailoring CBIR systems to specific domains can lead to better understanding and improved performance. Developing domain-specific CBIR systems can help meet the unique needs and behaviors of users in those domains.

Multi-Dimensional Indexing: As the collection of images on the web continues to grow, there is a pressing need for effective multi-dimensional indexing techniques. Proper selection of indexing methods is crucial, as it can significantly impact the retrieval performance of CBIR systems.

Performance Evaluation: Enhancements are needed in performance evaluation techniques and datasets used for evaluation. Ensuring scalability and content balance in evaluation datasets is important. Additionally, addressing the subjectivity of perception in performance evaluation can lead to more meaningful and accurate assessments.

Integration of Text-Based and Content-Based Retrieval: Combining text-based image retrieval with content-based image retrieval can provide a holistic approach to image retrieval. These two methods can complement each other effectively, and developing techniques that integrate them can yield improved retrieval results.

Overall, these research directions emphasize the ongoing evolution and potential for innovation in CBIR, making it an exciting and dynamic field for further exploration and advancement.

VIII. Conclusion

This paper extensively explores the concept of content-based image retrieval (CBIR), providing a thorough discussion of its principles and applications. The paper goes beyond theory and delves into the past and current systems for CBIR, reviewing the techniques used, assessing their accuracy, and presenting real-world results. To support these findings, the paper draws upon a rich body of research from various journal papers that delve deeply into the fundamental aspects of CBIR.

CBIR is established as an ongoing research topic with enduring relevance, and it is acknowledged that a generic approach is needed for achieving high-level semantic image retrieval. This involves integrating primitive feature extraction methods with high-level semantic extraction parameters to enhance the precision and effectiveness of image retrieval.

Importantly, the paper concludes that content-based image retrieval should not be viewed as a replacement for text-based approaches but rather as a complementary tool. Both methods have their unique strengths and can work together to provide more comprehensive and accurate information retrieval solutions.

Furthermore, the paper points to future research directions in the field of CBIR and highlights open research issues that require attention. This emphasizes the dynamic and evolving nature of CBIR, offering opportunities for ongoing exploration and innovation in this domain.

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