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A Detailed Survey on Content Based Image Retrieval (CBIR)

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Abstract. *Content-Based Image Retrieval (CBIR) has become a crucial technology for efficiently managing and searching extensive image databases based on visual content rather than relying on textual metadata. This paper offers a comprehensive survey of the current state of CBIR, examining its foundational concepts, key techniques, and the challenges that persist in the field. The survey explores critical areas such as feature extraction, similarity measures, and indexing methods, emphasizing the need to bridge the semantic gap between low-level image features and the high-level semantic concepts that users typically seek. Beyond these foundational aspects, the paper delves into advanced topics, including cross-modal retrieval, which integrates image retrieval with other modalities like text, audio, and video to enhance search capabilities. It also addresses pressing issues related to privacy and security, especially as CBIR systems are increasingly deployed in sensitive data environments. Scalability is another focus, particularly in managing the performance and accuracy of CBIR systems as image databases grow larger. Furthermore, the necessity for real-time processing capabilities is underscored, given the demand for instantaneous search results in various applications. By synthesizing existing research, this survey provides a thorough overview of CBIR, highlighting both the current advancements and the future directions of this evolving field. The paper serves as a valuable resource for understanding the ongoing developments in CBIR and the challenges that need to be addressed to fully realize its potential in diverse applications.*

Keywords: - CBIR, machine learning, image classification, image processing, Feature Extraction

I. INTRODUCTION

Content-Based Image Retrieval (CBIR) is a sophisticated technique used to automatically search for and retrieve images from vast databases based on the visual content of the images themselves, rather than relying on manually annotated metadata or textual descriptions. This approach involves the extraction of features such as color, texture, shape, and spatial relationships within the image. These features are then used to create a unique digital signature for each image, enabling the system to compare and identify images with similar characteristics. Advanced CBIR systems leverage machine learning and computer vision technologies to improve the accuracy and speed of the retrieval process. Applications of CBIR are widespread, ranging from medical image analysis and digital libraries to e-commerce and surveillance, where the ability to efficiently find and manage images based on their visual content is crucial. As digital image collections continue to expand exponentially, the development and refinement of CBIR technologies are essential for effectively navigating and utilizing this wealth of visual information. CBIR is a technique used to search and retrieve images from large databases based on their content rather than metadata or keywords. It involves analyzing the visual content of an image, such as color, texture, shape, and spatial layout, to create a unique signature or feature vector for each image. This feature vector is then used to compare and find similar images within the database. CBIR systems often employ machine learning and computer vision algorithms to enhance the accuracy and efficiency of the retrieval process. Applications of CBIR span various fields, including medical imaging, digital libraries, e-commerce, and security, where quick and precise image retrieval is crucial. As the volume of digital images continues to grow, the development of robust CBIR systems becomes increasingly important for managing and utilizing visual data effectively. An image database contains numerous images, and the initial step involves extracting features from these images to facilitate efficient retrieval. These features include low-level attributes such as shape, texture, and color, which are fundamental elements that define the visual content of the images. Shape features capture the geometric properties of objects within an image, texture features describe the surface characteristics and patterns, and color features represent the distribution and intensity of colors. Once these features are extracted, they are stored as feature vectors in a dedicated feature database. A feature vector is a compact and numerical representation of an image's content, making it easier to compare and retrieve similar images. A general block diagram of CBIR system is shown in figure 1.

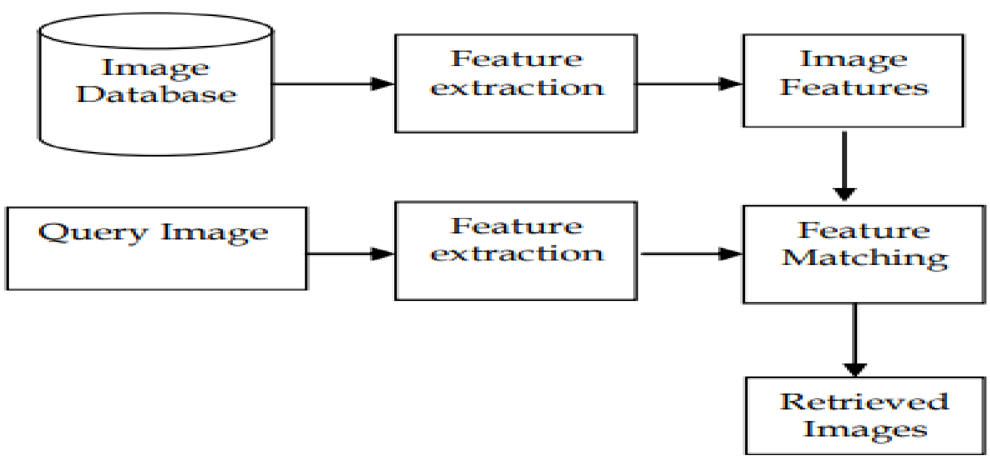

Figure 1: Block diagram of CBIR system

When a user inputs a query image into the system, the same feature extraction process is applied to the query image. This results in the creation of a feature vector for the query image, encapsulating its visual content. The next step is to compare the query image's feature vector with all the feature vectors stored in the database. Various approaches can be employed for this comparison, including similarity measures like Euclidean distance, Manhattan distance, Cosine similarity, and Mahalanobis distance. These methods quantify the degree of similarity between the query image and the images in the database, allowing the system to retrieve images that closely match the query. This process enables efficient and accurate retrieval of images based on their visual content, making it highly valuable for applications such as medical imaging, digital libraries, e-commerce, surveillance, and more.

II. KEY ASPECTS IN CBIR

CBIR examines visual contents in search results, instead of specific visual features of the image. To ensure that CBIR includes a query image as input, it computes visual content and visually similar images proximity in the feature vector is used to identify query-to-feature images. At the pixel level, some attributes control how the output looks (such as color, shape, and texture) but sorting is performed by the feature values that are found in the CBIR. The implementations of the above models in these areas have seen the incorporation of CBIR and feature extraction methods into numerous other fields such as medical imaging, meteorology, surveillance, and video analytics to significantly increase their use. The description of the fundamental concepts and mechanisms of image searching is provided in Figure 2.

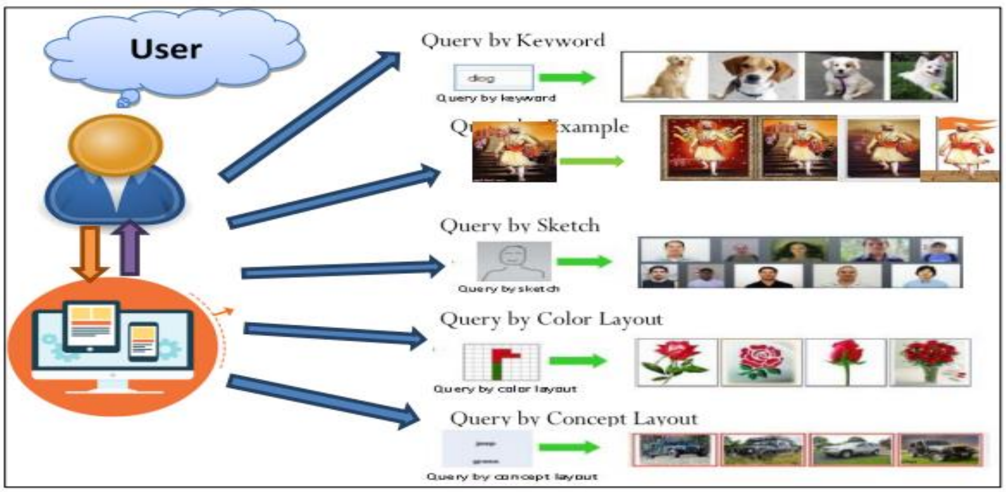

Figure 2: The fundamental concepts and mechanisms of image searching

By leveraging the intrinsic features of images, content-based image retrieval systems provide a powerful tool for managing and utilizing large collections of visual data. CBIR is a field within computer vision and information retrieval that focuses on the automatic indexing and retrieval of images based on their visual content. Here is a detailed overview of the key aspects and processes involved in CBIR-

(1) Feature Extraction

- **Color-** Color is one of the most prominent features in images. Techniques like color histograms, color moments, and color coherence vectors are used to capture the distribution of colors within an image.
- **Texture-** Texture provides information about the structural arrangement of surfaces and their relationship to the surrounding environment. Methods such as Gabor filters, wavelet transforms, and Local Binary Patterns (LBP) are used to describe texture.
- **Shape-** Shape features are crucial for identifying objects within an image. Techniques include edge detection (using algorithms like Canny or Sobel), contour-based methods, and region-based methods.

(2) Feature Vector Creation- After extracting the relevant features, each image is represented as a feature vector, a compact representation that encapsulates the essential visual information of the image. This vector is used to compare and retrieve similar images.
(3) Similarity Measurement- To retrieve images, the similarity between the feature vectors of the query image and the images in the database is calculated. Common similarity measures include Euclidean distance, Manhattan distance, Cosine similarity, and Mahalanobis distance.
(4) Indexing- Efficient indexing structures, such as KD-trees, R-trees, or hash tables, are used to store and quickly access the feature vectors in large image databases.
(5) Retrieval- When a query image is provided, its feature vector is extracted and compared against the indexed feature vectors in the database. The system retrieves images that have the most similar feature vectors to the query image.
(6) Relevance Feedback- Users may provide feedback on the retrieved results, indicating which images are relevant or irrelevant. This feedback can be used to refine the search algorithm and improve future retrieval accuracy through techniques such as query refinement or machine learning.

III. CLASSIFICATION OF THE CBIR METHODS

Content-Based Image Retrieval (CBIR) methods can be classified based on various criteria, such as the type of features used, the approach to matching, and the underlying technology. The classifications of the CBIR methods are broadly illustrated in Figure 3, with our focus primarily on global statistical features.

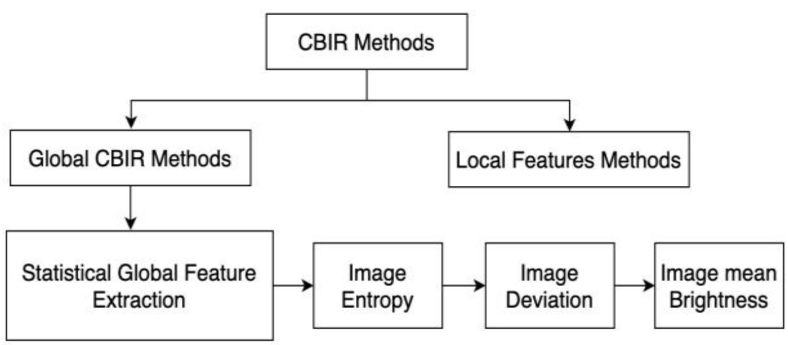

Figure 3: Classification of the CBIR methods

1. Feature-Based Classification
The feature extraction can be based on Color, Texture, Landscape features, and Signature can be done from image pixels as shown in Figure 4.

i **Color-Based Methods**

- **Color Histograms-** Represents the distribution of colors in an image. Common techniques include RGB histograms and HSV histograms.

- **Color Moments-** Statistical moments (mean, variance, skewness) of color distributions are used as features.

ii **Texture-Based Methods**

- **Statistical Methods-** Includes techniques like Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) to capture texture properties.
- **Structural Methods-** Analyzes texture patterns using techniques like Gabor filters and wavelet transforms.

iii **Shape-Based Methods**

- **Contour-Based-** Uses edge detection and contour information to represent shapes (e.g., Hough Transform, Canny Edge Detector).
- **Region-Based-** Focuses on the shape of regions within the image, using techniques like shape descriptors and region moments.

iv **Spatial-Based Methods**

- **Spatial Histograms-** Represents the spatial distribution of features, such as color or texture, in an image.
- **Spatial Relations-** Considers the relative positions and relationships of objects within the image.

v **Hybrid Methods**

- **Combination of Multiple Features-** Integrates color, texture, and shape features to improve retrieval accuracy.

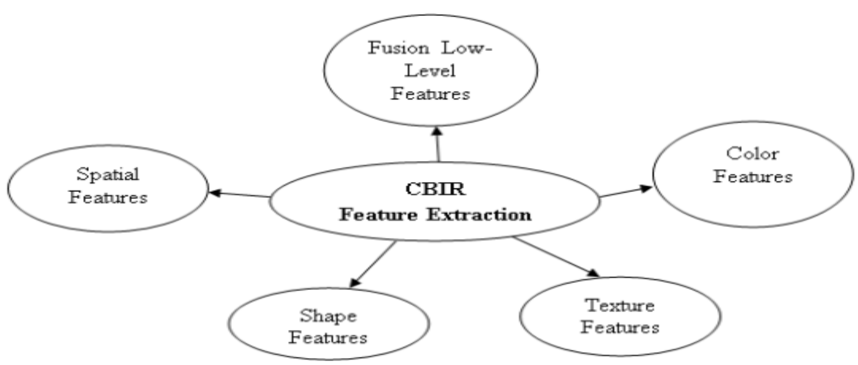

Figure 4: CBIR Feature Extraction

2. Representation-Based Classification

i **Global Representation**

- **Global Features-** Uses overall features of the entire image, such as global color histograms or global texture descriptors.

ii **Local Representation**

- **Local Features-** Focuses on specific regions or patches within the image, using techniques like SIFT, SURF, and ORB.

- **Feature Pyramids-** Combines local features at multiple scales to capture hierarchical information.

3. Similarity Measure Based Classification

i **Distance Metrics**

- **Euclidean Distance-** Measures the straight-line distance between feature vectors in a multidimensional space.
- **Cosine Similarity-** Evaluates the angle between feature vectors to determine similarity.
- **Hamming Distance-** Used for comparing binary feature representations.

4. Learning-Based Classification

i **Machine Learning Approaches**

- **Traditional Machine Learning-** Uses algorithms like Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) for classification and retrieval.
- **Feature Learning-** Automatically learns features from raw image data using techniques like Principal Component Analysis (PCA) and Independent Component Analysis (ICA).

ii **Deep Learning Approaches**

- **Convolutional Neural Networks (CNNs)-** Learns hierarchical features from images using deep architectures. Pre-trained models like VGG, ResNet, and Inception are commonly used.
- **Autoencoders-** Learns compressed representations of images for feature extraction and retrieval.
- **Generative Models-** Uses models like Generative Adversarial Networks (GANs) to create and retrieve images based on learned features.

6. Feedback-Based Classification

i **Relevance Feedback**

- **Implicit Feedback-** Uses user interactions like clicks and viewing time to improve retrieval results.
- **Explicit Feedback-** Involves users providing direct feedback on the relevance of retrieved images to refine search results.

7. Multi-Modal Classification

i **Text-Image Integration-** Combines textual metadata with image content for enhanced retrieval.

ii **Cross-Modal Retrieval-** Searches for images based on queries from other modalities, such as text or audio.

Each of these classifications highlights different aspects and approaches in CBIR, reflecting the diverse methods and technologies used to improve image retrieval systems.

IV. MACHINE LEARNING TECHNIQUES IN CBIR

The direct feature extraction is performed via CNNs allows for information to be recovered from images. The related researchers such as Michael Slepian, et.al, found researchers that use CNN for complex extraction of higher-level features from images both computer vision techniques, which filter unnecessary details from the image data to increase its accuracy of retrieval, and extraneous data in low detail by removing unnecessary ones. There is a limit to the number of features that can be retrieved by using additional convolutional layers: the ability to express more is proportional to the amount of time spent training on the model expansion. Using the analogy of one-based CNN to demonstrate our previous point, the authors have acquired results for two purpose-oriented CNN results and compared them to various computer vision fusion techniques in terms of precision. CNN's outstanding success in computer vision is attributable to its diverse application set, which includes neural network models like CBIR and support vector machines. In the vast majority of CNN implementations, only the last layer uses convolution with quantization, which may be limiting in the scope of features. In contrast to that, limiting the number of features in the last layer has a different form of performance loss, CNNs are often constrained by the number of times they can quantize local features. The survey demonstrated that taking the quantized model and extracting the functions using different levels, which is remarkably efficient, and also lowers the retrieval and storage costs. It's also noteworthy that the CRB-CNN is effective for learning complex images that have a distinct set of semantics. To extract the function from the image and locate the corresponding to the database, it is a very little space, it only takes ten milliseconds and has a maximum capacity of 10,000 rows end-to-to-to-ending tan describes a process in which only visual information is used, whereas CRB mission searchability's expansion requires no extra annotations or tags to accomplish function search, function extraction from visual images. As well as the database image retrieved in the large image, the ability to perform complex queries on this image was exemplary.

V. SUMMARY OF RECENT WORKS ON IMPROVING THE EFFICIENCY OF CBIR

Numerous researchers have contributed to improving the efficiency of CBIR systems in the past. This section sequentially reviews relevant research.

Dannina, Kishore et al. [6] proposed a retrieval system using statistical features from CS-SCHT, HVS color quantization, and SVM classifier. Syazwani, Izzati et al. [7] successfully retrieved 20 images from five classes using this method, achieving high accuracy in image retrieval with SVM. However, they only assessed a small dataset. R. Vani et al. [8] surveyed various genetic algorithms and neural networks to enhance SVM-based CBIR efficiency. M. R. Kapadia et al. [9] analyzed SVM kernels (Polynomial, RBF, Sigmoidal) for content-based image retrieval, with the RBF kernel performing well due to its exponential nature. G. Kaur et al. [10] compared SVM and decision tree methods' accuracy for CBIR. A. Jain et al. [11] evaluated the performance of various SVM-based ML techniques. Sharma, Neetu, Paresh Rawat et al. [12] presented a detailed description of a color histogram matching-based CBIR system, employing statistical parameter-based matching in RGB histograms for image retrieval. S., M., Pandey et al. [13] used different distance-based methods to evaluate CBIR system performance, demonstrating fuzzy performance for different cases. Vijayakumar et al. [14] presented the use of DL based on CNN models to enhance CBIR system performance, which proved efficient but requires a larger dataset and is computationally costly. Mrinaliyadav et al. [15] proposed a simple and efficient content-based image retrieval system using statistical soft computing and texture features, evaluating its performance on a large dataset of color images, aiming to overcome past complexities and case-specific methods. EL, Aroussi et al. [16] introduced a fast and efficient image indexing and search system utilizing color and texture features, improving image recognition and classification accuracy in CBIR. Minh-Tan et al. [17] achieved efficient and competitive results in texture-based image retrieval experiments using the Local extrema-based descriptor (LED) for encoding images. Mahmoud, S et al. [18] proposed deep learning (DL) based CBIR systems, combining

AlexNet features with DCT transform using PCA and SVM classifiers, though with low precision for subsequent retrieval levels. Jia and Wang [19] used an imaging database of 1000 images for a CBIR system, which has become standard. Ramsha Pallawkar et al. [20] proposed SVM-based ML methods to reduce retrieval time, using the Wang dataset. Pavithra, L. K., and Sharmila [21] have used edge detection and textures for retrieval. Table2. 1 provides a concise summary of the authors; methods/techniques used, and key findings from each study. Table 1 concludes that it is necessary to design a fast and efficient CBIR system; hence this paper aims to use a combination of statistical and texture-based LBP features for CBIR systems.

VI. APPLICATIONS OF CBIR

Content-Based Image Retrieval (CBIR) has a wide array of applications across various fields due to its ability to efficiently and accurately search and retrieve images based on their visual content. Here are some detailed explanations of the primary applications of CBIR and also shown in figure 5.

1. Medical Imaging- CBIR is extensively used in the medical field to assist in the diagnosis and treatment of diseases. Medical professionals can use CBIR systems to compare new medical images, such as X-rays, MRIs, or CT scans, with existing images in large medical databases.

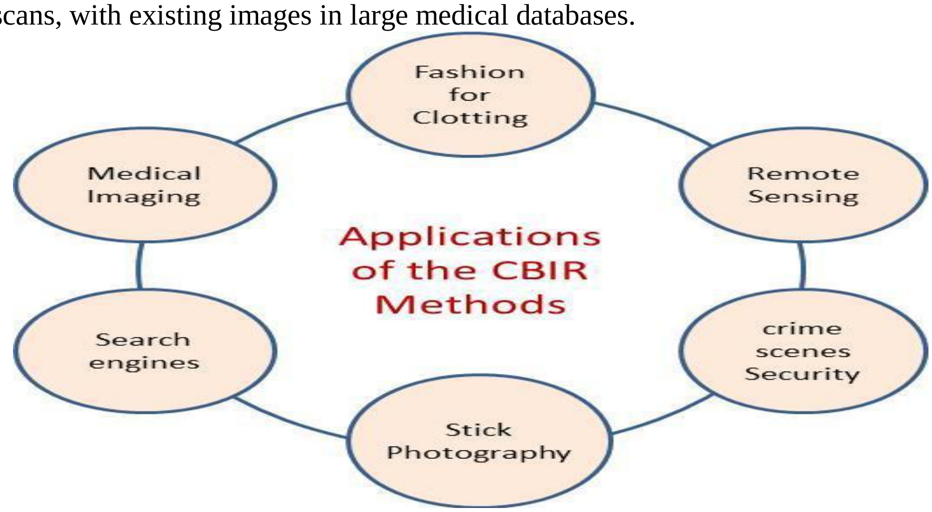

Figure 5: Applications of CBIR

2. **Digital Libraries and Museums-** Digital libraries and museums utilize CBIR to manage and access vast collections of visual art, photographs, and historical documents. Curators and researchers can search for images based on visual similarity, enabling them to find related artworks or documents without relying solely on textual descriptions.

3. E-commerce- In the e-commerce sector, CBIR is used to improve the shopping experience for customers. Users can upload images of products they are interested in, and the CBIR system retrieves visually similar items from the retailer’s catalog.

4. Surveillance and Security- Law enforcement and security agencies use CBIR to analyze and manage surveillance footage. CBIR systems can help identify suspects by comparing images or video frames with databases of known individuals.

5. Social Media and Entertainment- Social media platforms and entertainment companies use CBIR to manage and recommend visual content.

6. Satellite and Remote Sensing- CBIR is applied in satellite imagery and remote sensing to analyze and interpret large volumes of visual data. Researchers can use CBIR to monitor environmental changes, track urban development, and assess natural disasters.

7. Personal Photo Collections- CBIR helps individuals manage their personal photo collections by enabling image-based searches. Users can find specific photos by uploading a reference image, allowing them to organize and retrieve their pictures more effectively.

8. Scientific Research- In scientific research, CBIR is used to analyze visual data from experiments and simulations. Researchers can compare images to identify similarities, track changes over time, and draw conclusions based on visual evidence.

9. Fashion Industry- The fashion industry leverages CBIR to streamline design processes and trend analysis. Designers can use CBIR to find inspiration by searching for visually similar designs, patterns, or color schemes.

10. Cultural Heritage Preservation- CBIR is used in the preservation and restoration of cultural heritage artifacts. By comparing images of artifacts over time, conservators can monitor deterioration, plan restoration efforts, and ensure the longevity of cultural treasures.

Content-Based Image Retrieval continues to expand its impact across diverse domains, providing valuable tools for managing, analyzing, and utilizing visual data in innovative ways. As technology advances, the applications of CBIR are likely to grow, offering new possibilities for improving efficiency and accuracy in various fields.

VII. CHALLENGES IN CBIR

Content-Based Image Retrieval (CBIR) systems face several significant challenges that affect their performance, accuracy, and usability. Here is a detailed explanation of these challenges-

1. Semantic Gap- The semantic gap refers to the difference between the low-level features extracted by CBIR systems (such as color, texture, and shape) and the high-level concepts understood by humans (such as objects, scenes, and events). Bridging this gap is challenging because the same low-level features can represent different high-level concepts, and vice versa. For instance, images of the sky and the sea might have similar color distributions but represent different scenes. Addressing the semantic gap requires sophisticated algorithms capable of understanding and interpreting high-level semantics from low-level visual features.

2. Feature Extraction and Representation- Accurately extracting and representing features is crucial for effective CBIR. However, determining which features are most relevant for different types of images and queries can be difficult. Some features may be more important for certain applications but less relevant for others. Additionally, the choice of feature representation impacts the system's ability to discriminate between similar and dissimilar images, affecting retrieval accuracy.

3. Scalability- As image databases grow in size, CBIR systems must handle large volumes of data efficiently. Scalability involves both the storage of feature vectors and the computational complexity of searching through them. Techniques such as indexing, dimensionality reduction, and parallel processing are often employed to improve scalability, but balancing these methods while maintaining accuracy is challenging.

4. Variation in Imaging Conditions- Images can vary significantly due to differences in lighting, viewpoint, resolution, and occlusion. These variations can affect the consistency of feature extraction and make it difficult to match similar images accurately. Developing robust feature extraction methods that can handle such variations is a major challenge in CBIR.

5. Relevance Feedback and User Interaction- Incorporating user feedback into CBIR systems can improve retrieval accuracy by refining the search process based on user preferences. However, designing intuitive and effective user interfaces for providing relevance feedback is challenging. Additionally, integrating this feedback into the retrieval algorithm in a meaningful way requires sophisticated techniques that balance user input with system performance.

6. Computational Complexity- CBIR systems often involve complex algorithms for feature extraction, similarity measurement, and indexing. Ensuring that these processes are computationally efficient is crucial for real-time or near-real-time retrieval. High computational complexity can lead to slow response times, which are impractical for many applications, especially those requiring quick access to visual information.

7. Data Quality and Annotation- The quality of the images in the database and the accuracy of any associated metadata or annotations can significantly impact CBIR performance. Poor-quality images, such as those with noise, blur, or low resolution, can lead to inaccurate feature extraction. Additionally, inconsistencies or errors in manual annotations can affect the effectiveness of CBIR systems that rely on hybrid approaches combining visual and textual information.

8. Privacy and Security- CBIR systems often deal with sensitive visual data, especially in applications like medical imaging and surveillance. Ensuring the privacy and security of the images and the associated data is a critical challenge. This involves implementing robust encryption, access control, and anonymization techniques to protect the data from unauthorized access and misuse.

9. Domain Adaptation and Transfer Learning- CBIR systems trained on one type of image data may not perform well on another type due to differences in feature distributions. Adapting a CBIR system to new domains without extensive retraining is challenging. Transfer learning and domain adaptation techniques aim to address this by leveraging knowledge from related domains, but effectively implementing these techniques is complex.

10. Evaluation Metrics and Benchmarking- Evaluating the performance of CBIR systems requires appropriate metrics and benchmark datasets. Common metrics include precision, recall, and F1-score, but selecting the right metrics depends on the specific application and retrieval goals. Benchmarking CBIR systems against standard datasets is also crucial for comparing different approaches, but creating comprehensive and representative benchmark datasets.

VIII. CONCLUSION AND FUTURE SCOPE

In conclusion, Content-Based Image Retrieval (CBIR) continues to be a dynamic and rapidly advancing field, driven by the increasing need for efficient and effective image search techniques in the era of big data. This survey has highlighted the critical challenges and advancements within CBIR, including the ongoing struggle to bridge the semantic gap, the importance of privacy and security, and the integration of cross-modal retrieval techniques. As the field progresses, the emphasis on scalability and real-time processing will become even more crucial, particularly as image databases grow exponentially. Future research must focus on refining these areas to enhance the accuracy, efficiency, and applicability of CBIR systems across various domains. The insights presented in this survey underscore the importance of continued innovation and interdisciplinary collaboration to overcome the existing limitations and fully realize the potential of CBIR technology. Scalability in handling large-scale image databases efficiently is a critical challenge in content-based image retrieval (CBIR) systems, as is addressing the semantic gap between low-level visual features and high-level semantic concepts. Ensuring privacy and security in image retrieval systems is also paramount to protect user data. Additionally, the integration of cross-modal retrieval, which combines image retrieval with other modalities like text, audio, and video, is essential for creating more comprehensive search capabilities. Finally, enhancing the speed and efficiency of CBIR systems to support real-time processing is crucial for their application in time-sensitive scenarios.

REFERENCES

[1]. Kunal, B. Singh, E. K. Kaur and C. Choudhary, "A Machine Learning Model for Content-Based Image Retrieval," 2023 2nd International Conference for Innovation in Technology (INOCON), Bangalore, India, 2023, pp. 1-6, doi: 10.1109/INOCON57975.2023.10101215.

[2]. K. A and R. Lanke, "Image Retrieval based on Deep Learning - Convolutional Neural Networks," 2022 International Interdisciplinary Humanitarian Conference for Sustainability (IIHC), Bengaluru, India, 2022, pp. 757-762, doi: 10.1109/IIHC55949.2022.10060450.

[3]. Prasad B.D.C.N, M. Sailaja and V Suryanarayana, "Analysis on Content Based Image Retrieval Using Image Enhancement and Deep Learning Convolutional Neural Networks", ECS Transactions, The Electrochemical Society, Inc. Issue 1, Vol 107, 19777, 2022, https://dx.doi.org/10.1149/10701.19777ecst

[4]. Lande, M.V., Ridhorkar, S. (2022). A Comprehensive Survey on Content-Based Image Retrieval Using Machine Learning. In: Gupta, D., Polkowski, Z., Khanna, A., Bhattacharyya, S., Castillo, O. (eds) Proceedings of Data Analytics and Management . Lecture Notes on Data Engineering and Communications Technologies, vol 91. Springer, Singapore.https://doi.org/10.1007/978-981-16-6285-0_14

[5]. Agrawal, S., Chowdhary, A., Agarwala, S. et al. Content-based medical image retrieval system for lung diseases using deep CNNs. Int. j. inf. tecnol. 14, 3619–3627 (2022). https://doi.org/10.1007/s41870-022-01007-7

[6]. Dannina, Kishore.,Chanamallu, Srinivasa, Rao. (2020). A Multi-class SVM Based Content Based Image Retrieval System Using Hybrid Optimization Techniques. Traitement Du Signal, doi: 10.18280/TS.370207.

[7]. Syazwani, Izzati, Shahrom.,Norlyda, Mohamed., Siti, Fatimah, Kamarudin., Wan, Nur, Auni, Wan, Ghazali., Aminah, Abdul, Malek. (2021). Content Based-Image Retrieval Using Support Vector Machine. doi: 10.1109/ICCSCE52189.2021.9530873

[8]. R. Vani, T. Vyas and N. Tahilramani, "CBIR Using SVM, Genetic algorithm, Neural Network, Fuzzy Logic, Neuro-fuzzy Technique:A Survey," *2018 International Conference on Communication, Computing and Internet of Things (IC3IoT)*, Chennai, India, 2018, pp. 239-242, doi: 10.1109/IC3IoT.2018.8668197.

[9]. M. R. Kapadia and C. N. Paunwala, "Analysis of SVM kernels for content based image retrieval system," *2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS)*, Chennai, India, 2017, pp. 1409-1414, doi: 10.1109/ICECDS.2017.8389676.

[10]. G. Kaur and S. Saini, "Comparison of State Vector Machine and Decision Tree - Content Based Image Retrieval Algorithms to Perceive Accuracy," *2023 1st International Conference on Innovations in High Speed Communication and Signal Processing (IHCSP)*, BHOPAL, India, 2023, pp. 11-15, doi: 10.1109/IHCSP56702.2023.10127132.

[11]. A. Jain and S. Varshney, "Deep Analysis of Machine Learning Techniques for the Effective Retrieval of Images Based on Content," *2024 2nd International Conference on Disruptive Technologies (ICDT)*, Greater Noida, India, 2024, pp. 163-167, doi: 10.1109/ICDT61202.2024.10488968.

[12]. Sharma, Neetu, PareshRawat, and Jaikaran Singh. Efficient CBIR using color histogram processing. LAP LAMBERT Academic Publishing, 2012.

[13]. S., M., Pandey.,Madan, Lal, Saini., Sandeep, Kumar. (2020). A Comparative Study on CBIR Using Color Features and Different Distance Method. doi: 10.1007/978-981-15-0222-4_59

[14]. VijayakumarBhandi, Sumithra Devi K.A. “Image Retrieval Using Features From PreTrained Deep CNN” International Journal Of Scientific & Technology Research Volume 9, Issue 06, June 2020

[15]. Mranali, Yadav., Manish, Rai., Mohit, Gangwar. (2018). An Efficient Content Based Image Retrieval using Statistical Soft Computing and Texture Features. doi: 10.1109/ICACAT.2018.8933696

[16]. EL, Aroussi, El, Mehdi.,Silkan, Hassan., ELhoussif, Nourddine. (2017). A Fast and Efficient Image Indexing and Search System based on Color and Texture Features. Indian journal of science and technology, doi: 10.17485/IJST/2017/V10I39/119860

[17]. Minh-Tan, Pham.,Gregoire, Mercier., Lionel, Bombrun., Julien, Michel. (2016). Texture and Color-based Image Retrieval Using the Local Extrema Features and Riemannian Distance. arXiv: Computer Vision and Pattern Recognition,

[18]. Mahmoud, S., Sayed., Ahmed, A., A., Gad-Elrab., Khaled, A., Fathy., Kamal, R., Raslan. (2023). A deep learning content-based image retrieval approach using cloud computing. Indonesian Journal of Electrical Engineering and Computer Science, doi: 10.11591/ijeecs.v29.i3.pp1577-1589

[19]. Jia Li, James Z. Wang, ``Automatic linguistic indexing of pictures by a statistical modeling approach," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 25, no. 9, pp. 1075-1088, 2003.

[20]. RamshaPallawkar , UjwalHarode and SuchitraPatil “Content Based Image Retrieval with Machine Learning Classification for Reducing Computational Complexity” 4th International Conference on Communication and Information Processing (ICCIP-2022

[21]. Pavithra, L. K., &Sharmila, T. S. (2018). An efficient framework for image retrieval using color, texture and edge features. Computers & Electrical Engineering, 70, 580–593.