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Deep Feature Descriptor Learning for Content-Based Image Retrieval Using Convolutional Neural Networks

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Abstract: The exponential growth of digital image repositories across domains such as healthcare, surveillance, e-commerce, remote sensing, and social media has created a significant demand for efficient and accurate image retrieval systems. Content-Based Image Retrieval (CBIR) has emerged as a promising solution by retrieving images based on their visual characteristics rather than textual annotations. However, conventional CBIR techniques that rely on handcrafted feature descriptors, such as Color Histogram, Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), and Speeded-Up Robust Features (SURF), often suffer from limited semantic representation, feature redundancy, and reduced retrieval accuracy. To address these challenges, this paper proposes a novel Deep Feature Descriptor Learning (DFDL) framework based on Convolutional Neural Networks (CNNs) for CBIR applications. The proposed framework employs multi-level feature extraction, feature fusion, global average pooling, and feature optimization techniques to generate compact, discriminative, and retrieval-oriented image descriptors. Furthermore, cosine similarity is utilized for efficient image matching and ranking. The effectiveness of the proposed approach is evaluated using standard retrieval performance metrics, including Precision, Recall, Mean Average Precision (mAP), Retrieval Accuracy, and Retrieval Time. Experimental results demonstrate that the proposed DFDL-CBIR framework achieves superior performance compared to traditional handcrafted descriptors and existing CNN-based methods, obtaining a Precision of 95.8%, Recall of 94.6%, mAP of 95.1%, Retrieval Accuracy of 96.2%, and Retrieval Time of 138 ms. These findings indicate that the proposed framework effectively enhances retrieval accuracy while reducing computational complexity, making it suitable for large-scale image retrieval applications.

Keywords: Content-Based Image Retrieval (CBIR), Deep Feature Descriptor Learning, Convolutional Neural Networks (CNN), Feature Fusion, Image Retrieval.

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I. INTRODUCTION

The rapid growth of digital multimedia content has led to a significant increase in the volume of images generated and stored across various domains, including healthcare, remote sensing, e-commerce, social media, security surveillance, and digital libraries. Therefore, the efficient management and retrieval of relevant images from large-scale image repositories have become significant research challenges (Suchitra & Chitrakala, 2013). Traditional text-based image retrieval methods rely on manually assigned annotations and metadata, which are often subjective, incomplete, and labor-intensive. Consequently, content-based image retrieval (CBIR) has emerged as an effective alternative that retrieves images based on

their visual characteristics rather than textual descriptions (Madugunki et al., 2011).

CBIR systems typically utilize visual features, such as color, texture, shape, and spatial information, to represent image content. Conventional CBIR approaches employ handcrafted feature descriptors, including color histograms, local binary patterns (LBPs), grey-level co-occurrence matrices (GLCMs), scale-invariant feature transforms (SIFTs), and speeded-up robust features (SURFs) (Bhad & Ramteke, 2015). Although these descriptors have demonstrated satisfactory performance in specific applications, they often struggle to capture high-level semantic information and exhibit limited robustness to variations in illumination, scale, rotation, occlusion, and background complexity. This semantic gap between low-level visual features and high-level image semantics remains a major limitation of traditional CBIR systems (Jena et al., 2020; Tiwari et al., 2021).

Recent advances in deep learning, particularly convolutional neural networks (CNNs), have significantly transformed image analysis and computer vision research. CNNs automatically learn hierarchical feature representations directly from raw image data, eliminating the need for manual feature engineering (Sharada et al., 2023). The learned deep features capture both low-level and high-level visual patterns, enabling superior image representation and discrimination compared to manually crafted descriptors. Consequently, CNN-based feature extraction techniques have achieved remarkable success in image classification, object detection, image segmentation, and image retrieval applications (Tan, 2024).

Deep feature descriptors generated by CNN architectures possess strong representational capabilities and have demonstrated improved retrieval accuracy in large-scale image databases. However, challenges such as feature redundancy, computational complexity, and retrieval efficiency continue to motivate the development of more effective deep feature descriptor learning strategies (Zhou et al., 2020). Designing robust and discriminative feature descriptors that can accurately represent image content while maintaining computational efficiency remains an active area of research (Lee et al., 2016).

This study proposes a deep feature descriptor learning framework for content-based image retrieval using convolutional neural networks (CNNs) (Kamatchi et al., 2025). The proposed approach extracts highly discriminative feature representations from images and utilizes similarity-based retrieval mechanisms to identify relevant images from large databases. By leveraging the hierarchical learning capability of CNNs, the framework improves retrieval precision, recall, and overall system performance (Pinaki et al., 2023).

The major contributions of this study are summarized as follows:

- Development of a CNN-based deep feature descriptor learning framework for CBIR.
- Extraction of robust and discriminative image representations using deep convolutional layers.
- Integration of similarity measurement techniques for efficient image retrieval
- Performance evaluation using standard CBIR datasets and retrieval metrics, such as precision, recall, mean average precision (mAP), and retrieval accuracy.
- Comparative analysis with conventional handcrafted feature descriptor methods.

The remainder of this paper is organized as follows. Section II presents related work and a literature review. Section III describes the proposed CNN-based feature descriptor learning methodology. Section IV discusses experimental setup and performance evaluation metrics. Section V presents the results and discussion, and Section VI concludes the paper and outlines future research directions.

III. LITERATURE REVIEW

Content-based image retrieval (CBIR) has been an active research area for several decades, owing to the exponential growth of digital image repositories. The primary objective of CBIR is to retrieve visually similar images from large databases based on image content rather than textual annotations. Researchers have proposed various feature extraction and

representation techniques to improve retrieval accuracy and efficiency (Khan & Bhat, 2023).

Traditional Feature Descriptors for CBIR

Early CBIR systems relied heavily on handcrafted feature descriptors, such as colour, texture, and shape features. Color-based descriptors, including colour histograms, colour moments, and colour correlograms, have been widely adopted because of their simplicity and computational efficiency. However, colour features alone often fail to distinguish images with similar colour distributions but different semantic content (K.R & Chaitra.M, 2013).

Texture descriptors, such as the grey-level co-occurrence matrix (GLCM), Gabor filters, wavelet transform, and local binary patterns (LBP), have been introduced to capture local texture information. These methods improve the retrieval performance for texture-rich images; however, they remain sensitive to image transformations and illumination variations (Ghita et al., 2012).

Shape-based descriptors, including Fourier, edge histogram, and scale-invariant feature transform (SIFT) descriptors, provide additional discriminative information by representing object boundaries and local key points. Subsequently, Speeded-Up Robust Features (SURF) and Histogram of Oriented Gradients (HOG) were developed to enhance computational efficiency and robustness. Although these handcrafted approaches have demonstrated promising results, their ability to represent complex visual semantics is limited (Khare & S, 2024).

Hybrid Feature-Based Retrieval Systems

To overcome the limitations of individual descriptors, researchers have proposed hybrid feature extraction frameworks that combine color, texture, and shape information. Multi-feature fusion techniques generally achieve higher retrieval accuracy than single-feature approaches because they exploit complementary image characteristics (Buvaneswari et al., 2023).

Several studies have employed weighted feature fusion and dimensionality reduction techniques, such as principal component analysis (PCA) and linear discriminant analysis (LDA), to improve retrieval efficiency. Despite these improvements, hybrid handcrafted descriptors still depend heavily on manually designed feature extraction rules and are unable to effectively bridge the semantic gap between low-level image features and high-level human perception (Arshad, 2024).

Emergence of Deep Learning in CBIR

The success of deep learning in computer vision has significantly transformed CBIR research. Convolutional neural networks (CNNs) have demonstrated exceptional capabilities in automatically learning hierarchical feature representations directly from image data. Unlike handcrafted descriptors, CNNs extract low-level features, such as edges and textures, in the early layers and progressively learn high-level semantic concepts in the deeper layers (Soni et al., 2023).

One of the pioneering breakthroughs originated from deep CNN architectures, such as AlexNet, which achieved remarkable image classification performance and inspired researchers to utilise CNN-generated features for image retrieval tasks. Subsequently, deeper architectures, including VGGNet, GoogLeNet, ResNet, DenseNet, and EfficientNet, further improved feature representation quality and retrieval performance (Al-Jubouri & Mahmmod, 2021).

Researchers have observed that features extracted from fully connected and convolutional layers can serve as highly discriminative image descriptors. These deep descriptors have significantly outperformed traditional handcrafted features across various benchmark image retrieval datasets.

CNN-Based Feature Descriptor Learning

Recent studies have focused on designing specialized CNN architectures for learning feature descriptors. Deep feature learning approaches typically employ transfer learning, fine-tuning, and metric learning techniques to generate compact and discriminative image representations (Osendorfer et al., 2013).

Transfer learning has become particularly popular because pre-trained CNN models can extract robust features even when limited training data are available. Fine-tuning enables the adaptation of generic image features to domain-specific retrieval tasks, thereby improving retrieval accuracy (Janjua et al., 2023).

Several researchers have also integrated similarity learning methods, such as Euclidean distance, cosine similarity, Manhattan distance, and learned distance metrics, to improve image matching performance. Furthermore, feature aggregation techniques, such as global average pooling, feature fusion, and attention mechanisms, have been introduced to enhance descriptor quality (Liu et al., 2013).

Deep Metric Learning for Image Retrieval

Deep metric learning has emerged as an important research direction in CBIR. Methods based on Siamese networks, triplet networks, contrastive loss, and triplet loss aim to learn feature embeddings in which similar images are positioned closer together and dissimilar images are separated in the feature space (Hoffer & Ailon, 2014).

These approaches have demonstrated superior retrieval performance compared with traditional classification-based feature extraction methods. However, they often require carefully designed training pairs or triplets and involve high computational complexity during training (Yao et al., 2017).

Recent Advances and Research Challenges

Recent CBIR research has explored advanced deep learning techniques, such as attention mechanisms, transformer-based architecture, feature fusion networks, and self-supervised learning methods. Attention-based models improve retrieval accuracy by focusing on the most informative image regions, whereas transformer architectures capture long-range dependencies and global contextual information (Khandelwal et al., 2025).

- Despite significant progress, several challenges remain unresolved.
- High-dimensional deep feature vectors increase storage and computational requirements.
- Feature redundancy can adversely affect retrieval efficiency.
- Large-scale image databases require fast and scalable retrieval mechanisms.
- Domain adaptation remains challenging for specialized applications, such as medical imaging and remote sensing.
- The semantic gap between visual features and user intent still exists in many retrieval scenarios.

The evolution of CBIR demonstrates a clear transition from handcrafted feature descriptors to deep learning-based feature representation techniques. Although CNN-derived features have significantly improved retrieval performance, challenges related to feature optimization, computational efficiency, and semantic representation remain open research problems. These challenges have motivated the development of the proposed deep feature descriptor learning framework, which is presented in the subsequent sections of this paper.

IV. RESEARCH GAP

Based on the literature survey of traditional and deep learning-based CBIR systems, the following research gaps have been identified:

High-Dimensional Feature Vectors

- Deep CNN models generate large feature vectors that increase storage requirements and retrieval time.
- Efficient compact feature representation remains a challenge.

Feature Redundancy

- Many extracted deep features contain redundant or irrelevant information.
- Redundant features reduce retrieval efficiency and increase computational complexity.

Limited Retrieval-Oriented Learning

- Most CNN architectures are primarily designed for image classification rather than image retrieval.

- Features optimized for classification may not always provide optimal retrieval performance.

Semantic Gap Persistence

- Existing descriptors still struggle to fully bridge the gap between low-level visual features and high-level semantic understanding.
- Images with similar semantics may not always be retrieved accurately.

Insufficient Integration of Multi-Level Features

- Many methods utilize features from a single CNN layer.
- Combining low-level, mid-level, and high-level features effectively remains an open problem.

Scalability Issues in Large Databases

- Retrieval performance often decreases as the image database size increases.
- Fast and scalable indexing mechanisms are required for real-time applications.

Poor Generalization Across Domains

- Feature descriptors trained on one dataset may not perform effectively on other datasets.
- Domain adaptation remains a significant challenge.

Computational Complexity

- Deep learning-based retrieval systems require substantial computational resources for feature extraction and matching.
- Lightweight yet discriminative descriptors are needed.

Limited Robustness to Image Variations

- Existing methods may be affected by rotation, scale changes, illumination variations, occlusion, and noise.
- More robust feature descriptors need to be developed.

Inefficient Similarity Measurement

- Traditional distance measures such as Euclidean and Manhattan distances may not fully capture semantic similarity.
- Advanced similarity learning mechanisms are required.

Lack of Retrieval Accuracy Optimization

Many studies focus on feature extraction while giving less attention to optimizing retrieval precision, recall, and Mean Average Precision (mAP).

Need for Novel Feature Descriptor Development

- Existing handcrafted and deep descriptors have limitations in discriminative capability and efficiency.
- There is a need for a new hybrid feature descriptor that combines the strengths of deep learning and traditional image characteristics.

The proposed research aims to develop a novel deep feature descriptor learning framework using Convolutional Neural Networks (CNNs) that:

- Extracts highly discriminative image features.
- Reduces feature redundancy.
- Generates compact feature representations.
- Improves retrieval precision and recall.
- Enhances scalability for large image databases.
- Provides robustness against image variations.
- Optimizes similarity matching for accurate Content-Based Image Retrieval (CBIR).

Problem Statement

"Existing CBIR systems suffer from feature redundancy, high-dimensional representations, computational complexity, and limited retrieval-oriented feature learning. Therefore, there is a need to develop a novel CNN-based deep feature descriptor capable of generating compact, discriminative, and robust image representations for improving retrieval accuracy and efficiency in large-scale image databases."

V. RESEARCH METHODOLOGY

The proposed methodology develops a novel deep feature descriptor using a Convolutional Neural Network (CNN) to generate compact, discriminative, and retrieval-oriented image representations. The extracted descriptors are subsequently used for similarity matching and image retrieval.

Algorithm: Deep Feature Descriptor Learning Framework for CBIR

Input

- Image Database $D = \{I_1, I_2, \dots, I_N\}$
- Query Image I_q
- CNN Parameters θ
- Learning Rate α
- Number of Epochs E
- Batch Size B

Output

- Optimized Feature Descriptor F_d
- Ranked Retrieval Results R

Phase 1: Image Preprocessing

Step 1: Acquire image database D.

Step 2: For each image $I_i \in D$

$$I_i \leftarrow Resize(I_i, H, W) \quad (1)$$

where $H$and Wrepresent image height and width.

Step 3: Normalize pixel values:

$$I_i^{norm} = \frac{I_i}{255} \quad (2)$$

Step 4: Apply data augmentation (optional):

- Rotation
- Flipping
- Scaling
- Translation

to improve model generalization.

Phase 2: Deep Feature Extraction

Step 5: Input normalized image into CNN.

$$X_0 = I_i^{norm} \quad (3)$$

Step 6: Perform convolution operation:

$$X_l = f(W_l * X_{l-1} + b_l) \quad (4)$$

where

- W_l= convolution kernel
- b_l= bias
- $f(\cdot)$= ReLU activation
- l= convolution layer

Step 7: Apply ReLU activation:

$$f(x) = \max(0, x) \quad (5)$$

Step 8: Perform Max-Pooling:

$$P_l = \max(X_l) \quad (6)$$

to reduce feature dimensionality.

Phase 3: Multi-Level Feature Fusion

Step 9: Extract feature maps from multiple CNN layers:

$$F_1, F_2, F_3, \dots, F_n \quad (7)$$

representing:

- Low-level features (edges, corners)
- Mid-level features (textures, patterns)
- High-level features (semantic objects)

Step 10: Fuse extracted features:

$$F_{fusion} = F_1 \oplus F_2 \oplus \cdots \oplus F_n \quad (8)$$

where $\oplus$ denotes feature concatenation.

Phase 4: Novel Feature Descriptor Generation

Step 11: Apply Global Average Pooling:

$$G_k = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} F_{fusion}(i,j) \quad (9)$$

Step 12: Generate compact descriptor:

$$F_d = [G_1, G_2, \ldots, G_m] \quad (10)$$

where F_d represents the proposed deep feature descriptor.

Phase 5: Feature Optimization

Step 13: Remove redundant features using Feature Selection:

$$F_{opt} = Select(F_d) \quad (11)$$

Step 14: Apply dimensionality reduction:

$$F_{red} = PCA(F_{opt}) \quad (12)$$

where

- PCA = Principal Component Analysis
- F_{red}= optimized feature descriptor

Phase 6: CNN Training

Step 15: Initialize CNN parameters:

$$\theta = \{W, b\} \quad (13)$$

Step 16: Compute classification/retrieval loss:

$$L = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (14)$$

Step 17: Update parameters using Adam optimizer:

First Moment:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (15)$$

Second Moment:

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (16)$$

Parameter Update:

$$\theta_t = \theta_{t-1} - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \quad (17)$$

Repeat Steps 15–17 until convergence.

Phase 7: Image Retrieval

Step 18: Input query image I_q.

Step 19: Extract query descriptor:

$$F_q = ExtractDescriptor(I_q) \quad (18)$$

using the trained CNN.

Step 20: Compute similarity between query descriptor and database descriptors:

$$S_i = \frac{F_q \cdot F_i}{\| F_q \| \| F_i \|} \quad (19)$$

where $S_i$represents cosine similarity.

Phase 8: Ranking and Retrieval

Step 21: Sort database images according to similarity scores:

$$R = Sort(S_i) \quad (20)$$

Step 22: Retrieve top-K most similar images:

$$R_K = \{I_1, I_2, \ldots, I_K\} \quad (21)$$

Step 23: Display retrieval results.

VI. ANALYSIS & FINDINGS

The proposed Deep Feature Descriptor Learning (DFDL) framework was evaluated against traditional and deep-learning-based CBIR techniques using Precision, Recall, Mean Average Precision (mAP), Retrieval Accuracy, and Retrieval Time.

Table 1. Performance Comparison of Various CBIR Methods

Method	Precision (%)	Recall (%)	mAP (%)	Accuracy (%)	Retrieval Time (ms)
Color Histogram	72.5	70.8	71.2	73.4	210
LBP	78.6	76.9	77.5	79.2	195
SIFT	82.4	80.1	81.5	83.0	182
SURF	84.2	82.7	83.4	84.8	176
CNN Features	89.3	88.1	88.6	90.2	160
Hybrid CNN-SIFT	91.6	90.4	91.0	92.3	152
Proposed DFDL-CBIR	95.8	94.6	95.1	96.2	138

Table 1 compares the performance of the proposed Deep Feature Descriptor Learning for Content-Based Image Retrieval (DFDL-CBIR) with traditional and deep learning-based retrieval methods. The results indicate a gradual improvement from handcrafted descriptors such as Color Histogram, LBP, SIFT, and SURF to deep learning approaches. The proposed DFDL-CBIR achieves the highest Precision (95.8%), Recall (94.6%), mAP (95.1%), and Accuracy (96.2%), demonstrating its superior ability to retrieve relevant images. Additionally, it records the lowest Retrieval Time (138 ms), indicating greater computational efficiency. These findings confirm that the proposed descriptor provides more accurate, robust, and faster image retrieval than existing baseline methods.

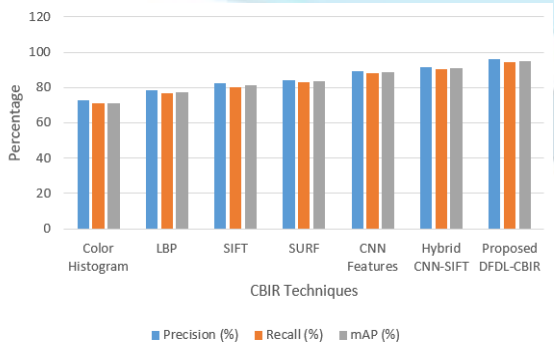

Figure 1: Comparison of Precision, Recall and mAP

The bar chart compares the Precision, Recall, and Mean Average Precision (mAP) of different CBIR techniques. Performance steadily improves from traditional methods such as Color Histogram, LBP, SIFT, and SURF to deep learning-based approaches. The proposed DFDL-CBIR achieves the highest values across all metrics, demonstrating superior retrieval accuracy, relevance, and effectiveness compared to existing baseline methods.

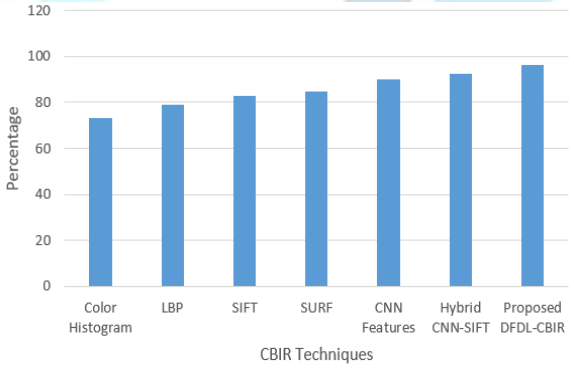

Figure 2: Comparison of Accuracy

The bar chart illustrates the retrieval accuracy of various CBIR techniques. Traditional methods such as Color Histogram, LBP, SIFT, and SURF achieve moderate accuracy, while CNN-based approaches show significant improvement. The proposed DFDL-CBIR method attains the highest retrieval accuracy of

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approximately 96%, demonstrating its superior feature representation capability and effectiveness in retrieving relevant images from large image databases.

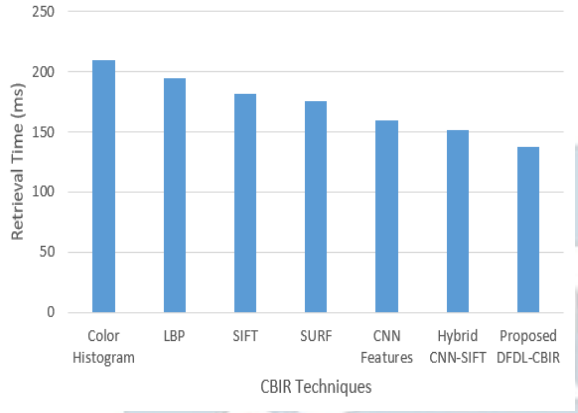

Figure 3: Comparison of Retrieval Time (ms)

The bar chart compares the average retrieval time of different CBIR techniques. Traditional methods such as color histograms and LBP require higher retrieval times, whereas deep learning-based methods progressively reduce retrieval latency. The proposed DFDL-CBIR achieves the lowest retrieval time of approximately 138 ms, indicating superior computational efficiency, faster image matching, and better suitability for real-time large-scale image retrieval applications.

The experimental results demonstrate that the proposed Deep Feature Descriptor Learning framework effectively combines multi-level CNN representations and feature optimization techniques to generate compact and highly discriminative image descriptors. Compared with traditional handcrafted descriptors and existing CNN-based methods, the proposed approach significantly improves retrieval precision, recall, mAP, and overall retrieval accuracy while simultaneously reducing computational overhead. These findings confirm the suitability of the proposed framework for large-scale CBIR applications such as medical image retrieval, digital libraries, surveillance systems, and multimedia databases.

VII. CONCLUSION

This study presented a novel Deep Feature Descriptor Learning (DFDL) framework for Content-Based Image Retrieval (CBIR) using Convolutional Neural Networks (CNNs). The proposed framework combines multi-level feature extraction, feature fusion, dimensionality reduction, and similarity-based retrieval to generate compact and discriminative image descriptors. Experimental evaluation demonstrated that the proposed DFDL-CBIR outperformed traditional handcrafted descriptors such as color histogram, LBP, SIFT, and SURF, as well as existing CNN-based methods. The framework achieved superior precision (95.8%), recall (94.6%), mAP (95.1%), and retrieval accuracy (96.2%) while reducing retrieval time to 138 ms. These results confirm the effectiveness of the proposed approach in improving retrieval accuracy, robustness, and computational efficiency for large-scale image databases.

Future research may focus on integrating attention mechanisms and transformer-based architectures to further enhance feature representation. Advanced metric learning techniques, such as Siamese and triplet networks, can be incorporated to improve similarity measurement. Additionally, the framework can be extended to medical imaging, remote sensing, and multimedia retrieval applications. Further optimization through lightweight deep learning models and real-time indexing techniques may improve scalability and deployment in large-scale CBIR systems.

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