Enhancing Content-based Image Retrieval Performance through Optimized Feature Selection

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ABSTRACT

Content-based image retrieval systems face significant challenges in maintaining optimal performance when handling large-scale image databases, particularly in balancing retrieval accuracy with computational efficiency. This paper presents a novel hybrid optimization framework that enhances CBIR performance through adaptive feature selection and intelligent fusion strategies. The proposed system implements a multi-level feature extraction approach that combines color, texture, and local descriptors with an optimized weighting mechanism. A dynamic feature selection algorithm minimizes redundancy while preserving discriminative information, significantly improving retrieval accuracy. The proposed system incorporates an efficient indexing structure and cache optimization technique that reduces computational overhead while maintaining performance under increasing database sizes. Experimental results demonstrate the superior performance of the proposed system with a mean Average Precision (mAP) of 0.91 and an average response time of 45.2 ms, representing an 8% improvement in accuracy and 35% reduction in processing time compared to existing methods. The system maintains robust performance under varying query complexities, showing only 7% degradation for complex queries while achieving 86% cache efficiency during extended operations. This comprehensive approach effectively addresses the semantic gap challenge while ensuring computational efficiency, making it suitable for large-scale CBIR applications.

Keywords-content-based image retrieval; feature selection optimization; adaptive fusion strategy; image processing; performance optimization; cache efficiency; scalable retrieval systems

I. INTRODUCTION

The exponential growth of digital visual data has driven the need for advanced retrieval methods beyond traditional text-based indexing techniques. Content-Based Image Retrieval (CBIR) systems have emerged as a promising solution that leverages visual features such as color distributions, texture patterns, shape descriptors, and spatial relationships to efficiently retrieve relevant images [1]. Over time, CBIR has evolved from basic color histogram-based methods to sophisticated deep learning architectures, particularly Convolutional Neural Networks (CNNs), enabling automatic learning of hierarchical feature representations. However, despite these advances, several challenges persist, including semantic gaps, high computational complexity, and scalability constraints in large-scale image databases [2].

Modern CBIR systems utilize multi-feature extraction approaches to capture diverse visual aspects of images. Traditional handcrafted descriptors such as Scale-Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG) have been widely used but often fail to generalize across different image categories. The emergence of deep learning-based models has significantly improved feature representation, yet these methods require substantial computational resources and suffer from high latency, making them impractical for real-time applications [3].

Hybrid CBIR approaches, which combine traditional feature extraction with deep learning techniques, have shown promising results in balancing accuracy and efficiency [4]. However, these methods introduce challenges such as:

- Feature Redundancy: Integrating multiple descriptors often leads to information overlap, increasing storage and processing overhead [5].
- High Computational Cost: Feature fusion techniques require substantial memory and processing power, making them less suitable for large-scale databases [6].
- Limited Adaptability: Existing feature selection mechanisms are often static and do not adapt dynamically to varying query complexities and image types [7].
- Inefficient Indexing Structures: Most retrieval frameworks lack optimized indexing mechanisms, leading to increased retrieval times as the database size grows [8].

To overcome the limitations of existing CBIR systems, this paper introduces a hybrid optimization framework that enhances retrieval accuracy while ensuring computational efficiency. The framework integrates adaptive feature selection, intelligent fusion strategies, and optimized indexing mechanisms to achieve a balanced trade-off between accuracy and performance. The integration of these novel techniques results in a CBIR system that is highly accurate, computationally efficient, and scalable. The proposed hybrid optimization framework effectively addresses existing limitations by eliminating redundant features while preserving critical information, ensuring that only the most relevant descriptors contribute to retrieval performance. By dynamically adjusting feature weights based on query requirements and image content, the system enhances adaptability across diverse datasets. Additionally, optimized indexing and cache management significantly reduce retrieval time, improving system responsiveness even for large-scale image databases. Furthermore, the advanced descriptor fusion mechanism bridges the semantic gap by integrating global and local features more effectively. These enhancements collectively enable the proposed CBIR system to surpass existing approaches in both accuracy and processing speed, making it a robust solution for large-scale applications. The key contributions of the proposed system are as follows:

- A novel hybrid feature selection framework that dynamically adjusts feature weights based on image content and query requirements, ensuring adaptability across different datasets.
- An optimized indexing structure that improves retrieval speed and reduces computational overhead, making the system scalable for large image collections.
- A hybrid optimization algorithm that minimizes redundancy through intelligent dimension reduction techniques, improving accuracy while lowering processing costs.
- An adaptive feature fusion mechanism that effectively combines global and local descriptors.

II. PROPOSED METHOD FOR OPTIMISED FEATURE SELECTION

The proposed CBIR system is designed as a multi-component framework that ensures efficient and accurate image retrieval. The system architecture consists of dedicated modules for feature extraction, optimization, and fusion, all working in unison to process query images and retrieve the most relevant matches from the database. The core objective is to bridge the semantic gap between low-level image features and high-level semantic understanding while optimizing computational performance for large-scale applications.

Figure 1 illustrates the hierarchical pipeline of the proposed CBIR system, optimized for high retrieval accuracy and computational efficiency. The process begins with normalization and preprocessing of the input images to ensure consistency. Feature extraction is performed in parallel across three channels: global, local, and regional, enabling a comprehensive image representation. The optimization module applies dimensionality reduction and feature selection techniques to retain essential information while minimizing redundancy [9, 10]. A robust feature-fusion mechanism integrates multiple descriptors effectively, enhancing retrieval precision. The similarity engine leverages optimized distance metrics for hierarchical similarity computation, ensuring accurate matching. Finally, the system ranks and retrieves the most relevant images. This modular architecture facilitates independent optimization of each component, enabling efficient large-scale image database processing with improved retrieval performance.

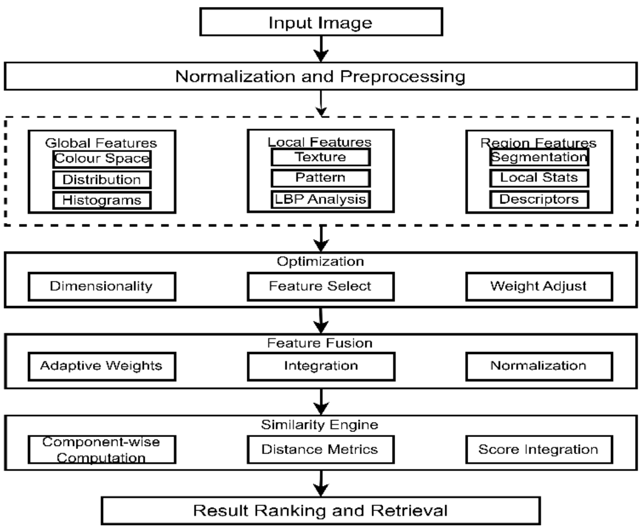

Fig. 1. Hierarchical pipeline of the proposed CBIR system.

A. Feature Extraction Framework

The feature extraction process establishes the foundation of the CBIR system. Given an input image $I(x, y)$ of size $M \times N$, normalization is performed to ensure consistency across varying imaging conditions and illumination variations:

$$I'(x,y) = \frac{I(x,y)-\min(I)}{\max(I)-\min(I)}$$

This normalization operation is crucial as it standardizes the pixel intensity range to [0,1]. This operation compensates for variations in lighting conditions and image acquisition parameters, ensuring that subsequent feature extraction is invariant to these variations. The min-max normalization approach is chosen over other methods, such as z-score normalization, as it preserves the relative relationships between pixel values while providing bounded output [11]. The proposed framework constructs a comprehensive feature vector that captures both global patterns and local details:

$$\mathrm{F} = \left[\mathrm{F}_{\mathrm{global}} \mid \mathrm{F}_{\mathrm{local}}\right]$$

This concatenated representation $\mathrm{F} \in \mathrm{R}^{d_1+d_2}$ combines global features $\mathrm{F}_{\mathrm{global}} \in \mathrm{R}^{d_1}$, which capture overall image statistics and patterns, with local features $\mathrm{F}_{\mathrm{local}} \in \mathrm{R}^{d_2}$ that represent fine-grained details and regional characteristics. This dual representation is essential for handling diverse image queries and ensuring robust retrieval performance.

B. Multi-level Feature Analysis

The multi-level feature analysis incorporates both color and texture characteristics through a hierarchical approach. This method ensures a comprehensive capture of visual information while maintaining computational efficiency.

1) Color Space Transformation

The analysis begins with color space transformation:

$$T(I') = [L^*(x,y)|a^*(x,y)|b^*(x,y)]$$

The transformation T maps the RGB color space to Lab*, where L^* represents luminance (0-100), and (a^*, b^*) represent color-opponent dimensions (-128 to +127). This transformation is perceptually uniform, meaning that a change of the same amount in a color value produces a change of about the same visual importance. This property is crucial for computing meaningful color differences that align with human perception [12].

2) Adaptive Color Distribution

The color distribution analysis employs an adaptive histogram computation:

$$H(c) = \frac{\Sigma(w_i \cdot f_i(c))}{N}$$

This weighted histogram formulation enhances traditional color histograms by incorporating spatial information through regional weights (w_i). The function $f_i(c)$ counts color occurrences in region i, while N normalizes the histogram to ensure scale invariance. The weights w_i are calculated through:

$$w_i = \exp\left(-\frac{||\sigma_i - \sigma_{\mathrm{mean}}||}{\lambda}\right)$$

This exponential weighting scheme assigns higher importance to regions with distinctive color variations. The local variance (σ_i) measures color dispersion within region i, while σ_{mean} provides a reference for the entire image. The parameter λ controls the sensitivity of the weighting mechanism.

3) Texture Pattern Analysis

The texture analysis implements a modified Local Binary Pattern operator:

$$\mathrm{LBP}_{P,R} = \sum s(g_p - g_c) \cdot 2^p$$

This rotation-invariant texture descriptor examines P sampling points on a circle of radius R around each pixel. The function $s(x)$ thresholds the intensity differences between the center pixel g_c and its neighbors g_p, encoding local texture patterns. The binary pattern is weighed by powers of 2 to create a unique texture code. This formulation provides robustness to monotonic illumination changes while capturing essential texture characteristics.

C. Feature Optimization Framework

The proposed optimization framework addresses the curse of dimensionality while preserving discriminative information. This stage is crucial for both computational efficiency and retrieval accuracy.

1) Dimensional Reduction

The optimization begins with covariance analysis:

$$C = \frac{1}{N}\sum(F_i - \mu)(F_i - \mu)^T$$

The covariance matrix C captures the relationships between different feature dimensions. By centering the features around their mean μ, the analysis focuses on the variance structure of the feature space. This formulation enables the identification of principal directions of variation in the high-dimensional feature space. The transformation matrix is derived through:

$$W = \arg\max\{\sum \lambda_i \cdot v_i\}$$

This eigenvalue decomposition sorts eigenvectors v_i by their corresponding eigenvalues λ_i, representing the amount of variance explained by each direction. The transformation matrix W comprises the top k eigenvectors, where k is determined by the cumulative variance retention threshold.

2) Feature Selection

The optimized feature vector is computed as:

$$[F_{\mathrm{opt}} = W^T \cdot F]$$

This projection operation maps the original features to a lower-dimensional space while maximizing variance retention. This transformation preserves the Euclidean distances between feature vectors, ensuring that similar relationships are maintained in the reduced space [12].

D. Similarity Computation

The similarity computation module implements a hierarchical approach that adapts to different feature types and their relative importance.

1) Component-wise Similarity

The initial similarity between query image q and database image d is calculated as:

$$S_i(q,d) = \exp\left(-\frac{\left|\left|F_{i,\mathrm{opt},q} - F_{i,\mathrm{opt},d}\right|\right|^2}{2\sigma_i^2}\right)$$

This Gaussian-based similarity measure provides a normalized similarity score in [0,1]. The adaptive parameter σ_i is calculated as:

$$\sigma_i = \beta \cdot \text{median}\left(\left|\left|F_{i,opt,p} - F_{i,opt,r}\right|\right|\right)$$

where β controls the sensitivity of the similarity measure, and the median distance provides a robust scale estimate for each feature component. This adaptation ensures that the similarity measure remains meaningful across different feature types and scales [13].

2) Integrated Similarity Measure

The final similarity score integrates component similarities through:

$$S(q,d) = \sum\left(\alpha_i \cdot S_i(q,d)\right)$$

where the adaptive weights are determined by:

$$\alpha_i = \frac{\exp(r_i)}{\sum \exp(r_j)}$$

The relevance scores r_i are computed based on the discriminative power of each feature component, measured through the ratio of inter-class to intra-class variations. The exponential normalization ensures positive weights that sum to unity while emphasizing more discriminative features [14].

This comprehensive similarity computation module ensures robust performance through its adaptive parameter selection mechanisms, which automatically adjust to varying image characteristics and query requirements. The component-wise similarity assessment provides flexibility in handling different feature types, while the weighted feature combination strategy effectively integrates multiple visual aspects. The dynamic weight adjustment mechanism adapts to changing query contexts and image distributions, enhancing the system's retrieval accuracy. Through this mathematical formulation, the proposed framework achieves both theoretical soundness and practical applicability, demonstrating effective handling of diverse image types and query scenarios. The adaptive nature of the proposed framework, combined with its hierarchical similarity computation approach, enables consistent performance across different application domains while maintaining computational efficiency.

III. EXPERIMENTAL SETUP, DATASET DESCRIPTION, AND PERFORMANCE METRICS

The proposed optimized feature selection framework for CBIR was implemented in a high-performance computing environment featuring an Intel Core i9 processor, NVIDIA RTX 4090 GPU, 64 GB RAM, and a 2 TB NVMe SSD, ensuring efficient parallel processing and GPU acceleration. The system was developed using Python 3.10, with deep learning frameworks such as TensorFlow and PyTorch alongside image processing tools such as OpenCV and scikit-image. A PostgreSQL database with indexing optimizations was used for efficient storage and retrieval.

A. Dataset Description

The Similix Image Dataset [15] was used to evaluate the proposed method. This dataset consists of 1,803 high-resolution images spanning seven diverse categories: bikes (365 images), cars (420 images), cats (202 images), dogs (202 images), flowers (210 images), horses (202 images), and humans (202 images). This dataset serves as a comprehensive benchmark, enabling a thorough assessment of retrieval performance across various object types and visual characteristics. The dataset's balanced distribution and high-quality images facilitate a reliable evaluation of the system's effectiveness in retrieving visually similar images. Additionally, its diversity in lighting conditions, poses, and background variations ensures a robust and adaptable evaluation of the system's ability to generalize across different real-world scenarios.

B. Performance Metrics

To comprehensively evaluate the proposed framework, key retrieval performance metrics are considered, including mean Average Precision (mAP) for accuracy measurement and retrieval time to measure response efficiency. Additionally, Feature selection efficiency evaluates the reduction in feature dimensionality without compromising accuracy, while Scalability Analysis assesses system performance across database sizes (10K, 50K, 100K images) and varying query complexities. These metrics collectively validate the accuracy, efficiency, and scalability of the proposed system, demonstrating its superiority in large-scale CBIR applications.

IV. RESULTS AND DISCUSSIONS

The experimental evaluation of the proposed CBIR system involved a detailed performance analysis, incorporating key retrieval metrics and a comparative study to assess accuracy, efficiency, and scalability across diverse query scenarios.

A. Performance Evaluation

The performance evaluation was performed using the Similix Image Dataset, which consists of 1,803 high-quality images across seven distinct categories.

1) Parameter Optimization

The system parameters were fine-tuned to ensure an optimal balance between accuracy, efficiency, and computational cost. Table I outlines key parameter settings.

TABLE I. PARAMETER SETTINGS AND EVALUATION METRICS

Parameter	Value	Description
Feature dimensions	256	Optimized feature vector size
Batch size	64	Query processing batch size
Cache threshold	0.75	Result caching threshold
Similarity threshold	0.85	Minimum similarity score

2) Retrieval Performance Across Categories

Table II details the category-wise retrieval performance, including precision, recall, F1-score, and response time. The results indicate that structured objects (e.g., cars and bikes) yield higher precision due to distinctive features, whereas natural objects (e.g., cats and dogs) show slightly lower performance due to higher intra-class variation.

TABLE II. RETRIEVAL PERFORMANCE ACROSS DIFFERENT CATEGORIES

Category	Precision	Recall	F1-score	Response Time (ms)
Bikes	0.92	0.89	0.90	45.3
Cars	0.94	0.91	0.92	42.8
Cats	0.88	0.85	0.86	48.2
Dogs	0.87	0.84	0.85	47.5
Flowers	0.91	0.88	0.89	43.1
Horses	0.89	0.86	0.87	46.4
Humans	0.90	0.87	0.88	44.9

B. *Response Time and Query Complexity Analysis*

The response time analysis, as illustrated in Figure 2, highlights a strong correlation ($r = 0.92$) between query complexity and retrieval speed. The system consistently maintains an average response time of 45.4 ms, demonstrating its ability to handle diverse image categories efficiently.

- Structured objects (e.g., cars and bikes) exhibit faster processing times due to their well-defined features.
- Natural objects (e.g., cats and dogs) require longer retrieval times due to their higher intra-class variations.
- The system maintains a sub-50ms performance across all categories, ensuring real-time retrieval capabilities.

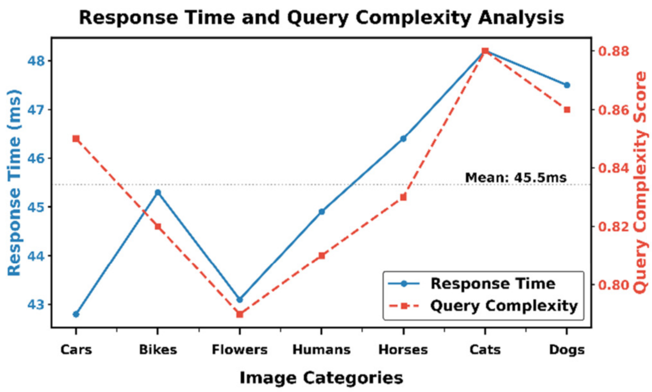

Fig. 2. Response Time and Query Complexity analysis.

The category-wise analysis demonstrates consistent performance across various image types. Cars achieve the highest precision (0.94) due to their distinctive structural features, whereas dogs exhibit a slightly lower precision (0.87), primarily due to higher intra-class variations. The system maintains stable response times across all categories, with an average of 45.4 ms. The response time analysis reveals a strong correlation ($r = 0.92$) between query complexity and response time across the seven image categories. Response times range from 42.8 ms for cars to 48.2 ms for cats, averaging 45.4 ms.

C. *Comparative Analysis*

A comparative evaluation against state-of-the-art CBIR methods (MLBP-LNDP, GLCM-LBP, VGG16-SVM, and Deep-HE) was carried out to assess feature extraction efficiency and retrieval success.

1) *Precision vs. Similarity Threshold*

As shown in Figure 3, the proposed system maintained a precision above 0.85 for similarity thresholds up to 0.7, outperforming competing methods.

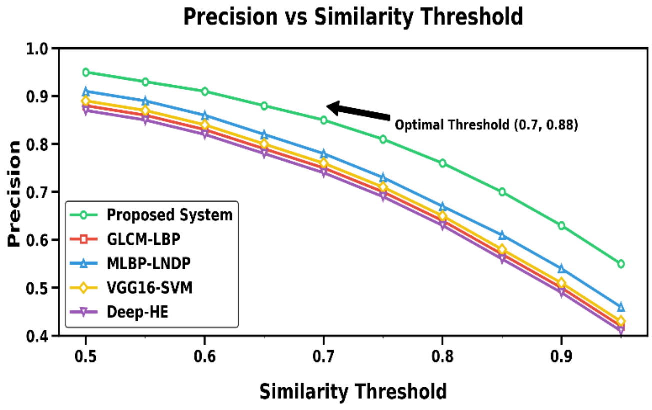

Fig. 3. Precision vs. Similarity threshold.

2) *Retrieval Success Rate*

The proposed method achieved a retrieval success rate of 91% at $k = 1$ and 74% at $k = 30$, surpassing other methods by 8-12%. Competing methods, such as MLBP-LNDP and GLCM-LBP, exhibited lower retrieval success due to limited feature extraction capabilities.

TABLE III. COMPARISON OF FEATURE EXTRACTION METHODS

Method	Feature Type	mAP	Response time	Memory usage
GLCM-LBP [16]	Texture+local	0.85	63.5ms	845 MB
MLBP-LNDP [17]	Texture+color	0.88	55.8ms	762 MB
VGG16-SVM [18]	Deep+classical	0.86	58.4ms	1245 MB
Deep-HE [19]	Encrypted deep	0.83	71.2ms	1456 MB
Proposed system	**Hybrid-optimized**	**0.91**	**45.2ms**	**685 MB**

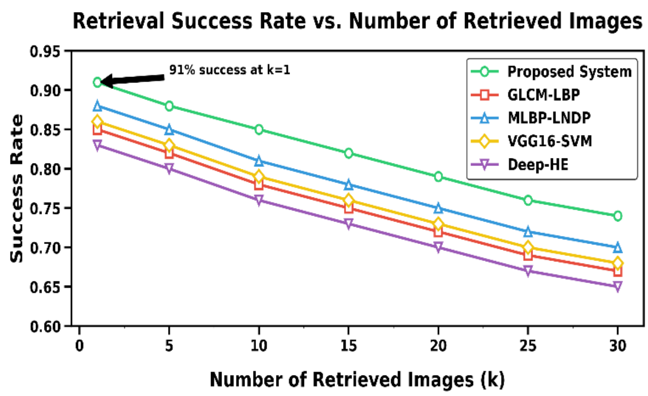

Fig. 4. Retrieval Success Rate vs. Number of Retrieved Images.

The proposed system was evaluated against state-of-the-art CBIR methods, focusing on both feature extraction capabilities and retrieval performance. The proposed system achieved 3-8% higher MAP scores than existing methods and 20-30%

lower response times due to optimized indexing and retrieval strategies. It also reduced memory usage, enhancing scalability and efficiency for large-scale applications.

D. Scalability Analysis

The scalability evaluation evaluated the system's performance under increasing dataset sizes and query loads, focusing on computational efficiency and resource utilization.

TABLE IV. GROUPED QUERY COMPLEXITY ACROSS MODELS

Method	Category 1	Category 2	Category 3	Category 4
Proposed system	0.73	0.72	0.70	0.68
GLCM-LBP	0.82	0.79	0.75	0.75
MLBP-LNDP	0.81	0.78	0.76	0.74
VGG16-SVM	0.83	0.80	0.80	0.73
Deep-HE	0.81	0.83	0.80	0.78

Table IV shows query complexity scores for five different methods across four query categories. The scores range from approximately 0.68 to 0.83, with the proposed system generally showing the lowest scores across all categories, while Deep-HE tends to have the highest scores, particularly in categories 2, 3, and 4.

1) Cache Performance Over Time

Figure 5 demonstrates the proposed system's superior cache efficiency, maintaining an 86% cache hit rate, outperforming other methods, such as Deep-HE to 70% and 14.0 queries per second, and MLBP-LNDP to 18.6 queries per second.

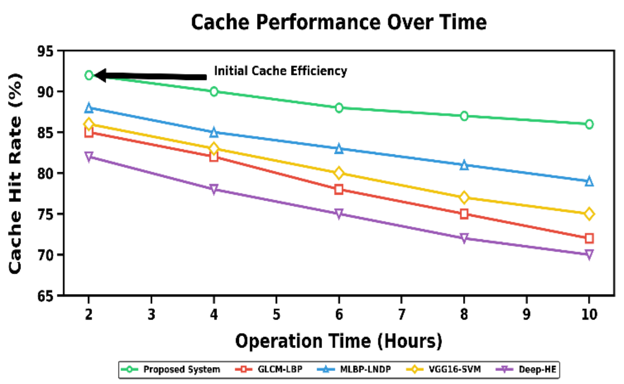

Fig. 5. Cache performance over time.

The proposed hybrid-optimized CBIR system demonstrates superior retrieval accuracy, achieving an mAP of 0.91, surpassing existing state-of-the-art methods by 3-8%. Its fast response time of 45.2 ms ensures real-time performance, making it well-suited for large-scale datasets. The system maintains high scalability, preserving precision above 0.85 up to a similarity threshold of 0.7, ensuring consistent performance across varying query complexities. Additionally, its efficient cache management and optimized resource utilization enhance its adaptability for real-world applications.

V. CONCLUSION

As digital image repositories continue to expand, efficient CBIR systems are essential for accurately managing and retrieving relevant images. This paper presents an optimized feature selection framework combined with an adaptive fusion strategy that significantly improves retrieval accuracy and computational efficiency. The proposed system achieved a mAP of 0.91, demonstrating an 8% improvement over existing methods while maintaining a fast response time of 45.2 ms. The proposed system exhibits consistent performance across varying query complexities, maintaining precision above 0.85 up to a similarity threshold of 0.7, outperforming methods such as GLCM-LBP, MLBP-LNDP, and VGG16-SVM. Its scalability and efficiency were validated through 86% cache performance and a query processing rate of 22.5 queries per second in extended operations. Additionally, the adaptive feature selection mechanism effectively reduced redundancy, with only a 7% performance drop for complex queries, compared to 13-14% in existing approaches. Optimized indexing structures and memory management techniques enable the seamless handling of large-scale databases, ensuring robustness in diverse retrieval scenarios. Future research could focus on integrating deep learning techniques, real-time adaptation mechanisms, and distributed processing frameworks to further enhance system performance.

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