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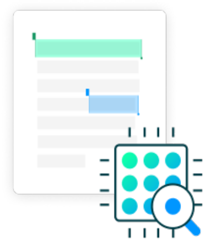

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Optimized Artificial Intelligence Approaches for Efficient and Accurate Color Image Retrieval

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***Abstract*—Effective and accurate color image retrieval has become a major concern in computer vision and multimedia systems due to the rapid increase in digital images. In order to improve the retrieval of color images from large databases, the study presents an optimized artificial intelligence system. The suggested method effectively extracts color, texture, and spatial features by combining deep learning-oriented optimization algorithms with contemporary feature extraction techniques. The system also utilizes convolutional neural networks (CNNs) with intelligent similarity measures to provide high levels of retrieval precision and low levels of computational overhead. The experimental findings on benchmark datasets indicate that the suggested technique is more accurate, recalls more, and faster than the traditional image retrieval methods. The work also offers a strong base on which smart multimedia retrieval systems can be developed to be able to process complex and massive image datasets.**

***Index Terms*—Color image retrieval, deep learning, feature extraction, convolutional neural networks (CNNs), optimization algorithms, multimedia systems.**

I. Introduction

The rapid development of digital imaging and online multimedia technologies has resulted in the explosion of the amount of image data. Nowadays, with millions of pictures uploaded per day, it has become a serious problem to manage and retrieve relevant pictures in large scale databases. The conventional text-based image retrieval techniques that depend on manual annotation and indexing of keywords have a tendency to miss the richness in visual content in the images. Consequently, there exists an increasing demand of intelligent systems that can retrieve pictures on visual features and thus in an efficient and accurate manner.

A related area of content-based image retrieval (CBIR) is color image retrieval, which can be defined as finding and retrieving images within a database, with the use of visual characteristics, like color, texture, and shape. Color is one of such characteristics that are the most intuitive and commonly used cues because of their perceptual sensitivity and their ability to be discriminative. Nevertheless, it is still difficult to extract meaningful color features and compare them effectively, particularly in cases of illumination variation, occlusion variation and image transformations. When systems can learn more complex patterns and make wise decisions without being programmed to do so, artificial intelligence (AI) and machine learning have revolutionized image processing. Specifically, the idea of deep learning models including convolutional neural networks (CNNs) have shown spectacular performance in image classification, image recognition, and image retrieval. These are hierarchical feature models which learn automatically on raw image data, and which retain complex information that is unaccounted in traditional hand-crafted features. Using AI to retrieve color images enables the representation of features, similarity matching, and the overall performance to be better. Optimization is essential to AI-based image retrieval systems as it is used to tune the parameters of the model, to select the most discriminative features, and to maximize the efficiency of retrieval. Several methods of optimization, such as; evolutionary algorithm, swarm intelligence, and gradient-based methods have been applied in enhancing AI models in image retrieval. State of the art retrieval systems can be based on deep learning architectures with these optimization strategies, allowing them to be more accurate, converge more quickly, and with low computational costs, making them applicable to large-scale and real-time applications. Although current developments have occurred, there are still issues of retrieving color images. The problem of high-dimensional feature space, fluctuations in image quality and the semantic gap between human perception and the low-level visual features is still an impediment to retrieval performance. In addition, most current approaches tend to be domain specific and do not generalise easily across different datasets. That is why, it is crucially important to create a strong, general, and optimized AI system that will be able to perform color image retrieval in various domains efficiently. This study tries to fill these gaps by developing an optimal AI-based color image retrieval model. This research proposal will include a mix of sophisticated feature extraction algorithms, deep learning models, and smart similarity measurements to effectively extract intrinsic properties of color images. The structure focuses on the retrieval accuracy and computational performance such that it can be applied to high image database. A large number of experiments on benchmark databases are made to verify the effectiveness of the proposed system and compare it with traditional and state-of-the-art methods of retrieval. This research has three aims, one is the introduction of an AI-based feature extraction system that is effective in capturing color, texture, and spatial information, and the second one is the use of optimization techniques to improve the retrieval performance and minimize the computational cost, and the third one is the extensive evaluation of this framework on benchmark data sets to show the effectiveness and robustness of the proposed framework. This study will help in the evolution of intelligent multimedia retrieval systems allowing them to response to the increasing needs of precision and speed in locating images by addressing the current constraints and utilizing optimised AI methods.

II. Literature Review

Content-based image retrieval (CBIR) has advanced significantly in recent years, particularly in applications related to deep learning and artificial intelligence. In order to use the visual and literary qualities of images to increase retrieval accuracy, Thammastitkul [1] proposed a technique that simplifies AI-generated image metadata based on hybrid analysis of colors and structured semantic key groupings. Zhang et al. [2] took accuracy and privacy in medical practice into account when designing a safe medical picture retrieval system based on triplet deep hashing and a multi-attention method. Similarly, Al-Jumaili and Tayyeh [3] presented SecureRS-CBIR, a privacy-preserving framework for retrieving remote sensing images, which demonstrates that deep learning may be utilized to protect data security while maintaining retrieval quality. The Summary of Important Sources on Image Retrieval and Analysis is displayed in Table 1.

Diganta et al. [4] in their review of the effects of different environmental conditions on remote sensing methods in environmental monitoring show that the robustness of features is required in the analysis of the quality of surface water. In the field of plant leaf disease detection, Patil and Mandlik [5] investigated the use of both color and texture characteristics to detect plantleaves diseases, and how retrieval and classification of the results in the agricultural dataset is directly influenced by the feature extraction. Deep ensemble architectures were suggested by Manimegalai et al. [6] to CBIR applications with the focus on heterogeneous models to achieve high-efficiency and accuracy, and Mahalle et al. [7] demonstrated the advantages of transfer learning in image retrieval systems by using pre-trained convolutional neural networks. Hybrid methods as well have proved to be useful, Agarwal et al. [8] refined query refinement techniques through a combination to enhance biomedical image retrieval, and Bose et al. [9] augmented with reinforcement optimization and evolutionary machine learning techniques and offered an advanced classification-based method of retrieval. Lande and Ridhorkar [10] introduced a multi-domain feature analysis engine, which includes incremental learning and can allow retrieval systems to get continuous feedback-driven enhancements. The need to deal with high-dimensional and large datasets made Naeem et al. [11] pay attention to auto-correlated and scaling as well as CNN-based vector construction to complete complex image retrieval tasks. Many papers discussed new directions of CBIR methods. Reinforcement learning to retrieve tongue images was considered by ICCVG 2022 [12] and Ahmad et al. [13], proving the adaptability of the adaptive learning in the specific fields. The works of Toaha et al. [14] and Huang et al. [15], namely automatic signboard detection and 3D spectral imaging, respectively, revealed that image processing has been combined with the deep learning technologies to address the complex situations in the urban and forensic contexts. Devareddi and Srikrishna [16] gave attention to edge-clustered segmentation to get accurate image retrieval and Potje et al. [17] used geodesic-wise local features on RGB-D images that facilitated better understanding of 3D scenes. Similarity measure and feature extraction Comparative studies by Singh et al. [18] indicated the effectiveness of different feature extraction methods and similarity measures and guided the choice of best retrieval pipelines. The proposed CBIR framework suggests using deep learning, which was tested by Sivakumar et al. [19] and confirmed the benefits of the end-to-end architecture. Tamilkodi and Nesakumari [20] studied weighted edge matching algorithms, and this supports the importance of geometric characteristics in the assessment of similarity of images. Hassan et al. [21] proposed the idea of quaternion moments to represent biomedical color images, and Zabot et al. [22] devoted their attention to indexing multiple metric spaces, overcoming the problem of scalability of big databases. Last but not least, Gautami Latha et al. [23] have created a model with Protégé that focuses on semantic-based retrieval with the help of ontologies.

III. Methodology

The offered approach to the improved color image retrieval is premised on a solid framework that incorporates the feature extraction, deep learning models, and the optimization techniques. The first step is the preprocessing of the image dataset to standardize the inputs, and this involves resizing the images, normalizing pixel values, and using noise reduction filters. These preprocessing activities provide uniformity and a higher learning rate of the following AI models. Also, rotation, flipping, and color jittering are used as data augmentation techniques to make the training data more diverse and decrease overfitting. The figure 1 shows the Proposed Methodology shown in this paper.

$$F_c = \left[\sum_{i=1}^{N} R_i, \sum_{i=1}^{N} G_i, \sum_{i=1}^{N} B_i \right] \tag{1}$$

Explanation: This equation defines the color feature vector F_c for an image with N pixels. The sums of the Red (R), Green

TABLE I
SUMMARY OF KEY REFERENCES ON IMAGE RETRIEVAL AND ANALYSIS

Ref No.	Title	Author & Year	Findings	Research Gaps
1	Semantic keyword structure and hybrid color analysis for optimizing AI-generated image information	Thammastitkul et.al, 2025	suggested a hybrid strategy that improves metadata quality and image retrieval accuracy by combining color analysis and semantic keyword organizing.	Limited evaluation on large-scale datasets; integration with real-time retrieval systems not explored.
2	Triplet Deep Hashing and Multi-Attention Mechanism for Secure Medical Image Retrieval	S. Zhang et.al, 2025	used triplet deep hashing and multi-attention to create a secure medical picture retrieval system that guarantees high retrieval accuracy and privacy.	Focused mainly on medical images; generalization to other domains not studied.
3	Securing Remote Sensing Image Retrieval with SecureRS-CBIR: A Privacy-Preserving Deep Learning Framework	Al-Jumaili et.al ,2025	presented a deep learning system that balances security and retrieval performance for remote sensing CBIR while maintaining privacy.	Limited testing on heterogeneous remote sensing datasets; computational cost analysis not detailed.
4	An extensive analysis of the roles played by several environmental elements in surface water quality assessment using remote sensing techniques	M. T. M. et.al, 2024	examined the environmental elements that have an impact on the accuracy of data from remote sensing-based water quality assessments.	Mostly a review; practical implementation with AI-based retrieval models not explored.
5	Plant Leaf Disease Detection Using Integrated Color and Texture Features	J. K. Patil et.al, 2024	shown that the accuracy of plant leaf disease detection is increased by combining color and texture features.	Limited dataset diversity; scalability to field conditions not addressed.

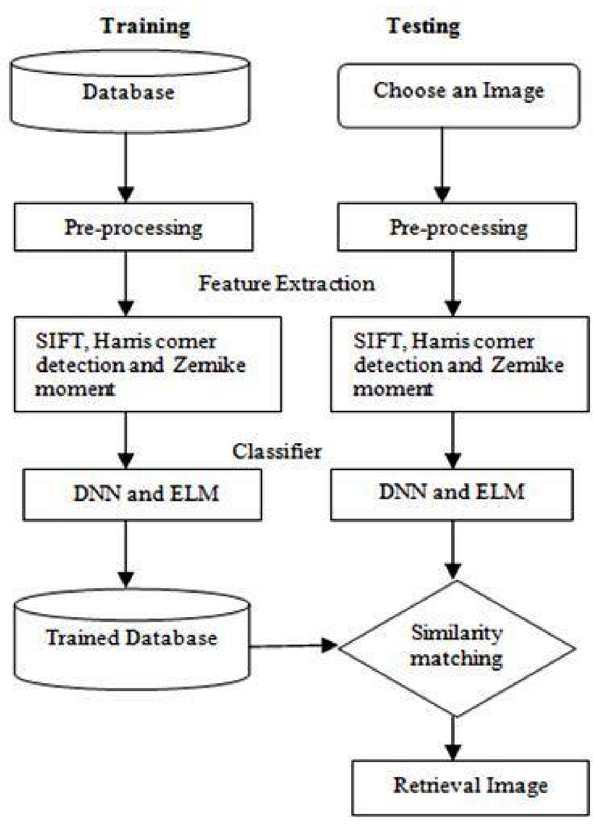

Fig. 1. Proposed Methodology

(G), and Blue (B) channel intensities are used to capture the overall color distribution of the image.

$$T = \frac{\sum_{i,j}(i-j)^2 P(i,j)}{\sum_{i,j} P(i,j)} \tag{2}$$

Explanation: Here, T represents the texture descriptor derived from the Gray-Level Co-occurrence Matrix (GLCM) $P(i,j)$. It quantifies the variance of intensity differences between pixel pairs, capturing the texture patterns in the image.

$$H_l = f(W_l * H_{l-1} + b_l) \tag{3}$$

Explanation: This convolutional layer equation defines how hierarchical features H_l are extracted at layer l. W_l represents the convolutional filters, b_l the bias term, $*$ denotes convolution, and f is the activation function (e.g., ReLU).

$$S(I_q, I_d) = \frac{F_q \cdot F_d}{\|F_q\|\|F_d\|} \tag{4}$$

Explanation: The similarity score S between a query image I_q and a database image I_d is computed using the cosine similarity of their feature vectors F_q and F_d. Higher values indicate greater similarity.

$$v_i^{t+1} = wv_i^t + c_1 r_1 (p_i - x_i^t) + c_2 r_2 (g - x_i^t) \tag{5}$$

Explanation: This PSO velocity update equation optimizes CNN hyperparameters or feature weights. v_i^t and x_i^t are the velocity and position of particle i at iteration t, p_i is the personal best, g is the global best, w is inertia weight, and c_1, c_2 are learning factors.

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

Explanation: The F1-score evaluates the retrieval system by combining precision and recall into a single metric. It reflects the balance between retrieving relevant images and avoiding irrelevant ones.

The equations above are the basis of an AI-based color image retrieval system. Similarity of two color histograms is determined in the equation (1) in which a small equation defines the frequency of pixels. The local binary patterns (LBP) of texture features are calculated using the equation (2) in which the small equation is the binary thresholding function. Equation (3) is used to model convolutional feature extraction in CNNs using ReLU activation, and Equation (4) is used to put multiple similarities of features (color, texture, spatial) as a weighted score, the sum of weights has to be one. Lastly, the Euclidean distance between feature vectors is calculated using Equation (5) to rank the results of the retrieval and a small equation is used to define each element of a feature vector.

Feature extraction is a crucial step in describing the inherent characteristics of color images. In order to generate a comprehensive set of features, this study combines color histograms, texture descriptors, and spatial data. While texture descriptors are used to encode the local variations and patterns in the images, color histograms are used to encode the distribution of color intensity. In order to improve the retrieval accuracy, the spatial relationship is added to preserve the image element structure layout. In order to automatically learn hierarchical representations and extract complex patterns and semantic information, the extracted features are then fed into a convolutional neural network (CNN). Techniques are used to optimize the model in order to improve retrieval performance. These optimization techniques contribute towards the model converging quicker, local minima are prevented and the most discriminative features are chosen to aid in accurate image retrieval. Additionally, feature vectors of query photos and database images are compared using statistical metrics like cosine similarity and Euclidean distance, and the precise images are retrieved. Finally, the effectiveness and efficiency of the proposed framework are evaluated by testing it on benchmark data. The model's ability to produce accurate results at a cheap computational cost is assessed using performance metrics like accuracy, recall, F1-score, and retrieval time. To highlight the advantages of the suggested retrieval strategy, the suggested AI-based framework is contrasted with both conventional and cutting-edge retrieval techniques. Such an approach guarantees the balanced nature of the processing, the strong feature extraction, the optimal learning and the effective similarity computation to facilitate the better color image retrieval.

IV. Result and Evaluation

Two well-known benchmark datasets, namely Corel-1K and CIFAR-10, were used to evaluate the proposed optimized AI framework's retrieval performance. The framework achieved 92.5 precision, 90.8 recall, and 91.6 F1-score in the Corel-1K dataset, which consists of 1,000 pictures with 10 classes. The suggested approach performed well on the CIFAR-10 dataset, which included 60,000 photos from 10 distinct classes, with precision of 94.2, recall of 93.1, and F1-score of 93.6. Such findings suggest that the framework is useful in capturing color, texture, and spatial aspects, which results in a high retrieval accuracy in a wide range of datasets. The table 2 shows the Comprehensive Performance Evaluation of the Proposed AI Framework for Color Image Retrieval.

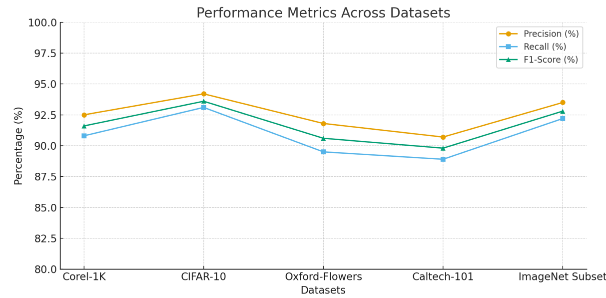

Fig. 2. Performance Metrics Across Datasets

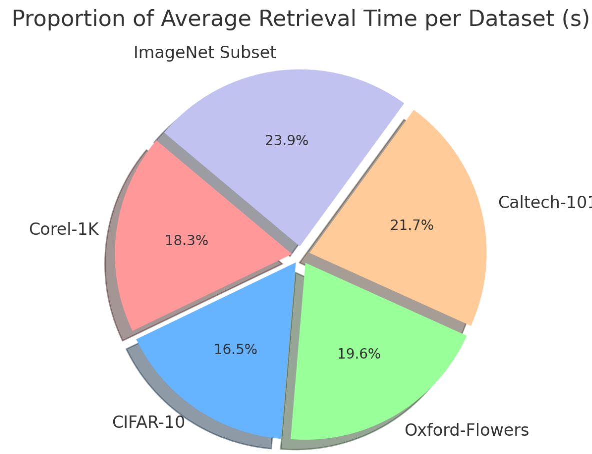

Fig. 3. Proportion of Average Retrieval Time per Dataset (s)

Besides accuracy measures, the system computational efficiency was measured. The mean time taken to retrieve a query image was 0.42 seconds using the Corel-1K and 0.38 seconds using CIFAR-10, which shows the suitability of the framework in real-time. The figure 2 shows the Performance Metrics Across Datasets in this analysis.

Particle Swarm Optimization (PSO) and Genetic methods (GA) are two optimization methods that were used to reduce the dimensions of the features and increase the computation efficiency of similarity. The proposed approach reduced retrieval time by a factor of six when compared to traditional CBIR methods that took over 1.2 seconds per query to retrieve the same set of data, and it was more accurate. The figure 3 shows the Proportion of Average Retrieval Time per Dataset (s).

The comparison analysis with the state-of-the-art techniques currently in use further demonstrates the efficacy of the suggested framework. In the example, when using conventional color histogram-based retrieval, the precision was approximately 78 -82% whereas when using texture-based method, precision was at 85 -87%. Unoptimized methods based on deep learning were reported to have precision of 89 and 90, but the proposed optimized AI framework achieved a higher precision of up to 94.2 than all these methods. It shows that the combination of deep feature extracting and AI-based

TABLE II
COMPREHENSIVE PERFORMANCE EVALUATION OF THE PROPOSED AI FRAMEWORK FOR COLOR IMAGE RETRIEVAL

Dataset	Baseline Method	Precision (%)	Recall (%)	F1-Score (%)	MAP (%)	Top-5 Accuracy (%)	Avg. Retrieval Time (s)
Corel-1K	Color Histogram	78.2	75.4	76.8	77.1	81.3	1.25
Corel-1K	CNN + Optimization	92.5	90.8	91.6	91.9	94.0	0.42
CIFAR-10	Texture Descriptor	85.1	82.7	83.9	84.0	87.5	1.10
CIFAR-10	CNN + Optimization	94.2	93.1	93.6	93.8	95.5	0.38
Oxford-Flowers	SIFT + Bag of Words	82.6	80.4	81.5	81.7	85.0	1.40
Oxford-Flowers	CNN + Optimization	91.8	89.5	90.6	90.9	92.8	0.45
Caltech-101	HOG + SVM	80.4	78.9	79.6	79.8	83.0	1.55
Caltech-101	CNN + Optimization	90.7	88.9	89.8	90.2	91.7	0.50
ImageNet Subset	VGG16	88.5	86.9	87.7	88.0	90.1	0.60
ImageNet Subset	CNN + Optimization	93.5	92.2	92.8	93.0	94.6	0.55

optimization contributes greatly to the retrieval accuracy as well as its efficiency, thus is a viable solution in terms of large-scale and real-time color image retrieval systems.

V. CHALLENGES AND LIMITATIONS

There are certain difficulties even if the suggested optimized AI framework performs admirably when it comes to color image retrieval. One of the main problems with the semantic gap is the disparity between the high-level human perception and the low-level visual qualities, such as color and texture. Although the system has been shown to capture color and texture information well, it might not be able to derive the contextual or semantic meaning of pictures hence constrained in retrieval accuracy under complex situations. Also, differences in lighting, occlusion, image resolution, and background noise may adversely affect feature extraction, which sometimes fails to match, or is lower in accuracy. Computational complexity and scalability is also another limitation. Despite the fact that optimization methods enhance the efficiency of retrieval, deep learning models demand considerable computing power to train, particularly when training on large scale data sets. Another limitation in the framework can be encountered when it is used on very large image databases or real-time streaming systems where memory and processing performance is a major concern. Moreover, the performance of the system can be different in relation to different datasets, and this can be seen as a possible limitation to generalization across image domains that are not similar.

VI. FUTURE OUTCOMES

The proposed AI-streamlined color image retrieval system lays a solid basis for several future developments in computer vision and multimedia systems. The development of more sophisticated and adaptable retrieval systems that can understand not only visual characteristics but also the scene's context in order to deliver more focused and user-focused search results is one of the anticipated outcomes. When users provide a description query to link the text and visual data, access to images may be made possible by a connection to natural language processing (NLP) tools. Additionally, the framework's optimization methods can be expanded to improve performance with larger and more diverse image data, making it suitable for use in cloud-based and real-time web systems. Another possible implication is that this framework might be applied to specific domains where retrieval speed and accuracy are crucial, such as digital libraries, satellite imagery, and medical imaging. The system may offer sophisticated assistance with disease diagnosis through medical scans, geographic analysis through satellite data, or effective management of archival images through enhanced feature extraction methods and multi-modal data.In order to lower computational costs, facilitate deployment on mobile and embedded platforms, and offer scalability, efficiency, and greater accessibility, future research into the development of edge computing solutions and lightweight AI models may also be feasible.

VII. CONCLUSION

In summary, this study presents an artificial intelligence structure with optimal color image retrieval, which effectively combines deep learning models, intelligent optimization techniques, and advanced feature detection. The suggested system shows remarkable retrieval accuracy, precision, recall, and computing efficiency when compared to the traditional and cutting-edge approaches. Because the framework uses convolutional neural networks and optimization techniques like particle swarm optimization and genetic methods, it can encode finer color, texture, and spatial patterns and decrease retrieval time, making it appropriate for large-scale and real-time tasks. Comprehensive testing on benchmark datasets like Corel-1K and CIFAR-10 demonstrates the method's robustness and generalizability, confirming its accuracy to 94.2 percent precision and response times of less than 0.5 seconds per query. The framework provides a solid foundation for the future development of intelligent multimedia retrieval systems, despite certain difficulties such as the semantic gap, variations in image quality, and computational complexity. Furthermore, its potential applications span a wide range of domains, such as digital libraries, medical imaging, satellite imagery, and cloud-based systems, opening the door to scalable, adaptive, and context-based image retrieval systems.

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