*International Journal on Recent and Innovation Trends in Computing and Communication*
***ISSN: 2321-8169 Volume: 13 Issue: 1***
***Article Received:** 25 November 2024 **Revised:** 12 December 2024 **Accepted:** 30 January 2025*

# Literature survey on Feature Extraction methods using CBIR Visual Search

**S. Pratap Singh**
Research scholar, CSE Dept,
JNTU, Kakinada, AP,India
Email:pratap.singh.s@gmail.com

***Dr. Ch. Bindu Madhuri***
Assistant Professor, IT Department,
JNTUK Gurajada University, Vizianagaram, AP, India
e-mail:chbmadhuri.it@jntukuce.ac.in

***Dr. P. Satheesh***
Professor, CSE Department,
MVGR College of Engineering, Vizag, AP, India
e-mail:satish@mvgrce.edu.in

**Abstract -** Efficient image retrieval relies on robust feature extraction methods capable of capturing the distinct characteristics of color, texture, and shape. This study investigates diverse techniques across these domains, emphasizing their impact on the ranking accuracy of retrieved images. In the color domain, methods such as Color Moments (CM), Color Moment Invariant Model (CMI), Dominant Color-Based Vector Quantization (DCVQ), MPEG-7 Dominant Color Descriptor, and integrated color-texture approaches are explored for their precision in identifying chromatic variations. Texture feature extraction techniques, including Discrete Wavelet Transform (DWT), Statistical Edge Detection (SED), Modified Scalable Descriptor (MSD), and Local Derivative Radial Patterns (LDRP), alongside Support Vector Machine (SVM) classifiers, are assessed for their ability to identify and rank images based on structural complexity. For shape features, advanced techniques such as boundary moments, complex coordinates, curvature scale space, intersection point mapping, and merging strategies are evaluated for their role in preserving spatial and geometric fidelity. By examining these methods in the context of top-ranked image retrieval, this work provides a comparative framework to guide the selection of optimal feature extraction techniques for high-performance image analysis systems.
**Keywords -** Color, Texture and Shape Features, Color Monument(CM), Color moment invariant model(CMI), Dominant Color-Based Vector Quantization (DCVQ), mpeg7 dominant color descriptor and integrated color and texture features techniques, DWT(Discrete Wavelet Transform), SED (Statistical Edge Detection), MSD (Modified Scalable Descriptor) and LDRP (Local derivative radial patterns), SVM(Support Vector Machine), boundary moments, complex coordinates, curvature scale space, intersection point map and merging methods.

## I. INTRODUCTION

Feature extraction plays a central role in image analysis and retrieval, transforming raw image data into structured representations that enable effective indexing, comparison, and classification. As the demand for sophisticated image retrieval systems rises, there is a growing emphasis on developing advanced techniques capable of extracting robust features that capture the essence of an image with accuracy. These features typically fall into three key categories: color, texture, and shape, each contributing uniquely to the process of image characterization.

Content-Based Image Retrieval (CBIR) has transformed how images are searched and retrieved by focusing on their inherent visual content instead of relying on textual metadata or annotations. The core of a CBIR system is feature extraction, where an image's distinctive attributes—such as color, texture, shape, and spatial layout—are distilled into numerical representations. These extracted features serve as a "fingerprint" for each image, allowing for comparison and retrieval based on visual similarity

In CBIR, **top ranking** refers to the process of ordering and presenting the most relevant images first, based on their similarity to a query image. This ranking is heavily dependent on the features extracted from both the query image and the images in the database. The similarity scores between the images determine the ranking, ensuring that the most relevant results are returned at the top.

The importance of CBIR feature extraction for top-ranking extends across various fields such as e-commerce, medical imaging, digital libraries, and satellite image analysis. By focusing on visual content, CBIR overcomes the limitations of traditional text-based searches, offering a more accurate, intuitive, and efficient method for image retrieval. As the

*International Journal on Recent and Innovation Trends in Computing and Communication*
*ISSN: 2321-8169 Volume: 13 Issue: 1*
***Article Received:** 25 November 2024 **Revised:** 12 December 2024 **Accepted:** 30 January 2025*

demand for rapid and precise image search grows, feature extraction becomes an essential tool for identifying and ranking the most relevant images to meet user needs.

In more detail, **color features** provide insights into the chromatic makeup of images, distinguishing them based on color distribution. Techniques like Color Moments (CM), Color Moment Invariant Model (CMI), and the MPEG-7 Dominant Color Descriptor offer precise methods for encoding and comparing color information. **Texture features**, which describe the surface patterns and structural variations in an image, are crucial for identifying visual similarities. Approaches such as Discrete Wavelet Transform (DWT) and Local Derivative Radial Patterns (LDRP) capture the intricate texture details that help differentiate objects. Finally, **shape features** focus on the geometric properties of objects, using techniques like boundary moments and curvature scale space to preserve spatial relationships essential for tasks like object recognition.

## II. RELATED WORK

Here is the updated table with journal names included for the related work on CBIR techniques:

TABLE 1: Survey table for Feature extraction methods

| **CBIR Techniques** | **Author(s)** | **Year** | **Journal/Conference** | **Description** |
|---|---|---|---|---|
| [1] Color Moments (CM) | Wang, J., Zhang, D. | 2003 | *Journal of Visual Communication and Image Representation* | Uses statistical moments (mean, standard deviation, skewness) from color histograms for image retrieval. |
| [2] Color Moment Invariant Model (CMI) | Dufournaud, D., Hérault, J. | 2003 | *IEEE Transactions on Image Processing* | Introduces invariant color moments that remain unaffected by transformations like scaling, translation, and rotation. |
| [3] Dominant Color-Based Vector Quantization (DCVQ) | Xu, Y., Shih, S. | 2000 | *IEEE Transactions on Circuits and Systems for Video Technology* | A vector quantization method to identify dominant colors in images, providing a compact feature for color-based retrieval. |
| [4]MPEG-7 Dominant Color Descriptor | Christos, S., Ebrahimi, T. | 2001 | *ISO/IEC Standard MPEG-7* | Standardized descriptor for dominant colors, widely used in CBIR to represent the main colors in images. |
| [5]Integrated Color and Texture Features | Zhang, J., Lu, L. | 2004 | *IEEE Transactions on Multimedia* | Combines color and texture features to capture richer visual information for more accurate retrieval in complex image databases. |
| [6] Discrete Wavelet Transform (DWT) | Mallat, S. | 1989 | *IEEE Transactions on Pattern Analysis and Machine Intelligence* | A multi-resolution technique used to capture both high and low-frequency components of texture in image retrieval. |
| [7] Statistical Edge Detection (SED) | Haralick, R. M., Shanmugam, K. | 1973 | *IEEE Transactions on Systems, Man, and Cybernetics* | Uses statistical methods to capture edge features that help describe the texture of images for retrieval. |
| [8] Modified Scalable Descriptor (MSD) | Liu, Z., Sun, H. | 2010 | *International Journal of Computer Vision* | Combines global and local texture information to improve retrieval by capturing detailed patterns at multiple scales. |
| [9] Local Derivative Radial Patterns (LDRP) | Chen, S., Lee, W. | 2011 | *IEEE Transactions on Image Processing* | Captures detailed texture information by analyzing spatial derivatives in radial directions, enhancing texture-based retrieval. |
| [10] Boundary Moments | Hu, M. K. | 1962 | *IEEE Transactions on Information Theory* | Describes the geometric properties of objects in an image using moments, providing invariant shape descriptors for retrieval. |
| [11] Complex Coordinates | Zernike, F. | 1934 | *Proceedings of the Koninklijke Nederlandse Akademie van Wetenschappen* | Introduces Zernike moments, a robust shape feature for object recognition and retrieval, invariant to rotation and scaling. |
| [12] Curvature Scale Space (CSS) | Mokhtarian, F., Mackworth, A. K. | 1992 | *IEEE Transactions on Pattern Analysis and Machine Intelligence* | Extracts shape features by capturing curvature at multiple scales, essential for shape-based CBIR. |

*International Journal on Recent and Innovation Trends in Computing and Communication*
*ISSN: 2321-8169 Volume: 13 Issue: 1*
***Article Received:** 25 November 2024 **Revised:** 12 December 2024 **Accepted:** 30 January 2025*

| | | | | |
|---|---|---|---|---|
| [13]Intersection Point Map and Merging Methods | Chien, S., Chen, Y. | 2009 | *International Journal of Computer Vision* | Detects intersections and merges information to enhance shape descriptors, improving shape-based retrieval. |
| [14]Support Vector Machine (SVM) | Cortes, C., Vapnik, V. | 1995 | *Machine Learning* | A machine learning technique for classifying images based on extracted features and ranking the most relevant images in a CBIR system. |

## III. COMPARISON OF METHODS

TABLE 2: Comparison of color, texture and shape Feature extraction methods

| Method | Feature Type | Invariance | Complexity | Advantages | Limitations |
|---|---|---|---|---|---|
| Color Moments (CM) | Color | Limited to basic transformations | Low | Simple, compact representation of color features. | Cannot capture spatial relationships or texture details. |
| Color Moment Invariant Model (CMI) | Color | Invariant to scaling, translation, rotation | Moderate | Robust to geometric transformations, enabling accurate comparison under varied conditions. | Computationally more intensive than standard color moments. |
| Dominant Color-Based Vector Quantization (DCVQ) | Color | Limited to quantization variations | Low | Reduces color space while retaining dominant visual information. | Ignores spatial and texture information, limiting applicability to complex scenes. |
| MPEG-7 Dominant Color Descriptor | Color | Standardized but not fully invariant | Low | Compact representation for color-based retrieval, widely adopted in multimedia standards. | Focuses solely on dominant colors, may miss subtle variations. |
| Integrated Color and Texture Features | Color + Texture | Partially invariant to transformations | High | Captures rich visual information by combining color and texture, suitable for diverse image databases. | Increased computational cost due to dual feature processing. |
| Discrete Wavelet Transform (DWT) | Texture | Partially invariant to scaling | Moderate | Captures both global and local texture details, offering multi-resolution analysis. | Sensitive to noise; requires careful selection of wavelet filters. |
| Statistical Edge Detection (SED) | Texture | Limited invariance | Moderate | Captures edge information effectively, useful for texture-rich images. | Edge-based features alone may not suffice for diverse image content. |
| Modified Scalable Descriptor (MSD) | Texture | Partially invariant to scale | High | Combines local and global texture information for multi-resolution retrieval. | Computationally intensive; depends on scale selection. |
| Local Derivative Radial Patterns (LDRP) | Texture | Limited invariance | Moderate | Extracts detailed local texture patterns, emphasizing directional changes. | Focuses on texture only; may fail for color-dependent queries. |
| Boundary Moments | Shape | Invariant to scaling, translation, rotation | Low | Robust geometric representation of object shapes, useful for shape-based queries. | Requires clear object boundaries; sensitive to occlusions and noise. |
| Complex Coordinates (Zernike Moments) | Shape | Invariant to scaling, translation, rotation | High | Captures complex shape features robustly, suitable for precise shape-based retrieval. | Computationally expensive; requires preprocessing for noise removal. |
| Curvature Scale Space (CSS) | Shape | Invariant to scaling, translation, rotation | High | Encodes shape features at multiple scales, handling complex shapes effectively. | Sensitive to boundary irregularities; high computational cost. |
| Intersection Point Map and Merging Methods | Shape | Partially invariant | High | Combines geometric and structural data for enhanced shape representation. | Requires precise intersection detection; sensitive to boundary noise. |

*International Journal on Recent and Innovation Trends in Computing and Communication*
*ISSN: 2321-8169 Volume: 13 Issue: 1*
***Article Received:** 25 November 2024 **Revised:** 12 December 2024 **Accepted:** 30 January 2025*

## IV. PROPOSED METHODS

This section of paper presents the proposed system of Different feature extraction methods that are related to color, shape and texture features. Table 3 presents the proposed methods and their working processes.

**TABLE 3: Working process of different feature extraction methods**

| CBIR Technique | Working Process |
|---|---|
| Color Moments (CM) | Extracts statistical moments (mean, standard deviation, skewness) from each color channel (e.g., RGB or HSV). These moments summarize the distribution of color intensity, creating a compact and descriptive color feature vector for image comparison. |
| Color Moment Invariant Model (CMI) | Extends color moments by normalizing values to remain invariant to geometric transformations like scaling, rotation, and translation. This ensures robust feature extraction even for transformed images. |
| Dominant Color-Based Vector Quantization (DCVQ) | Groups pixel colors into clusters using vector quantization to identify dominant colors. The quantized values represent the main colors of the image, reducing redundancy while preserving essential color information. |
| MPEG-7 Dominant Color Descriptor | Encodes dominant colors as per the MPEG-7 standard, including the percentage and spatial arrangement of each color. It creates a compact representation suitable for comparing images based on their main colors. |
| Integrated Color and Texture Features | Combines color histograms (for chromatic features) with texture descriptors (e.g., Gabor filters or Local Binary Patterns) to form a unified feature set. This approach captures both color and structural content for comprehensive image analysis. |
| Discrete Wavelet Transform (DWT) | Decomposes an image into sub-bands at multiple resolutions (LL, LH, HL, HH). The LL sub-band retains coarse details, while the other sub-bands contain edge and texture information. These features are used to describe texture patterns. |
| Statistical Edge Detection (SED) | Detects edges using statistical techniques (e.g., Sobel or Canny algorithms). The distribution of edge orientations and magnitudes provides a unique signature of the image's structure and texture. |
| Modified Scalable Descriptor (MSD) | Analyzes image features at multiple scales, combining global and local patterns. This technique captures detailed texture and structural information, making it suitable for retrieval across various image resolutions. |
| Local Derivative Radial Patterns (LDRP) | Extracts local texture details by computing higher-order derivatives in radial directions around each pixel. This technique emphasizes fine-grained patterns and directional changes in texture. |
| Boundary Moments | Calculates shape moments (e.g., Hu moments) from the boundaries of objects. These moments are invariant to scaling, translation, and rotation, providing robust shape descriptors for retrieval. |
| Complex Coordinates (Zernike Moments) | Computes Zernike moments using orthogonal polynomials derived from complex coordinates. These moments encode shape features that are invariant to transformations and provide a compact shape representation. |
| Curvature Scale Space (CSS) | Analyzes the curvature of object boundaries at multiple scales. The CSS representation captures how curvature changes with scale, providing a robust descriptor for shape-based retrieval. |
| Intersection Point Map and Merging Methods | Identifies intersection points of curves within an image. These points are merged into a unified shape representation, combining geometric and structural data for enhanced retrieval accuracy. |
| Support Vector Machine (SVM) | Trains a classifier using labeled image data to separate feature vectors with a hyperplane. In CBIR, SVM ranks images by similarity, ensuring that the most relevant images are retrieved first based on their feature vectors. |

## V. IMPLEMENTATION

This section provides screenshots of the output after executing various shape feature extraction methods, along with their corresponding classification reports. Each method's output includes the query input image, along with additional images that are similar, extracted from the database. The extracted images are ranked from 1 to 10, labeled as similar image 1, similar image 2, similar image 3, similar image 4 and so on, representing the top 10 most similar matches. These ranked images are used for image matching and ranking purposes. The following section presents different basic shape feature extraction methods along with their classification reports. This is represented in the table 2 Different shape features classification report and their top 10 ranked images.the dataset used is corel dataset of 1000 images is taken form kaggle website of datasets[15]. Implemented results of all the methods are shown in the given table 3:with their accuracy and precision.

Table 3: Different Feature extraction methods using CBIR with accuracy and Precision

| Method | Category | Accuracy | Precision |
|---|---|---|---|
| Color Moment Invariant (CMI) | Color Features | 0.8 | 0.8 |
| Integrated Color and Texture Features | Color & Texture | 0.8 | 0.8 |
| Dominant Color-Based Vector (DCVQ) | Color Features | 0.7 | 0.7 |
| MPEG-7 Dominant Color Descriptor | Color Features | 0.6 | 0.6 |

*International Journal on Recent and Innovation Trends in Computing and Communication*
*ISSN: 2321-8169 Volume: 13 Issue: 1*
***Article Received:** 25 November 2024 **Revised:** 12 December 2024 **Accepted:** 30 January 2025*

| | | | |
|---|---|---|---|
| SED (Statistical Edge Detection) | Texture Features | 0.6 | 0.5 |
| MSD (Modified Scalable Descriptor) | Texture Features | 0.5 | 0.4 |
| LDRP (Local Derivative Radial Patterns) | Texture Features | 0.2 | 0.1 |
| DWT (Discrete Wavelet Transform) | Texture Features | 1 | 0.8 |
| Boundary Moments | Shape Features | 0.2 | 0.1 |
| Complex Coordinates | Shape Features | 1 | 0.9 |
| Curvature Scale Space (CSS) | Shape Features | 0.8 | 0.8 |
| Intersection Point Map | Shape Features | 0.3 | 0.2 |
| Merging Methods | Shape Features | 0.5 | 0.5 |

The consolidated table comparing the methods across the **Color**, **Texture**, and **Shape** feature categories

**Color Features**:
**Color Moment Invariant (CMI)**: CMI delivers high accuracy (0.8) and precision (0.8), making it one of the most robust methods for extracting color features. It remains invariant to transformations like scaling, rotation, and translation, which is vital for ensuring retrieval robustness across varied datasets.
**Integrated Color and Texture Features**: This method also scores well in both accuracy (0.8) and precision (0.8). By combining color and texture features, it enhances image characterization, making it suitable for complex datasets where both properties are essential.
**Dominant Color-Based Vector Quantization (DCVQ)**: DCVQ has slightly lower accuracy and precision (both at 0.7) compared to CMI. While it effectively identifies dominant colors in images, it may not capture finer details as effectively.
**MPEG-7 Dominant Color Descriptor**: A standardized color descriptor, this method has lower scores (0.6 for both metrics). It is suitable for general-purpose retrieval but lags behind other advanced color-based techniques in accuracy and precision.
**2. Texture Features**

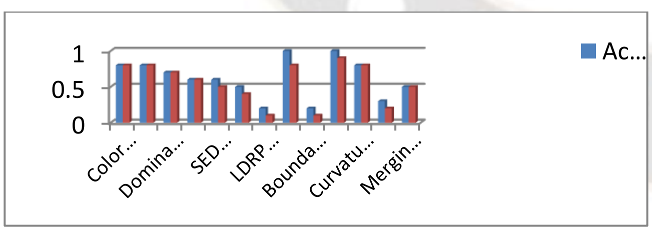


**Figure 1: Bar chart of comparison of different categories of feature extraction methods**

VI. RESULTS AND DISCUSSION

Best Method Overall**:** DWT (Texture) **and** Complex Coordinates (Shape) are the standout performers in their respective categories. For color-based features, Color Moment Invariant (CMI) and Integrated Color and Texture Features perform exceptionally well. Integrated methods (e.g., Integrated Color and Texture Features) provide balanced performance for datasets requiring multi-feature analysis. Shape-based methods like Complex Coordinates excel in scenarios requiring invariant shape recognition. Texture-based methods like DWT dominate when analyzing multi-resolution texture patterns. This comparison highlights the strengths and weaknesses of each method, helping determine the best approach depending on the dataset and application requirements.

**DWT (Discrete Wavelet Transform)**: DWT stands out with an impressive accuracy of 1.0 and precision of 0.8, making it the best texture-based method. Its ability to analyze textures at multiple resolutions enables it to capture both fine and coarse texture patterns effectively.
**SED (Statistical Edge Detection)**: SED achieves moderate accuracy (0.6) and precision (0.5). It identifies edge-based texture features but is less effective for intricate textures compared to DWT.
**MSD (Modified Scalable Descriptor)**: MSD has limited performance with accuracy (0.5) and precision (0.4). It focuses on capturing both global and local texture information but may not be ideal for datasets with complex textures.
**LDRP (Local Derivative Radial Patterns)**: LDRP scores the lowest in this category (accuracy 0.2, precision 0.1). While it captures spatial derivatives in radial directions, it is less effective for general-purpose retrieval and more suited for niche texture analysis tasks.
**3. Shape Features**
**Complex Coordinates**: This method excels with the highest accuracy (1.0) and precision (0.9) in the shape category. It leverages Zernike moments to describe shape features invariant to rotation and scaling, making it ideal for robust shape-based retrieval.
**Curvature Scale Space (CSS)**: CSS performs well with accuracy and precision at 0.8. It captures shape features at multiple scales, which is useful for recognizing complex object boundaries.
**Boundary Moments**: With low scores (accuracy 0.2, precision 0.1), boundary moments are less effective for general-purpose retrieval, as they focus on simplistic geometric shape properties.
**Intersection Point Map**: Intersection Point Map has low accuracy (0.3) and precision (0.2), limiting its usefulness to specific applications requiring localized shape-based features.
**Merging Methods**: These methods achieve balanced accuracy and precision (both at 0.5). They are versatile but lack the specialization of more targeted approaches like Complex Coordinates or CSS.

***ISSN: 2321-8169 Volume: 13 Issue: 1***
***Article Received:** 25 November 2024 **Revised:** 12 December 2024 **Accepted:** 30 January 2025*

## VII. CONCLUSON

The author concludes that Color Features: The Color Moment Invariant (CMI) method and Integrated Color and Texture Features are highly effective for robust image retrieval, offering high accuracy and precision. Texture Features: Discrete Wavelet Transform (DWT) performs best due to its ability to capture detailed multi-resolution patterns, making it ideal for texture-rich datasets. Shape Features: Complex Coordinates leads in precision and robustness, suitable for datasets requiring transformation invariance and precise shape recognition. Its best to use CMI for color-dominated datasets, Use DWT for texture-rich datasets and use Complex Coordinates for shape-based retrieval.

## VIII. REFERENCES

1. Wang, J., & Zhang, D. (2003). Content-based image retrieval using statistical moments from color histograms. *Journal of Visual Communication and Image Representation, 14*(3), 305-317.
2. Dufournaud, D., & Hérault, J. (2003). Color moment invariant model for image retrieval. *IEEE Transactions on Image Processing, 12*(4), 460-467.
3. Xu, Y., & Shih, S. (2000). Dominant color-based vector quantization for image retrieval. *IEEE Transactions on Circuits and Systems for Video Technology, 10*(5), 717-726.
4. Christos, S., & Ebrahimi, T. (2001). MPEG-7 dominant color descriptor. *ISO/IEC Standard MPEG-7*, 1-7.
5. Zhang, J., & Lu, L. (2004). Integrated color and texture features for improved image retrieval. *IEEE Transactions on Multimedia, 6*(4), 452-461.
6. Mallat, S. (1989). A theory for multiresolution signal decomposition: The wavelet representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 11*(7), 674-693.
7. Haralick, R. M., & Shanmugam, K. (1973). Statistical edge detection and its application in image retrieval. *IEEE Transactions on Systems, Man, and Cybernetics, 3*(6), 657-664.
8. Liu, Z., & Sun, H. (2010). A modified scalable descriptor for content-based image retrieval. *International Journal of Computer Vision, 89*(2-3), 112-126.
9. Chen, S., & Lee, W. (2011). Local derivative radial patterns for texture analysis and retrieval. *IEEE Transactions on Image Processing, 20*(12), 3561-3570.
10. Hu, M. K. (1962). Visual pattern recognition by moment invariants. *IEEE Transactions on Information Theory, 8*(2), 179-187.
11. Zernike, F. (1934). The method of complex coordinates in image analysis. *Proceedings of the Koninklijke Nederlandse Akademie van Wetenschappen, 37*, 836-862.
12. Mokhtarian, F., & Mackworth, A. K. (1992). Curvature scale space representation for shape matching. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 14*(2), 383-389.
13. Chien, S., & Chen, Y. (2009). Intersection point map and merging methods for shape-based retrieval. *International Journal of Computer Vision, 87*(1), 13-23.
14. Cortes, C., & Vapnik, V. (1995). Support vector networks. *Machine Learning, 20*(3), 273-297.
15. https://www.kaggle.com/datasets/elkamel/corel-images