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Ranking images based on shape features extracted using CBIR Techniques

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ABSTRACT

Content-Based Image Retrieval (CBIR) has emerged as a powerful technique for efficiently searching and retrieving images from large datasets based on visual features rather than textual metadata. This paper focuses on ranking images based on shape features extracted using CBIR techniques, employing methods such as boundary moments, complex coordinates, curvature scale space, intersection point map and merging methods. Each of these methods is utilized to analyze and extract distinctive shape features from images, which are then used for similarity matching and ranking. Ranking images based on shape features plays a vital role in Content-Based Image Retrieval (CBIR), where the goal is to efficiently retrieve and rank images based on their visual similarity to a query image. This study explores the extraction and utilization of shape-based visual features such as contours, geometric properties, and region-based descriptors for ranking images. A similarity measure is used to compare the feature vectors of the query image against those in a database. The retrieved images are ranked in descending order of similarity, ensuring relevance and precision in retrieval.

KEYWORDS: Content-Based Image Retrieval (CBIR), boundary moments, complex coordinates, curvature scale space, intersection point map, merging methods, Support vector machine (SVM).

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INTRODUCTION

The rapid growth of digital image repositories has created a pressing need for efficient methods to manage, retrieve, and rank images based on their visual content. Content-Based Image Retrieval (CBIR) has emerged as a prominent solution, enabling the retrieval of images from large databases by analyzing intrinsic visual features such as color, texture, and shape. Among these, shape features have proven to be particularly significant for identifying and comparing objects within images, as they capture the geometric structure of visual content. The working of CBIR is given in the block diagram figure1. The block diagram likely illustrates the flow of data through these stages, emphasizing how the CBIR system processes the query image, extracts features, compares them with the database, and ranks the results. It visually conveys the sequential nature of the retrieval and ranking process, highlighting critical points like feature extraction methods and the role of similarity measures.

Shape-based CBIR leverages the structural properties of objects, such as their boundaries, contours, and spatial distributions, to differentiate images effectively. Unlike traditional keyword-based retrieval systems, shape-based CBIR eliminates the reliance on textual metadata, making it a more versatile and scalable approach for image retrieval. The extraction and representation of shape features, however, pose several challenges, including sensitivity to noise, variations in object orientation, and differences in scale. Advanced techniques such as boundary descriptors, region-based moments, and contour analysis address these challenges by providing robust and invariant representations of shapes.

The process of ranking images based on shape features begins with the extraction of shape descriptors from both the query image and the images in the database. These descriptors are then compared using similarity measures to quantify the closeness of their features. The images are ranked based on their similarity scores, ensuring that the most relevant results are prioritized. This methodology is particularly beneficial in applications where shape is a defining characteristic, such as medical imaging for identifying anatomical structures, industrial inspection for detecting defective items, and trademark retrieval for matching logos. This paper delves into the techniques and methodologies for ranking images using shape-based features in CBIR systems. It highlights the importance of robust feature extraction and similarity measurement methods, providing insights into their applications across diverse domains. The study also evaluates the performance of different shape descriptors and ranking algorithms, demonstrating their efficacy in improving retrieval precision and relevance.

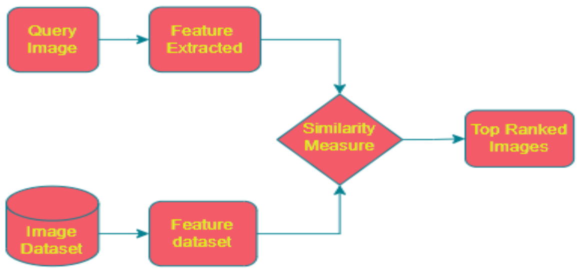


Figure 1: Block diagram of Content based image retrieval and ranking.

Shape feature extraction has emerged as a crucial area in computer vision and pattern recognition, playing a pivotal role in applications like object detection, classification, and content-based image retrieval (CBIR). Unlike other visual attributes such as color or texture, shape features provide a robust representation of an object’s structural and geometric properties, making them highly effective for differentiating between objects with similar visual characteristics. Techniques for shape feature extraction are widely applied across various domains, including agriculture, medical imaging, and industrial inspection, due to their ability to capture invariant properties such as scale, rotation, and translation.

Several advancements in shape feature extraction have been introduced over the years, ranging from traditional methods like shape signatures and boundary-based descriptors to modern approaches leveraging machine learning and deep learning frameworks. These techniques enable the precise extraction of shape characteristics, ensuring improved performance in real-world applications. Recent research has focused on optimizing shape feature extraction methods to enhance robustness and computational efficiency, addressing challenges like noise, occlusions, and varying imaging conditions. This study explores shape feature extraction and its integration into CBIR systems, leveraging state-of-the-art methodologies to rank images based on their shape features.

LITERATURE REVIEW

Numerous studies have contributed to the development of shape feature extraction techniques, each offering unique insights and methodologies tailored to specific applications. The author Hassoon (2021) provided a comprehensive review of shape feature extraction techniques, highlighting their applicability in analyzing fruits for agricultural purposes. The study emphasized the use of geometric and region-based descriptors to accurately capture fruit shapes[1]. Similarly, Raj and Balaji (2023) discussed advanced shape feature extraction methods for computer vision applications, showcasing their effectiveness in a wide range of scenarios, including object detection and recognition [2]. The author Mingqiang et al. (2008) conducted an extensive survey on shape feature extraction techniques, categorizing them into boundary-based, region-based, and hybrid methods. Their work laid the foundation for understanding the strengths and limitations of different approaches in pattern recognition tasks [3]. The authors Ding et al. (2019) introduced a shape-aware feature extraction technique for instance segmentation, leveraging deep learning frameworks to improve segmentation accuracy. Their approach addressed challenges related to overlapping objects and complex backgrounds, making it suitable for real-world applications [4]. The authors Mustaza et al. (2022) developed a directional shape feature extraction method using a modified line filter technique for weed classification. Their results demonstrated the robustness of shape descriptors in agricultural applications [5]. Ahmed et al. (2023) applied shape signature-based feature extraction to classify fish images, achieving significant accuracy by focusing on robust shape features [6]. Similarly, Kartika et al. (2018) employed a local binary pattern method combined with shape feature extraction to detect butterfly images, showcasing the utility of shape features in entomology [7]. The authors Wang and Zhang (2021) proposed an improved automatic shape feature extraction method based on template matching, achieving higher accuracy in detecting complex shapes[8]. Harjanti et al. (2022) combined shape and texture feature extraction with clustering techniques for mint leaf classification, demonstrating the benefits of integrating multiple feature types [9]. The authors Huang et al. (2023) introduced an edge-based feature extraction module for 3D point cloud shape classification, pushing the boundaries of traditional 2D shape analysis [10]. Mohan and Kurian (2022) designed a shape-based feature extraction engine for vision systems using Zynq SoC, focusing on hardware implementation for real-time applications [11]. The authors Y. Fang et al., in their paper introduced a deep learning-based 3D shape descriptor, improving object recognition in computer vision tasks by combining geometric features with learned representations, useful in robotics and augmented reality [12]. The authors H. Gao et al., introduced A novel method for hyperspectral image classification, combining random-shape convolutions with adaptive graph convolutions to better capture spatial and spectral features, enhancing classification accuracy for applications in environmental monitoring and agriculture [13].The authors Hu et al., introduced and approach that integrates Fourier shape descriptors into a deep learning model for accurately extracting building footprints from remote sensing images, benefiting urban planning and disaster management [14].The author Peng et al., proposed a method combining deformation feature extraction with a double attention feature pyramid network for detecting subtle surface defects in bearings, improving predictive maintenance in industrial systems [15].The authors J. Li et al., proposed a framework that enhances pillar-based 3D object detection by optimizing feature extraction, improving detection accuracy and efficiency, particularly for autonomous navigation systems [16]. The authors M. K. Nazir et al., combined texture and shape features (via DWT, LBP, and Invariant Moments) for textile image classification using SVM, improving accuracy for automated recognition in industries like textile manufacturing [17]. Iranmehr et al., introduced A method for unsupervised extraction of shape-based features to recognize incoming signals, particularly useful in sensor networks and real-time monitoring [18]. The authors P. Lv et al., proposed a Shape

Former model integrated shape features into Vision Transformers to enhance landslide detection from optical images, benefiting environmental monitoring [19]. The authors J. E. Tapia and C. Busch, Focused on visualizing face features to detect morphing attacks in biometric systems, contributing to security and forensics [20]. The authors D. S. Y. Kartika et al.,studed a combined color, texture, and shape features to improve the classification of butterfly species, relevant for biodiversity monitoring [21]. Madhu and R. Kumar Analyzed feature extraction methods like histograms and wavelets for improving image retrieval systems, crucial for applications in digital libraries and surveillance [22] the authors R. Dey et al., Introduced a hybrid feature extraction technique combining deep learning and traditional methods for better recognition of Devanagari and Bangla characters [23]. The authors T. Hafsia et al. Compared different edge and point detection methods, providing valuable insights into choosing the right techniques for specific image processing applications [24]. The authors W.-Y. Yu et al., proposed a ShaTure, a model for human pose and attribute transfer, utilized shape and texture deformation, improving realism in computer graphics and augmented reality [25].

PROPOSED METHOD:

In literature we could see many methods to represent the shape feature extraction from images. The proposed framework evaluates the effectiveness of some methods by measuring key performance metrics such as precision, accuracy, F1-score, and support. A dataset of over 1,000 images, categorized into diverse groups like beaches, buses, flowers, monuments, and more, is used to train and test the model. The results demonstrate the comparative strengths and weaknesses of the employed techniques in ranking images, with a particular focus on their ability to handle complex shapes, invariance to transformations, and computational efficiency. This study provides valuable insights into the selection and application of shape feature extraction methods for CBIR systems, emphasizing their role in achieving accurate and efficient image ranking in real-world scenarios. This paper propose the implementation of few basic methods like boundary moments, complex coordinates, curvature scale space, intersection point map, merging methods. Below is the working process of each proposed method of implementation:

1.Boundary moments are derived from the boundary (contour) of a shape. A shape's boundary is traced to obtain a series of points that represent the shape. These boundary points are then used to calculate geometric moments (e.g., geometric, central, or higher-order moments). For instance, the central moments are calculated using:

$$\mu_{pq} = \sum_{x,y} (x - \bar{x})^p (y - \bar{y})^q f(x, y)$$

Where f(x, y) is a binary image function, and $\bar{x}$, $\bar{y}$ are the centroids of the boundary.
The Hu moments, a set of seven invariant moments, are often computed from central moments. These moments are invariant to translation, scale, and rotation, making them useful for shape recognition tasks.

2. Complex Coordinates:
The boundary of the shape is represented using complex numbers. For each point (x, y) on the boundary, it is converted into a complex coordinate z=x+iy, where 'i' is the imaginary unit. The boundary is represented as a series of complex numbers, and by using Fourier Transform or similar methods, features can be extracted that capture shape characteristics.

1.Curvature Scale Space (CSS)
Curvature Scale Space is based on the curvature of the boundary of the shape at different scales. The boundary is first smoothed to different levels (scale space), and curvature values are computed at each scale.

Process:
1.Compute the boundary of the shape.
2.Smooth the boundary at different scales to create a series of images.
3.Calculate the curvature at each scale. Curvature can be computed as:

$$\kappa = \frac{d^2y}{dx^2} \Big/ \left(1 + \left(\frac{dy}{dx}\right)^2\right)^{3/2}$$

4.Track the changes in curvature across different scales and extract the most significant curvature features.
This method effectively captures details such as corners or sharp turns, which are invariant to translation, rotation, and scaling.

INTERSECTION POINT MAP

In this approach, predefined geometric primitives (like lines, circles, or other shapes) are used to probe the boundary of the target shape. The shape is analyzed to find intersection points between the boundary and these primitives.
The points of intersection are then used as features for shape representation.

Process:
1.Define a set of geometric primitives (e.g., lines, circles).
2.For each primitive, compute the intersection points with the shape's boundary.
3.Store these points as feature vectors or maps.

The method works well for shapes that can be well-approximated or decomposed into simple geometric primitives.

5. Merging Methods

Merging methods combine features from multiple extraction techniques (e.g., boundary moments, wavelet transforms, curvature analysis) to create a more robust shape feature representation. This can be done by concatenating the extracted features from different methods, or by using more sophisticated techniques like feature fusion or ensemble learning to merge the features effectively.

Process:

1. Extract features using multiple techniques (e.g., boundary moments, curvature scale space, wavelet transform).
2. Combine these features into a single feature vector (via concatenation, averaging, or more complex fusion methods).
3. Use the combined feature vector for shape recognition or comparison.

Table 1 : Comparison of different proposed methods with their strength, weaknesses and applications

Method	Strengths	Weaknesses	Applications
Boundary Moments	Simple, rotational invariance, effective for global features	Sensitive to noise, limited for complex shapes	Shape recognition, classification
Complex Coordinates	Compact, rotation and scale invariant	Complex to implement, less effective for irregular shapes	Shape classification, pattern recognition
Curvature Scale Space	Captures shape details at multiple scales, invariant	Computationally expensive, sensitive to noise	Object recognition, shape matching
Intersection Point Map	Captures geometric intersections, invariant	Sensitive to choice of primitives, not for irregular shapes	Geometric analysis, object recognition
Merging Methods	Combines multiple features for robustness	Computationally expensive, prone to overfitting	Complex shape recognition, classification

IMPLEMENTATION

This section of the paper outlines the implementation of various basic shape feature extraction methods, including boundary moments, complex coordinates, curvature scale space, intersection point map, and merging methods. The methods were implemented using the Python programming language, utilizing various Python libraries to generate the results. The implementation was carried out on a laptop equipped with an Intel i3 processor and 12GB of RAM. The evaluation metrics considered for these methods include precision, accuracy, F1-score, and support. The dataset comprises over 1,000 images, categorized into different groups such as beaches, buses, dinosaurs, elements, flowers, foods, horses, monuments, mountains and snow, and people and villages in Africa. The dataset was divided into two subsets: a training dataset, used to train the model, and a testing dataset, used to evaluate the model. The dataset employed for this study is the Corel dataset, sourced from the Kaggle website [26].

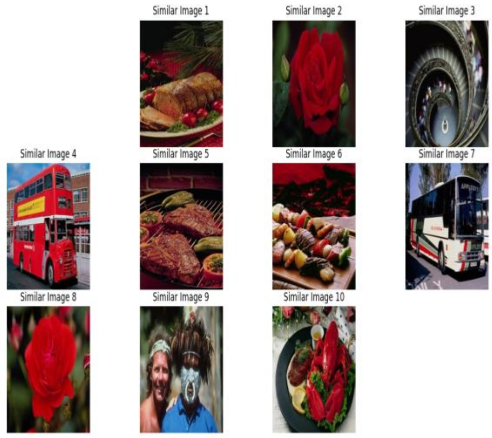
RESULTS AND DISCUSSIONS

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.

Table 2: Different shape features Classification report and their top 10 ranked images

	precision	recall	f1-score	support
beaches	0.00	0.00	0.00	23
bus	0.11	0.67	0.19	12
dinosaurs	0.18	1.00	0.30	19
elephant	0.00	0.00	0.00	19
flowers	0.00	0.00	0.00	21
foods	0.00	0.00	0.00	20
horses	0.00	0.00	0.00	17
monuments	0.00	0.00	0.00	14
mountains and snow	0.00	0.00	0.00	20
peolpe_and_villages_in_africa	0.00	0.00	0.00	15
accuracy			0.15	180
macro avg	0.03	0.17	0.05	180
weighted avg	0.03	0.15	0.04	180

Boundary moments classification report



Boundary moments top 10 ranked images

	precision	recall	f1-score	support
beaches	0.00	0.00	0.00	23
bus	0.07	1.00	0.12	12
dinosaurs	0.00	0.00	0.00	19
elephant	0.00	0.00	0.00	19
flowers	0.00	0.00	0.00	21
foods	0.00	0.00	0.00	20
horses	0.00	0.00	0.00	17
monuments	0.00	0.00	0.00	14
mountains and snow	0.00	0.00	0.00	20
peolpe_and_villages_in_africa	0.00	0.00	0.00	15
accuracy			0.07	180
macro avg	0.01	0.10	0.01	180
weighted avg	0.00	0.07	0.01	180

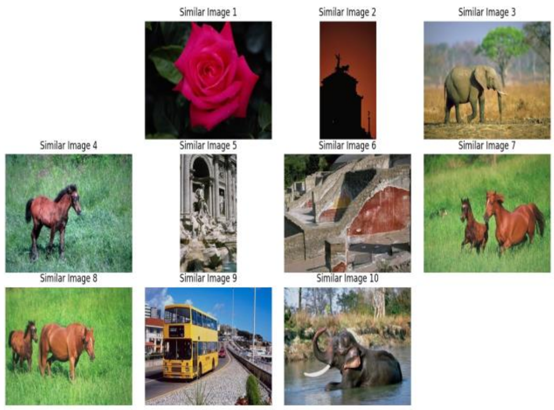
Complex coordinates classification report

Complex coordinates top 10 ranked images

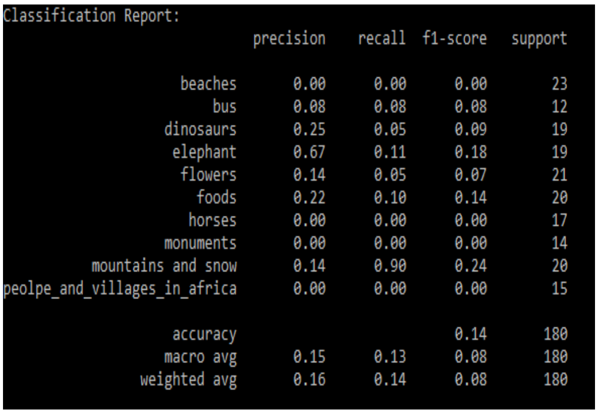
Classification Report:

	precision	recall	f1-score	support
beaches	0.39	0.30	0.34	23
bus	0.11	0.17	0.13	12
dinosaurs	0.95	0.95	0.95	19
elephant	0.31	0.21	0.25	19
flowers	0.22	0.19	0.21	21
foods	0.18	0.20	0.19	20
horses	0.40	0.47	0.43	17
monuments	0.18	0.21	0.19	14
mountains and snow	0.21	0.20	0.21	20
peolpe_and_villages_in_africa	0.00	0.00	0.00	15
accuracy			0.30	180
macro avg	0.29	0.29	0.29	180
weighted avg	0.31	0.30	0.30	180

Curvature scale space classification report



Curvature scale space top 10 ranked images

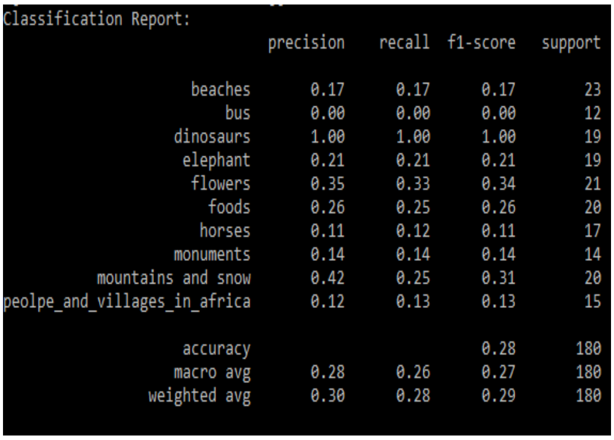


Classification Report:

	precision	recall	f1-score	support
beaches	0.00	0.00	0.00	23
bus	0.08	0.08	0.08	12
dinosaurs	0.25	0.05	0.09	19
elephant	0.67	0.11	0.18	19
flowers	0.14	0.05	0.07	21
foods	0.22	0.10	0.14	20
horses	0.00	0.00	0.00	17
monuments	0.00	0.00	0.00	14
mountains and snow	0.14	0.90	0.24	20
peolpe_and_villages_in_africa	0.00	0.00	0.00	15
accuracy			0.14	180
macro avg	0.15	0.13	0.08	180
weighted avg	0.16	0.14	0.08	180

Intersection point map classification report

Intersection point map top 10 ranked images



Classification Report:

	precision	recall	f1-score	support
beaches	0.17	0.17	0.17	23
bus	0.00	0.00	0.00	12
dinosaurs	1.00	1.00	1.00	19
elephant	0.21	0.21	0.21	19
flowers	0.35	0.33	0.34	21
foods	0.26	0.25	0.26	20
horses	0.11	0.12	0.11	17
monuments	0.14	0.14	0.14	14
mountains and snow	0.42	0.25	0.31	20
peolpe_and_villages_in_africa	0.12	0.13	0.13	15
accuracy			0.28	180
macro avg	0.28	0.26	0.27	180
weighted avg	0.30	0.28	0.29	180

Merging methods classification report

Merging methods top 10 ranked images

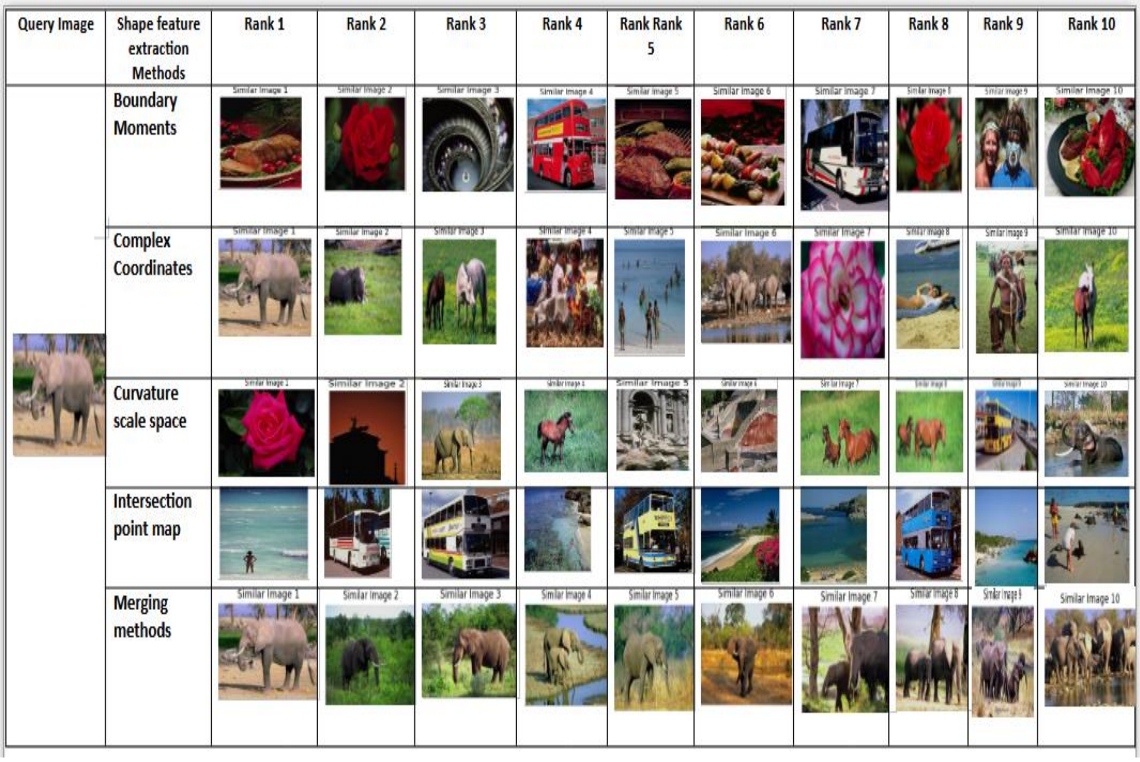


Figure: 2 Top 10 ranked images from database based on different shape feature extraction methods

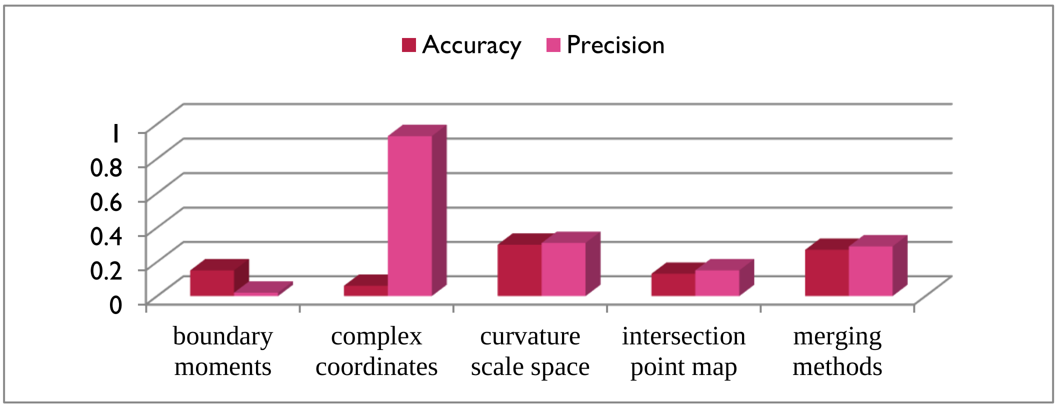


Figure 3: Bar chart for Comparison of different shape feature methods

The Figure 3 bar chart compares the accuracy (blue bars) and precision (red bars) of five shape feature extraction methods using SVM model:

a. Boundary Moments: Accuracy is relatively low, indicating this method struggles with correctly identifying shapes. Precision is also low, suggesting it has difficulty targeting specific relevant matches among the retrieved results.
b. Complex Coordinates: Achieves exceptionally high precision, nearing 1, indicating it performs well in retrieving highly relevant matches. However, its accuracy is low, suggesting it misses several correct results and might not generalize well.
c. Curvature Scale Space: Shows a balanced performance with moderate values for both accuracy and precision. This indicates it performs reasonably well in both identifying and retrieving relevant shapes.
d. Intersection Point Map: Both accuracy and precision are low, reflecting poor performance in both identifying and retrieving shapes effectively.
e. Merging Methods: Achieves relatively high values for both accuracy and precision, suggesting this method is robust and reliable for shape feature extraction, offering a balance between identifying correct shapes and retrieving relevant results.

CONCLUSION

The authors evaluates various shape feature extraction methods based on their accuracy and precision for image ranking using Content-Based Image Retrieval (CBIR) techniques. The analysis reveals significant differences in performance among the methods. While each method has its strengths and weaknesses, Merging Methods are the most effective overall, followed by Curvature Scale Space for balanced performance. Methods like Complex Coordinates are highly precise but require enhancements to improve accuracy. This analysis highlights the need for selecting appropriate methods based on specific application requirements in CBIR systems.

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