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Image Ranking based on Color Feature Extraction from Images using Different Content Based Image Retrieval Techniques

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Abstract: The content-based image retrieval (CBIR) technology enables users to find relevant images based on their content. A trustworthy content-based feature extraction approach is necessary to successfully extract the most of the information from the images. The important feature of a image include texture, color, intensity, shape and object form. This research paper examines the efficiency of color feature extraction from images using CBIR algorithms like 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. Retrieving and Ranking the images based on most similar images from the image database. And also classify the images from database using classification algorithm.

Keywords*:* content-based image retrieval (CBIR), Color Monument (CM), Color moment invariant model (CMI), mpeg7 dominant color descriptor and integrated color and texture features techniques.

INTRODUCTION: For more than a decade Content Based Image Retrieval is topic of interest for researcher. The three primitive visual features, namely, color, texture and shape refers to the term ‘content’ in content based image retrieval (CBIR). In recent decades, researchers have focused on content-based image retrieval due to inherent constraints in digital images. A CBIR system is required to effectively utilize information from image repositories. CBIR focuses on analyzing visual attributes such as color, shape, and texture rather than metadata like keywords, tags, and descriptions. The idea is to obtain relevant images based on their visual features and semantic value. The working procedure for CBIR techniques involves the following steps as shown in figure Fig 1: Block diagram of content – based image retrieval system.

Step1: Image database: This step is the repository of images which contains the collection of images with their metadata information such as file name, size and time stamp annotations and other information.

Steps2: Feature extraction: this step is the collection of features based on color feature extraction techniques like color moments and others.

Step3: Feature Representation: Once the features are extracted they are represented in suitable format by either normalizing or transforming them in to more compact formats.

Step4: Indexing: Feature representation for the images are indexed for efficient retrieval by using various indexing techniques so that efficient images may be well organized and searched in the search space efficiently.

Step5: Query Interface: when a user interacts with the CBIR system through a query interface, where they input queries in the form of images or textual descriptions.

Step6: Query Processing: The query image also undergoes the same feature extraction and representation process as the images in the database.

Step7: Similarity Measurement: In this step the similarity between the query image and the database image is calculated based on the extracted features of the database and query image. This similarity measurement can be done by using any of the distance metric such as Euclidean distance, cosine distance and other metrics.

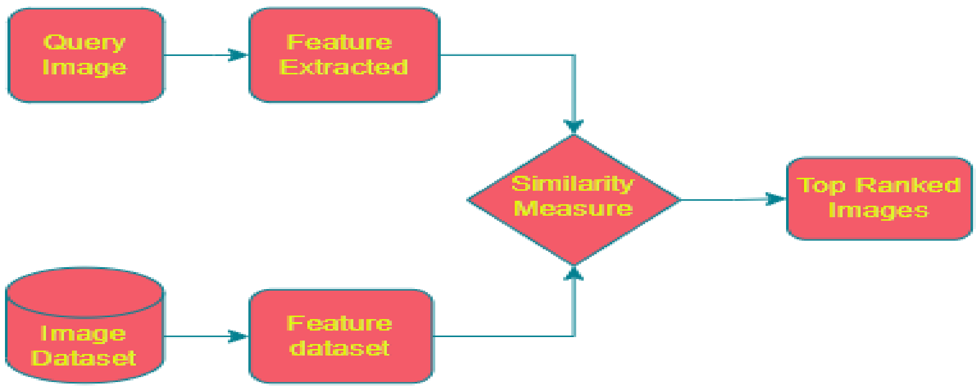

Fig1: Block diagram of content –based image retrieval system.

Objectives: 1.To classify the images in the dataset
2. Retrieve the images with similar features
3. Rank the retrieved images based on their similarity measure
4. Comparison of different algorithms used for ranking the images.
5. Provide the performance evaluation of the color based feature extraction techniques.

2. RELATED WORK:

Content-Based Image Retrieval (CBIR) is a critical area in computer vision, leveraging various techniques like color, texture, and shape for image search and matching. The following literature survey reviews several key contributions in CBIR, focusing on methodologies, advancements, and applications.

M. J. Swain and D. H. Ballard's color indexing method is a foundational study in content-based image retrieval (CBIR) [1]. Their work influenced subsequent works, including those in "Readings in Multimedia Computing and Networking" in 2002[2]. Stricker and Orengo's 1995 paper "Similarity of Color Images" introduced color moments, a more efficient representation of color information[3]. These advancements influenced the development of more sophisticated CBIR systems that integrate color with other visual features. Their contributions have shaped the evolution of image retrieval systems, leading to more advanced approaches that combine color with other visual features.

The author N. Keen 's study introduces color moments as a compact representation for color information in images, enabling efficient image indexing and retrieval. Three moments (mean, variance, and skewness) are calculated for each color channel, providing a robust method for color similarity comparison [4].

Shih and Chen expand on the basic concept of color moments by proposing an image retrieval system that uses **primitives of color moments**. This approach segments the image into regions and calculates color moments for each region, improving retrieval precision by incorporating spatial information. The method addresses some of the limitations of global color features, providing a more detailed representation [5].

J. Binisha Rose and N. Santhi 's study introduced a **Support Vector Machine (SVM)-based classifier** for CBIR that integrates multiple features such as color, texture, and shape. By employing a machine learning approach, the system enhances retrieval accuracy by training the SVM to recognize feature patterns across diverse image sets. The multi-feature approach compensates for the shortcomings of relying on a single feature type, leading to better retrieval results [6].

Velmurugan and Baboo[7] propose a CBIR system combining **Speeded-Up Robust Features (SURF)** with color moments. SURF, a fast and robust feature detector, is used to extract key points and descriptors, while color moments capture the color content. This hybrid method provides both **local feature** detection and **global color distribution** analysis, offering improved retrieval performance, particularly in images with rich textures and complex color patterns.

Justiawan et al [8]explores the application of **color moments** for a medical application—teeth recognition. The authors conduct a comparative analysis to determine how color moments perform in identifying different shades of teeth. This study demonstrates the utility of color-based image retrieval in specialized domains like healthcare, where precision in color differentiation is critical for diagnosis and treatment planning.Varma and Kaur[9] provide a comprehensive **survey of CBIR techniques**, focusing on the evolution of algorithms over the years. They categorize methods based on features (color, texture, shape) and highlight the transition from simple hand-crafted features to **machine learning-based methods**. The survey serves as a foundational reference for understanding the historical context and progress in CBIR. Dharani and Aroquiaraj[10] provide an overview of **CBIR algorithms**, focusing on the early methodologies that used low-level features like color histograms, texture, and shape. They discuss the transition towards **hybrid and machine learning-based approaches**, highlighting challenges and potential research directions in the field.***.W. Chen et al.,*** recent survey investigates the use of **deep learning for instance retrieval**, highlighting the success of convolutional neural networks (CNNs) in learning rich image representations. The paper covers different architectures and techniques for instance-based retrieval tasks, including object detection and semantic similarity search, showing how deep learning outperforms traditional methods in this area[11].

Hamad et al. propose a multi-feature-based CBIR system using **texture, color, and shape** along with regional segmentation. Their approach divides the image into meaningful segments and extracts features from each region, providing a more detailed analysis than global feature methods. This results in more accurate retrieval for complex images[12].

In this paper[13] The author D. Sun, X. Zhao, and J. Kan evaluates the performance of various color descriptors in CBIR systems under conditions of illumination variation their study acknowledges that changes in lighting can significantly impact the effectiveness of color-based retrieval systems. They tested several color descriptors, including traditional ones like color moments and more advanced models, to see how robust they are when illumination varies across images and their finding showed that no single descriptor performed best across all lighting

In this paper [14] The author M. Subramanian and etl., presents a comprehensive CBIR system that integrates **color, gray-scale, texture, and shape features** to enhance retrieval accuracy. It uses a **Random Forest Classifier** combined with **Particle Swarm Optimization (PSO)** to optimize the retrieval process. The system aims to improve the precision of CBIR by including a diverse set of image descriptors and applying machine learning techniques for classification. The authors concluded that their CBIR systems performance is better when compared with the traditional CBIR systems.

In this paper[15] authors D. Yuvaraj, M. Sivaram & etl., focuses on a CBIR system that integrates **shape(edge detection technique), color(color moments), and texture(gray level co-ocurrence MatrixGLCM))** features using a **fuzzy logic classifier**. The fuzzy logic approach is designed to handle uncertainty and improve classification accuracy by considering overlapping regions in the feature space, which is common in real-world images.

In this paper [16]the authors J. Jumi, A. Zaenuddin, and T. Mulyono ‘s investigates the performance of **shape(edge and geometric properties), color(histogram), and texture(local Binary Patterns(LBP))** features in the context of **face recognition** within

CBIR systems. It specifically examines how different feature types contribute to effective tracking and retrieval of facial information. Their study systematically analyzed the effectiveness of each feature type in face retrieval tasks, concluding that combining these features leads to improved performance, especially in facial recognition scenarios.

In this paper [17] authors V. P. Singh and R. Srivastava introduces **color-invariant moments**, an advanced feature extraction technique designed to enhance retrieval performance in CBIR systems. Traditional color moments are sensitive to changes in lighting conditions and camera settings, but color-invariant moments aim to mitigate these effects by creating a more robust representation of image color. Their experimental results showed that color-invariant moments significantly improved retrieval accuracy compared to traditional moments, especially in environments with varying illumination.

In this paper [18] Mihalik and Gladisova's 2020 paper explores the use of **vector quantization (VQ)** for developing **color content descriptors** in CBIR systems. Color content descriptors are crucial for accurately indexing and retrieving images based on their color composition. The authors propose a VQ-based approach for creating compact and efficient color descriptors that can represent the color information in an image while reducing data complexity. The results showed that VQ-based color descriptors are effective for **image retrieval** tasks, achieving a balance between performance and computational efficiency, making them suitable for large image databases. There are some application where this various color feature (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 are used. A few examples include developing color blindness test photos, drones and machine vision for landscapes, image restoration, and many more.

In this paper [19] Wibawa's 2017 paper presents a novel approach to creating **color blindness test images** using **vector quantization (VQ)** techniques. Vector quantization is a method of image compression that involves partitioning the color space into distinct regions (quantization), reducing the number of colors used to represent the image. The primary goal of this study was to design test images specifically for color blindness detection that would be easily distinguishable even by those with color vision deficiencies. Their study uses **VQ** to compress and simplify the color space in images, making it easier for individuals with color blindness to identify certain patterns. The approach ensures that the color distribution in the test images is optimized for distinguishing colors that are problematic for color-blind individuals, such as red-green and blue-yellow deficiencies. This method contributes to more effective and visually accessible color blindness tests, potentially improving diagnostic accuracy.

This paper [20] *P. Li and J. Khan,* focuses on utilizing **drones** and **machine vision** for landscape imaging and feature extraction. The authors propose a methodology for analyzing landscape features, such as terrain and vegetation, using aerial imagery captured by drones. **Machine learning algorithms** are applied to extract relevant features from these images, which are then analyzed for various applications like environmental monitoring and agricultural assessment.

In this paper[21] authors *C. K. M. Malik* introduced a **clustering-based method** for **content-based image retrieval (CBIR)**. That uses clustering algorithms like **k-means** to group similar images based on their features, such as color, texture, and shape. These clustering approach improves retrieval speed and accuracy by grouping similar images together, making it easier to find relevant images in large databases.

This paper [22] author *Y. Salehi, K. Zhou, B. Huang, and X. Zhang,* discusses an **image restoration** and analysis technique designed for predicting quality variables in industrial processes, specifically the **flotation process** in mineral processing. The authors employ image processing and **machine learning models** to restore and analyze images of the flotation process, which are used to predict key quality variables such as mineral grade and recovery rates.

This paper [23] *K. Li, H. Xuemin* & et al, focuses on predicting **eye fixation** in images using multiple attention mechanisms. Eye fixation prediction models aim to estimate where humans are likely to focus their gaze when looking at an image. The authors propose a **neural network model** that integrates multiple attention mechanisms to improve the accuracy of fixation prediction.

In this paper[24] author Shukran, M.A.M & et al., gives the comparison of various CBIR techniques based on color, shape, text and hybrid techniques. The parameters considered are precision, recall and response time and concluded that the CBIR technique with color feature is the fastest algorithm in terms of response time.

3: COMPARISON OF DIFFERENT BASIC METHODS OF COLOR FEATURE EXTRACTION

This section of paper presents the comparison of different color based feature extraction Content based image retrieval system with their descriotion, Main Component, advantages, disadvantages, applications, performance in retrival task and computational complexcity.

Table1: Comparison of different basic methods of color Feature Extraction

Feature	Color Moments (CM)	Color Moment Invariant Model (CMI)	Dominant Color-Based Vector Quantizatio n (DCVQ)	MPEG-7 Dominant Color Descriptor	Integrated Color and Texture Features
Description	Statistical measures of color distribution (mean, variance, skewness).	Extension of color moments with invariance to transformation s.	Quantization of dominant colors into a compact representatio n.	Describes dominant colors and their spatial distribution in an image.	Combines color features with texture descriptors for enhanced retrieval accuracy.
Main Components	Mean, variance, and skewness of color channels.	Invariant color moments against transformation s.	Dominant colors extracted and quantized for efficient representatio n.	Dominant color features encoded with spatial layout information .	Color features (e.g., moments, histograms) combined with texture features (e.g., Gabor, LBP).
Advantages	Simple, efficient, low-dimensional .	Robust to scaling, rotation, and translation.	Compact representatio n, efficient for large databases.	Well-defined standard, robust for practical applications .	More comprehensiv e image representatio n, better retrieval performance in complex datasets.

Disadvantages	Not invariant to transformations, may miss detailed color patterns.	Complexity in calculation, requires invariant transformations.	May lose detail on color distribution, relies on accurate dominant color extraction.	Standardized but may not capture all color variations effectively.	Increased computational complexity, may require more processing power and storage.
Applications	Image retrieval, object recognition.	Image retrieval, object recognition, where invariance is critical.	Real-time applications, such as video indexing and retrieval.	Content-based image retrieval, multimedia analysis.	Advanced image retrieval, scene understanding, and multimedia analysis.
Performance in Retrieval Tasks	Good for color-based retrieval but limited by lack of invariance.	Better performance in varied conditions due to invariance properties.	Effective in databases with dominant color emphasis but less detailed.	Reliable for standard color retrieval tasks, good for multimedia applications.	Enhanced performance in diverse scenarios by leveraging both color and texture information.
Computational Complexity	Low	Moderate	Low	Moderate	High

4. IMPLEMENTATION

This section of paper describes about the implementation of different color feature extraction algorithms like Color Monument, Color moment invariant model, Dominant Color-Based Vector Quantization (DCVQ), mpeg7 dominant color descriptor and integrated color and texture features algorithms. The software and hardware requirements for the implementation of this algorithm are as follows. The software used to for implementing these algorithms is by using python programming language where different library of python are used to generate the results. The hardware configuration for implementation of algorithms is carried out on laptop with i3 Intel Processor with 12GB RAM. The main evaluation parameter considered for this algorithms are Precision, accuracy, f1-score and support. The dataset consists of more than 1000 images and these images are classified as different groups like beaches, bus, dinosaurs, elements, flowers, foods, horses, monuments, mountains_and_snow and people_and_villages in Africa. These dataset images are divided into two groups as training and testing dataset of images. The training dataset are used to train the model and the testing model is used to the model. The Support Vector Machine (SVM) model developed for generating the results. The dataset used for this model is corel dataset from Kaggle website [25].

5. RESULTS AND DISCUSSIONS: This section presents the screenshots of the output after executing the different color feature extraction algorithm with their classification report.

The output screen shot of algorithms contains the query input image along with the other output images which are similar images extracted from the database. The extracted images after the execution of implemented algorithms are names as similar images with numbering from 1 to 5 (as similar image1, similar image 2, similar image3, similar images 4 and similar image 5.) This is the images which are considered as image ranks. Here only top 5 similar images are considered for similar matching and ranking the images. The following are the different types of basic color feature extraction algorithms with their classification report.
The provided figure fig: 2 below is a classification report generated by a machine learning model. It includes various performance metrics such as precision, recall, f1-score, and support for each class, as well as overall accuracy, macro average, and weighted average metrics. Here is an explanation of each component in the classification report:

Precision: Precision is the ratio of correctly predicted positive observations to the total predicted positives. It indicates how many of the predicted positive instances were actually positive.
Precision = (True Positive) / (True Positives + False Negatives)
Recall: Recall is the ratio of correctly predicted positive observations to the all observations in the actual class. It indicates how many of the actual positive instances were correctly predicted.
Recall = True Positives / True Positives + False Negatives
F1-Score: The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both concerns.
F1-Score = 2* (Precision*Recall)/(Precision + Recall)
Support: Support is the number of actual occurrences of the class in the dataset. It shows how many instances there are for each class.

5.1 Model-1 Color Moments invariant algorithm:
The figure fig2 overall metrics of Color Moments gives the performance of the Color Moments invariant algorithm for the classification of images in the dataset with their accuracy, precision, recall and F-1 Score. This figure with overall accuracy indicates that 76% of the total predictions were correct. The macro average(Precision: 0.76,Recall: 0.76,F1-Score: 0.75) is the unweighted mean of the precision, recall, and F1-score. The weighted average takes into account the support (number of true instances) of each class to calculate the average precision, recall, and f1-score (Precision: 0.78, Recall: 0.76, F1-Score: 0.76 and Accuracy: 0.76).
The Classes like "dinosaurs" and "horses" have high precision and recall, indicating that the model is very accurate for these classes and the Classes like "beaches" and "foods" have lower precision or recall, suggesting that the model may struggle more with correctly predicting these classes. The overall accuracy of 76% and balanced precision, recall, and f1-scores in the macro and weighted averages suggest that the model performs reasonably well across most classes.

Fig2: Screenshot of top 5 similar images from people_and _villages in_Africa and flowers for query image based on Color moment invariant Algorithm,

b) Dominant color-based vector quantization,

c) Integrated color and texture features

d) MPEG-7 dominant color descriptor, Algorithm

Fig3: Screenshot of top 5 similar images from people_and _villages in_Africa for query image based on b) Dominant color-based vector quantization, c) Integrated color and texture features, d) MPEG-7 dominant color descriptor, Algorithm

Classification Report:

	precision	recall	f1-score	support
beaches	0.86	0.52	0.65	23
bus	0.53	0.75	0.62	12
dinosaurs	1.00	1.00	1.00	19
elephant	0.71	0.89	0.79	19
flowers	0.80	0.95	0.87	21
foods	0.79	0.55	0.65	20
horses	0.94	0.94	0.94	17
monuments	0.56	0.64	0.60	14
mountains and snow	0.68	0.65	0.67	20
peolpe_and_villages_in_africa	0.73	0.73	0.73	15
accuracy			0.76	180
macro avg	0.76	0.76	0.75	180
weighted avg	0.78	0.76	0.76	180

a) Color Moment Invariant

Classification Report:

	precision	recall	f1-score	support
beaches	0.73	0.73	0.73	11
bus	0.50	0.43	0.46	7
dinosaurs	0.73	1.00	0.85	11
elephant	0.50	0.33	0.40	9
flowers	0.91	1.00	0.95	10
foods	0.86	0.55	0.67	11
horses	0.88	0.64	0.74	11
monuments	0.56	0.71	0.62	7
mountains and snow	0.67	0.57	0.62	7
peolpe_and_villages_in_africa	0.27	0.50	0.35	6
accuracy			0.67	90
macro avg	0.66	0.65	0.64	90
weighted avg	0.69	0.67	0.67	90

b) Dominant color-based vector quantization,

Classification Report:

	precision	recall	f1-score	support
beaches	0.87	0.57	0.68	23
bus	0.50	0.75	0.60	12
dinosaurs	1.00	1.00	1.00	19
elephant	0.71	0.89	0.79	19
flowers	0.80	0.95	0.87	21
foods	0.79	0.55	0.65	20
horses	0.94	0.94	0.94	17
monuments	0.56	0.64	0.60	14
mountains and snow	0.71	0.60	0.65	20
peolpe_and_villages_in_africa	0.73	0.73	0.73	15
accuracy			0.76	180
macro avg	0.76	0.76	0.75	180
weighted avg	0.78	0.76	0.76	180

c) Integrated color and texture features

Classification Report:

	precision	recall	f1-score	support
beaches	0.30	0.26	0.28	23
bus	0.43	0.50	0.46	12
dinosaurs	0.86	0.95	0.90	19
elephant	0.57	0.42	0.48	19
flowers	0.75	0.86	0.80	21
foods	0.65	0.65	0.65	20
horses	0.75	0.71	0.73	17
monuments	0.29	0.29	0.29	14
mountains and snow	0.46	0.55	0.50	20
peolpe_and_villages_in_africa	0.38	0.33	0.36	15
accuracy			0.56	180
macro avg	0.54	0.55	0.54	180
weighted avg	0.55	0.56	0.55	180

d) MPEG-7 dominant color descriptor. Algorithm

Fig4: Classification report with Overall Metrics with different color feature algorithms

5.2 Model-2 Dominant color-based vector quantization:

The figure fig3: a) above overall metrics of Dominant color-based vector quantization gives the performance of the Dominant color-based vector quantization algorithm for the classification of images in the dataset with their accuracy, precision, recall and F-1 Score. This figure with overall accuracy indicates that 66% of the total predictions were correct. The macro average (Precision: 0.66, Recall: 0.65, F1-Score: 0.64) is the unweighted mean of the precision, recall, and F1-score. The weighted average takes into account the support (number of true instances) of each class to calculate the average precision, recall, and f1-score (Precision: 0.69, Recall: 0.67, F1-Score: 0.67 and Accuracy: 0.66).

The Classes like "flowers" have high precision and "beaches" have high recall, indicating that the model is very accurate for these classes and the Classes like "Monuments" and "people_and_villages_in_africa" have lower precision or recall, suggesting that the model may struggle more with correctly predicting these classes. The overall accuracy of 76% and balanced precision, recall, and f1-scores in the macro and weighted averages suggest that the model performs reasonably well across most classes.

5.3: Model-3 Integrated color and texture features:

The figure fig 3: b) above overall metrics of integrated color and texture features gives the performance of the integrated color and texture features algorithm for the classification of images in the dataset with their accuracy, precision, recall and F-1 Score. This figure with overall accuracy indicates that 76% of the total predictions were correct. The macro average (Precision: 0.76, Recall: 0.76, F1-Score: 0.75) is the unweighted mean of the precision, recall, and F1-score. The weighted average takes into account the support (number of true instances) of each class to calculate the average precision, recall, and f1-score (Precision: 0.78, Recall: 0.76, F1-Score: 0.76 and Accuracy: 0.76).

The Classes like "flowers" and "horses" have high precision and recall, indicating that the model is very accurate for these classes and the Classes like "beaches" and "foods" have lower recall, suggesting that the model may struggle more with correctly predicting these classes. The overall accuracy of 76% and balanced precision, recall, and f1-scores in the macro and weighted averages suggest that the model performs reasonably well across most classes.

5.4: Model-3 MPEG-7 dominant color descriptor features:

The figure fig 3: c) above overall metrics of MPEG-7 dominant color descriptor gives the performance of the MPEG-7 dominant color descriptor algorithm for the classification of images in the dataset with their accuracy, precision, recall and F-1 Score. This figure with overall accuracy indicates that 56% of the total predictions were correct. The macro average (Precision: 0.54, Recall: 0.55, F1-Score: 0.54) is the unweighted mean of the precision, recall, and F1-score. The weighted average takes into account the support (number of true instances) of each class to calculate the average precision, recall, and f1-score (Precision: 0.55, Recall: 0.56, F1-Score: 0.55 and Accuracy: 0.56).

The Classes like "flowers" and "dinosaurs" have high precision and recall, indicating that the model is very accurate for these classes and the Classes like "beaches" and "monuments" have lower recall, suggesting that the model may struggle more with correctly predicting these classes. The overall accuracy of 56% and balanced precision, recall, and f1-scores in the macro and weighted averages suggest that the model does not perform well across most classes.

5.5 Comparison of Results:

Comparison of different algorithms with SVM model with their Accuracy and precision are shown in the table 2. The comparison is done by considering the SVM model which is common for all the methods. From the table it is clear that the Accuracy and Precision is 0.77 and 0.77 for color moment invariant and integrated color and texture feature methods respectively.

Table2: Comparison of different algorithms with SVM model with their Accuracy and precision

Algorithm	Model	Accuracy	Precision
Color moment invariant	SVM	0.76	0.77
Integrated color and texture features	SVM	0.76	0.77
Dominant color-based vector quantization	SVM	0.66	0.69
MPEG-7 dominant color descriptor	SVM	0.56	0.55

The Bar graph represents the pictural representation of the comparison of the CBIR color feature methods with their accuracy and precision.

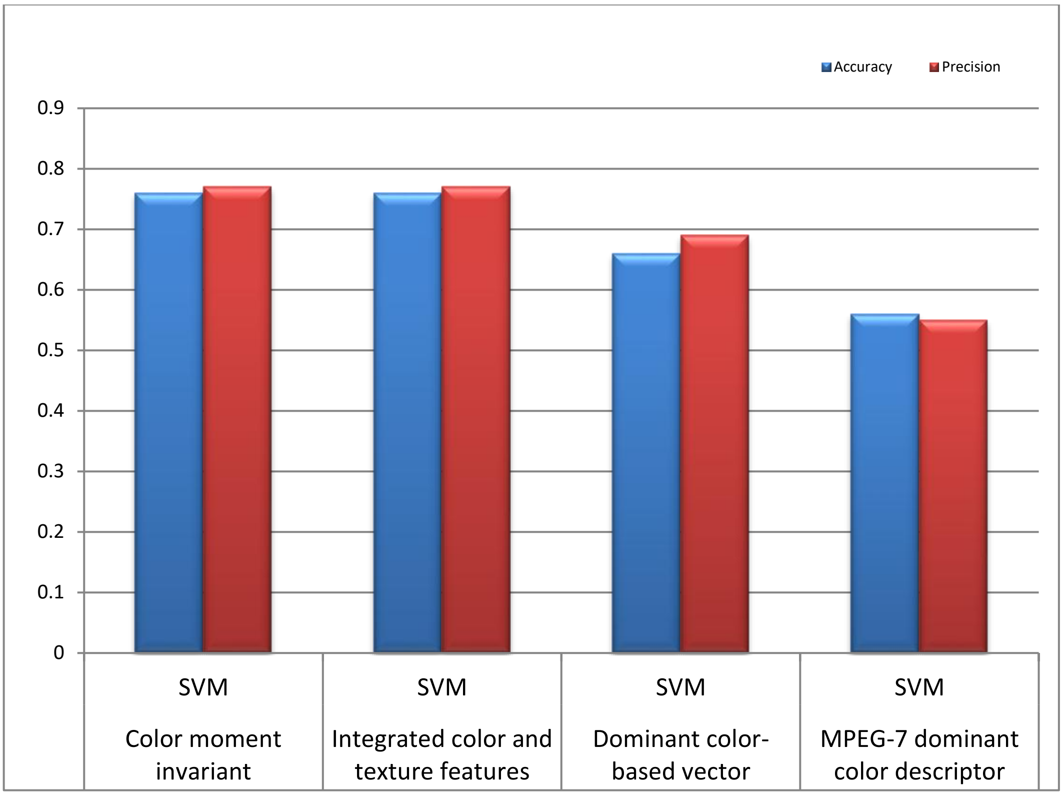

Fig5: Comparison of different algorithms with SVM model with their Accuracy and precision
Recommended models for CBIR on color features among the above methods are 1) Color moment invariant and 2) Integrated color and texture features as their precision and accuracy are more when compared to other two methods of Color feature extraction.

6. CONCLUSION: The CBIR techniques that are used in this paper find the most relevant images based on color feature content. The retrieved images are ranked based on the similarity between query image and retrieved image. The image with high similarity is ranked as the rank 1 image and with less similarity the next rank, this process continues for all the images. But in this paper we presented only the top 5 most similar images and ranked them from rank1 to rank 5. When the CBIR techniques are compared the performance of the integrated and color feature method gives the best performance when compared with other techniques.

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