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IMAGE RANKING BASED ON TEXTURE FEATURE USING CONTENT-BASED INFORMATION RETRIEVAL TECHNIQUES

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Abstract:

Now a day, extracting texture features from image are widely used techniques for image processing and computer vision. Texture feature are the characteristics of the texture that is present in an image. These features are used to identify the structures and patterns in an image that are not captured by some other traditional methods of feature extraction like color and shape. There are many methods for extracting the texture features from the image, but in this paper, an experimental analysis of texture feature extraction by using techniques like LDRP, SED, MSD and DWT are used. These features can be used for a variety of tasks, such as texture feature extraction, object recognition, image segmentation, and classification. The main ideation of the paper is to extract the texture features of images, and rank the images based on their similiarity score and evaluate the performance of algorithms. For obtaining these ranks the images with similar types of images are compared and most matching image are considered. For this process a comparative analysis of CBIR Texture feature techniques is carried out to show the most efficient techniques and most similar image. Ranking of images is done by comparing their texture features, the images with more similarity index is ranked first ,then next image with reducing similarity of texture feature is ranked next.

Keywords: DWT **(Discrete Wavelet Transform), SED (Statistical Edge Detection), MSD (Modified Scalable Descriptor) and LDRP (Local derivative radial patterns), SVM(Support Vector Machine),** Texture feature extraction, Similarity and Ranking.

1. Introduction

Content-Based Image Retrieval (CBIR) is a technique in image processing that enables the retrieval of images from a database based on their visual content rather than metadata or textual annotations. CBIR systems analyze features such as color, texture, shape, and spatial arrangements within images to identify similarities and rank results. This method has gained significant importance due to its ability to handle large datasets and deliver results that are more accurate than keyword-based search approaches. CBIR is widely used in applications like medical imaging, digital libraries, surveillance, and e-commerce, where automated, efficient image retrieval is critical. By leveraging advanced algorithms and feature extraction techniques, CBIR facilitates the comparison and ranking of images based on visual properties, enabling intuitive and precise searches. Content-Based Image Retrieval (CBIR) is a technique used to retrieve images from a database based on their visual content rather than textual metadata. The process involves multiple steps that allow the system to analyze, compare, and rank images based on their similarity to a query image. Here is an overview of the working mechanism of CBIR as shown in figure 1 : Block diagram of Content based image retrieval and ranking . In Content-Based Image Retrieval (CBIR), the first step involves extracting visual features from images. These features are numerical representations of the visual content and fall into categories like color features (histograms, color moments), texture features (GLCM, LBP, DWT), and shape features (edge detection algorithms). Features can be global (entire image) or local (specific regions of interest). Users can input an image to find similar images in the database. The

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query image undergoes feature extraction to create a feature vector. The feature vector of a query image is compared with feature vectors of images in a database using similarity or distance metrics like Euclidean Distance, Cosine Similarity, and Manhattan Distance. The images with feature vectors closest to the query image are deemed the most similar [1]. Once similarity scores are calculated for all images in the database, they are ranked based on their similarity to the query image.

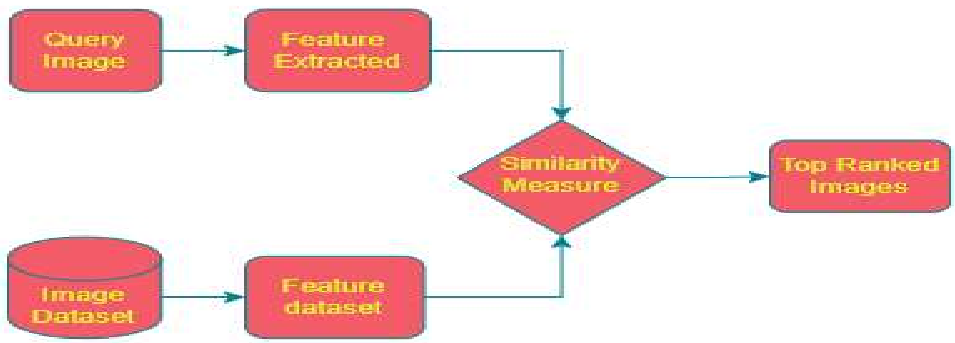

Figure 1: Block diagram of Content based image retrieval and ranking [1]

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This paper present the texture feature extraction and comparative analysis of various texture feature extraction techniques like DWT **(Discrete Wavelet Transform), SED (Statistical Edge Detection), MSD (Modified Scalable Descriptor) and LDRP (Local derivative radial patterns). Those** Texture analysis has been applied to various CBIR task it also gain its important in computer vision tasks where some important applications include: Image segmentation in which texture differences help identify objects or regions, even with unclear boundaries, such as in remote sensing applications. Object classification, using texture to infer physical or chemical properties, or diagnose diseases in medical images. Image and video compression, where texture aids in efficient and lossless compression. Content-based image retrieval, with texture descriptors enabling image searches without metadata.3D scene reconstruction, where texture helps infer 3D shapes from 2D images. Texture analysis is influenced by how human vision processes patterns, but formalizing it mathematically is challenging and context-specific [2]. **The below section describes about the related work carried by various authors.**

2. Literature review

The authors explore features in Computer-Based Image Retrieval (CBIR) systems like color, texture, and shape, as well as algorithms for feature extraction and evaluation metrics. Challenges include the semantic gap and scalability, with suggestions for future research like using machine learning and deep learning techniques to enhance accuracy.[3]

The paper by A. Humeau-Heurtier (2019) reviews techniques for texture feature extraction in images. It discusses effective methods, their strengths and weaknesses, and highlights the evolution and applications of texture analysis [4]

The authors Jacob et al.'s presents an innovative approach to chromatic texture analysis through the

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development of a deep learned inter-channel colored texture pattern descriptor. By leveraging deep learning techniques and focusing on the inter-channel relationships in color images, the study aims to enhance the extraction and representation of texture features. The findings suggest that this novel descriptor can improve the accuracy of texture classification tasks, contributing to advancements in image processing and computer vision applications [5].

The author's Ansari, Ghrera, and Mishra's introduces the Intuitionistic Fuzzy Local Binary Pattern (IF-LBP), an enhancement to traditional LBP for texture feature extraction. It addresses limitations of standard LBP, improving classification accuracy and contributing to the advancement of texture feature extraction techniques [6].

The paper by K. Robert Singh and S. Chaudhury (2020) provide a comprehensive comparative analysis of texture feature extraction techniques for rice grain classification, evaluating methods such as GLCM, LBP, Gabor filters, and wavelet transforms. Their systematic investigation reveals the performance of each technique in accurately classifying different rice grains, contributing valuable insights for agricultural applications and enhancing automated sorting and grading processes. The study underscores the significance of selecting appropriate texture analysis methods to improve classification outcomes in real-world scenarios[7].

The author Ammatmanee and Gan's 2021 study reviews content-based image retrieval (CBIR) research in the tourism industry over a decade. It evaluates its application, trends, and developments, focusing on information retrieval, customer engagement, and destination marketing. The study suggests combining CBIR with AR or VR for enhanced user experience and interdisciplinary approaches for future innovations [8].

Barburiceanu et al.'s study introduces a 3D texture feature extraction and classification method using GLCM and LBP-based descriptors, enhancing performance in distinguishing textures and contributing to 3D image analysis applications [9].

The author Jumi et al.'s study explores the role of shape, color, and texture features in facial recognition systems. It highlights the importance of a multi-feature approach for improved retrieval accuracy, By comparing the effectiveness of individual feature extraction methods and their combinations, gave importance of a multi-feature approach in enhancing retrieval accuracy where it is providing insights for future research [10].

The author's Barburiceanu et al.'s study uses Convolutional Neural Networks for texture feature extraction in precision agriculture, enhancing disease detection through hierarchical feature learning and transfer learning techniques, thereby enhancing crop management and disease intervention strategies [11].

The author's Venkatesvara Rao et al. presents a novel approach to real-time video object detection and classification using hybrid texture feature extraction methods. By combining various texture analysis techniques and implementing efficient detection and classification algorithms, the study aims to enhance the capabilities of video analysis systems. The findings suggest that hybrid feature extraction can significantly improve the accuracy and efficiency of object detection tasks, contributing to advancements in computer vision and its applications in real-time scenarios [12].

The author's Keyvanpour et al. provide an extensive review of texture feature extraction approaches, analyzing their methodologies, strengths, and weaknesses. By categorizing these techniques and discussing performance evaluation criteria. Texture analysis is crucial in applications like computer vision, medical imaging, and remote sensing. Techniques for extracting texture features include statistical methods, structural methods, spectral methods, model-based methods, and deep learning approaches. Performance evaluation criteria include

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accuracy, computational efficiency, and robustness to noise and lighting conditions. Current trends include the adoption of deep learning techniques for automated feature learning, but challenges include real-time processing, handling complex textures, and integrating texture features with other features. Future research should focus on hybrid approaches, unsupervised learning techniques, and robust methods to handle texture variations [13].

The authors suggest further research into hybrid models combining deep learning with traditional CBIR techniques, which could balance computational efficiency and retrieval accuracy. They also mention the potential of reinforcement learning and unsupervised learning to advance CBIR systems by reducing dependency on labeled data. This paper offers a comprehensive overview of CBIR, analyzing both technological progress and ongoing challenges, and suggests that hybrid approaches and more sophisticated machine learning techniques hold promise for future CBIR systems [14].

The paper "Content-Based Image Retrieval (CBIR): A Review" by D. Agrawal, A. Agarwal, and D. K. Sharma (2022) discusses key algorithms and techniques used in content-based image retrieval (CBIR). The authors highlight color-based techniques like color histograms, color moments, and color correlograms, which categorize images based on dominant colors. Texture-based techniques like GLCM, Gabor Filters, and Wavelet Transform capture repetitive patterns, providing detailed information on surface characteristics. Shape-based techniques like Fourier Descriptors and Edge Detection analyze object outlines or contours, making them suitable for object recognition tasks. Local feature descriptors like Scale-Invariant Feature Transform and Speeded Up Robust Features enable robust matching across different images. Machine learning algorithms like Support Vector Machines and K-Nearest Neighbors classify images based on extracted features, improving retrieval accuracy. Recent deep learning advancements, such as Convolutional Neural Networks, have transformed CBIR by providing more discriminative and detailed feature representations. Hybrid approaches combining traditional and deep learning methods offer a promising path forward for improving CBIR accuracy and robustness across diverse applications [15].

The author’s C. K. M. Malik's 2022 paper, "Content-Based Image Retrieval Using Clustering Method," presents a clustering-based approach to improve content-based image retrieval (CBIR) systems. The study uses K-Means clustering, a primary algorithm for organizing images based on visual features, to reduce retrieval time and enhance accuracy. Hierarchical Clustering is explored as an alternative, iteratively grouping images based on feature similarity. Feature extraction techniques, such as color histograms and Gabor filters, are employed to represent each image as a feature vector. Cluster-based indexing allows CBIR systems to quickly retrieve relevant images by limiting search space to specific clusters matching the query image's features. The combination of feature extraction and cluster-based indexing enhances CBIR performance, making it a valuable approach for large-scale image datasets [16].

The study by Subramanian et al. (2022) presents a comprehensive approach to content-based image retrieval (CBIR) that integrates multiple feature extraction techniques and employs an optimized classifier. The authors use color histograms to capture color distribution, Gray Level Co-occurrence Matrix (GLCM) to extract gray-level features, and advanced texture descriptors like Gabor filters and Local Binary Patterns (LBP) to capture complex textural patterns. Shape features are characterized using contour analysis and Fourier Descriptors. A Random Forest classifier is used to classify images based on the extracted features. Particle Swarm Optimization

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(PSO) is applied to optimize feature selection, focusing on the most informative features. The performance of the proposed CBIR system is evaluated using metrics such as accuracy, precision, recall, and F1-score [17].

The authors T. W. Harjanti et al.'s 2022 paper, "Classification of Mint Leaf Types Based on the Image Using Euclidean Distance and K-Means Clustering with Shape and Texture Feature Extraction," focuses on developing a method for classifying different types of mint leaves using image processing techniques. The study uses shape and texture features, such as area, perimeter, and aspect ratio, to differentiate leaf types based on their structural characteristics. The authors then use the K-Means clustering algorithm to group the extracted features into clusters representing different mint leaf types. The authors also use Euclidean distance as a distance metric to measure similarity between feature vectors. The study aims to improve the accuracy of mint leaf classification, contributing to agricultural research and plant identification [18].

The authors J. Li's and et, als., 2022 paper, "Research on Image Texture Feature Extraction Based on Digital Twin," explores the use of digital twin technology in image texture feature extraction. The digital twin framework, a digital replica of physical entities, is used to model the characteristics of objects in the real world, enabling a comprehensive analysis of their texture features. The paper discusses methods for extracting texture features from images captured by the digital twin, including techniques like Gray Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), and Gabor Filters. The digital twin can enhance traditional image processing techniques by providing contextual information about the object being analyzed, enabling dynamic updates and adjustments in the feature extraction process. The findings suggest potential applications in fields like manufacturing, quality control, and computer vision, where accurate texture analysis is critical for assessing product quality or identifying defects [19].

The study by Q. Cai, P. Li, and R. Wang (2023) presents a hybrid algorithm for detecting electricity theft. The approach combines Random Forest (RF) with a modified Support Vector Data Description (SVDD) method to improve detection accuracy and robustness in smart grid systems. RF handles feature selection and classification, while SVDD is modified with a weighting mechanism to prioritize features based on their relevance to theft detection. The hybrid model uses RF for feature filtering and classification, reducing the dataset's dimensionality and noise, and then processing the filtered features by the weighted SVDD model. The authors also implement optimization techniques for both RF and SVDD to achieve an optimal balance between accuracy and computational efficiency [20].

Zhang et al. (2024) propose a novel feature extraction method for hyperspectral image classification, focusing on capturing both structural and textural characteristics. They use edge-preserving filtering techniques to preserve structural information and reduce noise, while the Windowed Inherent Variance (WIV) technique analyzes pixel variance within a localized window in the hyperspectral image. Principal Component Analysis (PCA) is used to process extracted features efficiently, transforming high-dimensional feature space into lower-dimensional space while retaining important variance. Support Vector Machines (SVM) is used for classification, known for its effectiveness in high-dimensional spaces. The study's performance evaluation shows significant improvements in classification accuracy compared to traditional approaches. The research contributes to advancements in hyperspectral image analysis, emphasizing the importance of capturing and utilizing both structural and textural information [21].

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The authors presents a two-step approach for fingerprint recognition using the KNN-SIFT algorithm. The first step involves feature extraction using SIFT to identify invariant key points and descriptors from fingerprint images. The second step involves classification using KNN to classify fingerprint patterns based on the extracted features. The proposed KNN-SIFT algorithm shows improved accuracy and efficiency compared to traditional methods. The integration of SIFT with KNN allows for better handling of variations in fingerprint quality and orientation, leading to improved recognition rates [22].

From all the above literature review it has been seen that CBIR techniques are used in different application where texture feature are considered.

3. Proposed Experimental methods: This section focuses on extracting texture-based features from images by analyzing pixel intensity patterns and relationships. These numerical descriptors are used for tasks like image classification, segmentation, and retrieval. Common methods and their performance parameters are outlined below. Common methods for extracting texture features include statistical methods like Gray-Level Co-occurrence Matrix (GLCM), Histogram-Based Methods, and Local Binary Patterns (LBP). Structural methods involve edge detection techniques and texture segmentation. Transform-based methods include Fourier Transform, Wavelet Transform, and Gabor Filters for analyzing texture at different scales. Model-based methods like Markov Random Fields (MRF) and Fractal Dimension model texture using probabilistic processes or self-similar patterns to characterize texture complexity. These methods help in capturing and analysing various aspects of texture in images. The author in this paper presents three methods with their experimental results and find the ranks the images based on their similarity of matching with the query images. After getting the rank for the images the performance of the methods are presented. The three methods that are considered for experimental purpose are

1. Statistical method: LDRP
2. Structural method: Edge detection and texture segmentation and
3. Transform –based method: Wavelet transform.

1. LDRP: The Local Derivative Radial Pattern (LDRP) is a texture descriptor used in image processing for tasks like content-based image retrieval [23]. It improves image feature representation by encoding spatial information and gradient direction changes in a radial pattern. Key features of LDRP include capturing high-order local derivative information for better texture description, arranging neighborhood pixels in a radial pattern, providing rotation invariance by encoding patterns based on gradient directions, and effectively distinguishing between textures with fine structural differences. The steps involved in LDRP include preprocessing the image by converting to grayscale and reducing noise, calculating local gradients, encoding radial patterns, constructing histograms based on encoded patterns, representing feature vectors, and matching image similarities using metrics like Chi-square or Euclidean distance.

2. Structural method: Edge detection and texture segmentation

Structural Edge Detection (SED) is vital in image processing, especially for edge detection and texture segmentation. Edge Detection involves identifying image boundaries where intensity changes. Common techniques include Sobel Operator, Canny Edge Detector, and Laplacian of Gaussian. Texture Segmentation divides an image into regions with similar texture properties using

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methods like Gabor Filters, Local Binary Patterns (LBP), and Wavelet Transforms. The SED pipeline includes detecting edges with structural methods, analyzing texture regions with segmentation algorithms, and combining structural edges with texture analysis for segmentation refinement.

The Modified Scalable Descriptor (MSD) algorithm is commonly used in Content-Based Image Retrieval (CBIR) systems to improve retrieval efficiency by considering both global and local features of an image, which helps balance performance and computational cost. The MSD algorithm involves extracting global features such as color histograms or texture patterns that represent the overall content of an image, as well as extracting local features like keypoints or regions of interest with descriptors like SIFT or ORB. These global and local descriptors are then combined for robust retrieval, and a similarity metric like Euclidean distance or cosine similarity is used to rank images in the database. The steps of the MSD algorithm in CBIR include feature extraction, feature fusion, indexing and storage, query processing, and ranking and retrieval.

3. **Transform –based method: Wavelet transform:** The Wavelet Transform is a useful technique for extracting texture features in image processing. It allows images to be analyzed at different scales and orientations, capturing detailed texture information. The Discrete Wavelet Transform (DWT) is commonly used for this purpose because it captures both low-frequency (smooth) and high-frequency (sharp or fine) details. The Wavelet Transform decomposes an image into frequency components at different scales, enabling multi-resolution analysis for texture extraction. Images are typically separated into approximation coefficients (general features) and detail coefficients (high-frequency features like edges and textures). The advantages of using Wavelet Transform for texture extraction include multi-resolution analysis, directional information, and a compact representation of essential texture details. To extract texture features using the Wavelet Transform, images are decomposed using the DWT into different levels, each containing approximation and detail coefficients in different directions. Statistical features such as mean, standard deviation, energy, and entropy are calculated from these coefficients to create a comprehensive texture descriptor. Multiple levels of decomposition are used to capture textures at various scales.

4. Implementation

This section of paper describes about the implementation of different texture feature extraction algorithms like LDRP, SED, MSD, and DWT 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. A 10 concept groups of images composed each by 100 images and For each concept group the images are divided into 90 images for training and 10 images for test [24]. 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 data is used to test the model. The Support Vector Machine (SVM) model implemented for generating the results. The dataset used for this model is corel dataset from Kaggle website [24].

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4. Results and Discussions

This section presents the screenshots of the output after executing the different texture 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 or ranked 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 texture feature extraction algorithms with their classification report.

Input: Dataset with testing and training data. Each dataset with different classes: The Figure 4(a) shows the input dataset of training data to model of flower's class. As mentioned in the dataset these images are 90 images and for testing purpose 10 images of the same class are considered. Similarly the other classes are considered for training and testing the SVM model.

The figure 4(b) shows the top 5 images that are retrieved from the elephant dataset after the training the model and execution of the model with dataset.

The figure 4(c) represents the top 5 images that are extracted based on LDRP algorithm where flower class is considered for retrieval of similar images and ranking them.

The figure 4(d) represents the top 5 images that are extracted based on SED based texture feature extraction algorithm where the query image is the flower image an d retrieved top 5 images from the dataset.

The figure 4(e) represents the top 5 images that are extracted based on MSD based texture feature extraction algorithm where the query image is the flower image an d retrieved top 5 images from the dataset.

The figure 4(f) represents the top 5 images that are extracted based on DWT based texture feature extraction algorithm where the query image is the flower image an d retrieved top 5 images from the dataset.

gure 4(a) : Sample dataset images of flowers

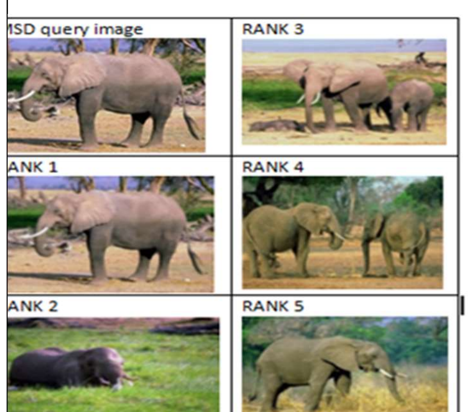

Figure 4(b): Top 5 ranked images for Elephant dataset

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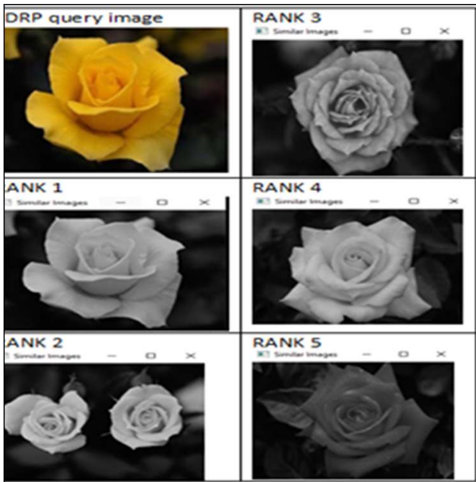
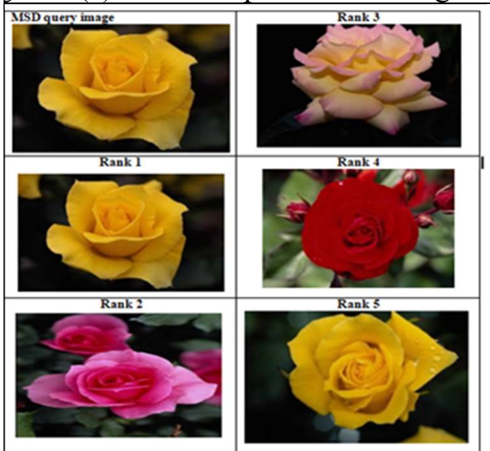


gure 4(c): LDRP top 5 ranked images

gure 4(d): SED top 5 ranked images



gure 4(e): MSD top 5 ranked images

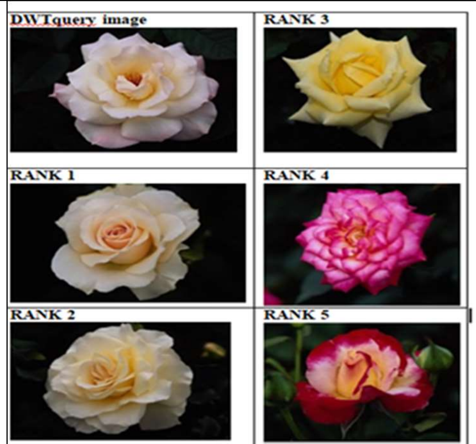


Figure 4(f): DWT top 5 ranked images

Figure: Screen shot for output images that are ranked top five from the given dataset with respect to different texture retrieval algorithm.

The provided figure 4(g) shown is a bar graph for classification report generated by SVM machine learning model. It includes performance metrics such as precision and accuracy of the model. This Diagram shows the comparison of texture feature extraction algorithm for the dataset COIL .

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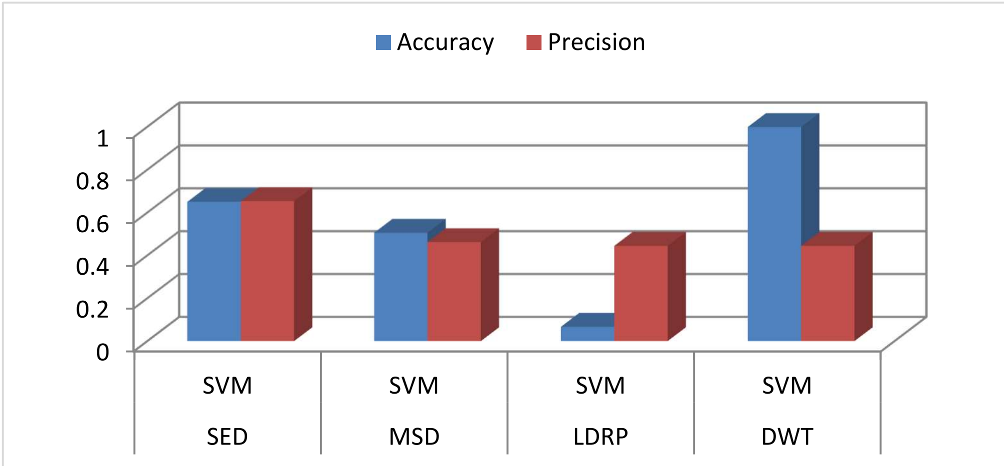

Figure 4(g) bar graph of Comparison of texture feature algorithms with their accuracy and precision

The bar graph compares the **accuracy** (in blue) and **precision** (in red) of an SVM model when different texture feature extraction methods—SED, MSD, LDRP, and DWT—are applied. From the graph it is clearly seen that DWT **(Discrete Wavelet Transform)** shows the highest **accuracy** and **precision** among all the methods and It appears to be the most effective feature extraction method for SVM classification in this analysis. **SED (Statistical Edge Detection)** has high and closely matched accuracy and precision, making it a reliable method. **MSD (Modified Scalable Descriptor)** demonstrates moderate performance in terms of both accuracy and precision, which are slightly lower than SED. **LDRP (Local Directional Rank Pattern)** has the lowest accuracy, indicating it might not be as suitable for feature extraction in this setup and Precision for LDRP is higher than accuracy, but it remains one of the least effective methods compared to others.

Conclusion:

The author's in this paper concludes that DWT is the most effective feature extraction method when paired with SVM, providing the best balance of accuracy and precision. **SED** is a good alternative, offering reliable performance. **LDRP** and **MSD** lag in performance, with LDRP being the least effective.

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