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AN EFFICIENT CONTENT-BASED YOGA ASANA RETRIEVAL SYSTEM FOR TREATING MUSCULAR DISORDERS

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Abstract: Due to the increasing prevalence of muscular disorders linked to modern lifestyles, yoga has regained attention for its therapeutic benefits, yet accurate and efficient pose recognition remains a challenge. This paper presents CBYAR-Net, a novel content-based yoga asana retrieval framework designed to address key challenges, including variability in asana appearance, dataset scarcity, and high computational demands. The proposed system integrates Structural Detail Descriptor (SDD) and Spatial Color Distribution Descriptor (SCDD) to capture fine-grained structural features and spatial color patterns, while an unsupervised SVM (U-SVM) clusters similar feature vectors for efficient retrieval. Experimental results demonstrate that CBYAR-Net outperforms traditional methods like KNN and Cosine Similarity, achieving 96.15% retrieval accuracy. The framework provides a robust, scalable, and computationally efficient solution for automated yoga pose recognition and retrieval.

Keywords: Yoga, Muscular Disorder, CBIR, Spatial Color Descriptor, Structural Detail Descriptor, Machine Learning

I. INTRODUCTION

The modern era, marked by rapid technological growth and urbanization, has witnessed a significant rise in lifestyle-related health issues, including muscular disorders, which limit daily activities and reduce quality of life [1]. Yoga, an ancient practice originating over 5,000 years ago in India, provides holistic benefits for physical and mental well-being [2]. Its asanas offer targeted stretching, strengthening, and balancing exercises that alleviate muscular problems and promote overall health. With global interest in Yoga rising, there is a growing demand for technologies that make Yoga practice accessible, personalized, and therapeutically precise [3]. Recent advances in Artificial Intelligence, including Machine Learning and Deep Learning, have enhanced Yoga monitoring systems [4]. Techniques such as Convolutional Neural Networks, LSTM networks, and hybrid models enable accurate pose recognition and corrective feedback [5]-[12]. However, most research focuses on pose estimation, leaving a gap in Content-Based Yoga Asana Retrieval systems, which face challenges from pose variability, dataset limitations, and computational efficiency.

To address these challenges, this study proposes CBYAR-Net, a novel framework for efficient and robust content-based retrieval of yoga asanas. CBYAR-Net combines two complementary feature descriptors, i.e., Spatial Color Distribution Descriptor (SCDD), which encodes color arrangements across spatial dimensions and Structural Detail Descriptor (SDD), which captures edges, boundaries, and intricate pose patterns. These features provide a holistic representation of each asana, ensuring robustness to variations in pose, lighting, and background. Furthermore, an Unsupervised Support Vector Machine (U-SVM) clusters similar feature vector to create an efficient indexing mechanism, reducing search space and enabling fast, accurate retrieval. By integrating these components, CBYAR-Net allows users to input an image and retrieve visually similar yoga asanas efficiently, providing both therapeutic guidance and enhanced accessibility for practitioners. The contributions of CBYAR are as follows

- Developed a robust CBYAR system integrating structural (SDD) and color (SCDD) descriptors for comprehensive asana representation.
- Introduced U-SVM-based clustering to enhance retrieval efficiency and reduce computational complexity.
- Created a diverse yoga asana dataset capturing realistic variations in pose, viewpoint, and environmental conditions.
- Enabled accurate and efficient retrieval of visually similar asanas, supporting therapeutic guidance and personalized Yoga practice.
- CBYAR-Net provides a scalable solution bridging the gap in content-based retrieval for yoga.

Further, the manuscript is organized in the following manner. Section II discusses existing yoga-based AI approaches, Section III presents methodology of CBYAR-Net and Section IV presents results of CBYAR-Net compared with baseline approaches. Finally, Section V concludes CBYAR-Net and provides future work.

II. LITERATURE SURVEY

This section discusses existing ML and DL approach presented in recent years for yoga asana prediction and classification. In [5], aimed at evaluating impact of Yogasanas on muscular disorders and developing an automatic identification approach for asanas, hence presented a dataset of yoga postures and employed a structured classification approach using SVM cascaded classifier. The findings on evaluations show that the approach showed 97% accuracy. In [6], aimed at improving yoga pose recognition using DL for handling challenges like camera movement, viewpoint shifts and occlusion. In this work, they collected dataset of six yoga poses performed by 10 subjects, which was created using RGB camera. The work applied OpenPose for feature extraction and Dense Bi-directional LSTM (D-Bi-LSTM) for capturing spatio-temporal variations. The D-Bi-LSTM was evaluated and compared with LSTM-based approaches, which showed better performance.

In [7], aimed at ensuring accurate yoga pose recognition and correction using AI for preventing injuries and improve yoga practice, hence, they collected a yoga asanas dataset, which were processed using posture estimators for extracting features, which was further applied to ML and DL approach. Further, presented an approach called LGDeep, which utilized Linear Discriminant Analysis (LDA) and Gaussian Discriminant Analysis (GDA) for feature extraction and integrated residual CNN with SqueezeNet, VGGNet and Xception, achieving better performance for yoga asana prediction. In [8], aimed at designing real-time yoga pose annotation and classification approach, hence employed TensorFlow for automation, performance monitoring and neural network development. Further, presented a time-distributed CNN with softmax, which was combined with PoseNet algorithm, which estimated the yoga poses. In this work, utilized PoseTrack dataset for evaluation and tracking, where the approach achieved higher accuracy compared to K-Nearest Neighbor (KNN) and SVM approach.

In [9], improved yoga posture detection despite issues of complex backgrounds an occlusion by using Yoga-16 dataset, which has 6561 images comprising of 16 classes. For feature extraction utilized Visual Geometry Group (VGG), mainly VGG19 and VGG16, followed by classifier, which included Extra Tree (ET), Random Forest (RF), Logistic Regression (LR) and SVM classifier. The findings show that feature extraction using VGG and SVM achieved 99.92% accuracy. In [10], aimed at enabling self-learning of yoga pose (Surya Namaskar) using automated pose classification, for which created a dataset having 1200 images, which went through preprocessing using bounding boxes, followed by feature extraction using Histogram of Oriented Gradients (HOG) and Speeded Up Robust Features (SURF). The classification was performed using KNN and Artificial Neural Network (ANN), using CNN as additional validation. Findings show that the approach showed better effective recognition.

In [11], aimed at developing home-based fitness monitoring approach which integrated dynamic exercises and static yoga poses for health management, hence utilized OpenPose-based key point approach for extracting posture features, while providing a scoring approach which evaluated pose accuracy. The evaluation of approach was done using five yoga exercises, where the approach achieved 99.9% accuracy for prediction, showing effective feedback for personalized and efficient training. In [12], aimed at reviewing real-time yoga asana prediction approaches, hence conducted a review on 3250 studies, where discussed different ML, DL and hybrid approaches, where they saw that current approaches achieved 99.92% accuracy, showing that integration of ML and DL improves yoga prediction.

Despite significant advancements in yoga pose recognition and classification, existing ML and DL approaches have notable limitations. The SVM-based cascaded classifier [5] achieves high accuracy but relies on handcrafted features, reducing robustness to lighting, background, and viewpoint variations. OpenPose with D-Bi-LSTM [6] improves spatio-temporal recognition but is limited to six poses and ten subjects, restricting generalizability. LGDeep [7] combines LDA, GDA, and residual CNNs but incurs high computational cost. Time-distributed CNN with PoseNet [8] improves accuracy but depends on PoseTrack, limiting adaptability. VGG-based feature extraction with multiple classifiers [9] achieves 99.92% accuracy but suffers from computational overhead. HOG and SURF methods [10] are effective for Surya Namaskar but lack scalability, while OpenPose-based home monitoring [11] and reviews [12] emphasize the need for integrated ML-DL approaches with efficient retrieval. CBYAR-Net addresses these issues by combining SDD and SCDD for structural and color-spatial features with unsupervised SVM clustering, enabling accurate, scalable, and computationally efficient yoga asana retrieval for diverse real-world scenarios.

III. METHODOLOGY

For addressing the above issues discussed in literature survey, this work presents a novel approach for efficient CBIR, called as CBYAR-Net, which has been designed for extracting features that are robust and accurate to variation in yoga asanas appearance. The architecture of CBYAR-Net is presented in Figure 1. In the CBYAR-Net, two feature descriptors are presented for enhanced retrieval performance, i.e., SCDD, which encodes arrangement of colors across spatial dimensions, providing better capability of capturing color patterns and spatial relationships effectively and SDD, which focusses on preserving fine-grained structural elements, capturing intricate patterns, boundaries and edges in yoga asana images. Further, a ML approach, i.e., a U-SVM classifier has been employed for similarity checks and retrieve the query image efficiently. The U-SCM is utilized for clustering similar feature vectors, i.e., it learns relationships between extracted features, groups visually similar images into clusters which act as indexing approach, thereby reducing search space during retrieval. Hence, when a query image is presented, its features are extracted and compared with clusters, assigning query to cluster having highest similarity. Further, the images having similar cluster are considered visually similar, ensuring accurate and efficient retrieval even under in different background, lighting and in pose variations.

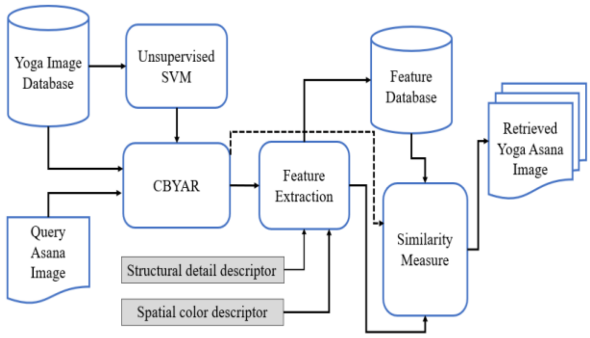


Figure 1. CBYAR-Net Architecture

A. Dataset

For the evaluation of the study, this work collected a dataset, as benchmark dataset for CBYAR does not currently exist, hence, this study prepared a custom dataset using 1080p High-Definition (HD) video recordings, which were captured from distance of 5 meters under variety of conditions, including outdoor scenarios, indoor environments, nighttime settings, camera movement and still shots. The dataset consists of seven yoga asanas, i.e., Bhujangasana, performed by lying on stomach and lifting upper body; Dhanurasanz, involving bending body into a bow shape while lying on stomach; Gomukasana, a seated pose with legs folded and arms positioned in cow's face configuration; Sukhasana, a simple cross-legged sitting posture; Tadasana, a standing pose emphasizing balance and stability; Trikonasana, where body stretches to form a triangle shape; and Vajrasana, performed by sitting on heels with straight spine. This dataset was designed to reflect realistic variations in how each pose was performed, as well as differences in capture conditions, providing a valuable resource for developing and evaluating CBYAR-Net.

B.CBYAR-Net

In CBYAR-Net, first the SCDD captures how colors are distributed across image, providing compact representation of spatial relationships and color patters. The SCDD process begins by transforming RGB image to $YCbCR$ color space, which separates luminance Y from chrominance (Cb and Cr), providing independent brightness processing and color information processing, improving robustness to lighting variations. The transformed image is further divided into P×Q grid of non-overlapping blocks, and average color values for each block are evaluated for summarizing local color information. Further, a 2-dimensional (2D) Discrete Cosine Transform (DCT) is applied to matrix representing Y, Cb and Cr channels, which decreases data size and makes descriptor invariant to minor variations. Only low-frequency DCT coefficient were considered in this work and were arranged in 1D vector using zigzag scanning and resulting vectors from all blocks were concatenated for forming final high-dimensional SCDD feature vector representing the image. The complete process of SCDD is presented in Algorithm 1.

Algorithm 1. SCDD Feature Extraction Process	
Input	Image I of dimensions $M \times N \times 3$, where M denotes height, N denotes width
Output	SCDD feature descriptor for all images in dataset and query image
Step 1	Start
Step 2	Transform image I from RGB to $YCbCr$ color space, i.e., I_{YCbCr}
Step 3	Initialize gird dimension $P \times Q$
Step 4	Divide I_{YCbCr} into non-overlapping grid $G = P \times Q$
Step 5	Create matrices A_Y, A_{Cb}, A_{Cr} of dimension $P \times Q$ and initialize all matrices with 0
Step 6	Determine dimension of grid $G_x = \lfloor \frac{M}{P} \rfloor$ and $G_y = \lfloor \frac{N}{Q} \rfloor$
Step 7	**If** $M \bmod P \neq 0$ or $N \bmod Q \neq 0$
	Pad I_{YCbCr} to ensure dimension are compatible with G
	End If
Step 8	**For** $i = 0,1,\cdots,P-1$ do
	For $j = 0,1,\cdots,Q-1$ do
	For each pixel (m,n) in grid cell $G_{i,j}$, pixel should satisfy condition $m \in [i \times G_x, (i+1) \times G_x - 1]$ else $n \in [i \times G_y, (j+1) \times G_y - 1]$
	Compute average color value for $G_{i,j}$ using $Y_{i,j} = \frac{1}{G_x \times G_y} \sum_{m,n \in G}^{within\ cell} Y(m,n)$, $Cb_{i,j} = \frac{1}{G_x \times G_y} \sum_{m,n \in G}^{within\ cell} Cb(m,n)$ and $Cr_{i,j} = \frac{1}{G_x \times G_y} \sum_{m,n \in G}^{within\ cell} Cr(m,n)$
	Store the obtained average value as $A_Y[i,j] = Y[i,j]$, $A_{Cb}[i,j] = Cb[i,j]$ and $A_{Cr}[i,j] = Cr[i,j]$
	End For
	End For
	End For
Step 9	**For** each matrix A_Y, A_{Cb}, A_{Cb}
	Apply $2D - DCT$ to obtain DCT coefficients in frequency domain
	For each frequency pair (u,v) do
	Similar computing procedure is applied for A_{Cb} and A_{Cr}
	End For
	End For
Step 10	**For** each block $DCT(u,v)$
	Retain only the first few low-frequency coefficients for a compact representation
	Discretized the DCT coefficient
	Arrange discretized DCT coefficients in $1D$ using zigzag scanning pattern
	End For
Step 11	Descriptor Formation
	Concatenate the *1D* arrays obtained from all blocks to form the final SCDD
Step 12	**Return SCDD**
Step 13	**End**

Further, in CBYAR-Net, SDD has been designed for capturing fine-grained structural information of yoga asana images, which includes intricate patterns, boundaries and edges extraction for retrieval tasks and pose classification. In SDD, the process starts by extracting RGB channels of image and converting to grayscale, which reduces computation complexity, while focusing on luminance changes important for structural analysis. The grayscale image is then partitioned into non-overlapping blocks, and a binary edge map is computed using Sobel operator. For each block and filter kernel, responses are calculated for vertical, horizontal, diagonal, and non-diagonal edges. A histogram is initialized to accumulate edge orientation information, and for each edge pixel, gradient and orientation are computed, with predominant edge type determined by maximum filter response. These histogram bins are then flattened and normalized to form the final SDD feature vector, providing a robust representation of structural characteristics. The complete process of SDD is presented in Algorithm 2

Algorithm 2. SDD Feature Extraction Process	
Input	Image I, Number of histogram bins N, block size B and histogram orientation bins M
Output	SDD feature descriptor for all the images in the database and query image
Step 1	**Start**
Step 2	Let I_r, I_g, I_b be the red, green, and blue channel of I respectively
Step 3	Convert the image I to grayscale I_g using $I_g(x,y) = 0.29 \times I_r(x,y) + 0.58 \times I_g(x,y) + 0.11 \times I_b(x,y)$
Step 4	Partition I_g into non-overlapping block B_{ij} uch that: $B = \left\{B_{ij} \mid 1 \le i \le \frac{H}{B}, 1 \le j \frac{W}{B}\right\}$
Step 5	**For each** pixel in I_g determine an edge pixel using a standard edge detection technique to generate the binary edge map E
Step 6	**For** each filter kernel k and for each block B_{ij}
	Compute filter responses
	Vertical Edge $mf_v(k) = \sum_0^3 \lvert a_k(i,j) \times f_v(k) \rvert$
	Horizontal Edge $mf_h(k) = \sum_0^3 \lvert a_k(i,j) \times f_h(k) \rvert$
	45° diagonal Edge: $mf_{45}(k) = \sum_0^3 \lvert a_k(i,j) \times f_{45}(k) \rvert$
	135° diagonal Edge: $mf_{135}(k) = \sum_0^3 \lvert a_k(i,j) \times f_{135} \rvert$
	Non-Diagonal Edge: $mf_{nd}(k) = \sum_0^3 \lvert a_k(i,j) \times f_{nd}(k) \rvert$
	End For
Step 7	Initialize a histogram $Histo$ with M bins
Step 8	**For each** block B_{ij} in B
	Extract sub-matrix S_{ij} from E: $S_{ij} = E[(i-1)B + 1 : iB, (j-1)B + 1 : jB]$
	For (x,y) in S_{ij} where $E(x,y) = 1$
	Compute gradient: $G(x,y) = \left(\frac{\partial I_g}{\partial x}, \frac{\partial I_g}{\partial y}\right)$
	Compute orientation: $\theta(x,y)$=arctan2$\left(G(x,y)\right)$
	Identify edge type using computed magnitudes
	Update the histogram bin $Histo[b]$
	End For
	End For
Step 9	Return $\overrightarrow{SDD}$ = normalized $(Flatten(Histo))$
Step 10	**End**

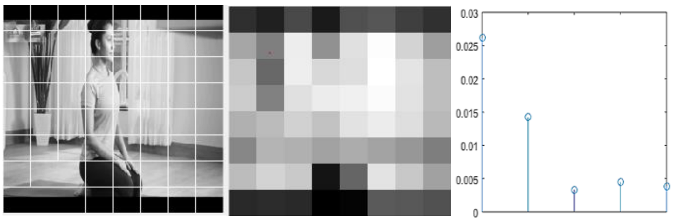
Finally, in CBYAR-Net, the U-SVM is employed in CBYAR-Net to cluster similar feature vectors for efficient retrieval. Unlike traditional SVMs, which separate classes, the U-SVM separates data from origin, maximizing margin between feature vectors and origin. The objective function minimizes the norm of the hyperplane vector while controlling margin violations, allowing features to be mapped into a higher-dimensional space for effective clustering. In CBYAR-Net, seven U-SVM models are trained, one for each asana, treating corresponding class as normal and all other classes as outliers. When a query image is presented, its extracted features are evaluated against each U-SVM, and the asana corresponding to the highest decision value is selected. Retrieved images are ranked based on these decision values, ensuring that the most visually similar poses are prioritized. The complete process of CBYAR-Net is presented in Algorithm 3.

Algorithm 3. CBYAR-Net	
Input	Dataset Images
Output	Retrieved Images
Step 1	Start
Step 2	Extract features F from SCDD and SDD for all images in dataset
Step 3	Train U-SVM for each asana type
Step 4	**For each** asana type A_j, use feature F_{A_j} of images from asana as training data
	Train U-SVM with F_{A_j} to ger SVM_{A_j}
	End For
Step 5	**For** a new query image Q, extract its features F_Q
Step 6	**For each** SVM_{A_j}
	Compute the decision function $D_j = SVM_{A_j}(F_Q)$
	End For
	End For
Step 7	The asana type corresponding to U-SVM with highest D_j is considered the most likely class for Q
Step 8	Based on the decision values D_j, the retrieved images will be ranked
Step 9	**End**

By combining features from SCDD and SDD, and using U-SVM-based clustering, CBYAR-Net enables efficient and accurate retrieval of yoga asanas, showing better outcomes as discussed in the next section.

IV. RESULTS AND DISCUSSION

This section presents performance analysis of CBYAR-Net. The entire analysis was carried out on a Windows 10, core i7 with 16 GB RAM. The outcome was analyzed concerning both visual analysis and numerical outcomes obtained in terms of retrieval accuracy, and processing time analysis. The effectiveness of CBYAR-Net was assessed using a yoga image dataset as discussed in Section 3.1. This dataset consisted of 3,377 images distributed across 7 unique asanas, where 145 images for Bhujangasana, 759 for Dhanurasana, 319 for Gomukhasana, 341 for Sukhasana, 220 for Tadasana, 932 for Trikonasana, and 661 for Vajrasana. The detail description of each asana has been already provided in the section 3.1. Further, Figure 2 presents visual analysis of extracted features using SCDD and SDD feature descriptors. Figure 2 shows a sample visualization of feature extraction for query image. Figure 2 (a) shows initial stage where image is divided into fixed-size blocks. Figure 2 (b) presents feature coefficient from SCDD, which act as symbolic representation of color distribution across spatial plane of block. Figure 2 (c) illustrates SDD feature coefficients which focuses structural analysis of intensity patterns within block.



(a) (b) (c)

Figure 2. Visual depiction of block partitioning and feature coefficient, i.e., (a) 8x8 block (b) SCDD feature coefficient and (c) SDD feature coefficient

In the experimental setup, the study designates 40% of dataset as query images, resulting in query set of 1,350 images distributed across seven yoga asanas: 58 images for Bhujangasana, 304 for Dhanurasana, 128 for Gomukhasana, 136 for Sukhasana, 88 for Tadasana, 373 for Trikonasana, and 264 for Vajrasana. The U-SVM model was rigorously evaluated to assess its ability to accurately retrieve yoga asana images from the database. Standard performance metrics, including accuracy, precision, recall, and F1-score, were employed to quantify the model's effectiveness in retrieving each asana type, providing a comprehensive evaluation of CBYAR-Net's retrieval capabilities. Figure 3 illustrates performance of U-SVM in CBYAR-Net across different yoga asanas. The results indicate that the model achieves high accuracy, ranging from 93.8% for Bhujangasana to 98.6% for Dhanurasana. Precision values remain consistently high, mostly in the mid-to-upper 90% range, indicating that the U-SVM generates very few false positives. Similarly, recall values demonstrate that the model effectively identifies true instances of each asana, rarely missing relevant images. Combined with F1-scores consistently above 92%, these results confirm that the proposed model is both accurate and efficient. This superior performance is attributed to the integration of SCDD and SDD feature descriptors, which provide precise and robust representations of structural and color-spatial characteristics, enabling reliable retrieval of yoga asana images under varying conditions

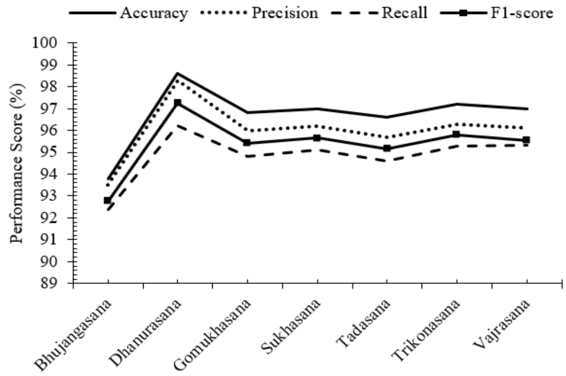


Figure 3. Performance analysis of U-SVM in CBYAR-Net for each yoga asana

Figure 4 presents a comparative analysis of three widely used CBIR models: Cosine Similarity, KNN, and the proposed U-SVM. Cosine Similarity evaluates cosine of angle between two non-zero vectors, providing a similarity measure independent of vector magnitude, while KNN, an instance-based learning method, classifies objects based on their proximity to training examples in the feature space. These models were selected due to their prevalent use and methodological relevance in CBIR. As shown in Figure 4, Cosine Similarity achieves a moderate accuracy of 93.5% and an F1-score of 92.1%, whereas KNN demonstrates a slight improvement with 95.1% accuracy and a 93.75% F1-score. In comparison, the proposed U-SVM, enhanced with SCDD and SDD feature descriptors, achieves superior performance, attaining 97% accuracy and a 95.56% F1-score. These results highlight effectiveness of U-SVM for CBYAR, demonstrating its ability to provide more precise and reliable retrieval of yoga asanas than conventional CBIR approaches.

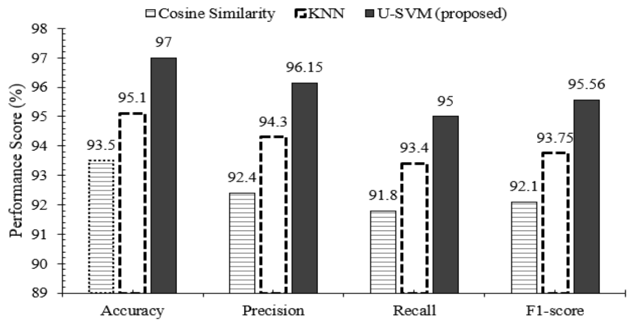


Figure 4. Comparative analysis with overall performance

Figure 5 illustrates the average retrieval time for each method, providing insight into their computational efficiency. A closer examination of the performance graph shows that the U-SVM is the fastest model, with an average retrieval time of 8.36 seconds. In contrast, KNN is the slowest, averaging 24 seconds, due to its nature as a lazy learning algorithm that requires comparing the query image to every image in the database to identify the closest matches. The efficiency of U-SVM arises from its ability to learn clusters by finding optimal hyperplanes for the feature space. Once these hyperplanes are established, the model can quickly determine the appropriate cluster for a new query image, significantly reducing retrieval time while maintaining accuracy. This demonstrates that U-SVM not only improves precision and F1-score but also offers superior computational performance for CBYAR.

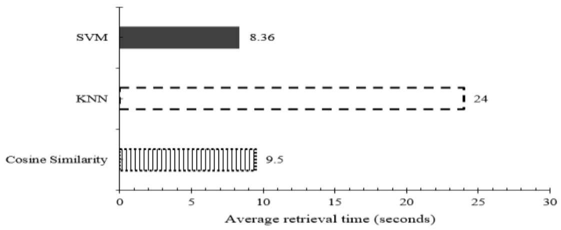


Figure 5. Analysis of average retrieval time

V. CONCLUSION

This work introduces CBYAR-Net, a novel CBYAR approach designed to overcome challenges of variability in pose appearance, limited datasets, and computational complexity. The CBYAR-Net approach integrates SCDD and SDD to capture both fine-grained structural features and spatial color patterns, providing a comprehensive and robust representation of yoga asanas. A U-SVM classifier is employed to cluster similar feature vectors, creating an efficient indexing mechanism that reduces search space and accelerates retrieval. Experimental results demonstrate that CBYAR-Net achieves high retrieval performance, with an average accuracy of 96.15%, and maintains consistent precision, recall, and F1-scores across all asanas. Additionally, the system exhibits superior computational efficiency, with significantly lower retrieval times compared to traditional methods. The proposed approach proves effective in handling noise, pose variations, and diverse image capture conditions, making it suitable for practical applications in yoga practice and therapy. Future work will focus on integrating DL techniques to enable automated feature extraction, further enhancing retrieval accuracy and adaptability for large-scale yoga asana datasets.

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