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SIFT and SURF Features based Classification of Yoga Hand Mudras Using Machine Learning Techniques

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***Abstract*---**Yoga is a unique spiritual discipline of self-development and self-realization that teaches us how to live our lives to the fullest. Yoga's integrative approach brings deep harmony and unwavering balance to body and mind to awaken our dormant capacity for higher consciousness, which is the true purpose of human evolution. The numerous documented physical and mental benefits of yoga have played a large part in the interest in yoga. Due to a lack of datasets and thus the necessity to identify mudra in real time, distinguishing yoga hand mudras seems to be a tough undertaking. The yoga hand mudras are used as input in the proposed study, and the two components Scale Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) are extracted, followed by classification utilising machine learning techniques including Support Vector Machine (SVM) and Random Forest. By comparing the experimental results the performance of SIFT with SVM yields better results.

***Keywords*---**random forest, SIFT, support vector machine, SURF, yoga hand mudras.

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Introduction

Today, yoga is a significant component of many people's lives. Although it is classified as a form of exercise, it has the ability to affect an individual's emotional and psychological well-being as well as their physical condition. Yoga has become a well-known discipline all over the world for keeping people in good physical and mental health. [1] Yoga is a Sanskrit word that means "to connect, synchronise, or energise," and it refers to the appropriate integration of body, mind, and spirit in order to reach one's full potential. Yoga helps us build awareness that transcends beyond our usual personal and human limitations by exponentially expanding our ordinary capacities [2].

Yoga is a system of physical and psychical controls designed to make the practitioner aware of his or her own identity. Yoga is beneficial to a wide range of physical conditions, but the ultimate goal of practicing it is to discover one's truth. Asanas are only one component of an eight-stage process in the pursuit of enlightenment. They prepare the body for meditation [3]. The benefits of yoga include reduced blood pressure, relief from anxiety, improved flexibility and decreased muscle and joint pain. Yoga becomes a lifestyle for many people all around the world in recent years. As a result, scientific analysis of yoga postures is required [4].

[5] Mudras aid in the balance of the human body's five elements. Nature has created a self-sufficient, self-contained, and nearly flawless human body. The elements are represented by the five fingers of the hand. The thumb represents the element of Fire (Agni), the index finger is associated with the Air element (Vayu), the middle finger is the representation of Space (Akash), the ring finger represents the element of Earth (Prithvi), the little finger is associated with the Water element (Jal).

[7] Mudras should be practised with both hands at the same time. They may be carried out at any time and at any location. Each mudra must be practiced for fifteen - forty five mins, with a least of five minutes, for the optimum results. The most key point to consider is that mudras must be done two hours post eating since the digestive process consumes energy and diverts energy concentration. They are not complete healers, but when paired with asanas and pranayama, they give the finest assistance.

Yoga hand mudras

Yoga Mudra is the science of employing hand gestures to alter or redirect energy flow throughout the body via acupuncture meridians, putting our energy body into perfect harmony or balance. Because the hands contain all of the acupuncture meridians, they are regarded as the body's control panel. The Pancha Mahabhutas, or five components of the body, are represented by the five fingers on a hand: fire, water, air, sky, and earth. Yoga Mudras are hand motions designed to improve the flow of energy, or Prana, in the body and mind for better health. Mudra is a Sanskrit word that roughly translates as 'hand gesture.' Mudras are used in many Hindu and Buddhist rituals, as well as many dance styles, to express deeper significance. The most energizing yoga mudras are classified in this work namely, Brahma, Chin, Chinmaya, Linga, Prana, Prithvi, Rudra, Surya, Varun, and Yoni that are shown in Fig. 1.

Figure 1. Types of Mudras

The input images are preprocessed before extracting the features, the feature extraction technique named SIFT and SURF are used and the machine learning models namely SVM and Random Forest are used to classify the features. Fig. 2 shows the block diagram of the proposed work.

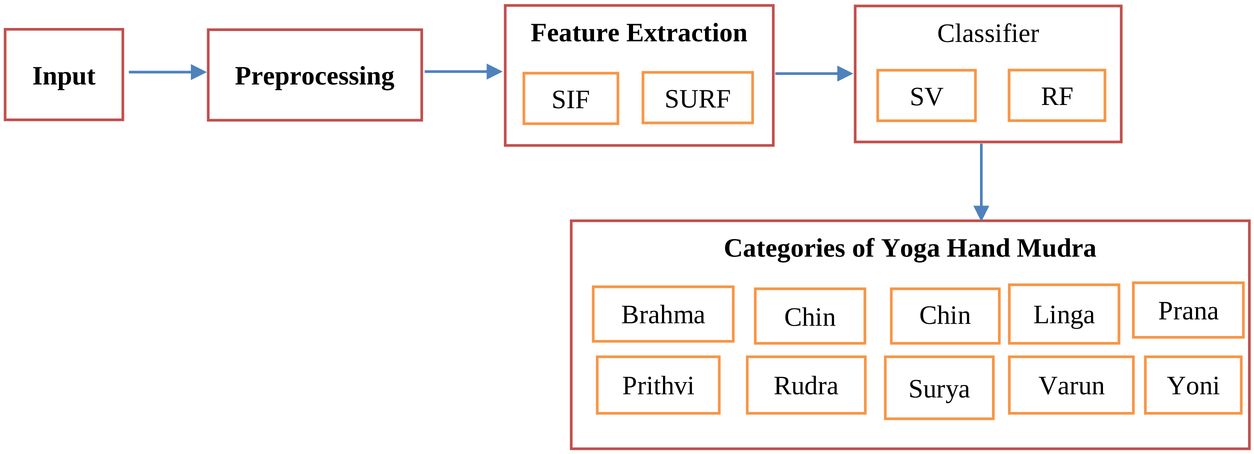

Figure 2. Block diagram of the proposed work

Literature Review

The research [6] was conducted by the yoga participants. The data set is took from yoga centers. The samples of 100 observations were obtained in this study for yoga participants in Ammapet - Salem. The maximum likelihood estimation (MLE) is used to evaluate the significance of the independent variable. In the dependent variable the effect of improvement in practicing yoga with two categories (i) 0 – no improvement and (ii) 1 – improvement. Then logistic regression model used to fit these data are four independent variable found to the significantly affect to the improvement by doing yoga. For namely the affected variables in practice yoga regularly, the reason why keep practicing yoga, health conditions and yoga style.

For the development of home and clinical yoga therapy for hard-to-reach populations, gesture analysis for yoga alignment training was used [8]. The experimental exergame provided here is a tool that rates yoga posture performance and gives improvement measures. In this study, statistical metrics were used to track improvements in yoga posture learning in young adults over a 10-week period. The training data for the research was captures from yoga instructors for evaluation, Kinect Studio is used to capture the yoga posture and to next process using KS Convert.

Preprocessing

The input yoga hand mudras are preprocessed before fed into extraction of features. Before categorization, the RGB images are transformed to HSV color space.

Space of color

A color space is defined as a one to four-dimensional spatial model of contrast enhancement in terms of pixel intensities. One of dimensions is a color module, often known as a color network. During preprocessing, RGB color is converted to HSV color space in this work.

Color space of hue, saturation, and value (HSV)

The color intensity is represented by the value, which is independent from the image color image. The hue and saturation components are linked to how the human eye perceives color, which is why cardio-pulmonary exercise image processing algorithms use them. [5] Because the related colors vary from red toward yellow, green, cyan, blue, as well as magenta finally returning to red as the hue numbers change from 0 to 1.0, there really are red values both at 0 and 1.0. As saturation increases from 0 to 1.0, colors (shades) vary between unsaturated (grey) and completely saturated (no white component). When the level, or brightness, goes from 0 to 1.0, the associated colors become brighter.

Conversion of color

Color conversion between color spaces that retain perceived color differences is required in order to utilise a suitable color space.

RGB to HSV conversion

To convert the ranges from 0..255 to 0…1, the Red, Green and Blue values were divided by 255 at first.

$$Red' = Red/255$$

$$Green' = Green/255$$

$$Blue' = Blue/255$$

$$C_{minimum} = \min(Red', Green', Blue')$$
$$\Delta = C_{maximum} - C_{minimum}$$

The RGB yoga hand mudra images are captured and transformed into HSV conversion in this suggested effort. For processing, the value image (intense) is used. The preprocessing screenshot of an image is shown in Figure 3.

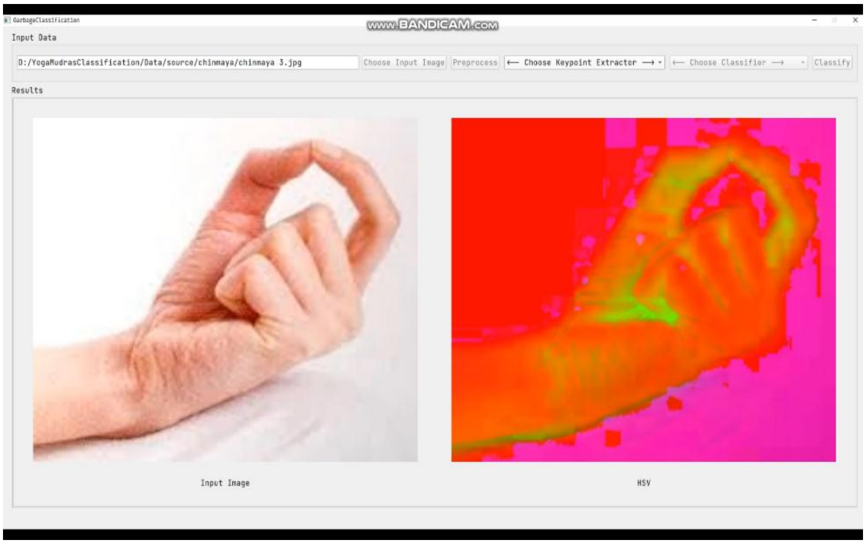

Figure 3. Preprocessing of input image

Feature extraction

The feature extraction techniques namely, SIFT and SURF to extract the attributes from the input image, are utilised.

Scale invariant feature transform (SIFT)

SIFT algorithm in 2004 [6] it has excellent robustness to handle image rotation, scaling, and affine deformation, as well as perspective change, noise, and light variations. SIFT algorithm has 4 main steps:

Detection of scale space extrema

Interest points could be found at a variety of scales, in part because detecting correspondences frequently demands comparing pictures at different sizes. In another feature, the first stage is to use scale space extrema to determine the location and sizes of significant spots. Inside this DoG (Difference-of-Gaussian) function with various values of: Within the DoG (Difference-of-Gaussian) functions, distinct values of: are convolved of pictures in scale space separated by a constant factor k.

$$DoG(a, b, \sigma) = (H(a, b, i\,\sigma) - H(a, b, \sigma) \times J(a, b)$$

The Gaussian function is H, and the image is J. Subtract the Gaussian images to obtain a DoG, and then factor 2 the Gaussian image to obtain a DoG for the sampled picture. To find the local maxima & minima of the DoG(a, b) local maxima.

SIFT descriptor construction

Picture gradient magnitudes and orientations are sampled everywhere around the key point position, as well as the size of the key point defines the degree of Gaussian blurring in the images [6]. The descriptor's dimensions are twisted relative towards the key fact orientation, and then the gradation orientations were rotated to provide orientation invariance. Each sample location is indicated by a little arrow on the left side of Figure 4.

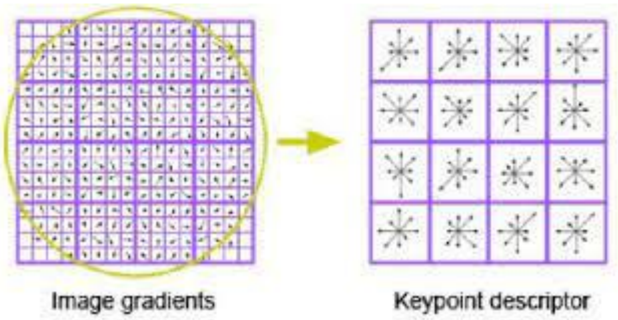

Figure 4. Descriptor of Keypoint

On the right side of Fig. 3, the key point descriptor is shown. By constructing orientation histograms spanning 4x4 sample sections, it enables significant changes in gradient locations. While contributes to the right-hand histogram, A gradient sample on the left may offset up to 4 sample locations. Each sample is equipped with a locator grid of 44 coils and 8 orientation cells. Key point descriptors have a dimension of 128 elements. Fig. 5 shows the SIFT features. The SIFT features are shown in Figure 5.

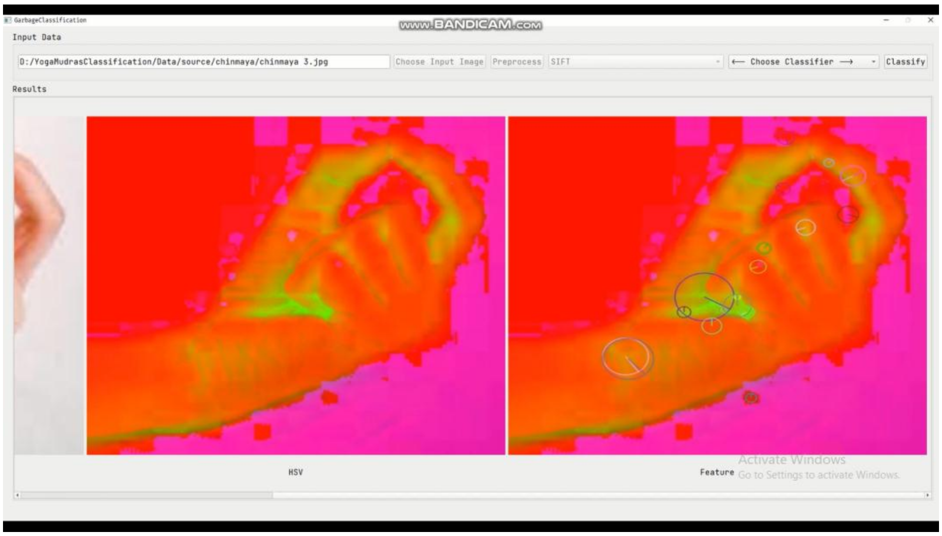

Figure 5. SIFT feature extraction

Speeded-Up robust features

The Speeded-Up Robust Features (SURF) algorithm follows the same concepts and phases as SIFT, however there are some differences in the details of each step. In the detection of points of interest, the description of the local neighborhood and the pairing are the three main components of the algorithm.

Detection

As a rough approximation of Gaussian smoothing, SURF employs square-shaped filters. Filtering the image with a square is much quicker if the entire image is used.

Scale-space representation and location of points of interest

Points of interest can be found at various scales, in part because detecting correspondences often requires comparing images to different sizes. In other characteristic detection approaches, scale space is commonly expressed as an image pyramid. [6] Even before being undersampled to generate the next top level of the pyramid, images are often flattened with a Gaussian filter. As a consequence, several levels or stairwells are calculated, each with its own mask dimensions. Each octave corresponds to a collection of responsive maps that cover a scale doubling, and the scale is split into octaves set. The lowest level of a grid points in SURF is produced by the outputs of the 99 filters. As a consequence, unlike previous systems, SURF implements scale spaces using box filters of varied widths. As a consequence, instead of repeatedly reducing the image size, the scale space is studied by increasing the filter size.

Descriptor

The objective of a descriptor is to offer a unique and trustworthy representation of an image feature, including as with the intensity variations of pixels around a point of interest. As a result, the majority of descriptors are created locally, result in a descriptor for each site of interest that has previously been defined. The first step is to use data of considerable circular significance at the point of interest to create a reproducible orientation. A square section aligned with the given guidance is then used to retrieve the SURF descriptor.

Orientation assignment

To ensure rotational invariance, the orientation of both the point of interest should be established [11]. From both the x and y directions, the Haar wavelet response is computed on the inside of a circular neighbourhood of radius 6s from the point of interest, where is the scale at which the point of interest was detected.

Matching

By assessing the descriptors obtained from various pictures, it is possible to discover matches.

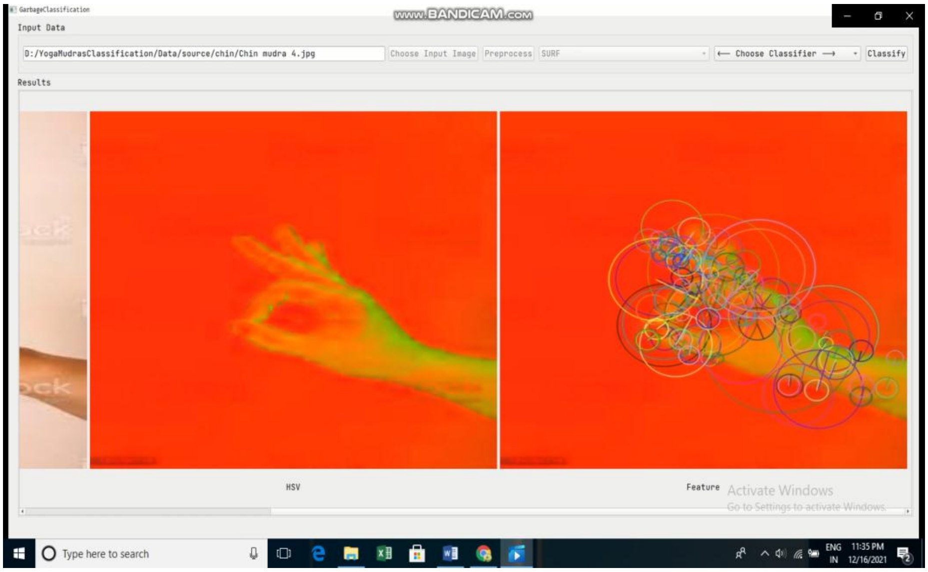

Figure 6. SURF feature extraction

Classifiers

In the proposed work Support Vector Machine and Random Forest are the two machine learning techniques used to classify the features.

Support vector machine (SVM)

SVM seems to be a statistic machine learning approach that has been successfully applied in the pattern matching sector and is based on the concept of structural risk reduction. SVM develops a straight tool to estimate choice capacity utilising non-direct class limitations in light of assistance vectors. [12] From a set of positive and negative values, SVM learns the best separating hyper plane.

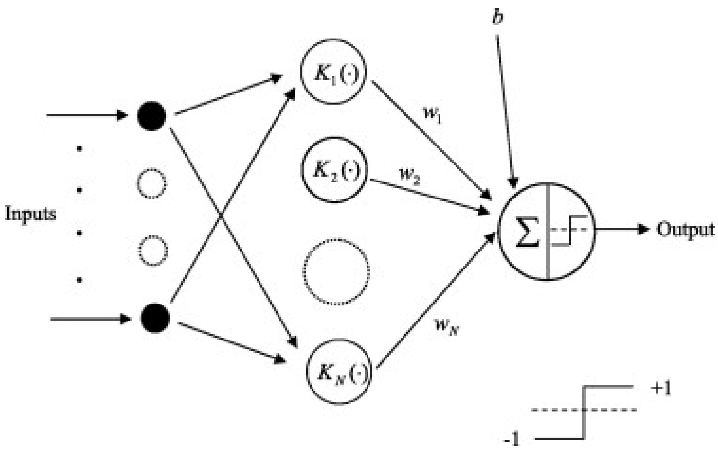

Figure 7. SVM Architecture

The architecture for the SVM is presented in Figure 7. Input models are mapped to a larger sub-space through non-linear mapping. A linear decision surface is then generated along this space of high-dimension characteristics. SVM is a linear classifier in the parameter space, so it becomes a nonlinear classifier because of the nonlinear mapping of an input model space in the high - dimensional space.

Random forest

A Random Forest (RF) is an ensemble made up of several different decision trees that operate together. The various trees in the random forest each provide a class prediction, as well as the class with the most votes will become the model's forecast. The basic idea of random forest is the wisdom of the masses, but it is a simple but powerful idea. Many uncorrelated trees that function as a committee will perform better than any member's individual models. The classification process of Random Forest shown in Fig.8.

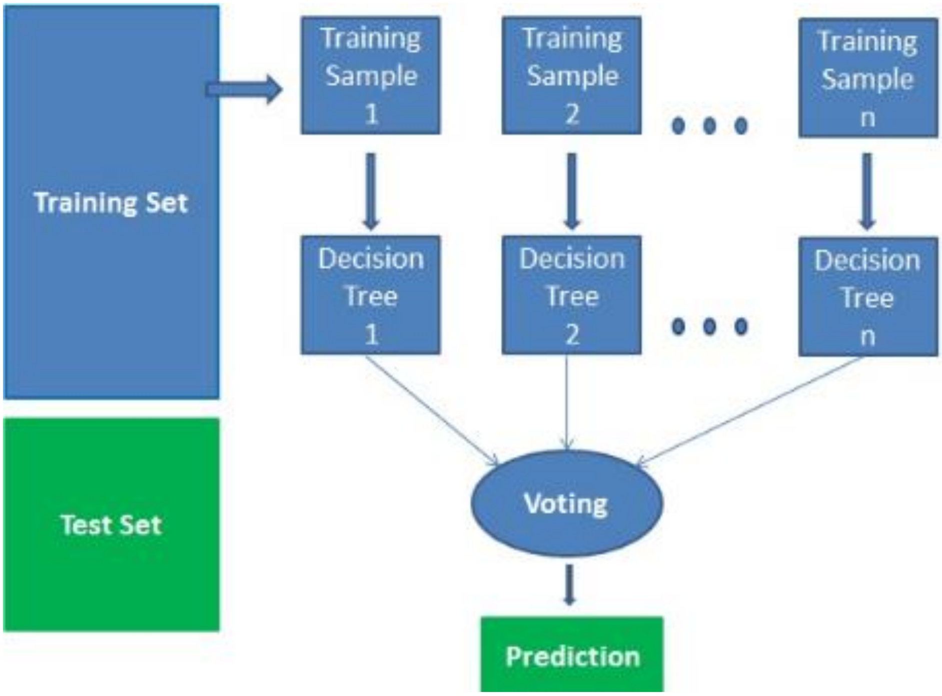

Figure 8. Classification process of random forest

Experimental Results

Datasets

The data are obtained from Center for Yoga Studies, Annamalai University. A total of 1000 yoga hand mudra images were collected, 75 % used for training and 25 % used for testing. 100 images of Brahma, Chin, Chinmaya, Linga, Prana, Prithvi, Rudra, Surya, Varun, and Yoni respectively.

Classification using SIFT and SURF with SVM

In the proposed work, the SIFT and SURF features are extracted from the images and the classifier SVM is used to classify the features. 128 dimensional SIFT features and 64 dimensional SURF features were extracted and the classifier SVM used to classify the Yoga hand mudras. The system yields 94.87 % of accuracy for SIFT features and 86.54 % of accuracy for SURF features. Fig. 9 shows the snapshot of the classification of yoga hand mudras using SIFT and SURF with SVM.

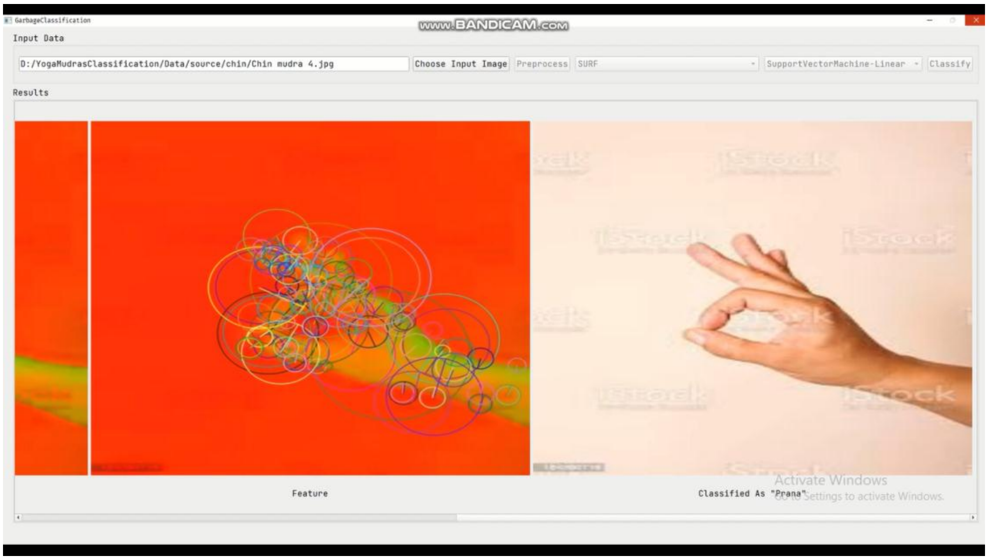

Figure 9. Classification of Yoga hand mudras

Classification using SIFT and SURF with random forest

The SIFT & SURF features are retrieved from the pictures in the proposed study, and the classifier RF is employed to categorise the features. 128 dimensional SIFT features and 64 dimensional SURF features were extracted and the classifier Random Forest used to classify the Yoga hand mudras. The system yields 94.23 % of accuracy for SIFT features and 89.74 % of accuracy for SURF features.

Performance measures

The overall performance of F-Score, precision and recall of yoga hand mudras classification is shown in Fig. 10. The overall accuracy is shown in Table 1. The accuracy of every hand mudra is calculated using the confusion matrix. The data can be trained and tested effectively. The precision, recall, F-Score and accuracy of the proposed work are

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

The preformance of SIFT and SURF with SVM and RF can be found in Fig. 10 and Fig. 11. The performance of SIFT with SVM yields better performance when compared to other models. The comparison of accuracy, recall and F-score is illustrated in the figure. 12. Table 1 shows the overall accuracy of the proposed work.

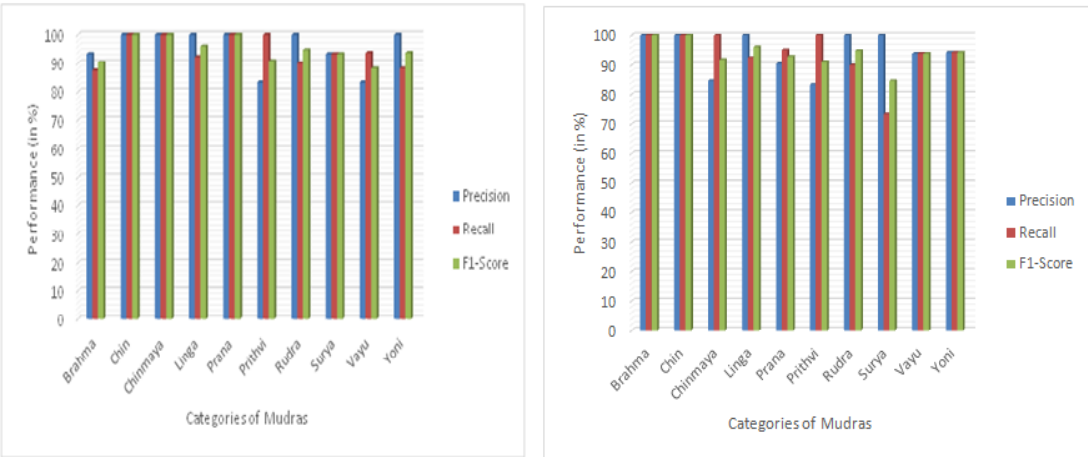

Figure 10. Performance of SVM using SIFT and SURF features

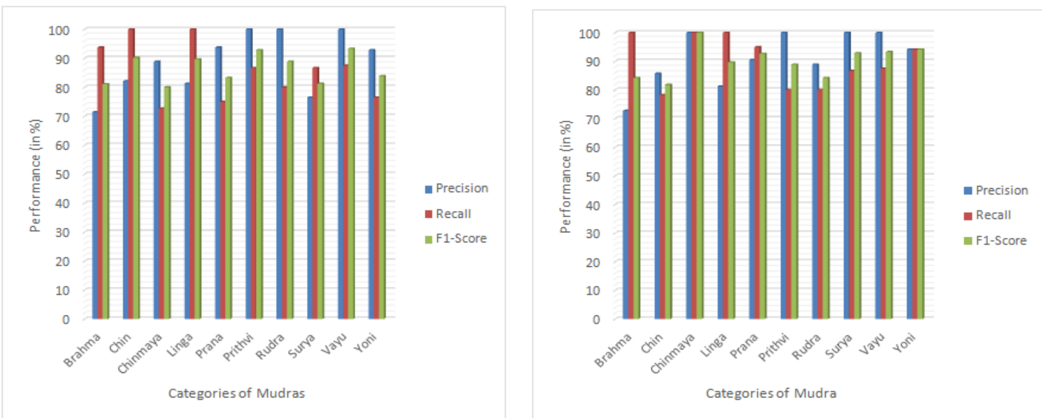

Figure 11. Performance of RF using SIFT and SURF features

Table 1
Overall accuracy

Features	Classifiers	Accuracy (in %)
SIFT	SVM	94.87
	Random Forest	86.54
SURF	SVM	94.23
	Random Forest	89.74

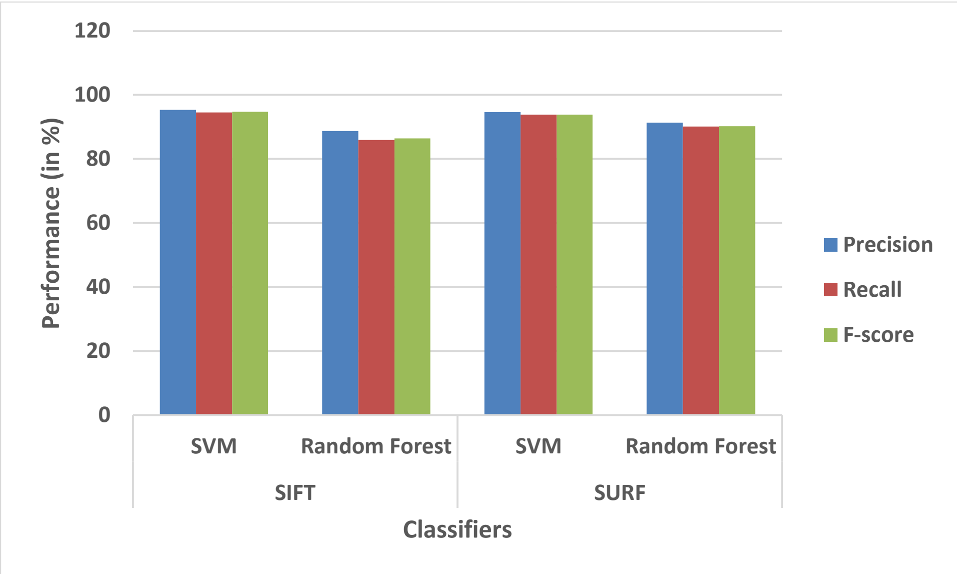

Figure 12. Comparison of this work

Conclusion

In this paper, the classification of yoga hand mudras has been proposed using the machine learning techniques SVM and RF, where SIFT and SURF as features to classify. Experimental results show that, the real time Yoga hand mudra images were collected. In this work, the performance of SVM with SIFT features gives the highest accuracy of 94.87 % when compared to other models. In future, the Yoga hand mudras and yoga asana will classify using deep learning models.

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