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Classification of Bharatanatyam postures using tailored features and artificial neural network

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ABSTRACT

Bharatanatyam is a classical dance form of India that upholds the rich culture of India. This dance is learned under the supervision of Guru, the teacher traditionally called in India. The scarcity of experts resulted in the decline of people practicing this dance. There is a need for leveraging technology in preserving and promoting this traditional dance and propagating it amongst the youth. In this research, it is attempted to develop a methodology for automated classification of Bharatanatyam dance postures. The methodology involves extraction of existing features such as speeded up robust features (SURF) and histogram of oriented gradients (HOG), which are used to train and test an artificial neural network (ANN). The results are corroborated with deep learning architectures such as AlexNet and GoogleNet. The proposed methodology has yielded a classification accuracy of 99.85% as compared with 93.10% and 94.25% of AlexNet and GoogleNet respectively. The proposed method finds applications such as assistance to Bharatanatyam dance teachers, e-learning of dance, and evaluating the correctness of the postures.

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1. INTRODUCTION

Bharatanatyam is a prominent Indian classical dance (ICD) [1] with a rich cultural heritage [2], which has embedded physical, mental, and emotional fitness qualities for the performers. Physical fitness is gained with the movements of legs and hands for a given posture, mental health is attained by releasing stress with happiness while performing during the concert, and emotional health is balanced by performing Navarasas, nine forms of facial expressions [3], [4]. The cultural and historical foundations of Bharatanatyam are very much evolved from the ancient temples of Tamil Nadu and South India. They use mudras, a form of sophisticated hand gestures, to portray various devotional characters belonging to Indian mythology. Every mudra has a specific meaning and significance. Along with the mudras, Bharatanatyam dance incorporates postures, body movements, and facial expressions to convey a bunch of narratives and emotions. This intricate combination of expressions and gestures brings the mythological stories to life, virtually carrying the viewers into a world of spiritual depth and divine beauty. Bharatanatyam is the synchronized sequential combination of different body postures, hand gestures, and facial expressions.

To exhibit these mesmerizing performances requires years of dedicated learning by the performer. Bharatanatyam students need to undergo intensive training to master the fundamental units such as mudras, adavus, and navarasas. Adavus laid the foundation for body strength, grace, and coordination. As per the scriptures, navarasas are the nine different human expressions. Abhinaya is an art of expression that helps the dancers to convey a set of emotions to the audience. The interplay of hand gestures, body movements, postures, footwork, and facial expressions allows the performer to become a storyteller, narrating the ancient Indian mythological stories to the audience. Through its captivating performances and universal themes, Bharatanatyam excels in cultural boundaries, promoting cross-cultural interactions and relations. With a sense of identity among communities and feel of pride, Bharatanatyam stands as an exemplification of India's rich cultural and artistic heritage.

This dance has to be learned from a Guru, a teacher, as it is governed by stringent and predefined rules for performing different postures [5]. Nowadays, the youth is not fascinated much by this classical dance as there are other modern dance forms across the world and a scarcity of experts to learn this dance. Since the youth is more attracted to digital and portable devices, it is essential to take leverage of technological advancements, such as digital image processing (DIP) [6]. Youth in today's generation are more inclined towards digital gadgets or mobile applications, and the essence of dance delivered through electronic equipment gains faster attention. When Bharatanatyam dance is taught or delivered with a mobile application or web application, there are high chances of gaining the attention and interest of the younger generation. Earlier researchers have worked on the classification of human postures and dance poses by using shape-based features, such as, speeded up robust features (SURF) and histogram of oriented gradients (HOG) with the help of machine learning classifiers, such as artificial neural networks (ANN). There are very few researches carried out on the utilization of combinations of features for pose classification, especially in the classification of Bharatanatyam postures. We have tried to make use of a combination of shape-based features in our research. Since the Bharatanatyam dance has different body postures combined with hand gestures, in this research we have presented a method for automated classification of postures. The prominent body postures are shown in Figure 1.

Figure 1. Some of the postures enacted while performing Bharatanatyam

A total number of 26 postures are classified of which 18 postures are from two families of postures called nattadavu and tattadavu and 8 postures are from namaskara postures, which are used for paying gratitude (salutation) to Guru in India. We have given suitable names for the different namaskara postures, namely, namaskara-1 to namaskara-8, which do not have exclusive names for individual postures. Similarly, nattadavu postures are also given names from nattadavu-1 to nattadavu-10 for implementation reasons. Adavu is a predefined sequence of postures [7]. For the purpose of research, we have considered the still images of those postures. Some of the postures have pre-defined names associated with them. The list of postures considered in the work is given in Table 1.

Table 1. List of Bharatanatyam postures considered

No.	Posture name	No.	Posture name	No.	Posture name	No.	Posture name
1	Namaskara-1	8	Namaskara-8	15	Tattadavu-4	22	Nattadavu-6
2	Namaskara-2	9	Sthanaka	16	Aremandi-3	23	Nattadavu-7
3	Namaskara-3	10	Aremandi-1	17	Nattadavu-1	24	Nattadavu-8
4	Namaskara-4	11	Tattadavu-1	18	Nattadavu-2	25	Nattadavu-9
5	Namaskara-5	12	Tattadavu-2	19	Nattadavu-3	26	Nattadavu-10
6	Namaskara-6	13	Aremandi-2	20	Nattadavu-4		
7	Namaskara-7	14	Tattadavu-3	21	Nattadavu-5		

Objectives of the research carried out are i) to leverage technology to promote and propagate Bharatanatyam dance; ii) to preserve the Indian cultural heritage and spiritual significance; and iii) to develop a methodology for automated classification of Bharatanatyam dance postures. The contributions made in this paper include i) classification of 26 still images of Bharatanatyam postures and classification from videos is not considered within the scope of this paper; ii) adoption of hand-crafted features, namely, HOG and SURF along with an ANN; and iii) pre-trained architectures such as AlexNet and GoogleNet are tested for the posture dataset. The task is considered challenging because of the complexities, such as obstructions caused by the attires of the performers, leading to misclassification of postures.

The remaining part of the article is organized into four sections. Section 2 gives a summary of the related works in the literature. Section 3 describes the proposed methodology. A comparison with existing works is given in section 4. Section 5 gives the conclusion.

2. RELATED WORK

We have carried out a literature survey to know about existing works in the classification of postures and other related works connected to dance such as body pose recognition. The idea of cited papers is as under. Machine learning and deep learning models are used in [3], [5] for the classification of ICD. The widely used deep learning architecture, AlexNet, is introduced by [8] and is adopted in research [9] for the recognition of human beings. The 22-layer deeper GoogleNet architecture is introduced by Szegedy *et al*. [10]. Multiple classifiers for the Indian sign language (ISL) classification are adopted in [11]. The most widely used scale and rotation invariant shape descriptors, SURF are introduced by Bay *et al*. [12]. Combinations of hand-crafted features and convolutional neural network (CNN) features are utilized in [13] for the classification of single-hand gestures of ICD. These hybrid feature vectors have given a classification accuracy of 95% when experimented with the VGG16 model. It is evident that hybrid features can play a better role in the classification of mudras. Attention-based features are used by researchers in [14] for recognition of Bharatanatyam poses. Deep learning architectures are effectively used in [15] for the identification of human beings. Ensembling of classifiers [16] and key points [17] are utilized in hand gesture and pose classification, respectively. Dalal and Triggs [18] have presented a HOG features for detecting human beings. Deep learning has also been proven to be effective in classifying fruits [19] along with their ability to classify ICD poses [20].

The HOG features are found to be relevant in estimating the orientation of the human body [21]. Deep learning is used by [22] for human pose estimation. Researchers have worked on dance pose recognition [23], dance choreography [24], and annotation of dance frames [25]. A combination of features, local self-similarity (HOG-LSS) is adopted in [26] for pedestrian detection and is found to be useful. Researchers in [27]–[32] have used shape-based features with machine learning classifiers and adopted deep learning architectures in classifying hand gestures, mudras, and postures of ICD. However, they have not attempted a combination of features. A rule-based approach utilizing key points for classifying Bharatanatyam mudras has given an accuracy of 72.04% [33]. Machine learning and deep learning classifiers are adopted in the detection of yoga poses [34], recognition of sitting postures [35], recognition of Bharatanatyam mudras [36], and recognition of dance movement [37].

In summary, certain works are attempted in recognizing human poses, classifying ICD and adavus, and identifying human beings using pre-trained deep learning architectures. Appearance-based features are used. There is less research carried out on applying a combination of shape-based features for the classification of Bharatanatyam poses. Deep learning approaches are adopted for the classification of human body poses and ICD poses. Since postures are fundamental units of Bharatanatyam, a work on the classification of different poses of postures is carried out.

3. PROPOSED METHODOLOGY

The methodology involves three stages, namely data acquisition, obtaining features, and posture classification, as shown in Figure 2. The setup used for data acquisition is given in Figure 3. A uniform black background is fixed before the acquisition of images.

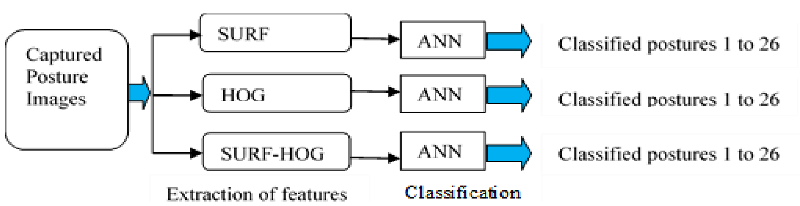
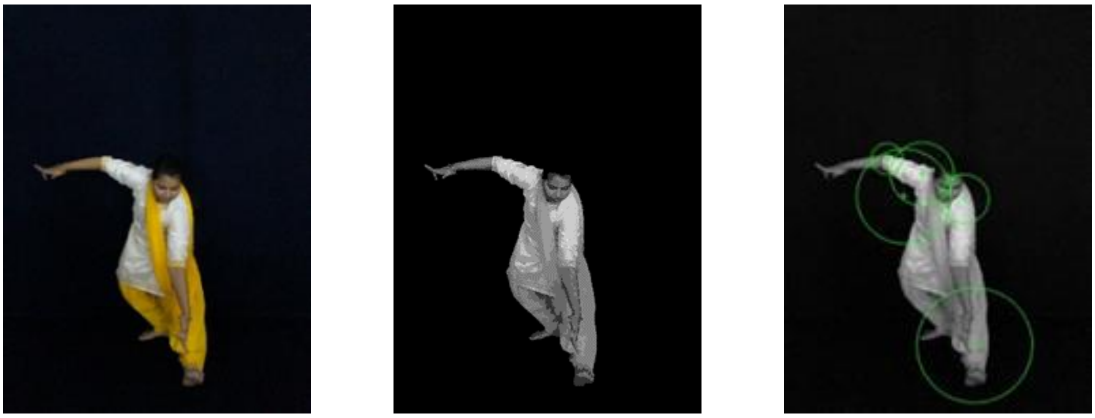


Figure 2. Proposed methodology for classification of postures

Figure 3. Process of capturing posture images

3.1. Feature extraction

The SURF and HOG features are extracted from captured posture images and deployed in classification. The dataset images are converted to grayscale before extracting the features. Figure 4 shows the process of extracting SURF features. The posture of nattadavu-9 and its grayscale image are depicted in Figures 4(a) and 4(b), respectively. The number of key points chosen is 5 and 64 features are extracted concerning each of the key points, as shown in Figure 4(c). A total of 320 feature values are obtained from each of the postures and used to train and test ANN.



(a) (b) (c)

Figure 4. Scenario of obtaining SURF features from Nattadavu-9 posture image of (a) Nattadavu-9 posture, (b) gray form of posture, and (c) extraction of SURF features

The HOG features are extracted by segmenting out the posture part from the background as depicted in Figure 5. Nattadavu-9 posture, extracted region of interest (ROI) of posture, the gray form of the ROI image, and the image resized to 128×64 are given in Figures 5(a) to 5(d) respectively. A bounding box is used to extract the posture part from the image, which is converted to grayscale and later resized to 128×64 pixels, the size used for calculation of HOG features [18]. A cell size of 16×16 is used for calculating HOG features and a total of 756 features are obtained for each posture image. The sample SURF feature values out of 320 features and sample HOG features out of 756 features, extracted from the nattadavu-9 posture image, are given in Table 2. The time elapsed in obtaining the adapted features, on groups of individual posture images, is also given in Table 2. The total time required for calculation of SURF features of our image dataset is 94.39 seconds and the time required for calculation of HOG features is 39.66 seconds. The experiments are conducted on a core i3-8100 processor at 3.60 GHz with a memory of 8 GB.

Figure 5. Scenario of obtaining HOG features from nattadavu-9 posture image of (a) nattadavu-9 posture, (b) ROI of posture is extracted, (c) gray form of the ROI image, and (d) image resized to 128×64

Table 2. SURF and HOG features of nattadavu-9 posture and time estimates of all the postures

SURF features		HOG features		Time estimate of SURF and HOG features					
No.	Value	No.	Value	Posture No.	SURF	HOG	Posture No.	SURF	HOG
1	0.000135	1	0.141226	1	5.46	1.23	14	3.04	1.56
2	4.67E-05	2	2.64E-01	2	4.78	1.68	15	2.99	1.61
3	0.000338	3	0.286343	3	7.65	1.85	16	3.20	1.60
4	8.01E-05	4	1.25E-01	4	3.05	1.57	17	3.09	1.62
.	.	.	.	5	5.79	1.46	18	3.18	1.66
.	.	.	.	6	4.00	1.58	19	3.12	1.52
				7	3.47	1.63	20	3.23	1.67
				8	3.37	1.42	21	3.05	1.53
				9	3.30	1.19	22	3.05	1.40
317	0.028662	753	0.124955	10	3.39	1.39	23	3.04	1.49
318	0.000175	754	0.030808	11	3.14	1.31	24	3.36	1.62
319	0.00017	755	0.108684	12	3.19	1.52	25	3.13	1.35
320	0.0002	756	0.382456	13	3.06	1.73	26	3.26	1.47

3.2. Classification

The dataset consisting of images of postures is created in natural environment. Both male and female dancers of different age groups are considered. MATLAB 2018a is utilized to implement the methodology. The dataset has a total of 6500 images, which include the images captured from both male and female Bharatanatyam dancers of different age groups, more than 10 dancers in each group. The devised methodology for the classification of postures is depicted in Figure 2. ANN is trained and tested for posture classification by using HOG and SURF features. The data augmentation is not performed during the process of model training as there are postures like nattadavu-5 and nattadavu-9 are looking flipped but they are different postures, as they are performed from two sides of the human body. Hence, the data augmentation techniques like flipping, and rotating are not done during the training process. The combined feature set SURF-HOG is also tested to classify postures. The ANN is constructed by using the neural network (NN) toolbox of MATLAB 2018a. Table 3 gives the parameters used to set up a neural network.

Table 3. Hyperparameters of ANN

Parameter	Used value	Parameter	Used value
Number of hidden layers	1	Transfer function	Log sigmoid
Metric used for	Accuracy	Number of neurons used at output layer	26
Function for learning	Learngdm	Number of neurons used at hidden layer	640 | 1512 | 2152
Function for learning	Traingdx	Number of neurons used at input layer	320 | 756 | 1076
Type of network adopted	Backpropagation	Initial learning rate	0.0001

When experimented with SURF features, a classification accuracy of 98.55% is obtained. Figure 6 shows some of the postures that conflict. For example, namaskara-1 and namaskara-4 postures are conflicting. Sthanaka and aremandi-1 postures are conflicting. Tattadavu-3, tattadavu-4, and aremandi-3 are conflicting. Nattadavu-5 and nattadavu-9 are conflicting. When experimented with HOG features, a classification accuracy of 98.71% is obtained. Postures Namaskara-1 and namaskara-2, namaskara-1 and sthanaka, aremandi-2 and aremandi-3 are found conflicting. When experimented with combined SURF-HOG features, a classification accuracy of 99.85% is obtained. The classification results produced by ANN are depicted in Figure 7.

Figure 6. Some of the conflicting postures

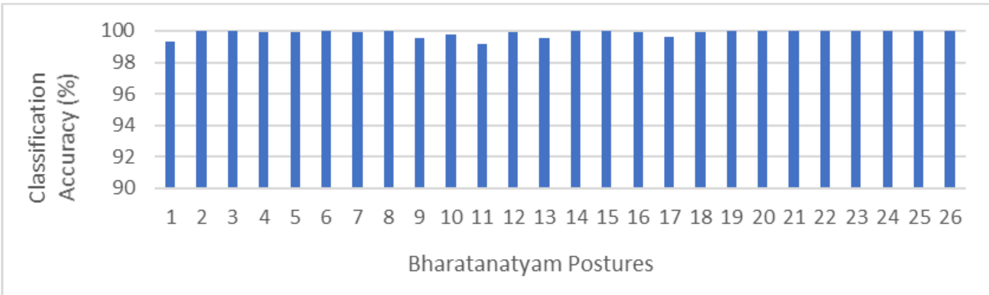


Figure 7. Classification results of each posture obtained by using SURF+HOG features

The ANN classification results are measured in terms of precision, recall, accuracy, and F1 score. These classification measures are given in (1) to (4) in which true positive (TP), false positive (FP), true negative (TN), and false negative (FN), respectively. The micro-averaging technique is adopted to calculate these classification measures. In the case of micro averaging, sums of FPs, FNs, and TPs are found to compute the global average F1 score. The obtained classification results are given in Table 4.

$$Precision = TP/(TP + FP) \tag{1}$$

$$Recall = TP/(TP + FN) \tag{2}$$

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{3}$$

$$F1\ score = 2TP/(2TP + FP + FN) \tag{4}$$

Table 4. Classification results of ANN with considered features

	Precision (%)	Recall (%)	Accuracy (%)	F1-Score (%)	Iterations	Training time
SURF	94.17	94.17	98.55	94.17	1339	95
HOG	96.27	96.27	98.71	96.27	751	318
SURF-HOG	98.13	98.13	99.85	98.13	935	732

To corroborate the results obtained by hand-crafted features deep learning architectures are tested. Deep learning applications significantly use the process of transfer learning. Two pre-trained deep learning architectures, namely, AlexNet and GoogleNet are used.

The AlexNet is trained with millions of images and is capable of classifying 1000 different object classes, such as keyboards, pencils, and animals. A fine-tuning of an AlexNet is made to suit the ICD posture classification. The architecture is made up of three fully connected layers and five convolutional layers. The input image of size 224×224×3 is fed to 1st convolution layer having 96 11×11×3 sized kernels, with a 4-pixel stride. The first layer output is normalized, pooled, and given as an input for the second layer. The filters with 256 kernels of size 5×5×48 is used at the second layer. No normalization and pooling layers are present between the 5th, 4th, and 3rd convolutional layers. There are 384 kernels, of size 3×3×256, in 3rd layer. There are 384 kernels, of size 3×3×192, in the 4th layer and 256 kernels with size 3×3×192 in the 5th layer [2]. The last 3 layers of this pre-trained architecture are fine-tuned for the Bharatanatyam posture image classification problem. The 3 layers are replaced with a fully connected layer, a softmax layer, and a classification output layer. As there are 26 classes in our problem, the size of the fully connected layer is set to 26. The images in the dataset are normalized to 227×227×3 as per the requirements of the architecture. The posture dataset is appropriately divided into a train set and a test set. The learning rate is set to 0.0001 and the setup has involved a single CPU, with 8 GB memory. The training cycle involved 1 epoch with 114 iterations. The total time elapsed to train and test our network is 9 minutes and 47 seconds. A validation accuracy of 93.10% is obtained.

GoogleNet, another pre-trained architecture, is tested on the posture dataset, wherein the images are normalized to 224×224×3, as per the requirements of the architecture. The GoogleNet, with increased width and depth, is a 22-layer deep network. It has inception, max pooling, and convolutional layers, which are core components of this architecture. The inception layer is a combination of 1×1, 3×3, and 5×5 convolutional layers. The inception layer output is concatenated as a single vector and is provided as input for the next stage [10]. The learning rate is set to 0.0001 and the setup involves a single CPU. The training cycle involved 6 epochs with 182 iterations per epoch, resulting in a total of 1092 iterations. The total time elapsed for training and testing the GoogleNet is set to 254 minutes and 37 seconds. GoogleNet has resulted in a validation accuracy of 94.25%. The summary of ANN and deep learning-based classifications is given in Figure 8.

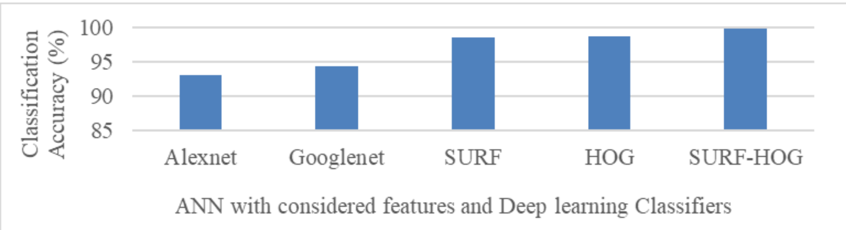


Figure 8. Classification results of Alexnet, Googlenet, and ANN classifiers with SURF, HOG, and SURF+HOG features

4. DISCUSSION AND COMPARATIVE STUDY

The discussion involves the interpretation of the obtained results from an ANN classifier and the comparison of considered SURF and HOG features in terms of their classification results and time efficiency. The SURF feature has produced a classification accuracy of 98.55%. When experimented with SURF features, a total of 4 postures are classified with an accuracy of 100%, which amounts to 15.38% of the total postures considered in the work. The remaining 24 postures are classified with accuracies ranging above 98% and less than 100%. The postures in the dataset are classified with accuracies not less than 98%. Some of the postures conflict with others in the dataset, which resulted in misclassification or reduced classification accuracy. This shows that SURF features are suitable to classify Bharatanatyam postures. The HOG feature has produced a classification accuracy of 98.71%. When experimented with HOG features, postures namaskara-1 and namaskara-2, namaskara-1 and sthanaka, aremandi-2 and aremandi-3 are found conflicting with each other. A total of 12 postures are classified with an accuracy of 100%, which amounts to 46.15% of the total postures considered in the work. The remaining 14 postures are classified with accuracies ranging above 98% and less than 100%. The postures in the dataset are classified with accuracies not less than 98%. This shows that HOG features can also better classify Bharatanatyam postures. The combined feature, SURF-HOG has produced an improved classification accuracy of 99.85%. When experimented with combined SURF-HOG features, a total of 14 postures are classified with an accuracy of 100%, which amounts to 50% images in the considered dataset. The remaining 14 postures are classified with accuracies greater than 99%. The postures in the dataset are classified with accuracies not less than 99%. With the results, it is evident that the misclassification of conflicting postures is reduced and overall classification accuracy has improved with the combined SURF-HOG feature. This classification accuracy is better compared to deep learning architectures, AlexNet and GoogleNet, which have given classification accuracies of 93.10 and 94.25%, respectively.

The time elapsed for training and testing ANN with SURF features is 1 minute and 35 seconds, with HOG features is 5 minutes and 18 seconds and with combined SURF-HOG feature is 12 minutes and 12 seconds. This shows that the time required by ANN for classifying postures with combined SURF-HOG features is more compared to individual SURF and HOG features. Even though the time required is more for classification with combined SURF-HOG features, the accuracy obtained for classification is more compared to individual features. The time elapsed for training AlexNet with the considered dataset is 9 minutes and 47 seconds. The time taken for training GoogleNet is 254 minutes and 37 seconds. The time taken by deep learning classifiers is more compared to ANN. The classification accuracies produced by AlexNet and GoogleNet, on our dataset, are less compared to the accuracy obtained by ANN with the combined SURF-HOG feature. With the results, it is evident that the misclassification of conflicting postures is reduced and overall classification accuracy has improved with the combined SURF-HOG feature. With these experiments, it is evident that the combined SURF-HOG feature is effective in terms of classification measures and time required for classification when compared with AlexNet and GoogleNet classifiers.

4.1. Comparative study

The proposed methodology is compared with existing and related works as presented in Table 5. The work is compared in terms of the problem domain, datasets, and classifiers used. The obtained classification accuracies are promising. Earlier researchers have used machine learning and deep learning classifiers for the classification of dance poses. Some researchers have used existing datasets and some researchers have created their own dataset. The number of classes and the corresponding reported classification results are less compared to our research. There are few attempts made in the utilization of a combination of features. Compared to earlier researchers, our research has attempted to use combination of shape-based features and more number of classes. Our methodology has produced better classification accuracy compared to earlier research.

Our research finds applications in developing mobile applications or web-based applications for assisting novice learners. Interactive applications can be developed to guide young learners and help them to correct their poses, in case of deviations by the learners. Our research has scope for further study. We have considered only 26 poses, containing poses of a few adavus and namaskara. There is scope for considering the classification of other adavus and the classification of facial expressions of Bharatanatyam dancers. Further research can be carried out in the direction of classification of Bharatanatyam postures from videos. Explainable artificial intelligence could be adapted in further study.

Table 5. Comparison with state-of-the-art works cited in the literature

Ref	Dataset	Technique	Experimental data	Number of classes	Classification accuracy (%)
[9]	ICD Mudra Dataset	SURF and HOG features are used with SVM	120 images of poses	24	98
[13]	Asamyukta Mudra dataset	Hu-Moments and VGG features	2610 images with 90 images of each class	29	95
[19]	Bharatanatyam pose	Genetic algorithm for pose generation	Skeletal of images	25	80
[27]	Bharatnatyam, Kathak, and Odissi	SVM classifier	100 images	15	90
[32]	Dance pose	Body skeleton is utilized with LSTM	Skeleton data of poses	10	95.2
[33]	Hand gesture dataset	Rules devised using Euclidean distance between joint angles	Keypoint images of MediaPipe	31	72.04
[37]	Balletto dance	Pose estimation algorithm and LSTM	Skeletal nodes of the human body	10	95.2
Our work	Bharatanatyam Adavu	SURF + HOG with ANN	6500 images of Adavu	26	99.85

5. CONCLUSION

The classification of 26 classes of Bharatanatyam postures is attempted in this work. The handcrafted features SURF, HOG, and combined SURF-HOG features are adopted and the classification results are measured in terms of precision, recall, accuracy, and F1 score. The time required for the calculation of considered tailored features is analyzed. ANN is used for classification using hand-crafted features. The SURF, HOG, and combined SURF-HOG features have produced classification accuracies of 98.55, 98.71, and 99.85%, respectively, on the considered dataset. To corroborate the obtained results, the pre-trained deep learning architectures, namely, AlexNet and GoogleNet are adopted and fine-tuned for the classification task. The validation accuracies of 93.10 and 94.25% are produced by AlexNet and GoogleNet, respectively. The time taken by ANN, AlexNet, and GoogleNet classifiers, for classification of images in our posture dataset, are compared. The combined SURF-HOG has produced better classification results over the deep learning architectures. Compared to existing works, the present work has used a larger number of images, and the results are corroborated with deep learning architectures. The proposed methodology can be adopted for the classification of other postures of Bharatanatyam and other human body postures, in general. Some of the envisaged applications of the method include evaluation of postures performed by Bharatanatyam dancers, e-learning of this ICD, and possibly delivery of automated commentary at the time of concerts.

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