IDENTIFICATION OF ASAMYUKTA HASTA MUDRA VINIYOGAS IN BHARATANATYAM USING CNN

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Abstract

Bharatanatyam is one of the most prominent types of Indian classical dance. Tutors are using traditional education processes for teaching this dance form. These days the practice of Bharatanatyam is being decreased due to the low availability of dance schools in remote areas. It is crucial to carry this rich culture to future generations. Many of the existing methods worked on the identification of the Asamukta hasta mudras (AHM), Samyukta hasta mudras (SHM), Adavus, etc. But most of them missed consideration of viniyogas of AHM mudras in Bharatanatyam. In this project, we proposed a method for the identification of viniyogas of AHM using Deep learning models like Convolution neural networks models. Here, we considered a customized dataset called the PDNV dataset consisting of a total of 600 images. In this dataset, 480 Photographs are used as a set for training purposes and 120 Photographs are considered for testing. These images are preprocessed by using resizing, and converting images to numpy arrays. Finally, the proposed method achieves a high degree of accuracy in terms of training and evaluation are 98.26% and 99.22%, respectively. Following the submission of an input image of a mudra, the model determines the class to which the mudra belongs and displays the associated meaning of the mudra.

Keywords: Bharatanatyam, Asamyukta hasta mudras, vniyogas, Convolution Neural Networks, CONV2D, Hand gesture.

I. INTRODUCTION

Bharatanatyam is an ancient and revered dance form that holds a special place in Indian culture. Originating in the southern part of India, it has evolved as a significant aspect of temple rituals, and is widely performed in temples across the country. As one of the eight recognized Indian classical dances, Bharatanatyam has been passed down from generation to generation, preserving its traditional techniques and expressions.

At the core of Bharatanatyam lies the intricate hand gestures, or hasta mudras, which come in two types: Asamyukta, which are one-handed gestures, and Samyuktha, which are two-handed gestures. The dance form also includes Adavus, which are full body postures that form the basic unit of Bharatanatyam.

Bharatanatyam serves as an authentic embodiment of the profound themes and spiritual ideologies inherent in the Hindu religion. With graceful movements, captivating facial expressions, and dazzling postures, dancers portray stories from Hindu mythology, conveying their message through this art.

While maintaining its traditional roots, Bharatanatyam has also evolved with the times. Dancers today are experimenting with fusion styles, blending traditional Bharatanatyam with other dance forms to create a unique and modern expression of this ancient art. Regardless of its form, Bharatanatyam continues to inspire and captivate audiences around the world with its beauty, grace, and rich cultural heritage.

Bharatanatyam is not just a form of entertainment, but it is also known for its numerous health benefits. Regular practice of Bharatanatyam can have a positive impact on physical as well as mental health. It helps to improve blood circulation and bone density, strengthens the heart, and enhances flexibility in the body.Here, are some ways Bharatanatyam dance can help in the medical field:

Improves physical health: Bharatanatyam dance involves a lot of physical movement and can help improve flexibility, balance, and coordination. It also helps in building stamina, strength and overall fitness, which is beneficial for the body.

Helps in rehabilitation: Bharatanatyam can be used in rehabilitation programs for individuals who have undergone surgery or have chronic illnesses. The movements involved in the dance can help improve mobility, flexibility, and reduce pain.

Reduces stress and anxiety: Bharatanatyam dance can help reduce stress and anxiety levels by providing a creative outlet for expression. It is also an effective form of meditation as it requires focus, discipline, and mindfulness.

Improves cognitive function: Learning Bharatanatyam requires a lot of memorization, focus, and attention to detail. It can help improve cognitive function, memory, and concentration.

Boosts self-confidence: Learning Bharatanatyam can help boost self-confidence and self-esteem as it requires discipline, dedication, and hard work. It can also help improve body image and self-awareness.

Overall, Bharatanatyam dance can be a beneficial form of therapy in the medical field, improving physical, mental and emotional wellbeing.

Apart from physical health benefits, Bharatanatyam also has significant mental health benefits. It can enhance memorization power, imagination strength, and creativity. The balanced body position maintained during the dance helps to cultivate a sense of stability and calmness in the mind. The expressive movements of the eyes in Bharatanatyam, known as Drishti, are a good workout for the muscles, which can also help in relieving stress and tension.

In addition, Bharatanatyam can also be used as a form of therapy for emotional and mental wellbeing. It can be an effective tool for anger management, and it can help to reduce anxiety and depression. The rhythmic movements and emotional expressions of the dance can have a calming effect on the mind, promoting a sense of inner peace and well-being.

Overall, Bharatanatyam is not just a beautiful art form, but it is also a powerful tool for promoting physical and mental health. Through its graceful movements, expressive gestures, and spiritual themes, Bharatanatyam has the power to uplift and inspire both the body and the mind.

Bharatanatyam, being a highly technical and intricate dance form, requires a great deal of skill and expertise to master. Earlier, Bharatanatyam tutors employed a traditional approach to teaching this dance, which involved a manual and individualized teaching method. The tutors would devote their time and attention to each student, providing hands-on guidance and personalized instruction to help them perfect their movements.

This method of teaching allowed the tutors to closely monitor each student's progress, identify areas of weakness and provide focused training to address them. The tutors also placed a great deal of emphasis on correct hand gestures or mudras, which are an essential component of Bharatanatyam. They would ensure that each student placed their mudras in the correct positions and executed them with precision and grace, making sure that the learner was able to learn the dance form precisely.

Moreover, the traditional approach also involved a holistic teaching approach, which emphasized the spiritual and emotional aspects of Bharatanatyam. The tutors would help students connect with the deeper meaning and symbolism behind each movement, which helped them imbibe the true essence of this beautiful dance form.

While digital tools and online resources have revolutionized the way Bharatanatyam is taught today, the traditional approach to teaching this dance form remains relevant even today. It provides a personalized and comprehensive learning experience that cannot be replicated by digital tools alone. The hands-on guidance and individual attention provided by tutors in the traditional method can help learners develop a deep understanding and appreciation of this art form, making it a valuable approach to learning Bharatanatyam.

Image processing techniques are used in the identification of different postures in Bharatanatyam. Image processing transforms the captured image into digital form and can get data from it such as pattern recognition, classification and segmentation. It also enhances the noise, contrast, brightness and resolution in images [3]. Digital image processing has various benefits and can be applied using a wide range of algorithms in machine learning and deep learning.

Research in this area involves developing algorithms and models that can segment and extract features from images of asamyukta hasta mudras. These features may include shape, texture, and color information, among others. Classification algorithms are then used to categorize these features into different mudra classes.

The use of asamyukta hasta mudra viniyogas identification can have numerous practical applications, such as in the development of virtual reality systems, gesture-controlled interfaces, and dance training tools. It can also play a pivotal role in the preservation and promotion of Indian classical dance genres.

In this paper, we will review the current state of the art techniques for identifying asamyukta hasta mudra viniyogas and their respective strengths and weaknesses. We will also explore the various challenges involved in this task and propose potential solutions for improving the accuracy and efficiency of the identification process. Ultimately, the goal of this paper is to contribute to the advancement of research in this area and to encourage further exploration and innovation in the domain of computer vision for AHM viniyogas identification.

This paper is structures as follows, segment I provides introduction, segment II presents literature survey, segment III describes proposed method followed by segment IV describing methodology. Experimental results are presented in segment V. Finally, segment VI concludes the paper by summarizing the key findings and outlining the possible future enhancements to the proposed method. By following this well-organized structure, readers can easily navigate through the paper and understand the research process and outcomes.

II. LITERATURE SURVEY

Himadri Bhuyan *et al.*(2022) [1] presented a motion pattern-based model in an attempt to solve the fundamental problem of motion recognising during the course of performance. Bharatanatyam, there is a distinctive pattern called the adavu that can be identified by the change in pattern from one frame to another and which is known as the adavu. To extract motion information motion histogram images are used. They examined every potential move using motion patterns and formulate a plan to handle the motion fluctuating frame count. Used an automated learning techniques CNN and SVM classifiers to identify Adavus in Bharatanatyam.

Himadri Bhuyan *et al*. (2021) [3] successfully suggested methods for extracting keyframes from Bharatanatyam dance moves and classifying different Adavus. The postures are the momentarily stationary poses of a dance performance. They have taken 166 videos and 700 to 1000 frames of each Adavu as a dataset and employed Support Vector Machine(SVM) and Convolutional Neural Networks(CNN) as a classifiers. The purpose is to distinguish the action frames of this dancing video from the fleetingly motionless frames (key frames). These keyframes are used to determine Adavus.

Himadri Bhuyan *et al.* (2021) [4] proposed a system for identifying the Adavus based on its series of characteristic postures. They have extracted the key postures from the video which helps in the extraction of the keyframes. Segmentation is not applied to these keyframes. Skeleton joint angle and RGB-HOG are the two features. SVM is used as a classification technique for classifying the keyframes. Natta and Mettu Adavus are recognised with an accuracy of 99%.

ShwetaMozarkar *et al.* (2013) [5] suggested a method to interpret a few static Bharatnatyam Mudras in order to tie the outcome to comprehending the corresponding expressions of Indian classical dance after detecting the sequence of mudra by utilizing pattern identification and image processing methodologies. Finally, an emotional description of the identified mudra picture is shown. The authors suggested a Saliency detection algorithm for picture pre-processing. A feature vector with an area props approach is used to extract features from photos. The photos are classified using the k- Nearest neighboring algorithm. 68 photos are utilized during the testing procedure, of which 58 are successfully recognized and 10 are misclassified. The obtained precision for recognition of the double-hand mudras in Bharatanatyam is 85.29%.

Dr Srimani *et al.* (2013) [6] proposed a method to recognize the identifying the 24 Samyuktha hasta mudras in Bharatanatyam in two-dimensional space and to fix the mudra, make the computer function as a tutor. In this article, pre-processing is accomplished through the use of segmentation and morphological filtering. In this scenario, as a feature vector for mudra categorization, the silhouette and the orientation histogram of the various movements are used. The images are present in diverse spatial orientations. The image is preprocessed here, features are retrieved from it, and classification is completed. The dataset is made up of 23 picture training sets, each has three photos. For testing, the sets are extracted from a single image. In each of the photos, three procedures were performed. The suggested approach may be utilized to recognize various hand double-hand motions in Bharatanatyam.

Basavaraj S. Anami et al. (2018) [7] Proposed a model for identifying various double hand gestures in Bharatanatyam. Three sections make up the proposed work. Mudra pictures are transformed to binary images in the initial stage of pre-processing. A boundary or counter is accomplished through the use of a sophisticated edge detection algorithm. Vertical and horizontal intersections as well as different characteristics of mudras are taken into account as features during the second stage of feature extraction. The grid size for the image is enhanced to help distinguish the interpolation mudras. By traversing the contour of the image, the gestures in Bharatanatyam are kept separate into isolated and non-isolated mudras. For the purpose of determining and categorising the unknown mudra, a rule-based classifier is created in the final stage. The mudras are speculated to have a gloomy background. 100 images from each of the 24 different dual-hand mudras are used to evaluate this approach, yielding a dataset of 2400 images. Conflicting mudras have an accuracy of 98.2% on average, compared to 100% for non-conflicting mudras. The cumulative double-hand mudra efficiency is 95.25 %.

According to Divya Hariharan and others (2011) [8], there has been an application developed for identifying single-hand mudras in Bharatanatyam in the space of two dimensions. The proposed system is a two-level decision-making system. pre-processing is accomplished through the use of arbitrary orientation and phase. At the first level orientation filter is used. At the second level silhouettes of the different motions are employed as a feature vector for mudra classification using a pattern recognition algorithm. The images are present in diverse spatial orientations. The dataset consists of 244 images.

R. Amrutha *et al.* (2016) [9] proposed a technique for identifying Bharatanatyam hand motions called Mudras. The authors address a few differences that arise during the identification of a gesture, such as shadow generation, filling gaps, and so on. In pre-processing images are cropped. The approach uses the Canny Edge Detection algorithm to carry out the segmentation based on skin to determine the boundary of the hand. The resultant gaps were filled using the flood fill technique. The feature extraction step begins with the chain code of whole hand contour, accompanied by normalization. Calculating Euclidean distance along 360 degrees from the centroid to the hand's outermost perimeter is also a part of the process. The images were classified using KNN (k nearest neighbor), Logistic Regression, Nave Bayes and Multiclass classification using SVM. There are two modes in the proposed system (Online and offline). The test image for online mode was captured throughout the run time. The test image is taken from testing data for offline mode and demonstrates an accuracy of 87.06%, 89.83%,88.47% and 92.3% using KNN (k nearest neighbor), logistic regression, Nave Bayes and SVM Multiclass classifiers, respectively. In Bharatanatyam, single-hand motions are detected with more satisfactory results. The testing picture in this system evaluates all four classifications and returns the best result.

By using the techniques of image processing, K. S. Varsha *et al.* (2020) [10] developed a system for determining the similarities between mudras in Bharatanatyam and their resemblances. As part of the Otsu algorithm, the segmentation of the image is performed using the Otsu technique. SURF, LBP, HOG and SIFT are the feature extraction methods used. SVM and KNN classification techniques are used for classifying the mudras. HOG feature extraction with SVM classification gives 92.33% accuracy.

For computerized recognition of single hand mudras in the dance form of Bharatanatyam, Lidia GhoshGhosh *et al.* (2013) [11] suggests a system with Fuzzy L membership mechanism that is flexible, and can be configured to recognize both single hand mudras simultaneously. An unknown single-hand motion was compared to a known static hand gesture. The author introduced the Fuzzy L membership function technique for matching unexpected hand gestures with known hand gestures. Using texture based segmentation, the dancer's hand is separated from the background. The sobel edge detection method was employed to determine the contour of the hand. The hand motion was correctly identified 85.1% of the time. The average computation time for recognizing the hand gesture is 2.563 seconds.

A four phase framework for automatic identification of single hand gesticulations in Bharatanatyam dance was suggested by SriparnaSaha *etal.*(2014) [12]. Initially, texture based segmentation is used to identify the dancer's palm from the back ground.The hand's border of the image is determined. The hand's perimeter is then approximately determined using straight lines in the following stage. In the third step, these slopes of each straight line are compared, and a chain code is formulated, which is represented by the sides of a decagon using the slopes of each straight line. In the final stage, an unknown chain code is matched with database chain codes with an accuracy rate of 89.3%.

According to S. Anami et al. (2019) [13] study, a model has been proposed which allows various single-hand gestures in Bharatanatyam to be identified. The dataset was gathered by photographing mudras against a black background. During pre-processing, counters are extracted. Eigen vectors, intersections and Hu-moments are recovered as features in the second stage. The artificial neural network (ANN) is used in the third phase to categorize the unknown mudra. 100 images from each of the 28 classes of mudras are used to evaluate this approach, yielding a dataset of 2800 images. A convolutional neural network is designed and evaluated to categorize the mudras. Overall precision of classification is 98% when using the eigen vectors, 96.9% using intersections, 97.1% when using Hu-moments, and 94.71% using deep learning. An artificial neural network with eigenvalues gives more accuracy. Additionally, it is suggested that deeper learning classifier's accuracy improves as the count of training images and the number of classification epochs increase, resulting in a longer classification time as the training images count and epochs increase.

A proposal made by K.V.V. Kumar *et al.* (2018) [14] to classify poses in Bharatanatyam and Kuchipudi dance forms based on a certain system of classification. Discrete wavelet transform (DWT) and LBP are the methods used for segmentation. During this process dancer shape and 2D cloud, points are extracted. Multi features like shape signature, Hu moments, LBP, Zernike moments, and Haar are extracted from the images that are segmented. Multiple feature fusion models are used during segmentation to concentrate on improving classification, and late fusion models are used after segmentation. Adaboost classifier is used for recognizing the poses. Finally, it identifies the dance form to which the pose belongs. The training dataset is recorded video and the testing dataset is online videos.

Six forms of Indian Classical Dance (ICD) are classified using a deep learning-based approach by Vinay Kaushik *et al.* (2018) [15]. ResNext-101 Kinetics, inception V3, novel pose signatures, 3D CNN, and pose signature are used as features. Symmetric Spatial Transformer Networks (SSTN) is used for recognizing different forms in ICD. A deep description of the handcrafts is provided as there are more similarities in ICD forms.

An artificial neural network technique is used for classifying ICD forms by P. V. V. Kishore *et al.* (2018) [16]. The frames extracted from the video and the images are pre-processed by resizing. The features obtained using the pooling technique. The ICD dataset is used. CNN is used for classifying the dance poses. Four convolution layers are used to improve the speed and accuracy. Finally, 93.33% accuracy is obtained for recognition poses in the ICD dataset.

Renu S Hiremath *et al.* (2017) [17] introduced a framework that instantaneously analyses a dance performance against golden standards and provides the performer with a scorecard in the form of graph along with comments and suggestions to perform in a better way. This system was trained using 1500 negative photos and 955 positive images. The author presented HAAR classification algorithm in this research to recognize body joints in each frame. A scoring system is used to score a dancer by comparing each frame to a gold standard. The precision of the tool attained while comparing the choreographer's video to itself, the score is 86%. Following the performance review, a scorecard is displayed. The dancer is considered to be on par with the expert if the final score is 8 or greater. A score of less than four is considered an amateur. The score will also provide recommendations to users. This approach facilitates self-study of Bharatanatyam. This program offers a less expensive method of judging a dance performance.

Mampi Devi *et al.* (2016) [18] suggested a two-level categorization technique for recognizing Sattriya dance single-hand gestures (Asamyuktha hasta/mudras). They addressed the problem by considering two levels and incorporating decision trees for further categorization. For this first-level categorization, the Support Vector Machine (SVM) is utilized. Because the SVM classifier produces superior results than other methods, it is widely employed. In addition, the class signification accuracy is tested using the open-source machine learning programme. Finally, in this work, total classification performance for Asamyuktha hastas in Sattriya choreography at the first-level is achieved. Following the identification of the group at the first level, the Decision tree classifier is employed to identify the Hasta at the second level. At this level, Group A's performance is detected as 71.62%, Group B's is 75.39%, and Group C's determined as 79.15%. At second level of categorization, the average accuracy is 75.45%. Based on an examination of the data sets utilized in the approach,both the simplicity and efficiency of the system employes actual data sets in the majority of the cases. This two-level categorization method's objective is to enhance the recognition performance of the developed system.

Lakshmi T.Bhavanam *et al.* (2020) [19] proposed a framework to identify mudras used in Kathakali dance by performers, through computer vision and machine learning instructional strategies. As classifiers, they used the CNN and SVM machine learning modeling techniques. They first took into consideration a dataset of kathakali hand motions, and then pre-processed the dataset in the next stage. In the third phase, the characteristics are retrieved using the Haar wavelet approach, canny edge detection and the contour extraction techniques. Finally, the classification of hand gestures is achieved by CNN and SVM techniques. There were 654 images taken from a scratch dataset, 480 images were to be considered a training dataset, 168 photographs to be considered a test dataset. They used a scratch dataset to collect the images. The recognition accuracy is 39% for the SVM model, and 74% for the CNN model.

The present study presents a comprehensive literature survey of the existing methods for identifying the Samyukta and Asamyukta hasta mudras in Indian Classical Dance (ICD) and Adavus in Bharatanatyam. However, it has been observed that these works have overlooked the viniyogas of Asamyukta Hasta Mudras (AHM) in Bharatanatyam, which are essential for portraying multiple stories to the audience through hand gestures. In light of this, the current research proposes a novel classification model based on CNN to accurately recognize each mudra.

III. PROPOSED METHOD

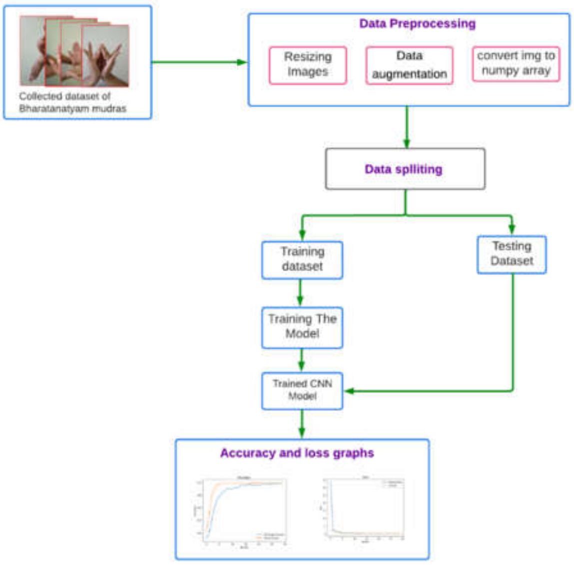

Fig 1. Architecture of proposed system

The suggested method employs a sequential model that incorporates CONV2D, maxpool2D, and dense layers with varying parameters. A detailed schematic of the architecture is presented in Figure 1. This approach is designed to optimize the performance of the system and achieve the desired outcomes efficiently.

Specifying the architecture is an essential step as it gives us a detailed roadmap of what's going on and what need to be done. In the first step the images of AHM viniyogas are collected. The next step deals with the pre-processing of dataset to fit the created model. which includes resizing, data augmentation, converting image to numpy arrays. Pre-processing is essential to boosting the model's accuracy. In the next step the dataset will be split into testing and training. The model was trained using the train dataset. Finally, an accuracy for classification of the data is obtained.

IV. METHODOLOGY

A. Dataset Collection

Though there are few publicly available datasets of various mudras and adavus. There is no dataset publicly available with images of viniyogas of asamyukta hasta mudras. So, we collected our own dataset of AHM viniyogas using a smart phone camera from various dance trainees with plain background. We named this customised dataset as PDNV dataset.

A dataset comprising 600 images of varying resolutions has been gathered for analysis, with each image belonging to one of twelve distinct classes, each of which corresponds to a specific mudra.

The dataset has been labelled according to the name of the mudra and each class is comprised of fifty images. The images will undergo further adjustments and preparation for analysis. This comprehensive dataset provides a valuable resource for studying and analysing mudras using computer vision and machine-learning techniques.

B. Pre-processing

Pre-processing seeks to improve image data by suppressing unwanted distortions or enhancing particular visual traits that are essential for analysis.

a. Resizing

The purpose of resizing is to standardize the size of the images so that they can be processed efficiently with the model. The images are resized as 100 x 100.

b. Data augmentation

In data augmentation we performed transformations like flipping, scaling and cropping the image to reduce overfitting. It is particularly useful when the available dataset is small or imbalanced and to boost the performance of the system.

c. Converting image to numpy arrays

Overall, converting an image to a NumPy array provides a convenient and flexible way to work with image data in Python, and allows to take advantage of the powerful array manipulation and analysis capabilities of NumPy.

By performing this pre-processing step, the input images can be fed into the pre-trained model, allowing the model to extract useful features from the images and classify the images. This step is essential in ensuring that the model can learn from the input images.

C. Classification

In this proposed work of CONV2D layers model, we considered a sequential model in which different layers like Conv2D layer, maxpool2D, Dropout, Flatten, Dense layers are place in a row in a specific order to create a training model. This uses ReLU as an activation function which helps in computationally efficient and can speed up the training of neural networks.The likelihood that the input belongs to the appropriate class is determined using the softmax activation function.

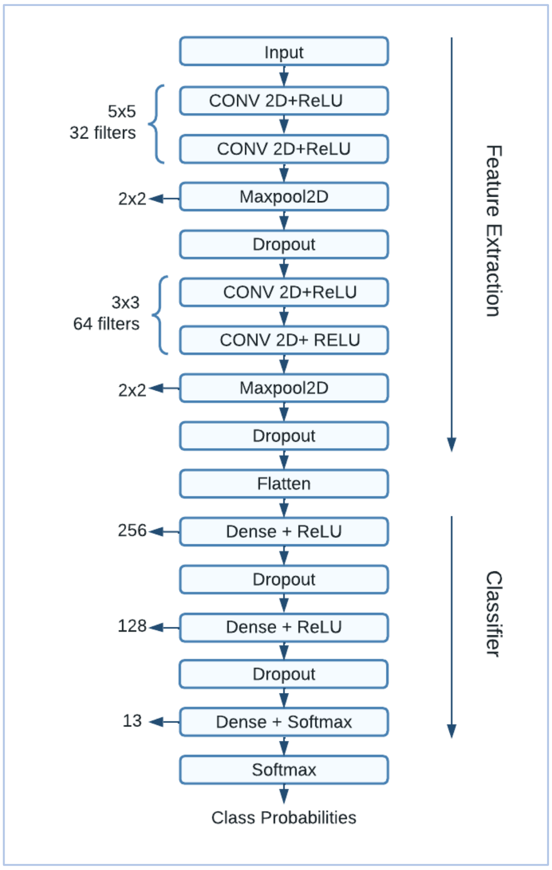

Fig .2: Architecture of CNN model for Classification

This model is a CNN designed for image classification tasks which is depicted in fig.2. It consists of four Conv2D layers with kernel size 5x5, 3x3 of 32, 64 filters respectively. Two maxpool2D layers of 2x2 pool size to down sample the feature maps. Four dropout layers with a rate of 0.25,0.5 to prevent overfitting. Three dense layer functions with 256, 128, 13 units with ReLU and softmax activation function to output class probabilities. This architecture has been shown to perform well on image classification tasks and can be further optimized by adjusting hyperparameters such as learning rate, batch size, and number of epochs during training.

D. Prediction

In order to make identify new mudra images and predict to which class does it belongs to. For this, we developed a prediction class as part of our overall mudra identification system. This class takes as input an image of a mudra and outputs the class of the mudra and give brief description for the identified image.

To predict the mudra, an image is inputted into the prediction class. Prior to prediction, the image is pre-processed by resizing it to a standard dimension of 100x100 pixels. The image is then converted to a numpy array and reshaped to a format suitable for the trained model. The prediction is made using the trained model, and subsequently converted to a class label using argmax, which enables identification of the specific mudra to which the image belongs. Finally, a description of the identified mudra is displayed. These steps represent a reliable method for accurately identifying mudras based on image inputs. The outputs of prediction class are displayed in Fig 3.

(a) (b)

Fig.3 Prediction outputs with description(a) Kapothe, (b) Padmadamini

Overall, the prediction class we developed using the CONV2D layer network model provides a highly accurate and efficient tool for identification of AHM viniyogas, with the ability to accurately predict to which class does the mudra belong to with a high level of accuracy and give description for the identified mudra.

V. RESULTS AND DISCUSSIONS

This section illustrates the Result and discussion in detail. The Results deal with the outcome of the proposed method. Discussion Deals with the comparison of proposed method with other existing methods.

Training and Validation analysis:

Results are the outcome of the study. In this section we are displaying the training and validation accuracy, training and validation loss.120 mudra images are used for the testing purpose. The collected dataset is randomly shuffled between the different mudra images to accurately evaluate the prediction capabilities of the model. The results Our proposed model showed an accuracy of 98%.

Fig.4 shows the accuracy graph for train and validation. Fig.5 illustrates the loss graph for train and validation.

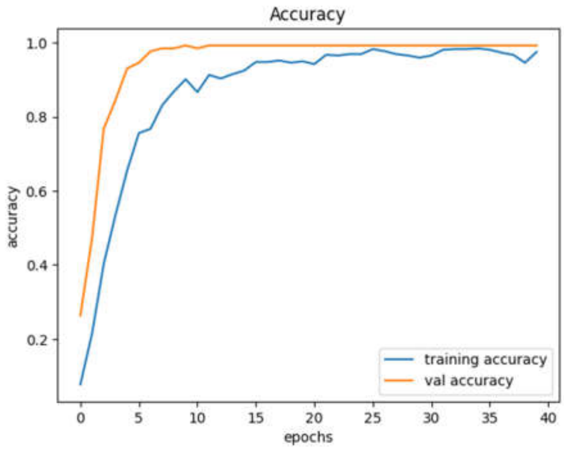

Fig .4 Training loss and Validation loss

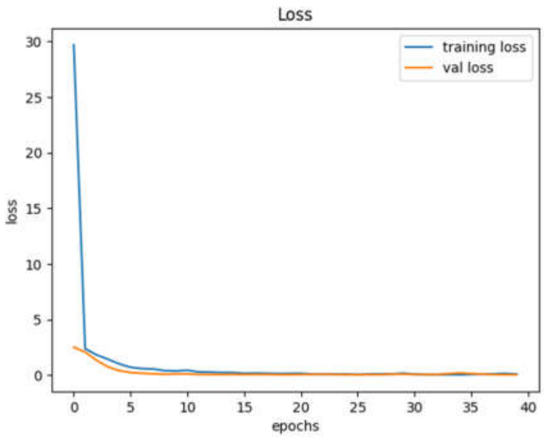

Fig .5 Training Accuracy and Validation Accuracy

VI. CONCLUSION

In conclusion, A novel approach for classification of mudras in Bharatanatyam using Convolution 2D layers is presented. By inserting Conv2D, maxpool2D, dense, dropout, flatten layers into the sequential model a new model is generated.Training this model on a large dataset of mudra images, A highly accurate and efficient model for mudra classification model is developed. And prediction class is used to predict the mudra and give description to the mudra. The use of Conv2D for identifying Bharatanatyam mudras shows great potential for improving the accessibility and understanding of this art form.

The results demonstrate that presented approach outperforms in classification of the AHM viniyogas by achieving high accuracy and precision rates on a variety of test datasets. This can be helpful in carrying this rich culture to future generation.

This work mainly focuss on identification of static viniyogas of mudras, this work can be further extended by considering dynamic movements of viniyogas of AHM and giving the description for each mudra.

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