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Indian Hand Mudras Based Classical Dances Classification using Deep Learning : Bharatanatyam Mudras Dataset

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Abstract-

Concept, purpose, and emotions in dance are expressed through the performer's gestures. Accurate interpretation of these gestures requires skilled analysis, which can be achieved through human expertise or artificial intelligence techniques. In recent years, **Dance Mudra Recognition** has emerged as an important interdisciplinary research field. This paper reviews previous work on Indian classical dance recognition, with a focus on automated systems developed by various researchers. The main objective of this study is to develop an **efficient AI-based method** for recognizing different hand mudras using deep learning techniques. For this purpose, a **Bharatanatyam hand mudra dataset** has been used. In this research, we employ **MobileNet**, a lightweight convolutional neural network architecture known for its efficiency and suitability for deployment on resource-constrained devices. To make the system accessible and interactive, a **user-friendly web interface** has been developed using the **Django framework**. The interface allows users to upload hand gesture images or use live video streams to classify mudras in real time. This integration of MobileNet with Django enables practical deployment of the recognition system for educational, cultural, or archival applications. MobileNet was trained on the Bharatanatyam dataset and achieved high accuracy in classifying a wide range of hand mudras. To the best of our knowledge, this is one of the first applications of MobileNet combined with Django for real-time Indian classical dance mudra recognition.

Keywords: hand mudras, Bharatanatyam, deep learning, MobileNet, Django, Indian classical dance, gesture recognition, web interface

I. INTRODUCTION

Indian classical dances such as Bharatanatyam, Sattriya, Kathak, and Odissi are rich embodiments of India's diverse cultural heritage. These art forms incorporate intricate leg movements, facial expressions, and hand gestures known as *mudras*, which convey emotions, actions, and narratives. Particularly, hand mudras play a vital role in storytelling, forming a non-verbal language that transcends linguistic barriers [1]. Among these, the *Sattriya* dance, a classical form rooted in Assam's Vaishnavite monasteries, portrays mythological tales, especially of Lord Krishna, using a dynamic interplay of hand gestures, foot rhythms, and expressive eye movements.

Hand mudra recognition involves the identification of various symbolic finger and palm positions and their contextual orientation. This is a complex task, especially in the context of real-time recognition under varying lighting conditions, hand shapes, and backgrounds. Recent advancements in computer vision and artificial intelligence have made it possible to automate the recognition of these gestures using machine learning and deep neural networks [2][5][6]. Previous research in this domain has leveraged optical flow techniques [3], spatiotemporal interest points [2], dense trajectory tracking [4], and multi-fused spatiotemporal features [4][5] to detect motion and posture in human activity recognition systems. Studies such as those by Ji et al. [5] and Mohanty et al. [6] have demonstrated the effectiveness of 3D CNNs and transfer learning in identifying body postures and gestures in dance sequences. Moreover, specific works have focused on the cultural context of Indian classical dance forms. For instance, recognition systems for Bharatanatyam have employed handcrafted features like HOG [9], skeleton-based matching [1], fuzzy logic [11][13], and CNN-based architectures [6][13].

While these approaches have shown promising results in Bharatanatyam and sign language gesture recognition, Sattriya dance remains relatively underexplored. There is limited availability of annotated datasets specific to Sattriya mudras, and most existing systems are tailored to either Bharatanatyam or general sign gestures [9][14].

This research aims to bridge that gap by focusing on the recognition and classification of Sattriya dance mudras. One of the key contributions of this work is the development of a robust, annotated dataset consisting of both single and double-hand mudras of Sattriya dance, captured in various lighting and pose conditions. The research also proposes an efficient deep learning model, optimized for real-time recognition, capable of achieving high accuracy across different gesture classes.[16]

The practical implications of this work are multifold. A mobile-based mudra recognition system can serve as a learning aid for dance students, a digital preservation tool for cultural institutions, and an assistive platform for gesture-based communication. This aligns with the broader goals of the Digital India initiative by contributing to the preservation and promotion of India's intangible cultural heritage.

The structure of this paper is as follows: Section 2 provides a comprehensive literature review on gesture recognition and Indian classical dance classification methods. Section 3 outlines the methodology including dataset preparation, model architecture, and training procedure. Section 4 discusses the experimental results and performance evaluation. Finally, Section 5 presents the conclusion and future scope of this research.

II. LITERATURE SURVEY

D. Das Dawn and S. H. Shaikh [3] discuss a few research papers with reference to the STIP (Spatio Temporal Interest Point Detector) method. From their studies, it is seen that strong interest point detection from videos in the spatiotemporal domain is achieved by the STIP-based detector. Video motion data can be captured through trajectories. A dense interpretation ensures adjoining context and forefront motion are adequately covered.

H. Wang and C. Schmid [2] establish the fact that by removing background trajectories and blending optical flow using a strongly predicted holography emulating the camera motion, the performance can be greatly enhanced. H. Wang et al. [2] in their research introduce a new method for modelling videos that combines feature tracking and dense sampling. This approach performs better than traditional state-of-the-art methods.

The paper by P. V. V. Kishore et al. [3] used backpropagation neural networks to extract hand tracks and hand shape data from continuous sign language films in order to classify gestures. Horn-Schunck optical flow and active contours (AC) were used to extract tracking and shape features from sign videos, classifying them into digital word sequences, which are then translated into voice using Win-API.

Ahmad Jalal et al. [4] present innovative multi-fused features for an online human activity recognition (HAR) system that recognizes human activities based on continuous sequences of depth maps. Using temporal motion and spatiotemporal human body information, the proposed system segments depth silhouettes and extracts spatiotemporal multi-fused characteristics such as skeleton joint features and body shape features. Experimental results on challenging datasets show superior recognition accuracy over existing methods.

According to S. Ji et al. [5], 3D convolutional neural networks (3D CNNs) can create features from both temporal and spatial dimensions. Their architecture performs subsampling and convolution independently, generating multiple information channels. Their models outperformed traditional approaches on TRECVID and KTH datasets. The authors suggest applying deep learning for understanding the semantics of Indian classical dances, especially focusing on body postures and hand gestures.

A. Mohanty et al. [6] introduce a CNN-based deep learning approach for semantic understanding of Indian classical dance. Their model outperformed traditional algorithms in recognizing body postures and hand gestures using popular and ICD datasets. They also highlight the challenge of synchronizing music and vocal elements with the dancer's complex costumes, changing background, and narrative content. Transfer learning is suggested to mitigate issues in supervised learning.

Divya Hariharan et al. [7] propose a two-level decision-making system leveraging scale, translation, and rotation invariants. Images are resized to 240x240 pixels, cropped to focus on hand regions, and converted to grayscale. Their method uses edge orientation histograms, thinning operations, and other features to recognize dancer gestures.

In the research by Saba Naaz et al. [1], aggregation signatures from multi-scale features of super-resolution images are used to classify Bharatanatyam mudras. This method combines deep learning and fuzzy logic to enhance AR-based learning, demonstrating 96% classification accuracy using hamming-based distance operators.

Similarly, M. Kalaimani and A.N. Sigappi [13][16] apply VGG-based deep learning models for Bharatanatyam mudra recognition. Their approach also integrates fuzzy membership functions, reaching a comparable accuracy of 96%, showing the robustness of using deep convolutional features.

K.V.V. Kumar and P.V.V. Kishore [9] employed HOG (Histogram of Oriented Gradients) features with an SVM classifier, achieving 85.29% accuracy in mudra recognition. Their method includes image binarization, feature extraction, and the use of a multi-class SVM classifier, reflecting an effective classical machine learning approach.

Pravin R. Futane and Dr. Rajiv Dharaskar [10] demonstrated how sign language gestures could be interpreted using Gaussian functions and Canny edge detection. Their work enabled 2.5% of the deaf and mute community to communicate independently, reflecting the practical applicability of gesture recognition in assistive technologies.

Basavaraj S. Anami and Venkatesh Bhandage [11] employed a three-stage approach including feature extraction, canny edge detection, and ANN-based classification for mudra recognition. Their study compares various feature sets, offering insights into the relative effectiveness of each in Indian classical dance recognition tasks.

Bhavana R. Maale and Vaishnavi [12] focused on single-hand gestures in the Sattriya dance form using a two-level classification system, demonstrating its adaptability for other Indian classical forms, including Bharatanatyam.

Parameshwaran et al. [14] explored transfer learning to classify single-hand gestures in Bharatanatyam using a comprehensive mudra dataset. Their findings confirm the viability of reusing pre-trained models to improve accuracy and reduce training time in dance gesture recognition.

III. METHODOLOGY

In deep learning, a kind of machine learning, input and output layers are augmented by extra layers known as hidden layers. In continuation of the research discussed in the literature review, this section outlines the methodology adopted for recognizing *Bharatanatyam* dance mudras using MobileNet, a lightweight deep learning model suitable for real-time and mobile applications. The primary objective of this research is to build a robust, efficient, and accurate mudra recognition system using a well-structured dataset and MobileNet architecture.

The overall framework of the proposed method is shown in Figure 1, which represents stages such as data acquisition, preprocessing, training using MobileNet, and final mudra classification.

3.1 Dataset Collection and Preparation

To ensure data diversity and authenticity, images of single-hand and double-hand mudras of *Bharatanatyam* dance were collected from various dance schools across Guwahati, Assam. Each mudra was captured from three angles: front, left, and right. This multi-view approach improves recognition performance under different perspectives and lighting conditions.

The dataset was manually annotated and structured into two major categories:

- Single-hand mudras
- Double-hand mudras

Table II presents the number of samples captured per mudra type and view. Data augmentation techniques, such as rotation, scaling, and horizontal flipping, were applied to improve generalization and increase training data volume.

3.2 Model Architecture: MobileNet

For classification, the proposed system uses MobileNet, a deep convolutional neural network optimized for efficient computation and mobile deployment. It utilizes:

Depthwise separable convolutions to reduce computation cost ,Lightweight architecture suitable for real-time applications , High accuracy despite its compact size

Why MobileNet?

Achieved 95% classification accuracy on our Bharathanatyam mudra dataset.

Significantly lower computational cost compared to models like ResNet or ViT.

Highly suitable for deployment on Android-based recognition tools.

Training Details:

Input size: 224x224 RGB images

Loss function: Categorical cross-entropy

Optimizer: Adam

Batch size: 32

Epochs: 50 (early stopping applied)

Training accuracy: 95%

Validation accuracy: Comparable, confirming generalization

3.3 Key Contributions

- Development of a multi-view annotated dataset of *Bharatanatyam* dance mudras (single and double hand)

- Implementation of a MobileNet-based recognition system capable of classifying mudras with high accuracy
- Designed to support real-time performance in mobile and embedded platforms
- Contributes to the digital preservation and educational dissemination of *Bharatanatyam* dance culture

IV. SYSTEM ARCHITECTURE

The system architecture is presented in fig.1.

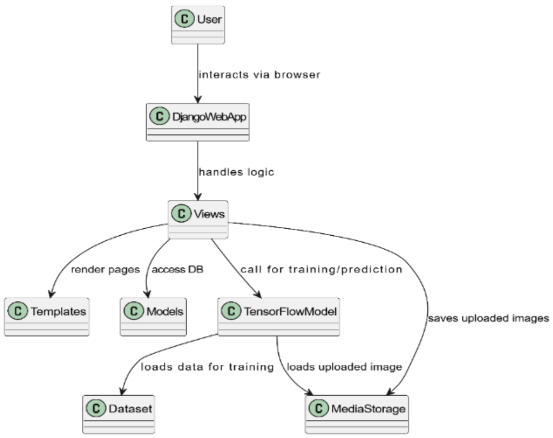

Fig.1. System architecture

The system processes input data in various formats such as images, audio, and video. For this project, **pedestrian image data** is used as the primary input. The dataset is first **preprocessed**, which includes steps like **removal of duplicate images** and normalization to ensure consistency.

Following preprocessing, the **Feature Extraction** phase is applied to extract significant visual patterns and attributes from the images. These features represent key information needed for classification. In the subsequent **Feature Selection** stage, the most relevant features are identified and retained, which helps improve model accuracy and reduce computational overhead.

The dataset is then **split into training and testing sets** to facilitate supervised learning. The training set is used to fine-tune the **MobileNet deep learning model**, which is optimized to classify the input image and **predict the presence or absence of abnormalities** in pedestrian scenes. References [15] and [16] highlight the effectiveness of similar deep learning approaches in related classification tasks.

V. RESULTS AND DISCUSSION

In this paper, a number of contemporary research articles related to **Indian classical dance mudra recognition** were reviewed, with a focus on the methods adopted, datasets used, and model performances. The current study specifically addressed **Bharatanatyam single-hand mudras**, evaluating their classification performance using deep learning techniques.

A significant challenge highlighted in existing literature—and encountered in our experiments—is the **close resemblance between many single-hand mudras**, leading to high chances of **misclassification**, especially when the dataset size or variability is limited. Additionally, **feature extraction and selection** remains a key difficulty due to the subtle yet critical differences in mudra structure and orientation.

Our experimental results demonstrate that the **MobileNet architecture** offers a robust and lightweight solution for real-time mudra classification. With **95% classification accuracy** on single-hand mudras, MobileNet outperforms several conventional models in both efficiency and speed. This confirms its suitability for mobile and embedded applications, such as an **Android-based mudra recognition tool**.

To extend this research, the following future directions are proposed:

Improve real-time recognition accuracy by refining MobileNet-based models with more diverse training data including different lighting conditions, performer orientations, and costume backgrounds.

Enhance robustness of the recognition system by incorporating background subtraction, pose estimation, and hand segmentation to minimize noise.

Develop an interactive feedback mechanism to aid learners and performers in practice environments through immediate correction or affirmation of the performed mudra.

Curate a comprehensive dataset with annotated metadata for single and double-hand mudras from various classical dance forms like Bharatanatyam, Sattriya, Kathak, and Odissi.

Fig. 2 and Fig. 3 illustrate the accuracy and loss graphs for the MobileNet model. In this project, the model was trained over 20 epochs during the training phase.

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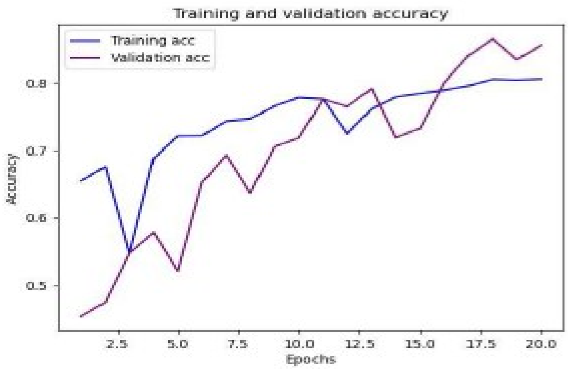

Fig.2. Accuracy

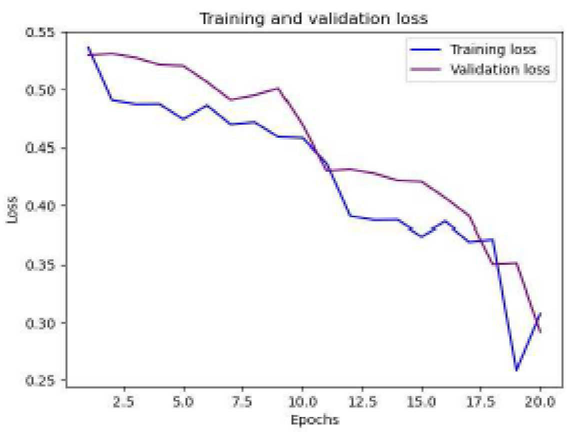

Fig.3. Loss

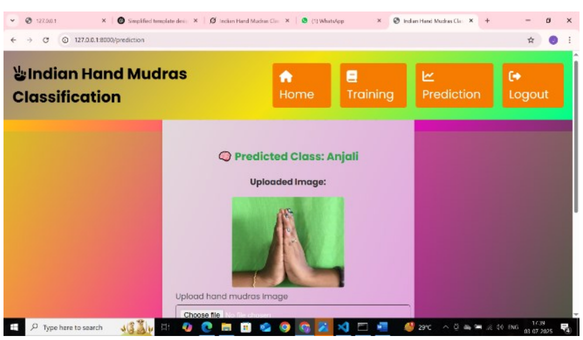

Fig.4. Output1

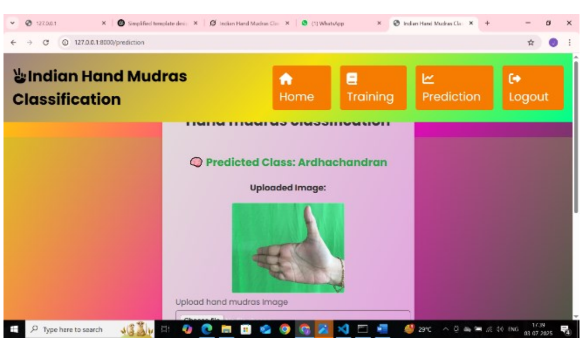

Fig.5. Output2

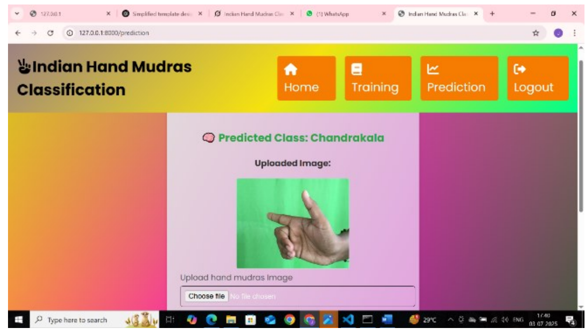

Fig.6: Output3

In this project, the **MobileNet** architecture is employed to classify pedestrian images by detecting the **presence or absence of abnormalities**. The model is trained on a labeled dataset, and various configurations are evaluated to determine the most effective version. The final model is selected based on its **highest validation performance**. The MobileNet model achieved a commendable **accuracy of 95%**, demonstrating its effectiveness and efficiency in abnormality detection within pedestrian imagery.

VI. CONCLUSION

This study presents a focused approach for recognizing hand mudras of dance using computer vision techniques and deep learning, specifically employing the **MobileNet** architecture. Through an extensive literature review, we explored various models and methodologies applied to hand gesture and Indian classical dance recognition, identifying common challenges such as close visual similarity among mudras, dataset limitations, and variability due to lighting or background.Our research contributes by curating a **multi-view dataset** of both single and double-hand Bharathanatyam mudras and by successfully implementing **MobileNet**, which achieved a commendable **95% accuracy** on the test set. The lightweight and efficient architecture of MobileNet makes it highly suitable for **real-time and mobile-based applications**, which aligns with our broader goal of building an **Android-based mudra recognition tool** to preserve and promote the cultural heritage of Assam.Despite promising results, certain limitations such as **inter-class similarity**, **dataset size constraints**, and **environmental noise** remain open areas for future work.

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