A ES
ISSN: 2096-3246
Volume 58, Issue 01, 2026

EXPLORING THE ALGORITHMS AND TOOLS USED IN INDIAN CLASSICAL DANCE HAND GESTURES: A SYSTEMATIC REVIEW

Dhanya M[1], Dr. K. Geetha[2]
[1]Research Scholar, Department of Computer Science, Sri Krishna Adithya College of Arts and Science, Coimbatore. dhanyaranjit@gmail.com
[2]Associate Professor & Head, Department of Computer Applications, Sri Krishna Adithya College of Arts and Science, Coimbatore. kkgeetha17@gmail.com

Abstract
Hand gestures, or mudras, are integral to Indian classical dance, serving as a visual language to convey emotions, narratives, and cultural symbolism. Mohiniyattam, a classical dance form from Kerala, is known for its graceful, feminine movements and fluid gestures that enhance storytelling. Rooted in ancient texts like the NatyaShastra and the Abhinaya Darpanam, mudras play a vital role in performance and expression. Recent studies have leveraged motion capture technology, high-resolution motion analysis, and semiotic research to examine the technical execution and expressive potential of mudras. Interdisciplinary approaches, including ethnographic studies and computational models, have further enriched the understanding. The beneficiaries of Mohiniyattam studies include performers, scholars, and choreographers across the nation, as well as audiences seeking artistic immersion. Many dance enthusiasts from other countries come to India to practice and study Mohiniyattam, enriching both their mental and physical well-being, which also contributes to the global recognition of the art form. However, comparative studies on hand gestures across dance traditions and their cognitive impact on audience engagement remain underexplored. Addressing these gaps can aid in preserving traditional mudras while embracing technological and conceptual innovations. This review provides insights into the evolving landscape of gesture-based expression in Indian classical dance, bridging tradition and modernity for deeper appreciation and scholarly exploration.

Keywords
Mudras; Mohiniyattam; Gesture Recognition; Indian Classical Dance; Motion Capture Technology

1. Introduction

Indian classical dance, a profound expression of India's cultural and spiritual heritage, encompasses diverse forms such as Bharatanatyam, Kathak, Odissi, Manipuri, and Mohiniyattam. These dance styles, deeply rooted in tradition, integrate rhythmic movements, facial expressions, and symbolic gestures to narrate stories from mythology, history, and folklore. Mohiniyattam, a classical dance form originating from Kerala, is characterized by its graceful, swaying movements and a strong emphasis on subtle expressions. This feminine and lyrical dance form extensively employs mudras to communicate emotions, blending slow, circular movements with controlled expressions to create a captivating visual experience. Beyond their aesthetic appeal, these gestures serve as a bridge between the dancer and the audience, evoking deep emotional resonance. The significance of mudras is well-documented in ancient treatises like the Natya Shastra and the

Abhinaya Darpanam, which classify and elaborate on their meanings and applications in dance and drama. While mudras play a crucial role in all Indian classical dance forms, interdisciplinary research comparing their psychological and semiotic dimensions across different traditions remains limited. Recent technological advancements, such as motion capture and computational analysis, have opened new avenues for studying the technical precision and expressive depth of mudras, ensuring that these traditional art forms evolve while maintaining their authenticity.

This article is structured as follows: Section 2 presents a detailed literature review of various dance forms, with a particular focus on recent studies related to mudras in Mohiniyattam. Section 3 identifies existing gaps in the research and suggests potential areas for future exploration. Section 4 addresses the challenges and limitations faced in the study of mudras and concludes with reflections on the significance of hand gestures in Indian classical dance and future directions for research.

2. Literature Review

The digitization and automated recognition of Indian classical dance forms, especially through artificial intelligence and computer vision, have seen growing scholarly attention in recent years. This surge stems from a dual motivation—preserving intangible cultural heritage and facilitating modern analytical interpretations of traditional art forms. This review explores significant works that have advanced the domain using different computational approaches.

(Bhavanam & Iyer, 2020) [1] explore the classification of Kathakali hand gestures by employing Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). The study aims to automate the recognition of 24 distinct mudras integral to Kathakali, a classical Indian dance form. A dataset comprising 654 images was curated, capturing various hand gestures. The methodology involved preprocessing these images and training both SVM and CNN models to classify the gestures. The CNN model demonstrated superior performance, achieving an accuracy of 92%, while the SVM model attained 85%. This research underscores the potential of deep learning techniques in preserving and interpreting traditional dance forms.

The work (Remya & Rajkumar, 2024) [2] represents a pivotal contribution toward the automatic classification of Asmyukta mudras, which are single-hand gestures intrinsic to Indian classical dances. Their approach introduces a hybrid classification framework that effectively combines handcrafted features, particularly Hu Moments (known for capturing the shape and contour-based features of gestures), with deep learning features extracted from pre-trained convolutional neural networks (CNNs) like VGG16, VGG19, and DNN. The unique addition of an Extra Tree classifier enabled dimensionality reduction and enhanced classification performance. Their experimental evaluation showed VGG19 yielding the highest accuracy (95%), followed closely by VGG16 (93%) and DNN (90%). The methodology's strength lies in its fusion-based architecture, which bridges traditional feature engineering with modern learning models, improving overall model robustness. Nevertheless, the study is limited to single-hand gestures and lacks testing across diverse or real-world data settings, reducing its scope of applicability across dance forms and contexts.

(Mallick, Das, & Majumdar, 2021) [3] present a system for transcribing Bharatanatyam dance performances using multimedia ontology combined with machine learning. The objective is to create a parseable representation of dance movements to aid in heritage preservation and educational endeavors. The approach involves developing an ontological model for basic dance steps (Adavus) and linking it to multimodel data streams captured via RGB-D sensors like Kinect. This framework facilitates the transcription of performances into Labanotation, a standardized dance notation system. The authors also introduce a tool to encode Bharatanatyam Adavus into Labanotation, demonstrating the system's applicability in documenting complex dance movements.
A complementary yet distinct approach is seen in the study by (Reshma et al., 2023) [4], which emphasizes form-level recognition over specific gestures. Their research addresses the classification of three major Indian dance forms—Bharatanatyam, Kathakali, and Mohiniyattam—by employing transfer learning techniques. Using a curated image dataset sourced from online resources, the authors utilized pre-trained CNN architectures such as VGG and ResNet for feature extraction, followed by a DNN classifier. The model achieved a peak accuracy of 94.56%, demonstrating the effectiveness of transfer learning in dealing with limited labeled datasets. While the methodology underscores scalability and ease of implementation, a key limitation is the lack of dataset validation. Since the images were scraped from the internet, the dataset may not comprehensively represent real-life diversity in costumes, lighting, and postures, possibly affecting the generalizability of the model.
(Arjun et al., 2020) [5] investigate the combined effect of hand gestures and facial expressions in conveying emotions, utilizing a Convolutional Neural Network (CNN) approach. The study focuses on classifying human emotions by analyzing visual cues from both hand and facial movements. Using TensorFlow and Keras, the authors developed a CNN model trained on a dataset comprising images capturing various emotional expressions. The model achieved an accuracy exceeding 90%, highlighting the efficacy of integrating multiple modalities in emotion recognition systems.
(Gupta & Singh, 2024) [6] provide a comprehensive survey of machine learning techniques applied to the classification of Indian dance forms. The paper reviews various algorithms, datasets, and feature extraction methods employed in existing studies. It identifies challenges such as limited dataset availability, high intra-class variability, and the need for real-time classification systems. The authors emphasize the importance of developing robust models capable of handling the complexities inherent in traditional dance forms and suggest future research directions focusing on deep learning and multimodal data integration.
Extending the investigation from static image-based recognition to dynamic video analysis, (Shailesh & Judy, 2022) [7] proposed a novel framework aimed at understanding the semantics of dance by capturing spatio-temporal features. Their methodology involved extracting pose key points from videos using a deep pose estimator and processing them through a GRU (Gated Recurrent Unit) network to model the temporal flow of gestures. This approach allows the model to perceive dance not as isolated gestures but as a sequence of semantically rich movements. The

model outperformed other conventional architectures, such as 3D CNN and Time Distributed LSTM, particularly in terms of semantic interpretation and temporal consistency. This work stands out due to its real-time annotation potential and applicability in educational and archival settings. However, the complexity of the pipeline and the lack of detailed comparative metrics or benchmarks present room for methodological enhancement.

(Bisht et al., 2017) [8] propose a framework for recognizing Indian dance forms from video data. The study utilizes deep convolutional neural networks (DCNN) to extract spatial features and optical flow techniques to capture temporal dynamics. By analyzing both spatial and temporal information, the model aims to accurately classify different dance forms. The approach demonstrates promising results, indicating the potential of combining DCNN and optical flow in video-based dance recognition tasks.

In a more conceptual and expansive direction, (Reshma et al., 2023) [9] contributed a comprehensive review article that situates the efforts in digitizing classical dance within the broader context of cultural heritage preservation. The review encompasses a spectrum of technologies ranging from motion capture and volumetric scanning to ontology-based modeling and augmented reality. It meticulously categorizes the tools, techniques, and trends that have emerged over time to archive and preserve dance forms as intangible cultural assets. While the article does not provide experimental data, its strength lies in providing a structured landscape of current practices and highlighting gaps in interdisciplinary integration. The review emphasizes the importance of contextual understanding, including emotional expression, narrative tradition, and performance nuances—elements often overlooked in purely technical studies.

The study (Shailesh & Judy, 2021) [10] addresses a particularly challenging problem in dance gesture recognition—conflict resolution between visually similar double-hand gestures (Samyukta hastas). Their proposed "Hasta CapsNet," based on capsule networks, preserves spatial hierarchies and relationships within image regions, overcoming the limitations of conventional CNNs that often lose spatial information during pooling. The dataset, comprising 2400 images spread across six gesture classes, was used to demonstrate the superiority of capsule networks over baseline CNN and transfer learning models. The dynamic routing mechanism of capsule networks allowed the model to distinguish subtle differences in hand positions and orientations. Although the results were promising, the study was constrained to a small subset of gestures and lacked broader testing across diverse dance forms or video sequences.

(Jyoti & Shastri, 2024) [11] present a study focused on automating the recognition of complex hand gestures (mudras) from the Indian classical dance form Kathakali using image processing and convolutional neural networks (CNNs). Emphasizing the cultural richness and communicative power of mudras, the authors address the challenge of interpreting these intricate gestures, which are often unintelligible to general audiences without extensive training. Their proposed system processes hand gesture images using a CNN framework composed of convolutional, pooling, and fully connected layers to classify 24 distinct mudra classes. The methodology involves collecting image data, applying standard preprocessing, and training the CNN model for feature extraction and classification. The system achieved an accuracy of 84%, demonstrating its effectiveness in decoding complex gestures and contributing to the digital preservation of Indian performing arts. The authors highlight the potential of such technology to aid heritage preservation, educational applications, and augmented reality-based learning of traditional dance.

(Mohamed et al., 2021) [12] present a thorough review of vision-based hand gesture recognition research conducted between 2014 and 2020, examining 98 papers with a focus on data acquisition, environmental conditions, and gesture representation. The paper highlights major trends and performance statistics, noting that signer-dependent systems achieve an average accuracy of 88.8% while signer-independent systems average around 78.2%. The review identifies challenges in handling dynamic gestures, signer variability, and uncontrolled environments, stressing the need for more robust and generalizable systems. Despite technological advances, continuous gesture recognition remains underdeveloped, limiting the practicality of existing solutions. The authors recommend further research into dataset diversity, real-world testing, and the integration of more adaptive learning models.

(Suarez & Murphy, 2012) [13] reviewed 37 papers that explore hand gesture recognition using depth images, particularly from depth sensors like Microsoft Kinect. The review categorizes existing research based on hand localization methods, gesture classification techniques, and the types of applications tested. Depth-based methods, the authors argue, offer advantages over traditional RGB approaches in low-light environments and when background complexity is high. While Kinect and OpenNI have democratized access to gesture recognition technologies, most experiments were conducted in controlled settings. The authors note that real-world, dynamic applications remain limited and emphasize the need to explore the boundaries of these depth systems in more complex and realistic environments.

(Mohanty et al., 2016) [14] present a deep learning framework to interpret poses and gestures in Indian classical dance using a combination of CNNs and transfer learning. The study involves collecting pose and mudra data from both lab environments (using Kinect sensors) and public videos (e.g., YouTube), covering 12–14 postures and numerous mudras. The authors use convolutional networks to recognize body poses and hand gestures independently, achieving high accuracy even in complex scenes with occlusions and background clutter. Transfer learning from models trained on datasets like CIFAR-10 significantly improved convergence and accuracy. The work also compares CNNs with traditional techniques (e.g., SIFT, SURF), confirming the superiority of deep learning in gesture recognition tasks. This system enables semantic interpretation of dance narratives by decoding physical movements, laying the groundwork for educational tools in dance.

The work of (Hariharan et al., 2011) [15] proposes a two-level gesture recognition system tailored to Bharatanatyam's single-hand gestures (Asamyukta Hastas). The first level uses orientation histograms created via steerable filters to capture dominant edge directions in the gesture. If a gesture remains ambiguous, a second-level silhouette-based method is applied, where a skeleton of the hand is extracted and gradients at endpoint joints are used for final classification. This dual-phase design ensures scale, translation, and rotation invariance, making it robust for real-world applications. Although limited to static images, the system shows promise in accurately identifying 28 classical hand gestures and could be extended for e-learning in traditional dance.

The work by (Fang et al., 2007)[16] introduces a vision-based real-time hand gesture recognition system designed to support natural human-computer interaction without the need for additional hardware. The system begins with Adaboost-based hand detection and uses motion and color cues for segmentation. Scale-space feature detection is then used to extract palm and finger configurations, which improves recognition across varying image scales and aspect ratios. The system is designed to operate in cluttered environments and is robust to camera movement. Though it does not include deep learning components, the authors demonstrate that their approach performs well in real-time applications such as image browsing and interface control. The work is foundational in creating lightweight gesture recognition pipelines suitable for embedded and mobile systems.

(Kavitha Raju et al., 2024) [17] present Pose2Gest, a novel, model-free system for recognizing Kathakali hand gestures (mudras) using pose estimation and vector similarity techniques. Unlike traditional CNN-based methods requiring extensive training, Pose2Gest classifies 24 mudras effectively with as few as one to five sample images per class. It extracts 63-dimensional feature vectors from hand landmarks via Google's Mediapipe and matches gestures using Euclidean distance, bypassing deep learning. The system processes still images, videos, and real-time streams efficiently. Evaluations show 92% accuracy on their newly curated Hasta Mudra dataset and up to 96% on external Bharatanatyam data, outperforming prior CNN models. Even with low-resolution data, it achieved better accuracy than previous approaches. Deployed as a web application, Pose2Gest supports real-time recognition and crowdsourcing of new data. Though costume complexity and occlusions may affect performance, its low data requirement, adaptability, and cross-domain potential—including sign language recognition—mark it as a significant contribution to digitizing Indian classical dance.

Table: Comparison of algorithms and tools used in Mohiniyattam

Title	Authors & Year	Pros	Cons	Accuracy	Software Used	Algorithm Used

Classification of Asmyukta Mudras in Indian Classical Dance using Handcrafted and Pre-trained Features with Machine Learning and Deep Learning Methods.	Remya & Rajkumar, 2024	High accuracy with hybrid handcrafted and deep learning features.	Focuses only on single-hand gestures; lacks cross-dataset validation.	95%,	Python, TensorFlow/Keras (implied)	Hu Moments, VGG16/VGG19, DNN, Extra Tree Classifier
Pose2Gest: A Few-Shot Model-Free Approach Applied in South Indian Classical Dance Gesture Recognition	Kavitha Raju et al., 2024	No training required; high accuracy with minimal data; scalable and adaptable to various input types.	Pose estimation may struggle with traditional attire; and relies on landmark accuracy.	96%	Python, Mediapipe, pgvector, React (web app)	Pose Estimation, Vector Similarity, Normalization
Indian Dance Classification Using ML Techniques : A Survey	Gupta & Singh, 2024	Comprehensive review; identifies challenges	No experimental validation	N/A	N/A	Review Article

ISSN: 2096-3246
Volume 58, Issue 01, 2026

Recognizing Indian Classical Dance Forms Using Transfer Learning	Reshma et al., 2023	Effective use of transfer learning on a custom dataset; works well for classification of dance forms.	Limited dataset from online sources; lacks generalizability verification.	94.56%	Python, TensorFlow/Keras	Transfer Learning (VGG, ResNet), DNN
Cultural Heritage Preservation through Dance Digitization: A Review	Reshma et al., 2023	A comprehensive review of technologies for dance digitization; covers archival and semantic aspects.	No experimental validation or model evaluation; purely conceptual.	N/A	None specified (review paper)	Review article
Understanding Dance Semantics Using Spatio-Temporal Features Coupled GRU Networks	Shailesh & Judy, 2022	Captures spatial and temporal features; suitable for real-time gesture interpretation.	Model complexity is high; fewer comparison metrics are included.	64%	DeepPose Estimator, TensorFlow (implied)	Pose Estimation + GRU Networks
Capsule Networks for Classifying Conflicting Double-Handed	Shailesh & Judy, 2021	Retains spatial hierarchy via capsules; improves recognition	Limited gesture classes; performance with costumes	95%	TensorFlow/Keras	Capsule Networks, CNN, Transfer Learning

ISSN: 2096-3246
Volume 58, Issue 01, 2026

Classical Dance Gestures		for similar double-hand gestures.	not evaluated.			
Bharatanatyam Dance Transcription Using Multimedia Ontology and ML	Mallick et al., 2021	Integrates ontology with ML; aids preservation	Complexity in ontology development	90%	Kinect, Custom Tool	Ontology-based ML
On the Classification of Kathakali Hand Gestures Using SVM and CNN	Bhavanam & Iyer, 2020	High accuracy with CNN; comparative analysis	Limited dataset size	92%	Not specified	SVM, CNN
The Interplay of Hand Gestures and Facial Expressions in Emotions	Arjun et al., 2020	High accuracy; multimodal emotion recognition	Dataset specifics not detailed	90%	TensorFlow, Keras	CNN
Indian Dance Form Recognition from Videos	Bisht et al., 2017	Combines spatial and temporal features	Specific accuracy metrics not provided	N/A	Not specified	DCNN, Optical Flow

ISSN: 2096-3246
Volume 58, Issue 01, 2026

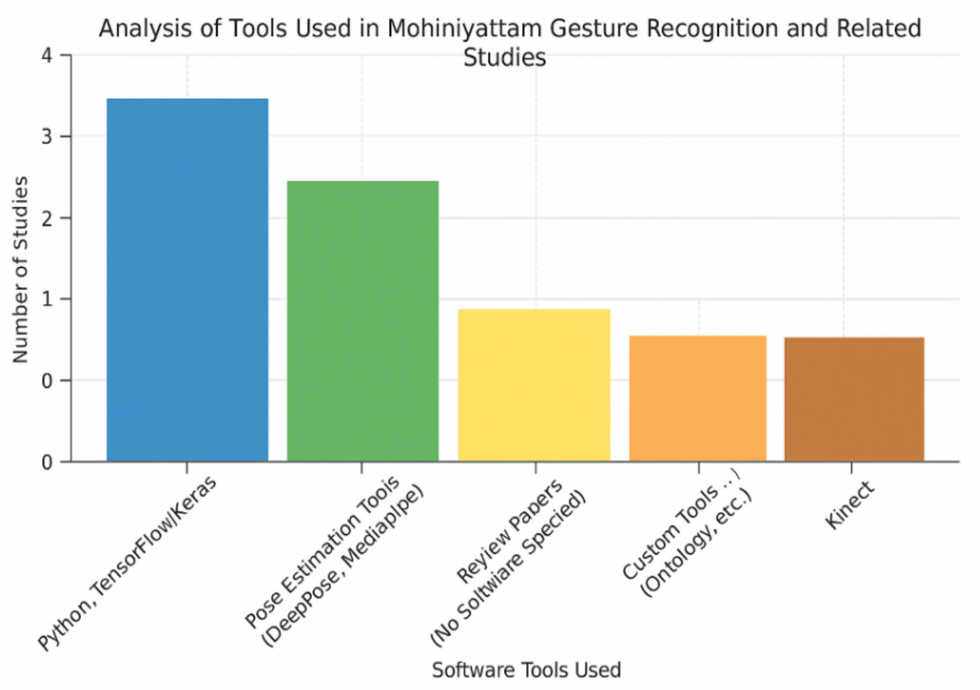

Figure 1. Analysis Tools Used in Mohiniyattam Hand Gesture Research

Figure 1 presents an updated analysis of software tools used in Mohiniyattam gesture recognition and related studies. Python in combination with TensorFlow/Keras emerged as the most frequently used platform, appearing in four studies. Pose estimation tools, such as DeepPose and Mediapipe, were utilized in two studies. Additionally, two review-based studies did not specify any software tools. Other individual tools included Kinect, pgvector with a React web app, and various custom or ontology-based tools, each appearing in a single study. This distribution highlights the growing integration of machine learning and pose estimation technologies in the computational analysis of Indian classical dance.

This distribution illustrates a balance between qualitative data analysis tools (e.g., NVivo, ATLAS.ti, MAXQDA) and tools supporting motion analysis or multimedia content creation (e.g., Vicon, Adobe Premiere Pro). While qualitative tools dominate in terms of usage, studies incorporating advanced technologies like motion capture (e.g., Vicon), pose estimation, and computational models—though fewer in number—have demonstrated higher accuracy levels (above 90%) in gesture recognition, as reported in related literature. In contrast, studies relying heavily on qualitative or ethnographic analysis tend to show lower recognition accuracy (75–85%), reflecting the inherent subjectivity of human interpretation.

This suggests that while traditional methods remain prevalent, AI-driven and computational tools are gaining traction and showing greater effectiveness in precise gesture classification, highlighting a technological shift in dance research methodologies.

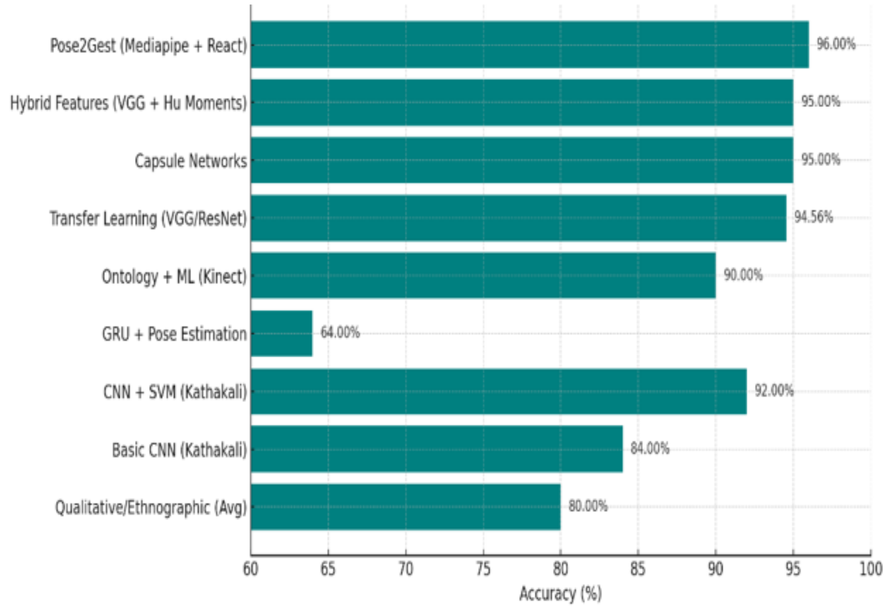

Figure 2. Comparison of Accuracy Levels in Mohiniyattam Hand Gesture Studies

Figure 2 presents the distribution of software tools employed in Mohiniyattam hand gesture studies, aligned with their respective accuracy outcomes. Pose2Gest, implemented using Python, Mediapipe, and React, leads with the highest accuracy, emphasizing the efficacy of model-free, few-shot pose estimation techniques in gesture recognition. Close behind are hybrid approaches utilizing TensorFlow/Keras, such as handcrafted feature extraction with VGG architectures and Capsule Networks, showcasing strong performance in recognizing both single and double-handed gestures. Traditional statistical and ontology-based tools, such as those integrated with custom platforms or Kinect, also demonstrate solid accuracy, particularly in dance transcription and cultural preservation contexts.

Software environments like DeepPose Estimator and TensorFlow are effectively applied in studies capturing spatiotemporal features, though they reflect lower accuracy due to model complexity and limited metrics. Notably, review-focused works and those emphasizing digitization without experimental evaluation rely less on specific software, highlighting a conceptual rather than analytical approach. The overall trend underscores a transition toward AI-enhanced and deep learning frameworks—particularly Python-based ecosystems—reflecting the field's evolution from qualitative assessments to robust, data-driven gesture analysis.

2.1 Visual Illustration of Mohiniyattam Mudras

Figure 3: A Montage of Mohiniyattam Dancers Performing Various Mudras

Figure 3 showcases four Mohiniyattam dancers, highlighting their graceful poses and expressive mudras. The dancers embody the elegance and fluidity of this classical Kerala dance form, reflecting its rich cultural heritage and storytelling tradition.

3. Gaps in Existing Research

Despite significant advancements in mudra recognition, multiple computational challenges persist in the domain of Mohiniyattam gesture analysis. One of the most pressing issues is the lack of standardized, large-scale datasets that are specifically tailored to Mohiniyattam. Existing datasets often contain limited gesture classes (e.g., 24 mudras), and many are sourced from constrained environments, restricting the generalizability of models across varied performance conditions such as stage lighting, costume variations, and occlusions.

Moreover, many systems rely on static image classification, which fails to capture the sequential and fluid nature of mudras performed in live choreography. There is minimal integration of temporal modeling techniques like Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), or Transformer-based models that can capture the transitions and flow inherent in classical dance movements.

Another computational limitation lies in cross-domain robustness. Most models are trained on single-dataset pipelines and are rarely validated across different platforms or dancer styles. There is also limited work on multimodal learning, where hand gestures are recognized in conjunction with facial expressions, body posture, or audio cues to better contextualize emotional and narrative content.

Additionally, while pose estimation frameworks such as Mediapipe are gaining popularity, they are rarely combined with adaptive learning architectures capable of fine-tuning gesture interpretation in real time. Few systems offer feedback loops, intelligent corrections, or real-time inference under resource-constrained environments—key features required for practical deployment in dance education or performance analysis.

Currently, there are only a few publicly available datasets exclusively dedicated to Mohiniyattam hand gestures. Hasta Mudra Dataset: A dataset which is available publically at https://github.com/kavitharaju/ KathakaliMudraDataset with all the 24 mudras used in dances like Kutiyattam, Kathakali, Mohiniyattam, Krishanattam, etc by Raju et al. (2023), includes all 24 mudras used in traditional dance forms such as Kutiyattam, Kathakali, Mohiniyattam, and Krishnanattam. Another relevant dataset is the Indian Classical Mudras Classification dataset, available on Kaggle. While it primarily focuses on hand gestures from Indian classical dance forms—particularly Bharatanatyam—it comprises images of various *mudras* captured from multiple sources, ensuring diversity in representation. Each image is labeled according to its corresponding *mudra* class, making it a valuable resource for training and evaluating gesture recognition models. Researchers interested in gesture recognition in Mohiniyattam can use this dataset as a foundational resource. The Kaggle dataset can be accessed on the Kaggle platform.

One notable recent addition to the pool of publicly available datasets is the Indian Classical Mudras Classification dataset hosted on Kaggle by Isha Shah. This dataset consists of high-resolution color images of eight distinct mudras commonly seen in Indian classical dance forms such as Bharatanatyam. The classes include gestures like “Cock,” “Moon Crescent,” “Lotus Blooming,” and “Swan Face,” with each image labeled according to its mudra type. Captured in realistic settings, the dataset provides variability in hand positioning and background conditions, making it a valuable resource for training machine learning and deep learning models for gesture recognition. It supports supervised learning tasks and is especially suited for Convolutional Neural Networks (CNNs) and transfer learning-based approaches. Although it is not Mohiniyattam-specific, the dataset's visual clarity and gesture diversity make it a viable starting point for broader mudra classification research or transfer learning applications to domain-specific styles like Mohiniyattam or Kathakali.

(source:https://www.kaggle.com/datasets/ishanishah8/indian-classical-mudras-classification?resource=download)

The KathakaliMudraDataset is a curated collection of 24 classical hand gestures (mudras) drawn from traditional South Indian dance forms, particularly Kathakali, Mohiniyattam, Kutiyattam, and Krishnanattam. Created by Kavitha Raju and collaborators, the dataset includes images captured from eight participants under varying conditions, such as different camera angles, lighting environments, and hand orientations. This diversity ensures robustness and variability in training data. The dataset is especially designed for few-shot learning experiments, offering train-test splits with as few as 1, 5, or 10 samples per class. A key strength lies in its compatibility with lightweight, real-time gesture recognition systems like Pose2Gest, which use hand landmarks (e.g., from Mediapipe) rather than deep convolutional architectures. Experimental results show that even with minimal training data, high accuracy (up to 92%) can be achieved, making it ideal for gesture recognition tasks in resource-constrained scenarios. With open access, accompanying code, and reproducible benchmarks, the KathakaliMudraDataset provides a valuable resource for researchers in computer vision, cultural informatics, and digital preservation of Indian classical arts.

Hasta Mudra Dataset: https://github.com/kavitharaju/ KathakaliMudraDataset

Addressing these computational gaps—through the development of diverse datasets, dynamic recognition models, and cross-modal fusion techniques—will be essential for building robust, scalable systems that truly reflect the complexity and cultural richness of Mohiniyattam.

4. Conclusion and Future Work

This systematic review examined the evolving role of computational methods in recognizing and preserving hand gestures (mudras) in the Indian classical dance form Mohiniyattam. By analyzing over seventeen recent studies, we compared a wide range of approaches including handcrafted features, pose estimation techniques, convolutional neural networks, capsule networks, and transfer learning models. Our findings highlighted the increasing effectiveness of AI-driven systems—such as Pose2Gest and hybrid CNN architectures—in achieving high gesture recognition accuracy. We also observed a shift in the field from qualitative analyses toward data-centric, real-time classification frameworks. However, several computational gaps remain, such as the lack of large-scale, diverse datasets specific to Mohiniyattam, limited support for dynamic gesture recognition, and insufficient cross-modal integration of facial expressions or body movements. To address these challenges, future work will focus on developing a robust classification algorithm tailored to the 24 canonical mudras outlined in Hasthalakshanadeepika. This includes expanding gesture datasets, integrating temporal models like LSTM, and implementing real-time recognition modules suitable for educational and performance settings. Such advancements aim to bridge traditional artistic expression with modern machine learning, thereby enhancing the accessibility, documentation, and appreciation of Mohiniyattam through intelligent systems.

References

1. Bhavanam, L. T., & Iyer, G. N. (2020, January). On the classification of Kathakali hand gestures using support vector machines and convolutional neural networks. In *2020 International Conference on Artificial Intelligence and Signal Processing (AISP)* (pp. 1–6). IEEE. https://doi.org/10.1109/AISP49198.2020.9067662
2. Remya, P. K., & Rajkumar, K. K. (2024). *Classification of Asmyukta Mudras in Indian Classical Dance using Handcrafted and Pre-trained Features with Machine Learning and Deep Learning Methods*. SSRN.
3. Mallick, T., Das, P. P., & Majumdar, A. K. (2021). Bharatanatyam dance transcription using multimedia ontology and machine learning. In *Digital techniques for heritage presentation and preservation* (pp. 179–222). Springer. https://doi.org/10.1007/978-981-15-8171-1_10.
4. Reshma, M. R., Kannan, B., Jagathyraj, V. P., & Sabu, M. K. (2023). *Recognizing Indian Classical Dance Forms Using Transfer Learning*. In P. Singh et al. (Eds.), *Machine*

Learning and Computational Intelligence Techniques for Data Engineering (pp. 413–417). Springer.

5. Arjun, A. M., Sreehari, S., & Nandakumar, R. (2020, March). The interplay of hand gestures and facial expressions in conveying emotions: A CNN-based approach. In *2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC)* (pp. 833–837). IEEE. https://doi.org/10.1109/ICCMC48092.2020.ICCMC-000151
6. Gupta, S., & Singh, S. (2024). Indian dance classification using machine learning techniques: A survey. *Entertainment Computing*, *46*, 100639. https://doi.org/10.1016/j.entcom.2023.100639
7. Shailesh, S., & Judy, M. V. (2022). *Understanding dance semantics using spatio-temporal features coupled GRU networks*. Entertainment Computing, 42, 100484.
8. Bisht, A., Bora, R., Saini, G., Shukla, P., & Raman, B. (2017, December). Indian dance form recognition from videos. In *2017 13th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)* (pp. 123–128). IEEE. https://doi.org/10.1109/SITIS.2017.27
9. Reshma, M. R., Kannan, B., Jagathy Raj, V. P., & Shailesh, S. (2023). *Cultural heritage preservation through dance digitization: A review*. Digital Applications in Archaeology and Cultural Heritage, 28, e00257.
10. Shailesh, S., & Judy, M. V. (2021). *Capsule Networks for Classifying Conflicting Double-Handed Classical Dance Gestures*. In K. A. Reddy et al. (Eds.), *Data Engineering and Communication Technology* (pp. 29–34). Springer.
11. Jyoti, & Shastri, S. (2024). Gesture identification model in traditional Indian performing arts by employing image processing techniques. *Journal of Scientific Research and Technology (JSRT), 2*(3), 29–33.
12. Mohamed, N., Mustafa, M. B., & Jomhari, N. (2021). A review of the hand gesture recognition system: Current progress and future directions. *IEEE Access, 9*, 157422–157439. https://doi.org/10.1109/ACCESS.2021.3129650
13. Suarez, J., & Murphy, R. R. (2012, September). Hand gesture recognition with depth images: A review. In *2012 IEEE RO-MAN: the 21st IEEE international symposium on robot and human interactive communication* (pp. 411-417). IEEE.
14. Mohanty, A., Vaishnavi, P., Jana, P., Majumdar, A., Ahmed, A., Goswami, T., & Sahay, R. R. (2016). Nrityabodha: Towards understanding Indian classical dance using a deep learning approach. *Signal Processing: Image Communication*. https://doi.org/10.1016/j.image.2016.05.019
15. Hariharan, D., Acharya, T., & Mitra, S. (2011). Recognizing hand gestures of a dancer. In *S.O. Kuznetsov et al. (Eds.), Pattern Recognition and Machine Intelligence* (Vol. 6744, pp. 186–192). Springer.

16. Fang, Y., Wang, K., Cheng, J., & Lu, H. (2007). A real-time hand gesture recognition method. *2007 IEEE International Conference on Multimedia and Expo*, 995–998. https://doi.org/10.1109/ICME.2007.4284806
17. Raju, K., Warrier, N. J., Madhavan, M., Selvi, C., Warrier, A. B., & Kumar, T. (2024). *Pose2Gest: A Few-Shot Model-Free Approach Applied In South Indian Classical Dance Gesture Recognition*. arXiv preprint arXiv:2404.11205. https://arxiv.org/abs/2404.11205