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Research Article

DHGNet: Devatha Hastha Gesture Network with Advanced Graph Enhancement for Gesture Identification and Recognition

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ABSTRACT

This study aims to develop an AI-powered system to classify and interpret Devatha Hasthas in Indian classical dance. By combining cultural preservation with modern technology, the system enhances accessibility and supports effective learning and documentation of intricate hand gestures, contributing to the promotion and understanding of traditional art forms. The study utilized a dataset of 16 Devatha Hasthas, MediaPipe hand tracking for segmentation, and feature extraction combining Hu moments and VGG19. Dimensionality reduction was performed using an ExtraTree classifier, followed by gesture classification through a Dense Neural Network. A Neo4j graph database was used for structured visualization and interaction. The system achieved an impressive classification accuracy of 96%, highlighting its effectiveness in accurately identifying Devatha Hasthas. Additionally, the integration of Neo4j graph database provided insightful interpretations of gesture relationships, demonstrating the potential of graph-based modeling to enhance the analysis of gesture interactions and cultural dynamics in classical dance. This study holds significant value for fields such as gesture recognition, AI, cultural heritage preservation, dance education, and digital humanities. By bridging traditional art forms with modern technologies, it empowers researchers, educators, and practitioners to enhance learning, fostering a deeper connection between cultural traditions and innovative technological advancements. This study introduces a novel integration of AI, deep learning, and graph-based modeling to interpret classical dance gestures, providing fresh perspectives on gesture interactions. It enhances current knowledge by bridging traditional art forms with advanced technologies, opening new possibilities for cultural studies, gesture recognition, and innovative approaches to preserving and learning intricate dance traditions.

Keywords: Devatha hasthas classification; Gesture Identification, Knowledge Representation , MediaPipe Segmentation, Meachine Learning , Neo4j.

INTRODUCTION

Devatha Hastha refers to the intricate and highly symbolic hand gestures used in classical Indian dance forms such as Bharatanatyam, Kuchipudi, and Odissi. Derived from Sanskrit, where "deva" means deity and "hastha" means hand, these gestures reflect their significance as sacred representations of divine entities. Deeply rooted in Hindu mythology, Devatha Hasthas symbolize various celestial beings, gods, and goddesses. Each of the 16 Devatha Hasthas [1] is characterized by specific hand positions, movements, and expressions, meticulously choreographed to convey particular meanings, emotions, and narratives within the dance performance [2]. To denote the Devatha Hasthas, various Asamyukta mudras or single hand gestures such as Pathaka, Tripataka, and Shikharam, along with their combinations, are employed, each representing specific divine attributes and characteristics that enhance the narrative and expression. These gestures are not merely aesthetic elements; they are imbued with profound cultural and spiritual significance. Each hastha involves precise finger positions and movements, which, when combined with facial expressions and body postures, create a powerful storytelling medium. Dancers use Devatha Hasthas to depict scenes from ancient epics, convey devotional themes, and express a wide range of emotions such as love, bravery, compassion, and divinity [3]. In classical Indian dance, the Hamsasya Mudra in the right hand and the Chatura

Mudra in the left hand together denote Brahma, the creator god, symbolizing the delicate and precise actions involved in creation and the richness, vision, and nourishment of the universe. The Tripataka Mudra in both hands at the chest represents Vishnu, the protector god, highlighting his authority, watchfulness, and protective nature in defending the universe from evil forces and maintaining cosmic order. Simultaneously, the Crossed Tripataka Mudra above the head symbolizes Indra's comprehensive role as the god of rain, thunderstorms, and war, reflecting his power and authority as the king of the gods and protector of the heavens[4]. Each of the 16 Devatha Hasthas has a special meaning, with corresponding mudras that embody the characteristics and roles of the respective gods or goddesses, using precise hand gestures to convey their divine functions and attributes within the dance[5][6]

The identification of Devatha Hasthas in classical dance is crucial as it allows for the precise depiction of deities, each embodying unique cultural and religious significance. Each Devatha Hastha may comprise different Asamyukta Mudras in the left and right hand, requiring detailed analysis for accurate identification. For instance, deities such as Vishnu and Indra or Lakshmi and Ganapathi might share similar mudras[7], however, their hand positions, such as being above the shoulder, can differ, altering their meaning. Despite the importance, no significant work has been done in this area. By accurately identifying both the mudra and its specific position using our model, we can overcome this problem, correctly distinguishing and representing the corresponding Devatha Hastha, thereby preserving the authenticity and richness of traditional dance performances.

Recent advancements in the field of gesture recognition have significantly enhanced the understanding and classification of hand gestures in classical Indian dance forms, particularly in Bharatanatyam and Kathakali. Madani, K., Rinaldi, A. M., & Russo (2021) introduced a human-robot interaction framework in a cultural heritage context, where robots serve as proactive guides, merging semantic and visual information[8]. Raj, R. J., Dharan, S., & Sunil, T. T (2022) focused on developing an extensive open dataset for Bharatanatyam gestures, achieving high classification accuracies using KAZE descriptors and random forest classifiers[9]. Chraa Mesbahi, S., Mahraz, M., Riffi, J., & Tairi, H (2023) leveraged YOLO models to advance hand gesture recognition systems, building on sign language foundations[10]. Vadakkot, G., Ramesh, K., & Divakaran (2023) addressed the challenges of distinguishing subtle differences in Asamyukta mudras, creating a CNN-based system with a substantial database of 29 mudras and incorporating eigenmudras for improved identification[11]. Malu G. (2024) presented GAMNet, a novel deep learning model that integrates structural features with traditional CNN features, achieving remarkable classification accuracy under challenging conditions[12]. Jyoti and Shastri (2024) developed a CNN model for recognizing Kathakali dance mudras, successfully classifying 24 distinct gestures[13]. Despite these impressive contributions, there remains a noticeable gap in research focusing specifically on Devatha Hasthas, a category of hand gestures used in Indian classical dance forms that have not been adequately addressed.

Current research predominantly focuses on the more widely recognized gestures in Bharatanatyam, Kathakali, and other forms, leaving Devatha Hasthas underexplored. Furthermore, while there has been progress in gesture recognition using deep learning and computer vision techniques, the application of these methods to Devatha Hasthas remains limited. This gap highlights the need for dedicated research that not only focuses on these specific gestures but also incorporates modern technologies to improve their classification accuracy. This study aims to fill this gap by developing an AI-based system for the recognition and classification of Devatha Hasthas, contributing to both the preservation and accessibility of these significant cultural symbols.

Our study's main contributions include the creation of a novel dataset of 16 different Devatha Hasthas, utilizing the MediaPipe[14] hand tracking module for precise hand segmentation from full-body images. We integrated handcrafted features (humoments) with deep learning features (VGG19) to form a robust feature set, and applied an ExtraTree classifier for efficient dimensionality reduction. This enabled the design of a Dense Neural Network (DNN) for accurate mudra classification of the right and left hands, addressing the complexity of Devatha Hasthas. Additionally, we implemented a Neo4j graph database to represent the classified hasthas, allowing for detailed inference and exploration. Graph structures for image representation and classification model images as nodes in a graph, with edges representing relationships or similarities between different regions or features. This approach allows capturing spatial, contextual, and hierarchical dependencies within images, enhancing the performance of classification tasks by providing a more structured and interpretable representation [15]

The paper is structured as follows: Section I presents a comprehensive literature reviews, highlighting existing research and identifying gaps that this study addresses. Section II covers dataset creation and preprocessing techniques while Section III details the methodology employed. Feature extraction and classification processes are discussed in Section IV. Section V elaborates on Neo4j graph representation followed by results and analysis in Section VI, and Section VII provides a detailed discussion and conclusion.

LITERATURE REVIEW

Gesture identification in Indian classical dance has witnessed notable progress, yet certain intricate elements remain underexplored. While widely recognized gestures in classical dance forms have been the focus of much research, the specific and delicate Devatha Hasthas are comparatively overlooked. Recent advancements in computer vision (CV), machine learning (ML), and deep learning (DL) have enabled sophisticated gesture recognition systems, showcasing significant potential across various domains. This highlights a critical need for research that integrates traditional expertise with these cutting-edge technologies to address the unique challenges posed by Devatha Hasthas.

Sharma (2020) explored various image detection and classification approaches for hand gesture recognition, focusing on datasets like American Sign Language (ASL) images. The study proposed a novel model combining Canny edge detection, ORB, and the Bag of Words technique for feature extraction. Preprocessing techniques such as Histogram of Gradients, PCA, and Local Binary Patterns were used to refine the data, which was then passed through classifiers like Random Forests, SVM, Naïve Bayes, Logistic Regression, k-NN, and MLP. The proposed model achieved a classification accuracy of 96.96%, demonstrating the effectiveness of combining advanced preprocessing with powerful classifiers in gesture recognition [16]. In the same year Sattriya dance, was the focus of a machine learning-based approach for classifying Asamyukta Hastas, proposed by Maale and Ukanal. They employed models like Logistic Regression, KNN, Naive Bayes, and multiclass SVM, with a methodology that involved image preprocessing, skin-based segmentation, and extracting hand contour chain codes as features. This approach yielded accuracies between 87.06% and 92.3%[17].

A memory-intensive capsule network, proposed by Shailesh and Judy in 2021, was designed for classifying six specific double-handed Bharatanatyam mudras, achieving a perfect accuracy of 100%. This performance significantly surpassed traditional Convolutional Neural Networks (CNN), which achieved 96% accuracy, and transfer learning models, which reached 98%. While the results were promising for these six mudras, further work is needed to extend this approach to a broader set of gestures and enhance its adaptability across various dance forms and gesture categories[18].

Raj (2022) conducted an extensive study on gesture recognition in Bharatanatyam, focusing on creating an open dataset comprising 15,396 single-hand and 13,035 double-hand gesture images. The research explored various feature descriptors, including SIFT, SURF, ORB, and KAZE, combined with classifiers such as SVM and random forest. The findings highlighted that the KAZE descriptor paired with the random forest classifier achieved the highest accuracy, with an average classification accuracy of 96%, emphasizing its potential for gesture identification[9].

Challapalli Jhansi Rani and Nagaraju Devarakonda (2022) presented an advanced approach to Indian classical dance (ICD) classification by leveraging deep learning techniques to classify intricate dance poses. Their proposed CNN-LSTM model, which incorporated pose estimation and joint-based kinematic relationships, achieved an accuracy of 98.53%. This study highlights the potential of combining deep learning architectures with human pose analysis for improving dance style classification in ICD[19]. During that year, Haridas et.al utilized the YOLOv3 convolutional neural network (CNN) framework to recognize single hand gesture or Asamyukta Mudras in Bharatanatyam. By segmenting images, predicting bounding boxes, and adjusting them according to probability values, they achieved a mean average precision of 73%[20].

In 2023, Vadakkot and colleagues developed an automatic mudra identification system using convolutional neural networks (CNN) and eigen-mudra projections. The concept of eigen-mudra involves extracting key features from mudra images and reducing them to a smaller set of representative features through dimensionality reduction techniques, which enables efficient recognition and classification. By combining both original and eigen-mudra images, their method achieved a 92% accuracy, matching the performance of raw image classification[21].

In the next year 2024, Jyothi and Shastri proposed a system for recognizing Kathakali dance mudras using Convolutional Neural Networks (CNN). Their approach, which focuses on the 24 distinct hand gestures of Kathakali, achieved an accuracy of 84%. This work highlights the potential of deep learning techniques in classifying intricate mudras, which are often challenging for the general public to interpret[13]. In 2024 itself Malu G (2024) introduced the Gesture Analysis Module Network (GAMNet), which enhances deep learning models by incorporating structural features, such as joint locations, to improve gesture recognition accuracy. By combining these structural values with Convolutional Neural Networks (CNN), GAMNet demonstrated impressive performance, achieving a classification accuracy of 96.80% despite challenges like lighting variations, noise, and changing camera angles. Compared to other well-established models like VGGNet, ResNet, and EfficientNet, GAMNet outperformed them in classifying dance gestures[12].

Recent studies have used graph-based representations for gesture recognition, treating images as graphs with nodes for key points and edges for spatial relationships. These approaches have proven effective in improving the accuracy and efficiency of gesture recognition by capturing complex dependencies between hand features. Yong Li (2019) explored skeleton-based hand gesture recognition methods using graph structures to model joint connections, noting that many approaches overlook the complex relationships between joints. Advanced methods, such as Graph Convolutional Networks (GCNs), were proposed to better capture joint connectivity, resulting in improved gesture recognition performance[22].

Zhuang, W., Zhang, T., Yao, L., Lu, Y (2022) proposed an image semantic refinement recognition method based on causal knowledge for product surface defects, utilizing an improved ResNet for enhanced image classification. A causal knowledge graph of surface defects is constructed and stored in Neo4j, which is then visualized through a platform that analyzes the causal relationships driven by the network model's output data[23]. Although there has been notable progress in gesture recognition across various cultural contexts, including a variety of classical dance forms such as Bharatanatyam and Kathakali, a gap still exists in the comprehensive classification of Devatha Hasthas in Indian classical dance. Existing studies often focus on single-hand or double-hand gestures, and few incorporate both handcrafted and deep learning features, as well as advanced graph-based representations like Neo4j, to enhance classification accuracy and provide detailed inference. This paper aims to address these gaps by developing a hybrid model leveraging both feature types and Neo4j for an improved and detailed classification of Devatha Hasthas.

DATASET

The dataset created for this study comprises a total of 2,940 high-quality RGB images, organized into 21folders, each containing 140 images representing various Devatha Hasthas. This dataset includes 16 classes, each depicting different hand gestures associated with deities such as Lord Brahma, Lord Shiva, Lord Vishnu, and others. Due to the unavailability of an existing online dataset, the images were specifically generated to capture the intricate details of these Devatha Hasthas, Sample images used in the study are shown in Fig. 1. Among the classes, the representation of Lord Shiva includes four variations, while both Lord Ganapati and Goddess Saraswati are represented with two variations each, so a total of 21 hastha classes. The images feature various performers in natural backgrounds, ensuring diversity while maintaining consistency and clear visibility of hand gestures. Each image was labelled with the corresponding hastha class and organized into folders named after each class. To ensure uniformity and enhance model performance, the images were resized, normalized, and augmented with techniques like rotation, scaling, and flipping. This carefully curated and comprehensive dataset is designed to facilitate accurate classification and recognition of the Devatha Hasthas, aiding in the preservation and study of classical Indian dance and enhancing the depth and richness of the research.

METHODOLOGY

The methodology (shown in fig:1) involves collecting a comprehensive dataset of Devatha Hasthas images, which are pre-processed using the MediaPipe hand tracking module to segment hand portions. Feature extraction is performed using both handcrafted techniques (like HuMoments) and pretrained models (such as VGG19), with dimensionality reduction applied using an extratree classifier. These features are fed into a Dense Neural Network for identification. The results are then represented in a Neo4j graph database, enabling detailed analysis and querying of mudra data, facilitating knowledge representation in graph form, and aiding in the identification of mudras through Neo4j's powerful graph technology.

MediaPipe Segmentation is an advanced tool designed for real-time, high-accuracy segmentation of images and videos, making it particularly effective for tasks such as background removal and object detection. It uses machine learning models to segment an image into distinct regions, identifying which parts belong to specific classes or objects. The process begins by inputting an image or video frame into the model, which then applies a deep neural network to predict a segmentation mask. This mask assigns a class to each pixel, enabling the precise separation of different regions within the image[24][25].

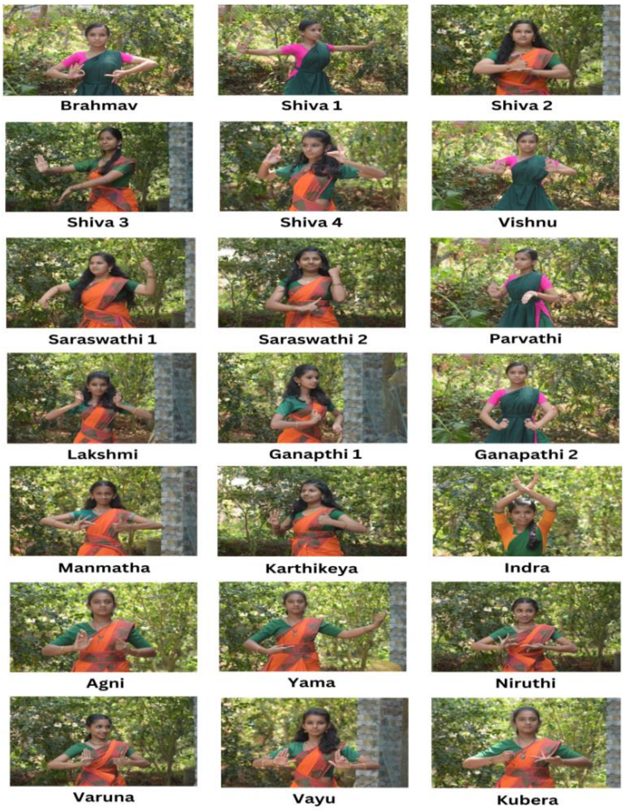

Fig. 1. Sample images from the dataset

To process the full-body images and extract hand portions, we employed the MediaPipe algorithm, renowned for its real-time object detection capabilities. The MediaPipe hand tracking module was used to detect and localize the right and left hands within the full-body images set against natural backgrounds (shown in Fig. 3). This process leverages a deep neural network to identify hand landmarks and generate a segmentation mask, which classifies each pixel to clearly separate the hand regions from the rest of the background. The hand portions were then cropped based on these landmarks, resulting in two distinct subsets, one for the right hand and one for the left hand. Each hand portion was saved into separate folders corresponding to its subset, effectively organizing the dataset into clear categories of right and left hand gestures. This precise extraction facilitated the subsequent feature extraction and classification steps, enabling accurate analysis of the individual hand gestures as part of the Devatha Hasthas.

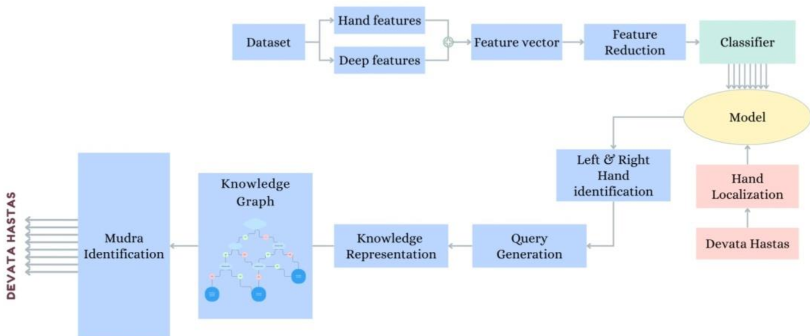

Fig. 2. Proposed Methodology

We tried another algorithm YOLO[26], it is struggle with accurately detecting hands, that vary significantly in size, orientation, or aspect ratio within images. This variability can lead to inconsistencies in bounding box placement and may require additional preprocessing or tuning to handle effectively. MediaPipe provides an efficient and robust framework for hand portion detection, and it has been utilized with the our dataset to achieve accurate recognition of specific gestures. The system begins by detecting hands in input images using a palm detection model, which identifies and isolates hand regions in a single frame. These regions are then processed by a hand landmark model, which predicts 21 precise 3D landmarks for each detected hand. The framework extracts both the coordinates of the landmarks and their connections, which are analyzed to recognize the hand gestures in the dataset.

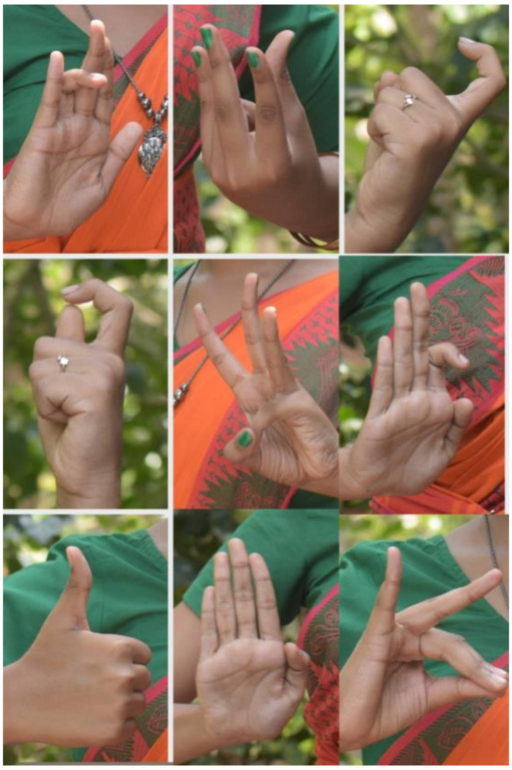

Fig. 3. Cropped images of left and right hands

FEATURE EXTRACTION AND CLASSIFICATION

For feature extraction in our model, we In my work, I trained a model using single-hand gestures and utilized Hu moment invariants for feature extraction(extract 2695 features). These moments serve as effective shape descriptors, capturing the geometric properties of each mudra while remaining invariant to scale, rotation, and position changes. By computing the seven Hu moments from each extracted hand gesture, a distinct set of numerical values is generated to represent the mudra's shape. Additionally, I extracted deep features using a pretrained VGG19 model(extract 8192 features), where I removed the classification layer to obtain the relevant feature representations. The two sets of features Hu moments and deep features were then input into an Extra Trees classifier[27] to reduce dimensionality and select the most relevant features for classification. The reduced feature vector was subsequently fed into a dense neural network, which performed the final classification of the mudras.

After feature fusion and reduction, the dataset is split into training and testing sets using an 80-20 ratio, followed by conversion of target labels into 2D floating-point arrays to ensure compatibility with the neural network. The DNN architecture consists of multiple fully connected layers, with the input layer taking the combined feature vector as input. Five hidden layers with ReLU activation progressively learn hierarchical feature representations, with the number of neurons decreasing in each layer to extract meaningful patterns efficiently. The final output layer uses softmax activation to classify the input into class count categories, representing different mudras. The model was trained to identify mudras in the left and right hands separately, leveraging the distinct features extracted for each hand to accurately classify the specific hand gestures in the context of Devatha Hasthas.

NEO4J GRAPH REPRESENTATION

Neo4j is a graph database that represents data using nodes, relationships, and properties, providing a highly effective way to model and query complex, interconnected data. Nodes represent entities such as people, places, or things, and are connected by relationships that define how these entities are related. Each node and relationship can have properties, which are key-value pairs that store information about them[28][29]. For example, in modeling classical dance mudras, nodes could represent different mudras, while relationships could define how these mudras are associated with specific deities or positions. This graph structure allows for efficient querying and traversing of the data, making it easy to discover patterns, connections, and insights that might be difficult to extract from traditional relational databases. For instance, in our context, we use Neo4j to map hand positions with specific mudras, enabling precise identification and classification of dance gestures based on their spatial relationships and attributes.

To represent the classification of Devatha Hasthas using Neo4j, we structured our data in a way that leverages its graph database capabilities effectively. Each deity and their associated hand gestures were mapped as nodes in the Neo4j graph. For instance, nodes were created for Brahma, Shiva, Vishnu, Saraswathi, Parvathi, Lakshmi, Ganapathi, Manmatha, Karthikeya, Indra, Agni, Yama, Niruthi, Varuna, Vayu, and Kubera, each with properties describing their left and right hand gestures. Fig:8 shows the node and edge representation for the mudras Brahma and Vishnu. Relationships between these nodes were established based on the type of hand gesture (left or right) and its associated mudra label. This graph structure (shows in fig 9) allows for detailed querying and inference capabilities, enabling us to retrieve specific information about each deity's mudras and their respective positions (Q1-Q4). By employing Neo4j, we facilitate a comprehensive and intuitive representation of our classification model, supporting detailed analysis and exploration of Devatha Hasthas within the context of classical Indian dance. Sample query representation of mudra in Neo4j. The positions of hands with respect to the shoulder are represented as follows: Q1 indicates the left top, Q2 the right top, Q3 the right bottom, and Q4 the left bottom.

[(“Brahmav”,”left_label”,”Chadura”), (“Brahmav”,”left_position”,”Q4”)]

[(“Brahmav”,”right_label”,”Hamsasya”), (“Brahmav”,”right_position”,”Q3”)]

[(“Shiva”,”left_label”,”Mrgashersha”), (“Shiva”,”left_position”,”Q1”)]

[(“Shiva”,”right_label”,”Tripathaka”), (“Shiva”,”right_position”,”Q2”)]

[(“Vishnu”,”left_label”,”Tripathaka”), (“Vishnu”,”left_position”,”Q4”)]

[(“Vishnu”,”right_label”,”Tripathaka”), (“Vishnu”,”right_position”,”Q3”)]

[(“Saraswathi”,”left_label”,”Kapitham”), (“Saraswathi”,”left_position”,”Q1”)]

[(“Saraswathi”,”right_label”,”Soochi”), (“Saraswathi”,”right_position”,”Q3”)]

[(“Parvathi”,”left_label”,”Ardhachandran”), (“Parvathi”,”left_position”,”Q4”)]

[(“Parvathi”,”right_label”,”Ardhachandran”), (“Parvathi”,”right_position”,”Q3”)]

[(“Lakshmi”,”left_label”,” Kapitham”), (“Lakshmi”,”left_position”,”Q1”)]

[(“Lakshmi”,”right_label”,” Kapitham”), (“Lakshmi”,”left_position”,”Q2”)]

[(“Ganapathi”,”left_label”,” Kapitham”), (“Ganapathi”,”left_position”,”Q4”)]

[(“Ganapathi”,”right_label”,” Kapitham”), (“Ganapathi”,”right_position”,”Q3”)]

[(“Manmatha”,”left_label”,” Shikaram”), (“Manmatha”,”left_position”,”Q4”)]

[(“Manmatha”,”right_label”,” Katakamugha”), (“Manmatha”,”right_position”,”Q3”)]

[(“Karthikeya”,”left_label”,” Thrishoola”), (“Karthikeya”,”left_position”,”Q4”)]

[(“Karthikeya”,”rightt_label”,” Shikaram”), (“Karthikeya”,”right_position”,”Q3”)]

[(“Indra”,”left_label”,” Thripathaka”), (“Indra”,”left_position”,”Q1”)]

[(“Indra”,”right_label”,” Thripathaka”), (“Indra”,”right_position”,”Q2”)]

[("Agni","left_label"," Kankoola"), ("Agni","left_position","Q4")]

[("Agni","right_label"," Tripathaka"), ("Agni","right_position","Q3")]

[("Yama","left_label"," Pasham"), ("Yama","left_position","Q1")]

[("Yama","right_label"," Soochi"), ("Yama","right_position","Q3")]

[("Niruthi","left_label"," Katuva"), ("Niruthi","left_position","Q4")]

[("Niruthi","right_label"," Shakatam"), ("Niruthi","right_position","Q3")]

[("Varuna","left_label"," Shikaram"), ("Varuna","left_position","Q4")]

[("Varuna","right_label"," Pathaka"), ("Varuna","right_position","Q3")]

[("Vayu","left_label"," Ardhapathaka"), ("Vayu","left_position","Q4")]

[("Vayu","right_label"," Arala"), ("Vayu","right_position","Q3")]

[("Kubera","left_label"," Alapadmam"), ("Kubera","left_position","Q4")]

[("Kubera","right_label"," Mushti"), ("Kubera","right_position","Q3")]

Using Neo4j for graph representation facilitates complex connections between gestures, meanings, and cultural contexts. Its querying capabilities allow efficient searches and analyses of relationships among mudras and their attributes.

By storing Mudra-God Relationships Neo4j helps structure this information in a connected format. We can efficiently retrieve the correct mudra for a deity's left or right hand using queries.

For eg: If left-hand mudra = X and right-hand mudra = Y, left hand postion=T1, right hand position =T2 then deity = Z.

Since some deities have the same mudras for each hand but differ in position, Neo4j helps visualize and analyze these variations systematically. For example, both Vishnu and Indra use the Pathaka mudra in both hands, but their positions are different. This Graph representations enable clear visualizations of how different mudras relate to one another, simplifying the understanding of their interconnections and classifications.

RESULTS

To evaluate the performance of our model, we present several key metrics and visualizations. The confusion matrix provides a detailed overview of the classification accuracy for each mudra, highlighting areas of strength and potential improvement. Precision-recall graphs illustrate the trade-off between precision and recall across different thresholds, offering insights into the model's ability to balance these metrics(shown in fig 4 to 7). The loss graph depicts the model's learning process over time, showing the reduction in training and validation loss, indicating effective training. Overall performance metrics include precision, accuracy, F1 score, sensitivity, and recall, each quantifying different aspects of the model's performance. These metrics collectively demonstrate the robustness and reliability of our approach in accurately classifying Devatha Hasthas, supporting the validity of our results. Table 2 denotes the performance matrics of the model.

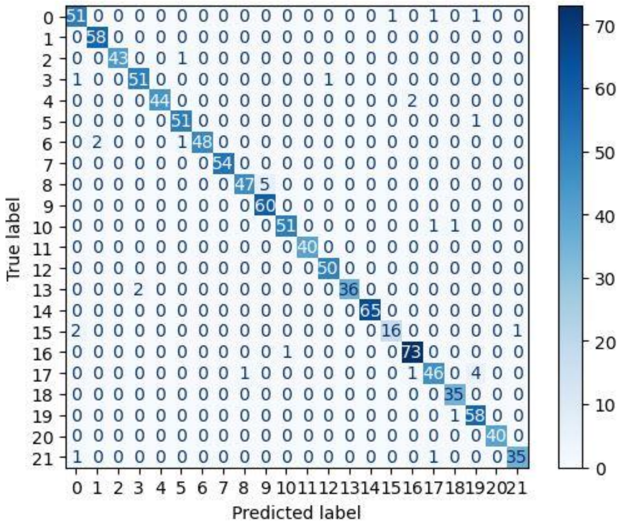

Fig. 4. Confusion Matrix

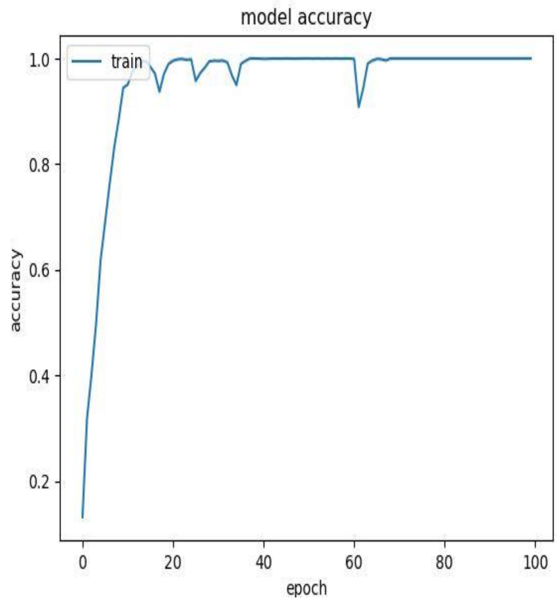

Fig. 5. Model Accuracy of classification model

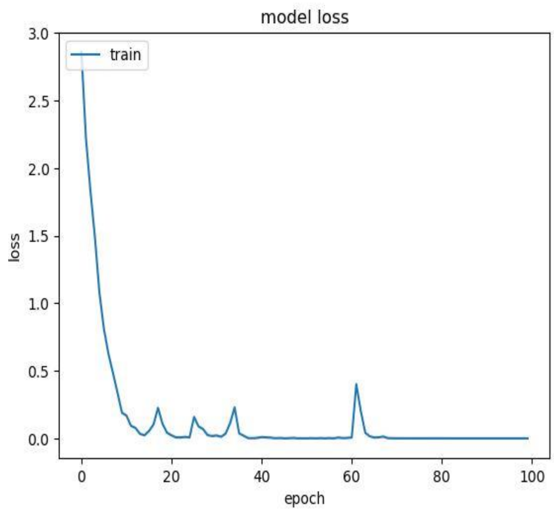

Fig. 6. Model Loss

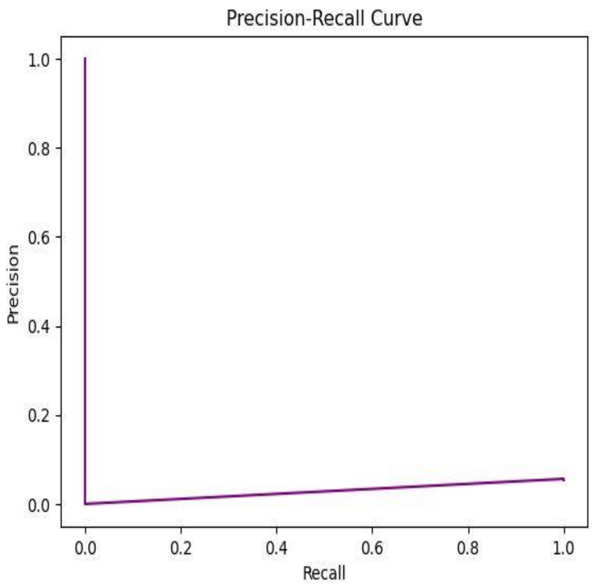

Fig. 7. Precision- Recall Curve

The mudra classification using a comprehensive dataset of Devatha Hasthas images, pre-processed with the MediaPipe hand tracking module, achieved strong performance. Features extracted through HuMoments and VGG19, followed by dimensionality reduction with an ExtraTree classifier, were processed by a Dense Neural Network. The results showed Precision of 97%, Recall of 96%, Sensitivity of 96%, F1 Score of 97%, and Accuracy of 97%. Neo4j integration enabled efficient querying and analysis, enhancing the identification of mudras.

In our study, we encountered several challenges during the classification of Devatha Hasthas and implemented strategies to address them effectively. One significant challenge was accurately extracting hand images from full-body images, crucial for precise feature extraction and classification. To overcome this, we utilized MediaPipe, renowned for its robust object detection capabilities, to accurately localize and extract left and right hand portions from complex natural backgrounds. Another challenge was variability in hand gestures due to different angles and perspectives, affecting the model's predictive accuracy. By focusing on images captured in natural backgrounds, we ensured consistent lighting and minimized distractions, improving the model's robustness to varying angles. This approach enhanced the accuracy of classification results and underscored the advantage of natural background images in maintaining consistency and improving the reliability of our classification system for Devatha Hasthas.

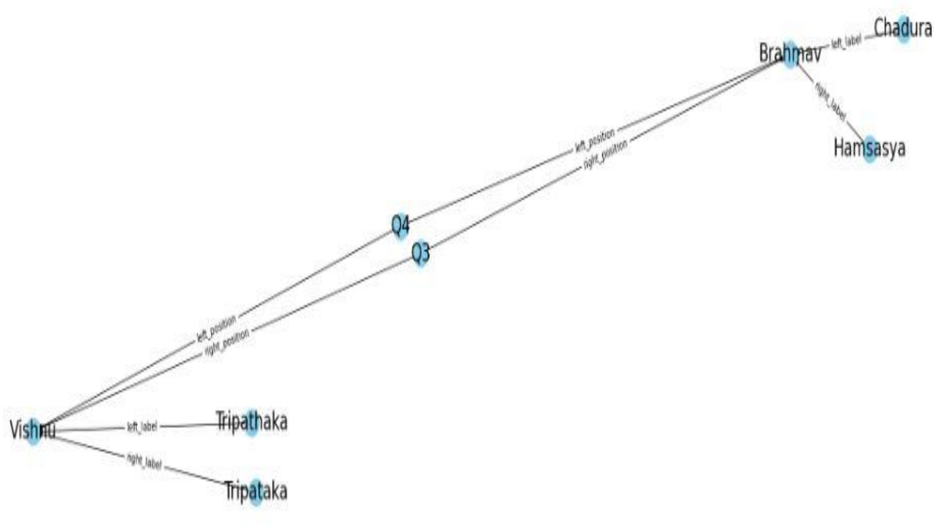

Fig. 8. Graph representation for Two Mudras

Table 2: Overall Performance of the classification model

Matrics	Value
Precision	0.97
Recall	0.96
Sensitivity	0.96
F1 Score	0.97
Accuracy	0.97

DISCUSSION

The classification model and the use of Neo4j significantly enhance the accuracy and accessibility of mudra identification in classical dance, aiding practitioners in learning and preserving traditional gestures, and providing researchers with powerful tools for data analysis and visualization. Neo4j's efficient data representation and powerful query capabilities make it ideal for managing and exploring complex relationships within the mudra dataset. For classical dance practitioners, this technology supports improved learning, performance analysis, and cultural preservation by ensuring accurate mudra execution.

A notable limitation of the classification model is its sensitivity to the angle at which photos are taken, often resulting in incorrect predictions. Future work should focus on improving the model's robustness to variations in photo angles, potentially incorporating more advanced techniques for pose normalization and augmented training datasets to enhance accuracy under diverse conditions

The integration of AI and graph-based technologies in this study has led to notable advancements in the classification and interpretation of Devatha Hasthas, significantly enhancing both the accuracy and accessibility of mudra identification in Indian classical dance. This study utilized a combination of deep learning models and Neo4j graph databases to capture the intricate details of hand gestures, which not only aids practitioners in learning and preserving traditional gestures but also provides researchers with powerful tools for analyzing and visualizing data.

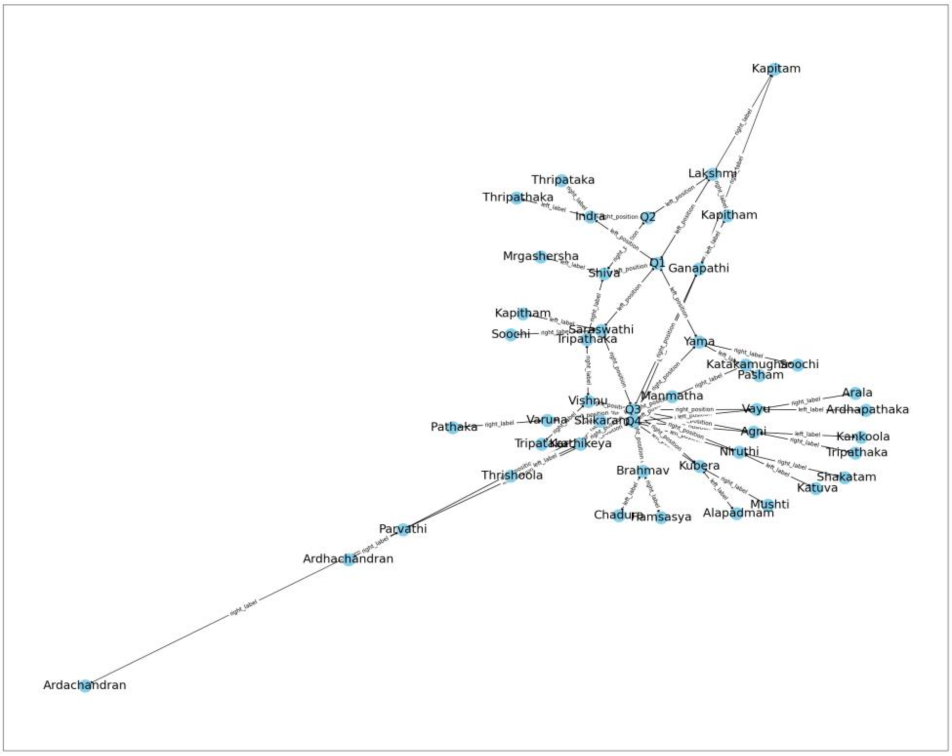

Fig. 9. Graph representation for Mudra set

CONCLUSION

The study analyzed Devatha Hasthas in Bharatanatyam, one of the Indian classical dance forms, by developing a model that combines VGG19 and Hu moments. This model achieved high accuracy and could predict mudras for both the right and left hands. The process involved data preprocessing, feature extraction, and classification, with the Extra Tree classifier employed to reduce dimensionality and complexity. After identifying each Hastha, a query representation was generated, and the results were stored as knowledge in the Neo4j graph. This research provides a framework that enhances the comprehension and classification of complex mudras in Indian classical dance, offering valuable insights for dancers, researchers, and enthusiasts, while also contributing to the preservation and understanding of cultural heritage. This research can also be applied to sign language recognition systems by adapting the mudra classification techniques to accurately identify and classify hand gestures, enhancing communication for the hearing impaired and providing a more efficient method for real-time gesture interpretation.

Limitations and study forward

This study presents significant advancements in gesture recognition for classical dance, but several limitations justify consideration. A key limitation is the model's sensitivity to variations in image angles, which can lead to misclassification, necessitating the incorporation of pose normalization and 3D hand pose recognition techniques for improved robustness. Additionally, the dataset's limited diversity in terms of performers, backgrounds, and environmental conditions may impact generalizability. The system currently lacks an integration of cultural context and symbolic meanings behind the gestures, which could enhance its educational value. Future research should focus on expanding the dataset, incorporating cultural annotations, and enhancing the system's real-time performance capabilities. Furthermore, optimizing the computational load would make the system more accessible and applicable in real-world scenarios. The methodologies employed could also be extended to other fields such as sign language recognition, human-computer interaction, and healthcare, offering potential interdisciplinary applications. Addressing these challenges will further enhance the model's accuracy, applicability, and contribution to preserving and advancing cultural heritage, making classical dance more accessible and engaging for diverse audiences. Exploring real-time mudra identification on devices with constrained resources, like smartphones, offers a promising research direction.

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