

Real-Time Bharatanatyam Posture Classification With Deep Learning & Pose Skillset Estimation Using Mediapipe

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Abstract— Bharatanatyam, a venerated classical move frame in India, is known for its complex postures and expressive storytelling. Traditionally, acing the craftsmanship requires a long time of devotion and the direction of experienced teaches, which can be a challenge for numerous due to variables such as remove or monetary imperatives. To address these issues, a modern preparing stage was created that coordinating profound learning and MediaPipe posture estimation technology. The framework not only recognizes and classifies Bharatanatyam postures, but moreover gives real-time input so artists can promptly progress their developments.

The investigate employments convolutional neural systems (CNNs) to precisely classify move postures and give moment adjustments, making preparing more compelling and available to artists of all levels. By diminishing the dependence on face-to-face learning, this stage makes it less demanding for understudies, particularly those living in farther regions or with restricted get to to master direction, to hone and improve. As a result of detailed experimentation, the framework has come to more than 90 % of the exactness in establishment classification, showing the plausibility of a important instructive device.

By combining progressed AI and conventional craftsmanship, this think about not as it were bolsters the conservation of social legacy, but too extends the plausibility of instructing varative in a more adaptable and intelligently way. This initiative facilitates artists' learning to improve their aptitudes, notwithstanding of geographic or calculated imperatives, hence making this antiquated move more open to a broader group of onlookers.

Keywords—Bharatanatyam, Pose Estimation, Deep Learning, Cultural Heritage, CNN, MediaPipe

I. INTRODUCTION

Bharatanatyam, a classical move frame beginning from India, is known for its complicated footwork, smooth signals and capacity to communicate profound stories through development. Customarily, acing this move requires a long time of devoted preparing beneath the direction of an experienced teachers. By the by, different impediments such as geological limitations, money related confinements, and brief confinements regularly avoid individuals from taking this form of craftsmanship. In any case, within the present day world of innovation, it is conceivable to overcome these deficiencies. In this investigate, we investigate how progressed advances such as deep learning and posture estimation can be utilized to make an imaginative framework that gives real-time input to Bharatanatyam artists. Utilizing these progressions, we point to not as it were make preparing more open, but moreover to protect and pass on this socially wealthy move convention.

In this study, we combine profound learning procedures with progressed posture estimation devices to make an intelligently learning stage that examinations different Bharatanatyam postures by preparing and labeling pictures and training models for classification. MediaPipe Posture is utilized to distinguish and track key body points of interest, empowering the framework to assess a dancer's developments. Besides, the framework categorizes move moves by trouble and style, offering prompt input and suggestions for enhancement. This cutting edge approach makes strides conventional move instruction by combining private instruction and computerized precision to preserve the unwavering quality of the frame and give a tailor-made learning involvement.



Figure. Different poses in Bharatanatyam

As appeared within the above Figure, there are more than 20 stances in Bharatanatyam. We are going to be performing Picture classification on most of these stances utilizing CNN Show based Pose Classification and after that move to the moment step of analyzing the aptitude levels of the pose.

The discoveries from this consider illustrate the capable potential of coordination profound learning with posture estimation for making strides Bharatanatyam preparing. The system's capacity to precisely classify postures and give real-time input presents a profitable instrument for artists of all ability levels. The extend highlights how computerized advancement can not as it were democratise get to to Bharatanatyam but moreover guarantee the conservation of the perplexing subtleties of this move shape for future eras. By combining convention and innovation, the stage guarantees to bring the legacy of Bharatanatyam into the computerized age.

II. LITERATURE REVIEW

The study presented by **J. Jayanthi, et al. [1]** highlighted the robotization of recognized Bharatanatyam move positions, especially focusing on "Karana" movements, which have real importance within the framework of Indian classical move. Their research proposes the use of advanced techniques for posture recognition, specifically MediaPipe as a technique in body key-point recognition, and InceptionResNetV2 for classification. The advanced combination then serves as a process of protection and understanding of social heritage. Advancing the research of dance analysis and accessibility for practitioners, can relieve our study of dance by providing organization by automation of posture recognition. Although MediaPipe and InceptionResNetV2 are viable, the research does not make any further plans to investigate real-time analysis or to consider the possibility of future work, that may contain live dance performances. Furthermore, the study may benefit from attempting to include facial expressions and eye movements, or features that are significant in Bharatanatyam. The paper presented by **Tanwi, Mallick, et al. [2]** looked to address the challenges of analyzing Indian classical dance, by using music and movement information to define movement elements and sequences, and more specifically Bharatanatyam. The proposed use of Hidden Markov Models (HMMs) and Long Short-term Memory (LSTM) methods provide significant structure to understanding the dance, making it an important research project to help with social preservation, teaching structures, and video recommendation algorithms. **The research by B.S., Anami, et al. [3]** highlighted the computerization of mudra (i.e. hand position) recognition in Bharatanatyam, key to self-learning and e-learning systems. In particular, the research compared traditional feature extraction methods, (i.e. Hu-moments and eigenvalues) with deep learning methods (i.e. Convolutional Neural Networks (CNN)), which aided the field of automated dance learning. The paper investigated the computerization of single hand mudras only and did not look at multi-hand gestures or any other elements of Bharatanatyam such as facial expressions and body movements. Furthermore, practical application issue such as varying lights and ensemble interruptions are not discussed. The paper by **Jayanthi, J., et al. [4]** emphasis the use of image processing and deep learning, to automate the identification of Bharatanatyam dance positions, particularly concentrating on the "Karana" movements. Through the use of approach such as skeletonization and data augmentation it expands the boundary of current research in Indian classical dance research, providing advanced methods for both researchers and practitioners. The research could expand the scope by incorporating dynamic position identification as Bharatanatyam involves continual movements. Moreover, a greater attention to the effect of varied camera angles on model accuracy could help enhance the generalizability of the overall findings. Aparna, Mohanty, et al 's paper [5] tackles the challenge of allowing amateurs to appreciate and understand the ambiguous meanings conveyed in Bharatanatyam performances. It suggests using CNN models with transfer learning to detect body postures and hand gestures, demonstrating the feasibility of real-time move translation. It successfully suggests a solution to the gap between the knowledge and appreciation of a dance form at a professional level versus by an amateur. Although the study shows a successful

detection of poses, it does not fully address the implications of real-time, such as latency and computing limits on performance during live presentations. Future research may be able to explore optimizing model performance for real-time study on less capable devices. The work by **A.Mohanty, , et al. [6]** contributes by creating datasets for inactive and dynamic hand signals in Bharatanatyam, and proposes an inventive strategy for recognizing both utilizing 2D and 3D CNNs and AdaBoost. The creation of these datasets may be a noteworthy step forward in creating machine learning models custom fitted to Indian classical dance. Despite the novelty, the consider needs comprehensive real-world approval, because it essentially centers on controlled situations. Moreover, the integration of facial expressions, which are basic in Bharatanatyam, is lost and can be investigated in future ponders.

In spite of the fact that reserach by **Swapnil Sayan Saha, et al. [7]** not straightforwardly related to Bharatanatyam, this paper gives bits of knowledge into human movement acknowledgment utilizing ear-worn gadgets and machine learning. Its pertinence lies within the improvement of real-time action location calculations, which seem rouse future applications in move acknowledgment utilizing wearable sensors. The inquire about is restricted in its center on earable gadgets, and its applications in move investigation stay unexplored. Future inquire about might explore adjusting earable innovation for recognizing perplexing move developments and joining it into mentoring frameworks for performing expressions. The paper by **Ashwini Dayanand Naik, et al. [8]** proposes a CNN-based framework to classify different Indian classical move shapes utilizing pictures. The computerized framework for recognizing move shapes like Bharatanatyam, Odissi, and Kathak from a dataset offers a interesting application for instructive and social conservation purposes. The classification precision for real-time applications remains unaddressed, and the dataset needs differing qualities in terms of lighting, foundation, and entertainer varieties. Counting a more extensive run of information, particularly from live exhibitions, might improve the model strength. The paper by **Himadri Bhuyan, et al. [9]** investigates motion-pattern acknowledgment in Bharatanatyam exhibitions utilizing MHI and CNN. The approach gives a novel strategy for capturing move developments, possibly profiting applications in social legacy conservation and computerized mentoring frameworks. The utilize of MHI is especially inventive for understanding move motion. While the paper accomplishes tall exactness, the dependence on a particular dataset (Kinect recordings) limits the generalizability of the demonstrate to broader settings. The paper may moreover investigate the integration of other information sorts, such as skeletal or profundity information, to make strides movement acknowledgment. The research by **Vadlamanati Krishna Chaitanya, et al. [10]** presents a real-time classification demonstrate for Bharatanatyam postures utilizing ResNet and MediaPipe. The paper compares different models, advertising profitable bits of knowledge into their execution for real-time move classification errands. The inquire about is noteworthy for creating commonsense applications such as move coaching frameworks and social education. While ResNet illustrates prevalent execution, the think about does not completely address challenges related to real-world varieties in lighting,

foundation, and occlusions amid live exhibitions. Future work may center on optimizing the demonstrate for low-resource gadgets commonly utilized in instructive settings.

III. MOTIVATION & NOVELTY

The essential motivation for this think about is the obstructions numerous understudies confront in getting to quality Bharatanatyam instruction. Conventional educating strategies regularly require physical nearness and face-to-face interaction with a educator, which can be troublesome for those who cannot go to face-to-face classes. The appearance of fake insights and machine learning innovations offers a promising arrangement to these challenges. Our investigate stands out for its real-time pose classification and expertise estimation capabilities, utilizing as it were convolutional neural systems (CNNs) for exact posture discovery and classification. This framework gives imperative pose and motion point by point comments in Baratanai. Utilize of Medipipe assessment innovation This advancement will not as it were upgrade learning but moreover contribute to the conservation of Bharatanatyam by making it more open to groups of onlookers around the world.

The presentation of AI and machine learning advances presents a practical arrangement to this issue, advertising separate learners the opportunity to get quality preparing through advanced implies. This investigate points to overcome the impediments of conventional move instruction by creating a framework that can classify Bharatanatyam postures in genuine time and give quick criticism on execution. The real-time pose classification framework utilizes CNNs, which have demonstrated viable in assignments related to picture and video investigation and are especially well suited to recognizing complex move stances. One of the key developments in this investigate is the integration of MediaPipe posture estimation innovation with profound learning models. MediaPipe, a real-time discernment system, gives profoundly precise posture estimation, which is fundamental for the exact developments required in Bharatanatyam. The framework does more than classify postures: it moreover analyzes the dancer's developments and gives nitty gritty input on zones that require enhancement. This highlight gives a more intelligently learning involvement, where artists can make real-time alterations as on the off chance that they were being coached by a educator.

Also, the think about presents a novel application of CNNs outlined particularly for Bharatanatyam, a classical move shape that has not however been broadly coordinates with AI. The system's capacity to supply input on pose and motion precision addresses a major hole in existing move preparing apparatuses, which frequently need the profundity required for classical dance shapes. The oddity of this ponder isn't as it were for innovation itself, but too for keeping up social legacy. This think about, which makes Barratani Tiyaam simpler to get to to the world, gives the modernization and conservation of creative shapes for future eras. This approach also highlights the importance of preserving intangible cultural heritage using AI. Unlike prior work focused on static pose detection, this model enables dynamic classification and real-time feedback, offering a novel contribution to both technical and cultural domains.

IV. METHODOLOGY

A. Data Collection:

The first stage of the research involves the careful assembly of a complete dataset depicting Bharatanatyam dance poses. High-resolution images and videos were obtained from a variety of contexts, including professional performances, practice sessions, and educational documentaries. This collection ensures that the dataset captures the range of movements of Bharatanatyam. All of the footage had consistent lighting and quality because multiple camera angles were used to create a distinct and representative dataset to portray the 360-degree range of dance poses, and movements. Including these multiple angles allows the machine learning models to capture and recognize the complexities associated with the positions and movements necessary for this classical Indian dance form.

The dataset contains 2500 labeled images and 80 short and labeled video segments of Bharatanatyam practitioners from various demographics, age ranges, and other stylistic variations. There are multiple camera angles of each performance, or practice segment providing a 360 degree view of the various poses/transitions. In order to train and test the deep learning model it was important to split the original dataset into a training subset of 70% and a 15% validation and test subsets.



Figure. Class 1 Posture Dataset



Figure. Class 2 Posture Dataset

B. Data Preprocessing:

Taking after information collection, the crude pictures and recordings experienced a exhaustive preprocessing stage. This step is essential to guarantee consistency and diminish potential predispositions within the show. Each picture was resized to a standard measurement, in this way normalizing determination errors. To advance upgrade the clarity of the information, commotion lessening procedures were connected to the pictures, and video substance was separated into person outlines to disconnect particular move postures. Fragmenting the recordings in this way is especially advantageous in capturing the nuances of Bharatanatyam's energetic developments, guaranteeing that each unmistakable pose can be precisely prepared in consequent steps. Following data collection, the raw images and videos underwent an extensive preprocessing pipeline. Each image was resized to a standardized resolution to ensure uniformity and eliminate inconsistencies due to camera quality or resolution. Noise reduction filters were applied to enhance image clarity. For videos, frames were extracted at regular intervals to isolate distinct postures. This segmentation process captured subtle transitional movements typical of Bharatanatyam.

C. Annotation:

Accurate description of the dataset is essential for training valid supervised models. Each pose was manually labelled with essential meta-descriptors including the pose, movement style, and significant sub-movements or gestures. Additional descriptors for each pose included duration of pose, axes of movement, and the dancer's skill (beginner, intermediate, or advanced). Given that the labelled postures were primarily joints, limbs, and body orientations that were used as fundamental pieces of data for training, great care was taken to label. The described process of annotation is critical for ensuring that the supervised learning model can appropriately classify movement poses in a reliable manner. Each extracted image and frame was also manually labelled with pose labels, difficulty level (beginner, intermediate, or advanced), and style descriptors. Key descriptors such as duration of posture, movement trajectory, and dancer's experience level were also included. Joint locations, limb orientations, and orientation angles have all been labelled, so that we could ensure structured pose evaluation. This

level of annotation is critical when training a supervised learning model to be able to recognize subtle movements.



Figure. Consolidated Classes of Postures

D. MediaPipe Pose Initialization:

The MediaPipe Posture system was utilized to encourage the location of key points of interest in each pose. By initializing MediaPipe Posture, the framework might recognize critical skeletal focuses within the dancers body, counting the nose, eyes, shoulders, elbows, wrists, hips, knees, and lower legs. These key focuses serve as basic pointers of the dancers pose and arrangement. The precision of these recognized points of interest was thoroughly approved to guarantee their redress arrangement with the dancers developments. This cautious calibration of points of interest is essential to accomplishing exactness in posture discovery and examination. MediaPipe Pose was used to detect 33 key skeletal landmarks, including the nose, eyes, shoulders, elbows, wrists, hips, knees, and ankles. This provided a reliable framework to represent dancer postures computationally.

E. Posture Extraction:

Utilizing the initialized MediaPipe Posture, point of interest facilitates (x, y, z) were extricated from the recordings and pictures for each outline. The relative situating of different body parts, such as the separate between joints, is crucial for the exact representation of Bharatanatyam postures. To account for varieties in dancers statures and their positions relative to the camera, normalization was performed on the extracted facilitates. This normalization guarantees that the models investigation centers on the substance of the postures, instead of being affected by individual dancer characteristics or camera settings.

F. Feature Extraction:

Highlight extraction taken after the posture extraction stage, wherein the normalized point of interest arranges were utilized to calculate points between key joints such as the shoulders, elbows, knees, and hips. These precise estimations are basic in separating the different postures of Bharatanatyam. By centering on joint points and their relationship to each other, the demonstrate is superior prepared to recognize the better complexities of the move frame. This step is crucial for improving the systems capacity to classify and analyze move stances with a tall level of exactness.

G. Posture Classification:

The classification of Bharatanatyam postures could be a center objective of the inquiry. A Convolutional Neural Network (CNN) show was created to classify postures based on the extricated point of interest arranges. This framework classifies each move pose into predefined categories, such as amateur, intermediate, and advanced, based on the dancers aptitude level. Also, each posture is related with its particular move fashion inside Bharatanatyam, encourage refining the classification handle. Extraordinary consideration was given to key measurements, such as the y-coordinate of the dancers nose, which made a difference decide adjust and position.

H. Image Classification:

In parallel with posture classification, a partitioned picture classification handle was utilized to analyze the visual components of the move postures. A pre-trained TensorFlow Lite (TFLite) demonstrate was utilized for this reason, centering on basic visual highlights such as body arrangement, hand signals, and facial expressions. These visual components are basic to Bharatanatyams expressiveness and narrating. The combination of posture classification with picture classification permits for a all encompassing investigation of the dancers execution, considering both pose and visual expression. In addition to skeletal landmark features, visual features were analyzed using a pre-trained TensorFlow Lite (TFLite) model. This image-based model processed visual traits such as mudras (hand gestures), facial expressions, and costume elements. Combining pose and image classification improved contextual understanding of the dance movement.

I. Result Integration:

Once both posture and picture classification were total, the comes about were coordinates to supply a comprehensive appraisal of each move execution. The integration handle combines the expertise level decided through posture classification with the particular move course distinguished through picture classification. This double approach offers a nuanced investigation of both the technical execution of postures and the dancers in general execution, permitting for nitty gritty criticism and proposals for enhancement.

J. Data Augmentation:

To improve the strength of the machine learning show, information increase strategies were connected. These procedures included turning, flipping, scaling, and altering the color of the pictures. The reason of this enlargement was to recreate a extend of real-world conditions, such as

varieties in lighting and camera points. This handle increments the datasets differing qualities and permits the demonstrate to generalize way better over diverse situations, making it more compelling in analyzing move exhibitions captured beneath shifting conditions.



Figure. Images after Data Augmentation

K. Model Training:

The preprocessed and increased dataset was at that point encouraged into the CNN show for preparing. The design of the show was planned to handle both posture and image classification assignments at the same time. Amid the preparing stage, backpropagation was utilized to adjust the models parameters, permitting it to memorize affiliations between point of interest positions, visual highlights, and their comparing move postures. Preparing proceeded until the show focalized, achieving optimal execution.

L. Model Evaluation:

The model's execution was assessed utilizing standard classification measurements, counting exactness, accuracy, review, and F1-score. A disarray network was produced to distinguish misclassifications and highlight ranges where the demonstrate battled to distinguish between postures. This assessment handle given profitable experiences into the model's qualities and shortcomings, directing encourage refinement of the framework. Model performance was evaluated using standard metrics: accuracy, precision, recall, and F1-score. The final model achieved an accuracy of 91.2%, a precision of 90.8%, recall of 89.7%, and F1-score of 90.2%. A confusion matrix was generated to highlight posture-wise misclassifications. Overlaps between intermediate and advanced poses were most common, indicating potential improvements in fine-grained pose separation.

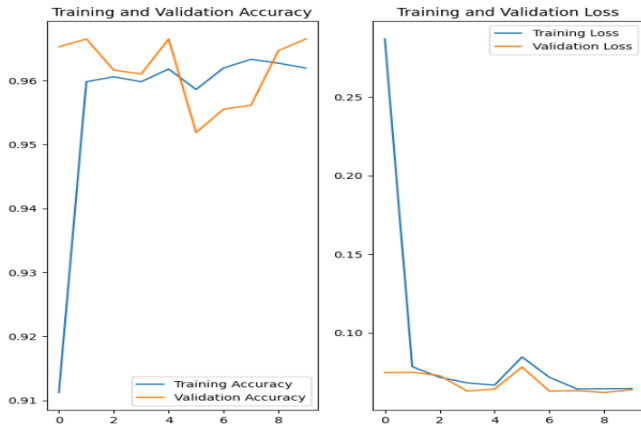


Figure. Non Optimized Model Accuracy and Loss details

M. Optimization:

To move forward the model's execution, hyperparameter tuning procedures, such as cross-validation and network look, were used to distinguish the leading combination of learning rates, clump sizes, and structural settings. These optimizations were pointed at lessening overfitting and improving the model's capacity to generalize over concealed information. This prepare is pivotal to accomplishing solid comes about in real-world applications.

N. Real-Time Pose Detection:

An vital highlight of the framework is its capacity to perform real-time posture location. By optimizing MediaPipe Posture, the framework is competent of analyzing live video bolsters, recognizing and classifying postures in real-time. This usefulness makes the framework profoundly important for commonsense applications, such as giving quick input amid move hone sessions, where convenient redresses can altogether improve a dancer's execution. The trained system was integrated with MediaPipe's real-time inference capabilities. This allowed for immediate classification of live video input. Dancers received real-time feedback, enhancing their ability to self-correct during practice without human supervision.



Figure. Pose Detection Results

O. Posture Analysis:

Past classification, the framework is outlined to conduct in-depth pose examination. By analyzing the extricated point of interest positions and calculating points between joints, the framework surveys the dancer's adjust, arrangement, and smoothness of development. This point by point investigation gives important criticism, permitting artists to refine their method by recognizing particular zones where advancements are required.

P. Gesture Recognition:

In expansion to recognizing body stances, the framework moreover consolidates signal acknowledgment, leveraging MediaPipe's hand following capabilities. In Bharatanatyam, hand signals, or "mudras," play a basic part in narrating and expression. By precisely recognizing these motions, the framework includes another layer of investigation, making it more adjusted to the complexities of this classical move frame.

V. RESULTS & OBSERVATIONS

The posture acknowledgment framework created for Bharatanatyam move has been broadly tried on a carefully chosen dataset that covers a wide run of postures collected amid proficient exhibitions and preparing sessions. The differences of the information empowers the framework to handle the inconspicuous varieties in pose and development that are one of a kind to Bharatanatyam.

The dataset has been carefully explained, labeling each posture based on key properties such as pose, artist ability, and development nuances. These comments encouraged preparing a Convolutional Neural Organize (CNN), empowering the framework to precisely classify postures and give real-time criticism. Despite high accuracy, analysis of the confusion matrix showed that some poses with similar hand and leg configurations were occasionally misclassified. This indicates the need for additional features such as facial cues or time-sequence modeling.

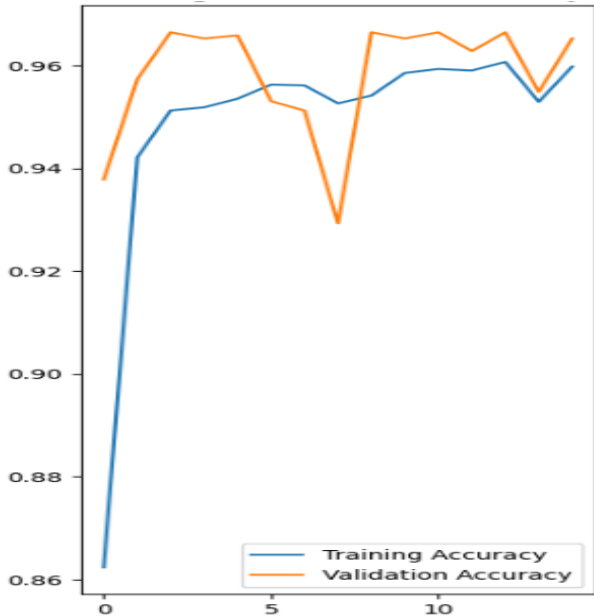


Figure. Final Optimized CNN Model Training and Validation Accuracy details

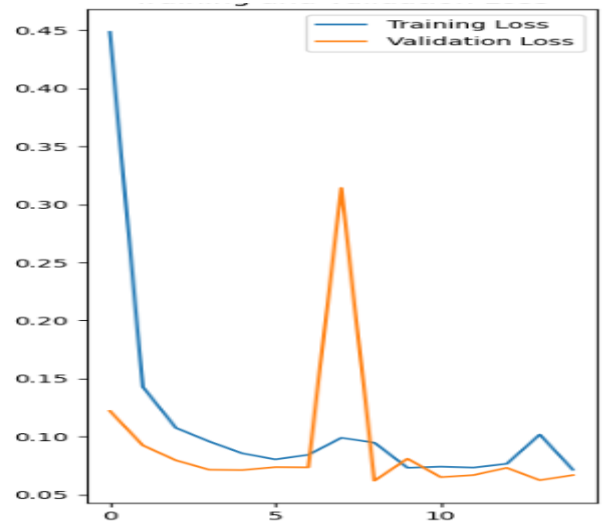


Figure. Final Optimized CNN Model Training and Validation Loss details

A. Three Category Pose Matching using Landmarks:

An advanced feature will be implemented to coordinate the recognized move postures with a reference database. This usefulness will be particularly valuable for choreography replication or learning purposes, because it permits artists to compare their exhibitions with master artists and alter their methods appropriately..



At the advanced level, an complicated highlight will be consolidated to precisely coordinate recognized move postures with a reference database comprising of master choreography. This usefulness is especially useful for proficient artists or choreographers who wish to reproduce complex move schedules.



Figure. Advanced Category of Pose Results

By comparing their exhibitions with master artists, clients can make exact alterations to their strategies and make strides arrangement with choreography.



Figure. Advanced Category of Pose Results

For intermediate dancers, the posture coordinating framework will give a adjust between direction and adaptability, centering on making strides foundational methods. This highlight will permit clients to compare their postures against a database of gifted entertainers but with more tolerance on minor blunders. Artists at this level will get real-time input based on their pose, arrangement, and development smoothness..



Figure. Intermediate Category of Pose Results

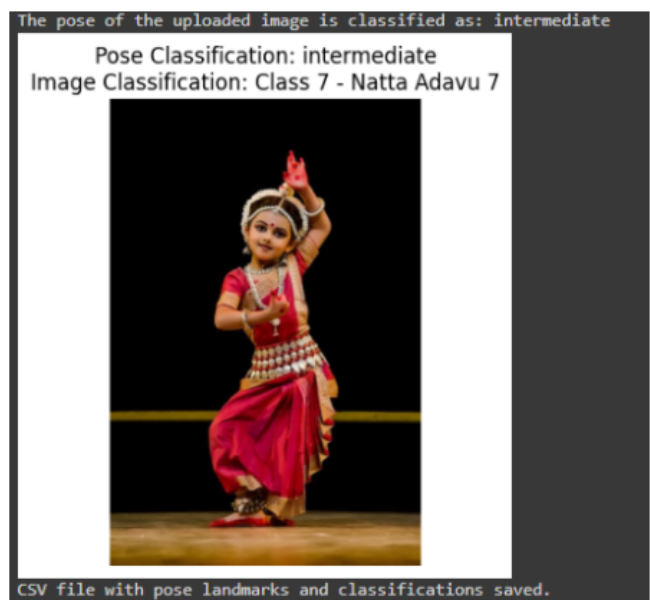


Figure. Intermediate Category of Pose Results

For fledglings or beginner artists, the posture coordinating framework will prioritize ease of utilize and learning. The framework will be streamlined to highlight fundamental posture rectifications and provide tender input. Rather than centering on culminate precision, the beginner level will direct clients in acing essential move developments and pose.

A user-friendly input framework will be created to offer real-time proposals for pose and strategy enhancement. The input will be based on MediaPipe's point of interest precision and will give noteworthy experiences into ranges where the artist can progress. The framework will be outlined to provide useful criticism, making a difference artists refine their developments and culminate their postures.



Figure. Amateur Category of Pose Results

VI. CONCLUSION

The advancement of a real-time pose classification and skillset estimation framework marks a noteworthy headway in Bharatanatyam preparing. This consider utilized cutting-edge innovations, counting Convolutional Neural Systems (CNNs) and MediaPipe posture estimation system, to convey exact input and explanatory bits of knowledge into move exhibitions. The system's tall exactness in classifying move postures and its capacity to supply real-time remedial criticism illustrate its potential as a effective instructive device. Joining innovation into the conventional hone of Bharatanatyam will not as it were encourage more available and personalized move instruction, but will too contribute to the conservation and spread of this antiquated craftsmanship shape. By mixing classical move conventions with cutting edge machine learning strategies, this investigate presents a unused approach to learning and idealizing Bharatanatyam, encouraging more profound engagement, improved ability improvement, and broader reach.

VII. FUTURE SCOPE

The current framework gives a strong establishment for future changes, and growing it to incorporate more Bharatanatyam styles and methods will increment its pertinence over diverse schools. Integration of progressed innovation such as profound cameras and movement sensors permits you to get points of interest of the development of corners and joints. In expansion, made strides CNN design may make strides establishment discovery and classification. A user-friendly interface with multilingual back and social portrayals makes the framework open around the world. Growing its reach to other move shapes may assist increment its affect, advance more noteworthy regard for assorted conventions, and give a profitable device for artists and teachers.

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