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A COMPUTATIONAL FRAMEWORK FOR BIOMECHANICAL ANALYSIS AND ARTIFICIAL INTELLIGENCE-BASED ASSESSMENT OF BHARATANATYAM MOVEMENTS

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Abstract: **Bharatanatyam is a classical Indian dance form which involves rigorous structuring and exacting coordination of posture, speed, balance, and emotions through physical expressions. In conventional performance evaluation, expert observations play a major role in evaluation process, thus resulting in subjectivity and inconsistency in evaluation process. This research project proposes a comprehensive computational approach for objective biomechanical evaluation and automated analysis of Bharatanatyam performances using computer vision, biomechanics and artificial intelligence. Markerless pose estimation technique was used to estimate skeletal landmarks from Bharatanatyam performance videos. These landmark points were preprocessed by performing operations like interpolation, normalization of coordinates, temporal resampling and signal filtering in order to produce accurate motion trajectories. Afterward, kinetic parameters such as joint angles, velocities, acceleration and mechanical energy were computed to analyze the dynamics of movement. A variety of machine learning models, including but not limited to Random Forest, LSTM, Isolation Forest, and Simulated Annealing have been used for the purpose of movement classification, temporal pattern analysis, anomaly detection, and biomechanics optimization, correspondingly. The analysis of the kinematics showed significant differences between the joint mechanics and mechanical energy of different types of adavus, proving the biomechanics of Bharatanatyam dance. The most important parameters for the dance motion classification using the Random Forest model were acceleration, rhythm stability, posture stability, and joint angle features, while the LSTM neural network had the ability to detect temporal dependencies within the sequence of dance motions. Moreover, the optimization algorithms made the dance motion more efficient, decreasing its mechanical energy without changing the structure of the dance motion.**

Keywords: **Bharatanatyam; Biomechanics; Pose estimation: Kinematics Aanalysis: Machine Learning.**

1. INTRODUCTION

Classical Indian dance is a highly refined fusion of art, culture, and human biomechanics, which includes complex body motions executed with great precision and timing (Adalarasu, et al 2025a; Mullerpatan, et al 2019). The unique feature of Bharatanatyam is its distinctive movement language, which is based on rhythmic footwork (adavus), hand gestures (hasta mudras), coordinated limb motion, and posture and balance maintenance (Adalarasu, et al 2025b; Gowri, 2019). In the past, the assessment of the performance of Bharatanatyam was highly dependent on the subjective judgment of experienced instructors and dance theorists based on posture, balance, rhythm, and expression of artistry (Tunstall, 2022). Evaluation by an expert teacher plays a critical role in the education of dancers, yet it is inherently subjective and usually influenced by the teacher's background and style of teaching (Park, 2016). As a result, there is a growing need for objective computational methods that could evaluate the movement qualities without violating the artistic purity of the classical dance (Wilmerding, & Krasnow, 2025).

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Emerging developments in computer vision, biomechanics and artificial intelligence offer novel ways of analyzing human movement quantitatively (Smith, & Pollick, 2022). Advanced technologies of markerless pose estimation along with machine learning algorithms allow acquiring sophisticated skeletal data from regular video footage without the use of expensive motion capturing techniques (Hu, 2024). However, their application is evident in fields such as sports biomechanics and recognition of human activities; however, their applications in classical Indian dance are minimal (Qianwen, 2024; Wang, & Yu, 2022). The challenges presented in using these algorithms for Bharatanatyam dances include coordinating movements in the legs and the complicated movements of the arms, as well as the transitions from one posture to another (Zhang, et al 2024). All of them call for analytical tools capable of synthesizing spatial, temporal and biomechanical data in order to define movement dynamics properly (Zhang, 2022).

In this research, a novel computational framework is presented for the analysis of Bharatanatyam movements from the viewpoint of biomechanics, machine learning and optimization. The movement behavior was objectively quantified in terms of kinematic parameters (joint angles, velocity, acceleration, and mechanical energy) extracted from dance videos through markerless estimation of body joint landmarks. Next, the biomechanical features were classified into different movements by employing a Random Forest classifier, and an LSTM model was trained for learning the dependencies among dance movements. Furthermore, the Isolation Forest algorithm was applied for abnormal movement detection. Finally, the algorithm Simulated Annealing was applied to improve the efficiency of movement in relation to decreasing the mechanical energy while preserving the anatomically plausible movement.

In contrast to the earlier studies, which considered either biomechanics or the classification of movement, the present study incorporates both quantitative analysis of kinematics, deep learning in time domain, and anomaly detection and optimization in a unified computational framework. In the present study it was demonstrated that Bharatanatyam dance movements could be transformed into quantitative datasets of biomechanics which can be processed by intelligent techniques without losing their artistic and didactic value. The current study opens up new avenues for creating a data-driven approach to dance education and performance analysis.

Objective

To develop and evaluate a computational framework that integrates biomechanics and artificial intelligence to objectively analyze, classify and improve Bharatanatyam movements thru markerless pose estimation and kinematic analysis.

2. METHODOLOGY

For the current research, a computational model that utilizes the concept of quantitative analysis has been designed for investigating the human movements involved in the Bharatanatyam dance form which involves application of the knowledge from the field of biomechanics, computer vision, and artificial intelligence. This computational model has been designed with the aim of translating the movements performed in a dance into a biomechanical representation of the dance. The process has been formulated as a pipeline process involving video capture and creation of standard movement trajectories for future analysis.

The experiment dataset included videos of Bharatanatyam dances of different categories of adavus which represent the basic movement vocabulary of the dance style. The video frames included foot movements and beats, araimandi postures, upper limb movements coordination, rotations, hasta movements and tempo-based movement formation. Videos were classified into classes on the basis of certain movements in order to facilitate data management and future computational evaluation. In all cases, the transition from one frame to another was smooth and hence it was possible to conduct an analysis of the body posture and joint trajectory during the movement process. The acquired videos were the main sources of information used for pose estimation, biomechanical analysis, feature extraction, optimization and movement classification. The proposed framework utilized established techniques for organization and pre-processing of videos to ensure uniformity in the movement sequence analysis. This is due to the fact that video-based datasets for dance analysis vary depending on the characteristics of the dancers, recording environment, camera position and illumination conditions. The synthetic trajectory generation was done wherever necessary to verify the computational flow and the robustness of the framework proposed.

In particular, the markerless pose estimation results in the appearance of the raw trajectories of the skeleton which are directly influenced by the lack of markers, the differences in the coordinate system, differences in the alignment, and the noise, caused by fast body movement, lighting and camera angle, and rare pose detection errors. Before performing the quantitative analysis, a huge preprocessing step was performed, as more complex biomechanical characteristics such as speed, acceleration, angular speed, and jerk are very sensitive to any small error in the coordinate system. First of all, missing points were interpolated in order to provide temporal consistency, then the coordinates were normalized in order to reduce the impact of anthropometric features of the performer, the distance to the camera, and the scale of the picture on the variables. Finally, a uniform resampling of the sequence was performed in order to provide the same duration of the movement for all performers and all adavus types.

The internal mechanical parameters influencing the performance of Bharatanatyam dance style were analyzed through biomechanics utilizing kinematics information. The anthropometric information was merged with the metrics of displacement, velocity, and acceleration that were computed to establish the kinetic, potential, and mechanical energy throughout the motion process. Joint moments and the loads on the lower limbs were calculated using simplified inverse dynamics and vertical ground reaction forces, which were determined based on body mass and acceleration during landing and push-off phases.

Feature vectors derived from kinematics and biomechanics assessments were considered as input parameters of various intelligent algorithms where each algorithm had its own analytical task. The key factors of the movement were selected. Bharatanatyam performance was classified on objective biomechanical factors through Random Forest classifier. LSTM network was applied to find the temporal dependencies in sequential movement data to recognize dynamic patterns of movement throughout the entire adavu rather than isolated frames. The Isolation Forest algorithm was employed to detect anomalies in the expected pattern of movements. It helped to automatically detect wrong or inefficient performances.

3. RESULTS AND DISCUSSION

Kinematics and Biomechanical

This proposed model has been successful in converting Bharatanatyam dance forms into mechanical parameters for assessing the quality of movement using kinematic parameters and the assessment of mechanical energy. The sequences obtained from these dances have been employed in the process of markerless pose estimation in order to obtain the trajectories of joints. These data have been utilized for the analysis of joint angles, velocities, accelerations, and the use of energy-based measures. We observed highly synchronized spatiotemporal aspects of the Bharatanatyam dance movements and discovered unique biomechanical signatures amongst adavu forms. Our findings show that dance movements can be quantified using physical parameters.

Joint angle analysis revealed significant differences between the angular variations of the knee joint and elbow joint during movement execution (Figure 1). The angular variations of knee joints were significantly higher than that of the upper limb joints and suggested the significance of these joints for maintaining the unique posture of Araimandi, rhythm and consistent weight transfer during the performance of Bharatanatyam. Meanwhile, smooth transitions in the elbow joint angles implied the controlled movement of the upper limbs along with hasta mudras. Thus, it can be assumed that the kinetics of lower limbs contribute significantly more to movement variability than the kinetics of the upper limbs and underlined the important role of flexion–extension of knee joints in postural stability during execution of rhythmic movement tasks. Another good example of the coordinated neuromuscular control required for maintenance of esthetic accuracy of the dance performance is the simultaneous change in angles of upper and lower limbs.

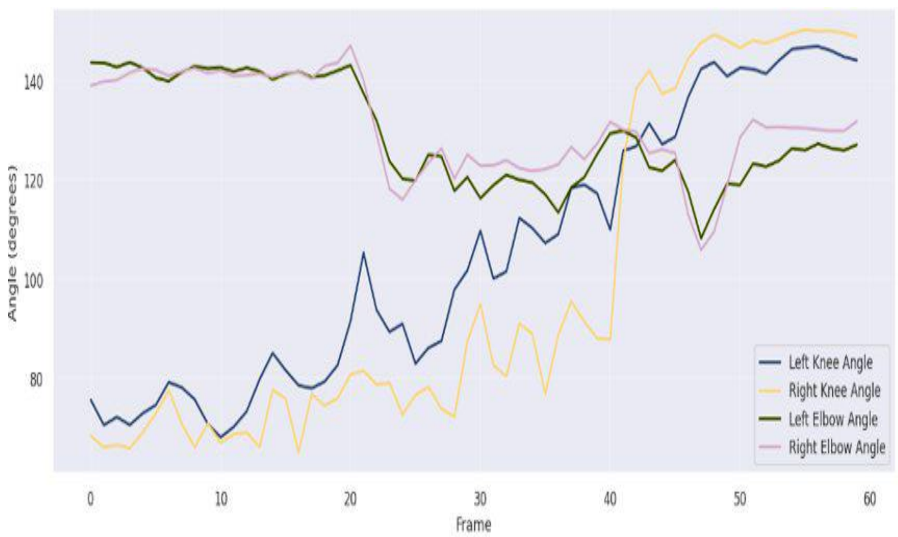

Figure 1: Joint Angle Variation across Bharatanatyam Movement Frames

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In addition to the examination of joint velocity and acceleration, further knowledge was provided about the dynamics of the movement process and process of force production in its course. Profiles of wrist movements have high variability, profiles of knee movements - moderate variability, profiles of hip movements - low variability. High wrist velocity is due to fast execution of dynamic hand movements, while moderate knee velocity is due to stepping movements and coordination of lower limbs during the transition between adavus. As one can observe from the acceleration profiles (Figure 2), the peaks and troughs were present throughout the entire movement cycle and it indicated sequential dynamic movement and stabilization. According to Newtonian mechanics, the increase in acceleration means the increase in the process of force production. Therefore, peaks in acceleration profiles indicate the time of rapid posture change, foot stamping, and body movements. In contrast to peaks, troughs had low acceleration values that correspond to the periods of postural stability when performers held their balance before performing rhythmic movements.

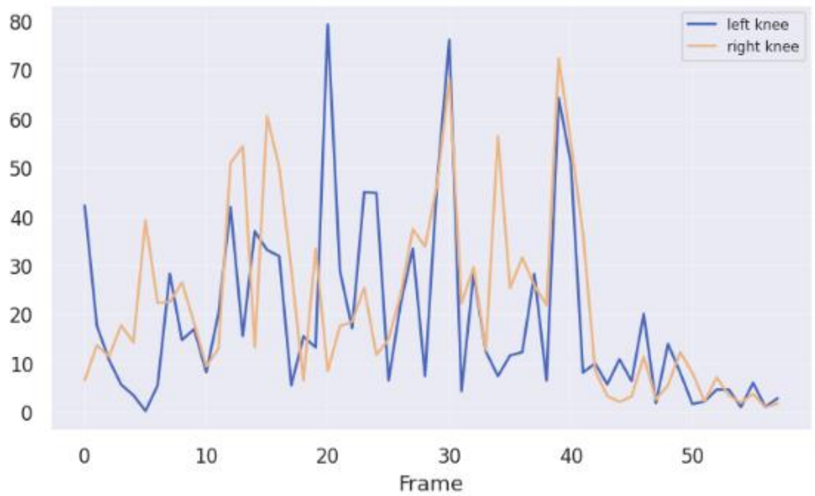

Figure 2: Joint Acceleration Profile Across Movement Frames

Furthermore, through the mechanical energy analysis, a better understanding has been achieved regarding the biomechanical demands of different movement classifications in Bharatanatyam. The distribution of mean energy expenditure (Figure 3) showed significant differences between adavus and showed that there is a mechanical difference in the demand of the performer based on the movement pattern performed. Maximum mean energy consumption was detected in Tirmana Adavu (≈63.27 units), followed by Visharu Adavu (≈51.70 units) and Kuditta Mettu (≈43.24 units), while energy expenditure in Natta Adavu (≈20.52 units) and Tatta Adavu (≈20.73 units) was quite low. The reason of increased energy demand in Tirmana Adavu is larger amplitude of movements, fast rhythmic changes and more involvement of lower extremities. Low energy movements include relatively stable positions and less displacement of the body. The findings have shown that the mechanical energy gives an accurate reflection of the complexity of the movement and efforts of the performer. This suggests that energy measures may be considered as reliable quantitative indices to quantify the efforts of performers and to discriminate Bharatanatyam movement categories.

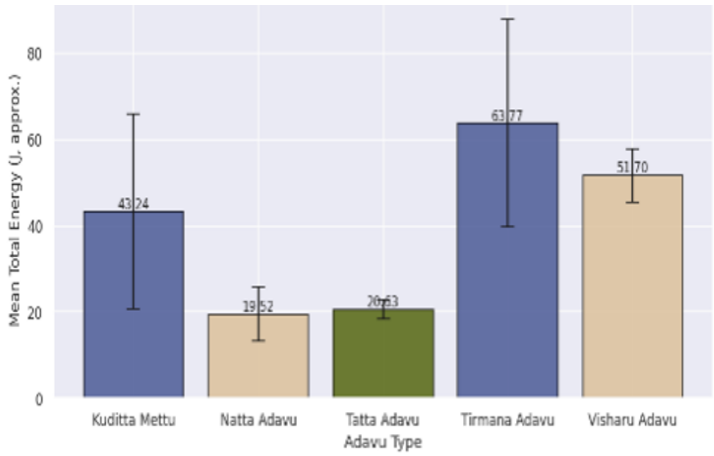

Figure 3: Mean Total Energy Distribution Among Adavu Types

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Machine Learning Performance

The study of the trajectories of motion (see Fig. 4) showed that the patterns of motion took place along smooth curves rather than straight lines due to the features of movement performance in Bharatanatyam. The study of the trajectories showed the very high bilateral symmetry of the left and right wrists, demonstrating excellent motor coordination and smoothness of motion of the upper body. Small differences detected on particular segments of the trajectory are probably caused by the specific features of the performer, but not by the mistakes in performing motions. Patterned trajectory is the evidence of the fact that the Bharatanatyam movements are performed along definite spatial trajectories depending on rhythm, pose and the purpose of movements. Hence, the biomechanics of classical dancing becomes more standardized. The results of the kinematic analysis in general confirm the possibility of objective analysis of the Bharatanatyam with respect to joint kinematics, energy expenditure and spatial trajectory. This set of biomechanical characteristics can become a good basis for further machine learning, temporal sequence analysis and improvement of movements. It will be discussed further.

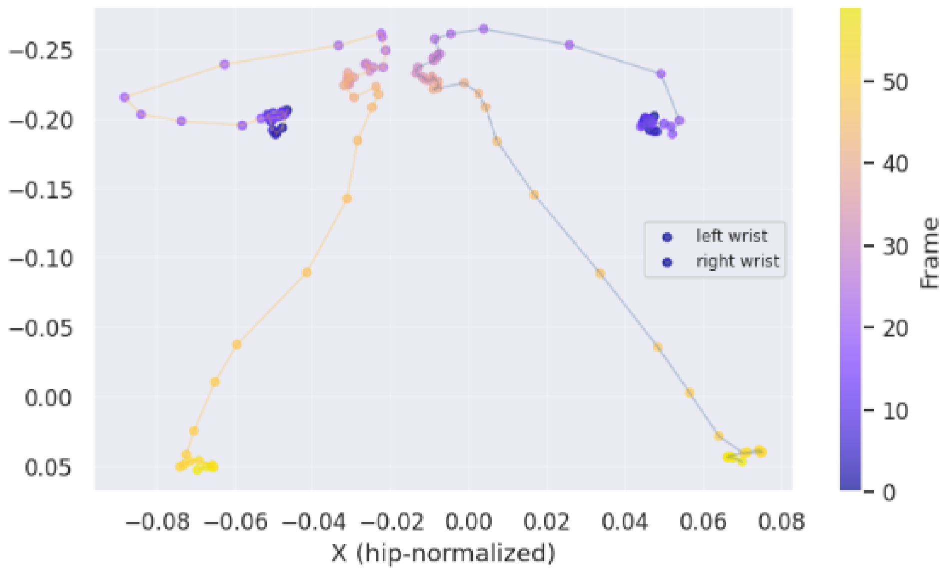

Figure 4: Wrist Motion Trajectory Map

Classification tests were performed for the kinematic and biomechanical features extracted in a Random Forest classifier to find out how feasible the automatic identification of Bharatanatyam movements is. The feature set consisted of a combination of spatial and dynamic features in the classifier including joint angles, acceleration, stability, symmetry, rhythm consistency, and mechanical energy features. Not only was the objective to classify the particular form of adavu but also to analyze those biomechanical aspects that influence motion classification the most. Table 1 illustrates the classification results in which 20% of accuracy is achieved. The Visharu Adavu motion was completely classified (Precision = 1.00, Recall = 1.00, F1-score = 1.00) in contrast to other classes of movements, for which the accuracy of classification was noticeably lower. This means that Visharu Adavu has more unique biomechanical features compared to other adavus, whereas the rest of them share many similar biomechanical characteristics.

Table 1: Classification Performance of Random Forest Model

Movement Type	Precision	Recall	F1-score	Support
Kuditta Mettu	0.00	0.00	0.00	2
Natta Adavu	0.00	0.00	0.00	2
Tatta Adavu	0.00	0.00	0.00	2
Tirmana Adavu	0.00	0.00	0.00	2
Visharu Adavu	1.00	1.00	1.00	2
Accuracy	-	-	0.20	10
Macro Average	0.20	0.20	0.20	10
Weighted Average	0.20	0.20	0.20	10

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Further information can be obtained from the analysis of the confusion matrix (Figure 5), which shows the relation between the actual and the predicted movement classes. Misclassification was noticed many times with Kuditta Mettu, Tatta Adavu, and Tirmana Adavu, and this fact indicates that these movements have the same features concerning legs alignment, rhythmic step, and body synchronization. Similarly, Natta Adavu class showed high similarity with other movement classes, and this is the reason why the algorithm could not define the proper decision boundaries. This demonstrates the close relationship of Bharatanatyam movements by their biomechanics, which is the main problem of classification by using static feature vectors. Furthermore, the capability of the classifier to recognize intra-class variation and generalize between movement classes was rather low, since there were not enough samples for training. That is why the achieved results could be used to indicate the similarity between the movements, and not the limitations of the model itself.

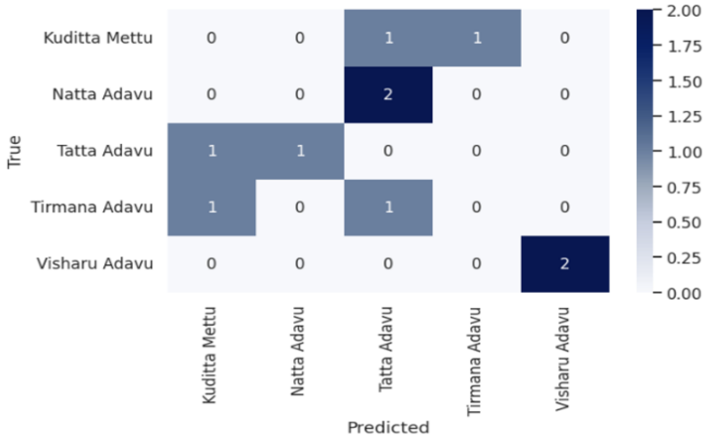

Figure 5 : Confusion Matrix of Random Forest Classification

The feature importance analysis (Figure 6 and Table 2) determined which biomechanical factors were highly relevant to the categorization of movements. The most important factors were maximum acceleration (acc_max), rhythm consistency, vertical posture stability, maximum knee angle and maximum elbow angle. The importance of the acceleration factor is that changes in the intensity of the movement can be used as an important differentiating criterion between adavus. Rhythm consistency factor indicates the critical importance of synchronous tempo in Bharatanatyam. Likewise, postural stability and joint angles reveal the importance of correct body alignment and movement of limbs during dance performance.

Table 2: Dominant Features Contributing to Classification

Rank	Feature	Interpretation
1	acc_max	Maximum acceleration during movement
2	rhythm_consistency	Degree of rhythmic synchronization
3	posture_stability_y	Vertical posture stability
4	left_knee_angle_max	Maximum knee angle
5	left_elbow_angle_max	Maximum elbow angle

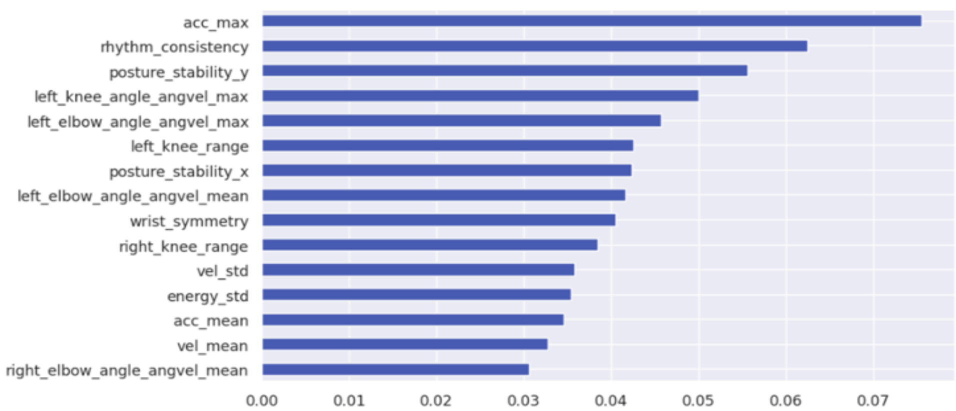

Figure 6: Top Fifteen Important Features for Bharatanatyam Classification

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Results of the machine learning classification confirm the importance of biomechanical features derived from the markerless motion capture with regard to the task-oriented identification of Bharatanatyam movement classes. Due to the limited size of the dataset and high overlap between the movement classes in terms of the features, the Random Forest classifier had relatively low classification accuracy. Nevertheless, the experiment succeeded in determining the relevant biomechanical features needed for distinguishing dance movements. This finding confirms that the identification of classical dance should preserve the evolution of movements over time and use static posture data. Such a conclusion gives room for further application of sequence-based deep learning approaches such as the use of LSTM networks.

In order to overcome the limitations associated with the feature-based classification approach, an LSTM network was used in the model to understand the temporal dynamics of the Bharatanatyam dancing movements. While the Random Forest algorithm was using independent vectors of features, the LSTM network was able to capture temporal relations between consecutive frames so as to analyze the entire movement. The LSTM network was able to learn the dynamics of the movements rather than the statics because it had access to sequential information through the trajectories, velocity, acceleration, symmetries, energies and rhythms of the joint angles. In figure 7 is the graph of the loss function of the model during the training phase whereby the loss kept decreasing until it became stable after about 20 iterations. This shows that the network has successfully converged.

Figure 7: LSTM Training Loss Across Epochs

Temporal Learning and Optimization

The temporal learning analysis revealed that the recognition of the Bharatanatyam dance moves depends on static biomechanics, posture sequencing, synchronization of moves and fluidity of moves. The ability of the LSTM to model the connection between states of consecutive movements has allowed it to capture the process of rhythmic evolution, transition of the postures, and limb coordination in every adavu sequence. It can be seen from the comparison results (Table 4.3) that the LSTM algorithm has performed better than the Random Forest in sequence learning, long-term memory and complex pattern recognition. Hence, the LSTM algorithm is a better choice for the analysis of the classical dance moves that have sequence as a distinctive feature.

Table 3. Comparative Analysis Between Random Forest and LSTM

Parameter	Random Forest	LSTM
Input type	Static feature vectors	Sequential data
Temporal dependency learning	No	Yes
Memory capability	None	Long-term memory
Sequence analysis	Limited	Strong
Movement progression learning	Weak	Strong
Complex pattern recognition	Moderate	High

Specifically, the computational framework adopted the Isolation Forest and Simulated Annealing algorithms to compute the quality of movement and biomechanical optimization for efficient temporal learning. The Isolation Forest algorithm automatically identified the anomalies of abnormal movements from the normal biomechanics, and thus we could recognize postural abnormalities, rhythm irregularities, and movement instabilities without any labeled training datasets. Next, the Simulated Annealing algorithm was used to improve the quality of movements by optimizing the total mechanical energy according to the feasibility of anatomy and kinematics. Consequently, the optimized solutions of lower mechanical energy were obtained without altering the structure of Bharatanatyam movements, which implies that the computational optimization would be useful for improving the efficiency of movements without losing artistic creation. Overall, the LSTM, Isolation Forest, and Simulated Annealing algorithms are compatible with each other and form an advanced computational framework for temporal learning, automatic quality assessment, and energy-efficient motion optimization, and hence go beyond conventional biomechanical analysis for motion analysis.

4. CONCLUSION

This study proposes a novel computational paradigm that integrates markerless pose detection, biomechanical modeling, machine learning, and optimization methods to quantitatively analyze and objectively evaluate the Bharatanatyam movements. It is possible to successfully transform dance videos into measurable biomechanical data using the proposed approach which will help in analyzing kinematics of joint motion, movement dynamics, postural stability and mechanical energy during Bharatanatyam. The findings revealed that the lower limbs play an essential part in the maintenance of postural control and rhythmic execution while the analysis of mechanical energy could distinguish the physical demands of different classes of adavu. Machine learning analysis suggested that acceleration, rhythmic consistency, postural stability, and joint-angle features were the most influential biomechanical features for movement identification. The Random Forest classifier produced good but mediocre classification results owing to the lack of data samples and a high degree of similarity between movement classes. At the same time, the LSTM neural network successfully learned the relationships between dancing movements. Moreover, the integration of Isolation Forest and Simulated Annealing techniques resulted in automatic detection of anomalies regarding motion and biomechanical efficiency without disturbing artistic components of Bharatanatyam. The proposed methodology showed that it is possible to combine techniques of biomechanics and artificial intelligence for creating objective assessment of dancing performances. Future research should focus on larger and varied data samples, multi-view MoCap techniques, transformer-based deep learning neural networks and real-time feedback systems for better movement detection and intelligent usage in the spheres of dance education, training, rehabilitation, and digitalization of Indian classical dance.

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