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Article

Investigation of hip flexibility training on dancesport optimization using machine learning video analysis

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Abstract: Dancesport, particularly the Paso Doble, requires high agility, coordination, and flexibility, especially in the hips. This study investigates the impact of an eight-week targeted Hip Flexibility Training (HFT) program on the performance of professional Paso Doble dancers. The need for this research stems from the lack of objective, data-driven evaluations in the field, where traditional methods rely heavily on subjective assessments. Previous studies have examined general flexibility in dance, but few have focused on the direct Biomechanical Effects (BF) and Physiological Effects (PE) of specific HFT on dancers. Further, such studies could not accurately measure hip joint movements and their coordination in order to achieve dance performance efficiency. The proposed study used motion-capturing devices to collect key movement data that impacts performance efficiency. The collected data is analyzed using the hybrid receptive field block (RFB) and residual network (ResNET) ML models to study the pre- and post-HFT results. Twelve highly trained dancers were assigned to have biomechanical and physiological metrics measured after and before the training. The data analysis has shown that there has been a significant increase in hip flexion from 65.4 ± 4.5° to 75.2 ± 3.7° ($P < 0.05$), hip extension from 25.3 ± 2.4° to 30.1 ± 2.1° ($P < 0.05$), and joint velocity from 1.18 ± 0.15 m/s to 1.32 ± 0.12 m/s ($P < 0.05$). Physiological metrics also showed improvements, such as a reduction in Oxygen Consumption (OC) from 2.02 ± 0.21 L/min to 1.85 ± 0.18 L/min ($P < 0.05$) and Energy Cost (EC) from 50.1 ± 7.2 kJ/min to 45.6 ± 6.4 kJ/min ($P < 0.05$).

Keywords: biomechanical effect; dancesport optimization; hip flexibility training; movement patterns; physiological metrics; machine learning; receptive field block

1. Introduction

Hip flexibility is an attribute that is needed in any form of physical activity and is essential for persons involved in dance sports [1]. The dancesport is a competitive form of ballroom dancing that requires technical precision and physical agility [2,3]. This demands the dancers to have more flexible hips to make more complex movements [4,5]. The dancesport includes styles categorized as ballroom and Latin, each demanding a different combination of dance fluidity, strength, and expressive motion [6]. No matter the dance's form, hip flexibility is crucial to discriminating between sharp, angular movements and dramatic postures [7]. Hip flexibility helps perform more precise and fluid transitions in dance postures, which increases the performer's winnability.

Many dancers join exclusive Hip Flexibility Training (HFT) programs to enhance their skill set [8]. However, minimal studies have been completed on how Flexibility Training (HFT) programs impact dancers' performance [9–11]. Little studies that have been done earlier have focused only on the general features of hip movements and their impact on performance efficiency [12,13]. So, the need to recognize the influence of HFT programs and their impact on performance optimization becomes essential and motivates the carrying out of this study [14]. This study focused on analyzing the impact of the HFT program in enhancing the performance of dancers performing the Paso Doble dance sport. Paso Doble is a Latin dance that mimics the styles of Spanish bullfighting, having sharp, angular, and dramatic hip movements. Such a dance style requires a high level of HFT to execute precise and fluid transitions between the postures to achieve higher performance quality [15,16].

There is less or no data on the physiological and kinematic changes or improvements achieved using the HFT training in professional dancers [17,18]. This gap further motivates me to study how such training impacts dance routines' overall performance, coordination, and energy efficiency. Existing studies have considered general physical conditioning and technique refinement but not exclusively focused on HFT's impact on movement efficiency and control [19,20]. Moreover, the performance evaluation was done using adjudicators, which is considered subjective as it introduces variability and bias into performance evaluations, which can undermine the reliability of the assessments [21]. Also, limited works incorporate advanced models like Machine Learning (ML) to perform objective movement analysis from trained and untrained dancers and make accurate classifications [22].

A new Metaheuristic Optimization (MO)-based selection of superior gait features may be employed to detect significant variations in sports and pathological gait patterns. The method extracts 800 group gait datasets, eliminates redundant variables, and selects the optimal gait feature using a MO algorithm model. Four classification algorithm models detected the gait feature. The accuracy results were compared to two standard Feature Selection (FS) methods and earlier research to verify the technique. The final FS were used to rebuild the data pattern and determine the gait feature's biomechanical value. The newly developed gait pattern recognition method performed FS-based sorting, sequential forward selection, and past research with an accuracy of $99.81\% \pm 0.53\%$. The FS enhanced the interval between rebuilt waveform-high and low curves during the posture phase. MO-based selection improves gait pattern recognition, while population-based MO is useful for sports and healthcare gait recognition.

This study attempts to address the limitations discussed above by proposing an ML-based model to analyze the impact of the HFT program on the performance of Paso Doble dancers. The study was conducted using 12 participants, all of whom were experts in the selected dance domain. The work collected key data like Oxygen Consumption (OC) (L/min), Heart Rate (HR) (beats/min), Energy Cost (EC) (kJ/min), Rating of Perceived Exertion (RPE), Reposition Time (RT) (s), Hip Flexion Angle (HFA) (°), Hip Extension Angle (°), Hip Abduction Angle (°), Hip Adduction Angle (°), Joint Velocity (m/s), Stride Length (cm), Movement Coordination (%). The dancers undergo an eight-week HFT program customized for the Paso Doble dance movements. After the training, the key data was sourced again, and the pre and post-data values were fed to the proposed Receptive Field Block (RFB) and Residual Network (ResNET) models to analyze movement patterns, joint coordination, and performance efficiency. The findings were analyzed to investigate how well the HFT program had enhanced the dancer's performance.

The primary objectives of this study are as follows:

Evaluate the Impact of Targeted HFT: To assess how an 8-week HFT program influences key physiological and kinematic performance metrics, such as hip range of motion, joint coordination, and energy efficiency, in professional Paso Doble dancers.

Analyze Movement Patterns Using ML: To apply advanced ML models, specifically the RFB-ResNET model, to objectively analyze movement patterns and joint coordination before and after the HFT program.

Quantify Performance Improvements in Dancesport: To measure the improvement in performance efficiency, movement symmetry, and balance control resulting from the HFT program, providing a detailed comparison of pre- and post-training outcomes.

Address the Limitations of Subjective Dance Evaluation: To reduce the subjectivity associated with traditional dance performance assessments by employing data-driven methods for evaluating the Biomechanical Effects (BE) and Physiological Effects (PE) in dancers following HFT.

Contribute to the Optimization of Dancesport Training: To offer insights that can inform the development of more effective, scientifically backed training programs to enhance performance, coordination, and injury prevention in professional dancers.

The paper is organized as follows: Section 2 presents the theory related to the work, Section 3 presents the methodology, Section 4 presents the analysis of the results, and Section 5 presents the conclusion.

2. Theory

Movements of the hip

As shown in **Figure 1**, sourced from Cleveland Clinic 2022, The hip joint connects two significant bones: the pelvis, which consists of the ilium, pubis, and ischium, and the femur, the upper leg bone. The ball-and-socket mechanism is formed by the head of the femur fitting into the pelvis socket, known as the acetabulum. This allows the hip to perform a wide range of movements in dancesport. Key muscles surrounding the hip, such as the gluteus maximus, adductor muscles, psoas major, and quadratus lumborum, combine to support complex movements in Paso Doble. The hip joint performs 6 primary movements such as i) Flexion, ii) Extension, iii) Abduction, iv) Adduction, v) Internal Rotation, and vi) External Rotation. **Table 1** describes each of the movements and their importance in dance.

All these hip movements, particularly flexion, extension, and rotation, help maintain sharp, strong lines while allowing for smooth transitions between rigid, angular postures. Therefore, the need for flexible hip joints is key to performing precision and control during the performance of Paso Doble.

Table 1. Hip movement and its importance in dance sport.

Movement	Description	Importance in Dancesport
Flexion	Lifting the leg forward and upward.	Critical for executing dynamic dance steps, adding agility and expression.
Extension	Moving the leg backward and upward.	It is essential in dances like the Paso Doble for creating strong, dramatic lines and extensions.
Abduction	Moving the leg away from the body's midline.	It plays a significant role in maintaining balance and creating space between partners in open-position movements.
Adduction	Bringing the leg toward the midline.	For close-position movements, dancers' legs must cross or align closely.
Internal Rotation	Rotating the leg inward.	Maintaining fluidity and precision is Necessary for smooth transitions during turns and pivots.
External Rotation	Rotating the leg outward.	Enables sweeping, elegant movements that add flair and control to the performance.

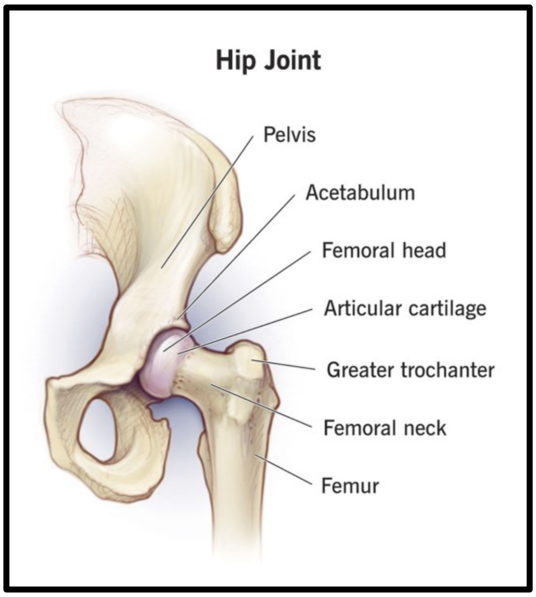

Figure 1. Illustration of Hip Joint.

3. Methodology

3.1. HFT program

The HFT program spanned 8 weeks; the training session lasted 45 min.

The training session was divided into two formats such as:

Dynamic Flexibility Exercises: Each training session began with dynamic exercises (**Figure 2**) to warm up the muscles and prepare the hip joints for the intense movements. The exercises include:

1) Leg swings are performed forward and backward, engaging both the hip flexors and extensors to increase mobility and control.
2) The hip circle exercise used large, circular movements to warm up the hip joint and its range of motion in all planes.
3) Walking lunges were performed to stretch the hip flexors and, at the same time, maintain better alignment and control.
4) Hip openers that involved step-and-turn movements were performed to prepare the dancers for the rotational hip motions.

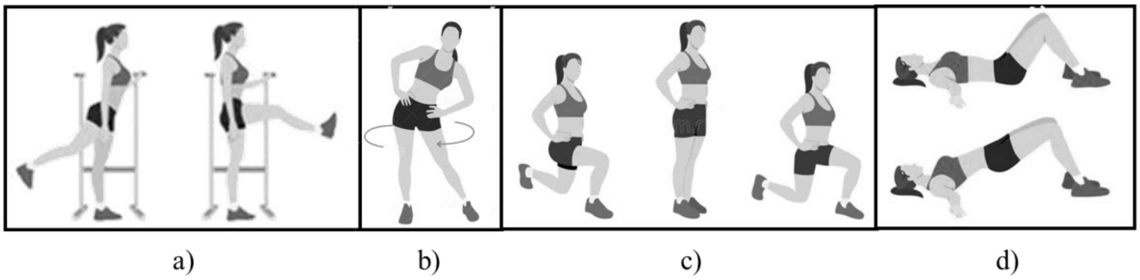

Figure 2. Flexibility exercises.

Static Stretching: After completing the dynamic exercises, participants engaged in a series of static stretches (**Figure 3**) to promote muscle lengthening.

1) The seated forward fold was done to stretch the hamstrings and lower back, which improves hip mobility by relieving tension in the surrounding muscles.
2) The butterfly stretch is performed to help the groin and inner thigh muscles and for lateral hip movements.
3) The pigeon pose was practiced to stretch the hip flexors and rotators that help in twisting and rotational movements.
4) The hip flexor stretch was performed in a lunge position to increase flexibility in the hip flexors.

Each session concluded with a cool-down period that included additional static stretches and relaxation exercises to prevent injury and promote recovery. **Table 2** describes the list of exercises used in the training and their focus area.

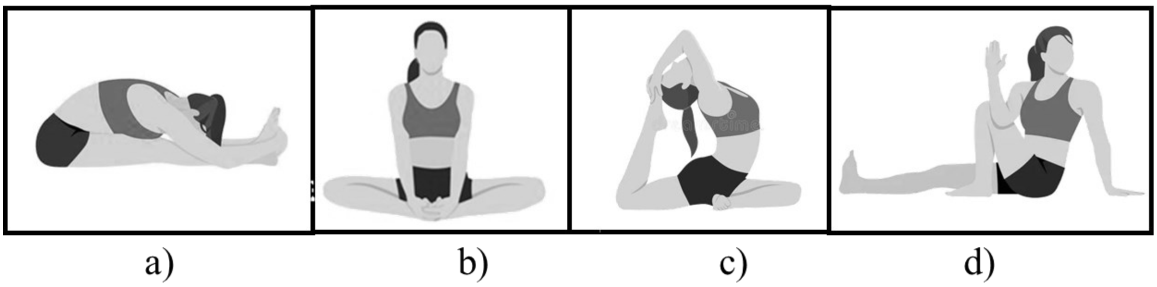

Figure 3. Stretching exercises.

Table 2. HFT training program.

Training Component	Exercise	Focus Area	Duration/Reps
Dynamic Flexibility	Leg Swings	Hip flexors, extensors	10 reps in each direction
	Hip Circles	Hip joint mobility (all planes)	10 reps in each direction
	Walking Lunges	Hip flexors, overall alignment	10 steps on each leg
	Hip Openers	Hip rotators	10 reps on each side
Static Stretching	Seated Forward Fold	Hamstrings, lower back	30–60 s
	Butterfly Stretch	Groin, inner thigh muscles	30–60 s
	Pigeon Pose	Hip flexors, rotators	30–60 s
	Hip Flexor Stretch (Lunge)	Hip flexors	30–60 s
Cool Down	Additional Static Stretching	Full-body flexibility, relaxation	5–10 min

3.2. Participants

Twelve highly trained Male and Female Paso Doble dancers participated in this study (Mean ± SD: 25 ± 4 years; Height: 172 ± 6 cm; Weight: 65 ± 7 kg). All participants were professional dancers with at least 5 years of competitive experience in Paso Doble and were actively competing at national and international levels. The participants were selected for their high skill level and physical conditioning, as Paso Doble demands significant control, coordination, and flexibility, particularly in the hips. During the initial assessment, the average HR for Male participants was recorded at 170 beats per minute (bpm). In contrast, Female participants averaged 179 bpm during high-intensity portions of their dance routines, classifying the exercise as extremely heavy based on Astrand and Rodahl's (1977) classification.

Oxygen Consumption (OC) during performance was also measured, with Male dancers averaging 2.1 ± 0.2 L/min and Female dancers averaging 1.9 ± 0.3 L/min. The EC for Male dancers was estimated to be around 54.1 ± 8.1 kJ/min, while female dancers expended approximately 36.1 ± 4.1 kJ/min. The participants were informed about the study's objectives, procedures, and potential risks. They provided written informed consent following the ethical guidelines of the Declaration of Helsinki. **Table 3** presents the demographic statistics of the study participants.

Table 3. Participant demographics and statistics.

Demographic/Statistic	Male Participants (n = 6)	Female Participants (n = 6)	Overall (n = 12)
Age (Years)	25.8 ± 3.2	24.3 ± 3.7	25.0 ± 3.5
Height (cm)	178.2 ± 5.1	166.4 ± 3.9	172.3 ± 6.2
Weight (kg)	70.3 ± 6.4	60.5 ± 5.2	65.4 ± 6.8
HR (beats/min)	170.4 ± 4.9	179.1 ± 5.8	N/A
OC (L/min)	2.12 ± 0.18	1.93 ± 0.25	N/A
EC (kJ/min)	54.1 ± 8.1	36.1 ± 4.1	N/A
Years of Competitive Experience	5 ± 1	6 ± 2	5.5 ± 1.4

Addressing subject find gender ratio.

Gender ratio: Flexibility training results are contingent upon gender, muscle structure, and biomechanics. For balanced results and generalizability, a gender ratio that includes equal male and female people is selected. This identifies gender differences in hip flexibility training performance and offers gender-specific dancer guidelines.

Gender differences in analysis: If a gender ratio is not feasible, researchers should investigate gender-specific factors such as physical activity responses between men and women. Biological and biomechanical factors may explain differences in all types of motion, movement elasticity, and function. Women may be more flexible, while men may be more powerful and stable.

3.3. Experimental design

Twelve participants, all highly trained Paso Doble dancers, took part in this study. While all participants had significant experience with Paso Doble, they were provided one familiarization session before the main testing. On the testing day, both video motion capture and 3D body kinematics were recorded during the dance routines. The testing began with a 10 min warm-up session, which included light dynamic stretching exercises to increase HR to approximately 60%–70% of the participant's maximal heart rate (HRmax). After the warm-up, participants performed their standard Paso Doble routine. Two main conditions were assessed during testing: Pre-training (baseline) and Post-training (after 8 weeks of HFT). Both conditions included similar movements to ensure consistency in performance assessment.

Each test consisted of three 2 min dance sequences and a 3 min rest interval. During each test, the participants' performance was captured through motion analysis systems to track body movement, joint angles, and range of motion, mainly focusing on the hips. Participants were monitored for HR and OC during the routines to measure the intensity of the exercises. HR was measured, with males averaging 170 ± 5 bpm and females averaging 179 ± 6 bpm during the high-intensity phases of the performance. For each condition, participants followed the same routine order: first, they completed the pre-training baseline, and then, after the 8-week training program, they repeated the same dance routines for the post-training condition. The changes in hip flexibility and control between pre- and post-training performances were analyzed using the RFB+ResNET model. **Figure 4** presents the design architecture of this study.

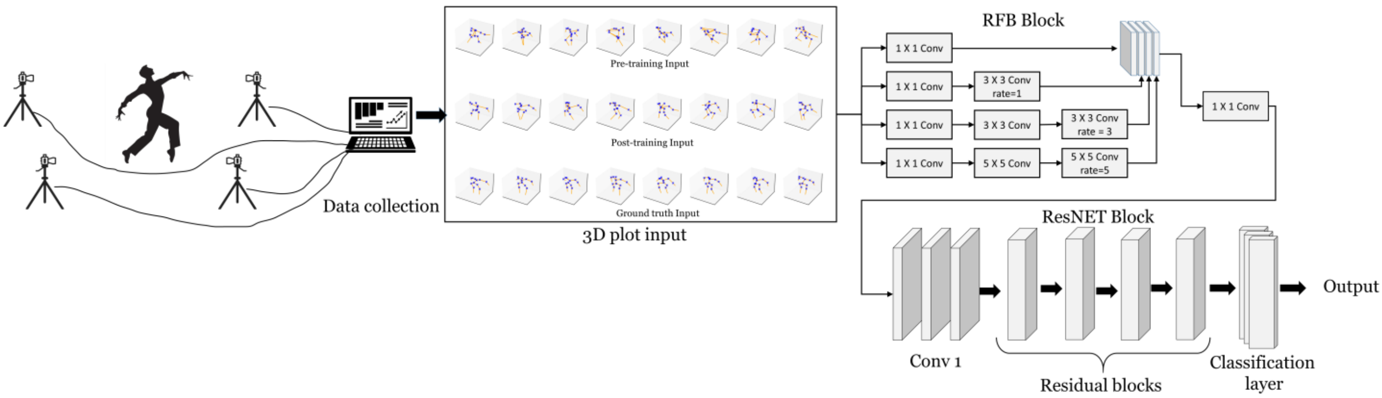

Figure 4. Experimental design of the study.

3.4. Protocol and measurements

Before each testing session, participants completed a warm-up followed by the Paso Doble routine. HR (beats per minute) was recorded throughout the trials, with an average calculated from the final 2 min of each 3 min dance sequence. OC (mL/kg/min) was averaged to assess the aerobic demands of the dance. Anthropometric measurements were taken for each participant, including height, leg length, hip width, and upper body measurements (chest circumference, upper arm length). For the 3D kinematic model, 27 reflective markers (spherical, 7 mm) were attached to key anatomical landmarks (**Figure 5**), including the pelvis, thorax, and right and left extremities.

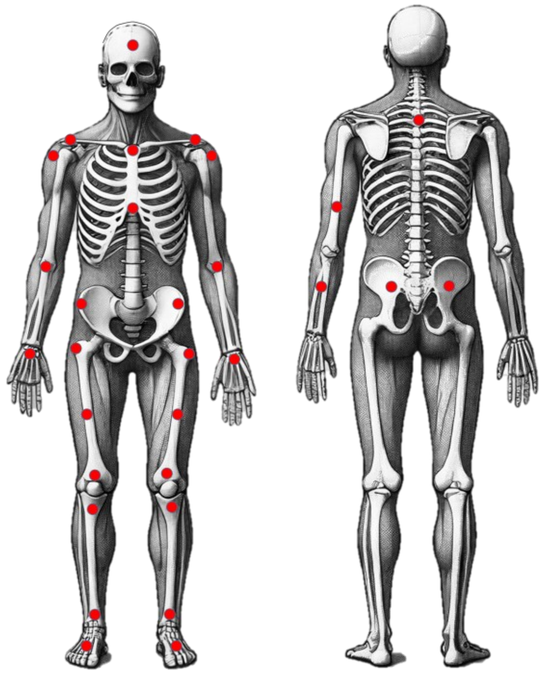

Figure 5. Reflective marker positions in the body.

The motion capture system recorded the 3D kinematics of the body in the final 30 s of each routine, with recordings lasting 15 s at a sampling rate of 300 Hz. Video analysis using the RFB+ResNET model was employed to assess further the quality and efficiency of the dancers' movements.

3.5. Data collection

To accurately capture the participants' movements, four high-definition digital cameras (Sony Alpha 7 III, 24.2 MP) were positioned around the performance area. Two cameras were placed before the participants, and two were positioned laterally. Each camera was mounted on tripods at a height of 1.5 m, positioned at a distance of 4 m from the participants. Reflective markers, each 7 mm in diameter, were attached to key anatomical landmarks, including the hips, knees, and ankles. Fixed reference points were established using markers placed at known distances—2 m apart horizontally and 1.5 m vertically—creating a reference grid. Video footage was captured at 60 frames per second. The recorded footage was processed using a desktop computer (Intel i9-11900K CPU, 32 GB RAM, NVIDIA GeForce RTX 3080 GPU). The data collected from the reflective markers was further analyzed and visualized using the Matplotlib library in Python. Using the Axes3D module, 3D plots of joint movements were generated (**Figure 6**), showing the trajectories and range of motion of the hips, knees, and ankles during the routines. All video recordings and kinematic data were stored on a 4TB external SSD (Samsung T7 Portable SSD) and backed to a cloud-based server.

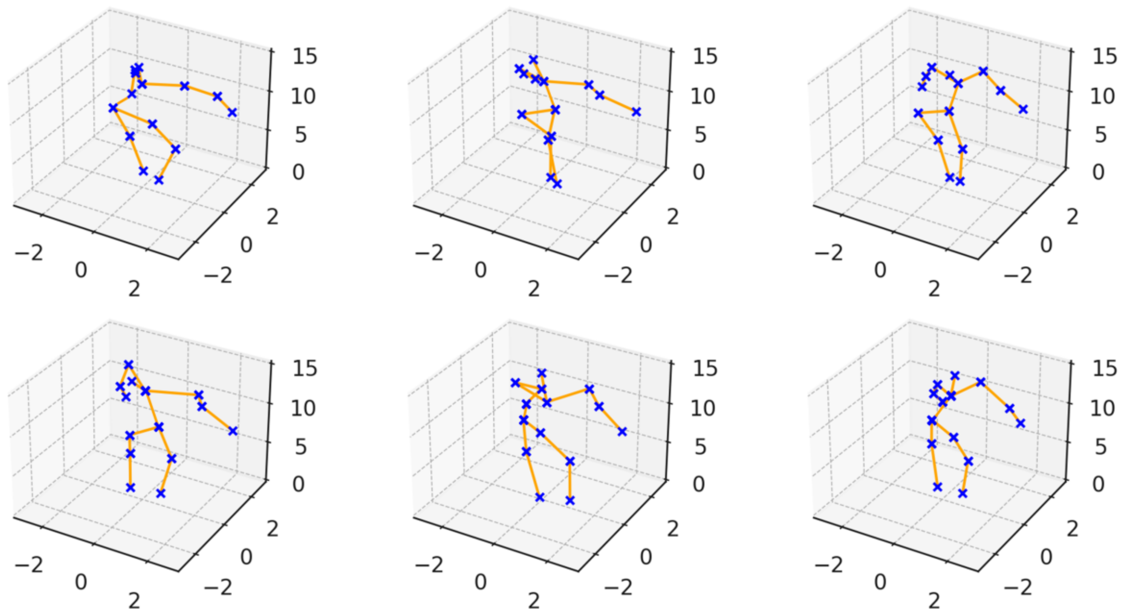

Figure 6. 3D plot conversion of joint movements.

3.6. Proposed RFB-ResNET learning model

i) RFB block

The Receptive Field Block (RFB) is a multi-branch convolutional structure used for feature extraction. It contains a multi-branch convolution layer, applying different kernel sizes to simulate receptive fields of varying sizes. This helps capture localized movements (e.g., hip adjustments) and broader movements (e.g., leg movements). Each branch begins with a 1×1 convolution layer (bottleneck layer) to reduce the number of channels. Then, convolutional layers with different kernel sizes are applied. To reduce parameters, two stacked 3×3 layers replace larger kernels (e.g., 5×5). Additionally, $1 \times n$ and $n \times 1$ convolutions are used in place of square kernels.

The output of each branch's convolution is:

$$F_{branch}(x) = Conv_{n\times n}\left(Conv_{1\times 1}(x)\right) \quad (1)$$

where, $F_{branch}(x)$ is the output feature map, $Conv_{1\times 1}(x)$ reduces the feature map size, $Conv_{n\times n}(x)$ performs feature extraction. After the convolution layers, each branch applies a dilated convolution layer. Dilated convolutions increase the receptive field size without increasing the number of parameters or reducing resolution. The dilation rate d controls the spacing between kernel elements.

The dilated convolution output is:

$$F_{dilated}(x) = Conv_{n\times n,d}(x) \quad (2)$$

where $Conv_{n\times n,d}(x)$ is the dilated convolution with kernel size $n \times n$ and dilation rate d.

The outputs from all branches are concatenated to form a single feature map, combining features from different scales:

$$F_{RFB}(x) = Concat\left(F_{branch_1}(x), F_{branch_2}(x), \ldots, F_{branch_n}(x)\right) \quad (3)$$

This allows the model to capture fine and broad movements in the dancers' routines.

ii) Residual network (ResNet) block.

The ResNET block is used to classify features extracted by the RFB. It uses skip connections to avoid the vanishing gradient problem, allowing deeper networks to learn effectively. A ResNET block uses skip connections to bypass specific layers, helping the network learn an identity function if deeper layers don't improve learning.

The residual block is represented as:

$$y = F(x, \{W_i\}) + x \tag{4}$$

where x is the input, $F(x, \{W_i\})$ represents the output of the convolutional layers with weights W_i, y is the final output after input x (skip connection) is added. The ResNET block has two convolutional layers, with a skip connection that adds the input directly to the output. Convolutional layers use 3×3 kernels to extract features.

These are followed by batch normalization (BN) and a ReLU activation function:

$$F(x, W) = \mathrm{ReLU}\left(\mathrm{BN}(\mathrm{Conv}_{3\times3}(x, W))\right) \tag{5}$$

where, $\mathrm{Conv}_{3\times3}(x, W)$ is the convolution operation with a 3×3 kernel and weights W, BN is batch normalization, and ReLU is the activation function. The skip connection adds the input x to the final layer output:

$$y = \mathrm{ReLU}\,(F(x, W) + x) \tag{6}$$

ResNET blocks are stacked to form a deep network. The final layers perform classification based on the learned features, identifying differences between pre-and post-training performances. The classification is formalized as:

$$O(x) = \mathrm{SoftMax}\,(W_{out} \cdot F_{ResNet}(x)) \tag{7}$$

where $F_{ResNet}(x)$ is the output from the ResNET, W_{out} represents learned weights, $O(x)$ is the predicted class label (e.g., improved flexibility), determined by the softmax function.

iii) RFB/ResNet Benefits:

1) Improved Multi-Scale Feature Extraction: The framework detects specific and overall movement patterns using RFB's fine-grained movement detection and ResNet's deep learning framework.
2) Improved Behavior of Complex Motion Sequences: ResNet collects dynamic dance movements and prevents data loss, while RFB improves visual perception between dimensions.
3) Enhanced Generalization: Using these two approaches improves dance movement evaluation, as well as the flexibility and adaptability of the approach for a variety of dance styles and mobility ranges.

4. Analysis

The results in **Table 4** and **Figure 7** of the Physiological and Aerobic Metrics indicate clear improvements in the dancers' physiological performance following the 8-week HFT program. The OC decreased from 2.02 ± 0.21 L/min pre-training to 1.85 ± 0.18 L/min by the end of the training period ($P < 0.05$), demonstrating enhanced aerobic efficiency. HR presented a similar trend, dropping from 172 ± 6 bpm to 165 ± 5 bpm by week 8 ($P < 0.05$), indicating a reduced cardiovascular load during the routine. EC also decreased, from 50.1 ± 7.2 kJ/min to 45.6 ± 6.4 kJ/min ($P < 0.05$), reflecting more efficient energy use in performing the dance movements. The RPE fell from 16.7 ± 1.1 to 14.8 ± 0.9 post-training ($P < 0.05$), suggesting that participants felt less exertion during performance after the HFT program. Reposition time was improved from 1.02 ± 0.10 s to 0.91 ± 0.07 s ($P < 0.05$), highlighting enhanced agility and quicker movement transitions.

Table 4. Physiological and aerobic metrics.

Variable	Pre-Training	Post-Training (Week 4)	Post-Training (Week 8)	Significant Difference
OC (L/min)	2.02 ± 0.21	1.98 ± 0.19	1.85 ± 0.18	$P < 0.05$ (Week 8 vs. Pre)
HR (beats/min)	172 ± 6	168 ± 5	165 ± 5	$P < 0.05$ (Post vs. Pre)
EC (kJ/min)	50.1 ± 7.2	47.8 ± 6.9	45.6 ± 6.4	$P < 0.05$ (Week 8 vs. Pre)
RPE	16.7 ± 1.1	15.2 ± 1.0	14.8 ± 0.9	$P < 0.05$ (Post vs. Pre)
Reposition Time (s)	1.02 ± 0.10	0.96 ± 0.08	0.91 ± 0.07	$P < 0.05$ (Post vs. Pre)

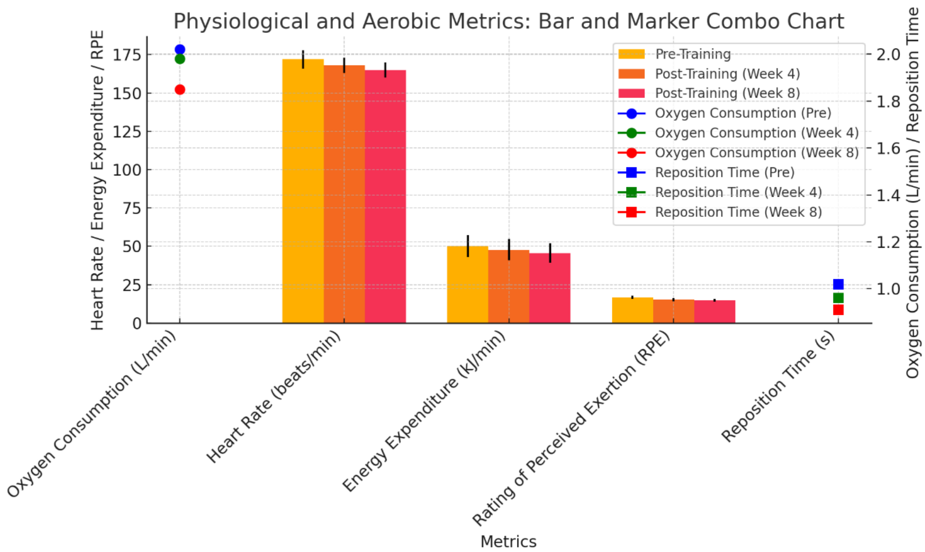

Figure 7. Analysis of physiological and aerobic metrics.

The results in **Table 5** and **Figure 8** show the improvement in Kinematic Performance following the 8-week HFT program. Hip flexion increased from 65.4 ± 4.5° pre-training to 75.2 ± 3.7° post-training, while hip extension improved from 25.3 ± 2.4° to 30.1 ± 2.1°, both showing significant differences ($P < 0.05$). Similarly, hip abduction rose from 41.2 ± 4.0° to 47.8±3.5°, and hip adduction increased from 22.7 ± 3.5° to 26.3 ± 2.8°. Joint velocity also showed a marked improvement, going from 1.18 ± 0.15 m/s pre-training to 1.32 ± 0.12 m/s by the end of the program ($P < 0.05$). Stride length increased from 110.2 ± 8.5 cm to 118.3 ± 7.8 cm, and movement coordination improved from 78.4 ± 5.3% to 85.6 ± 4.5%, indicating better overall performance post-training.

Table 5. Kinematic performance metrics.

Variable	Pre-Training	Post-Training (Week 4)	Post-Training (Week 8)	Significant Difference
Hip Flexion Angle (°)	65.4 ± 4.5	70.8 ± 3.9	75.2 ± 3.7	$P < 0.05$ (Post vs. Pre)
Hip Extension Angle (°)	25.3 ± 2.4	28.6 ± 2.2	30.1 ± 2.1	$P < 0.05$ (Post vs. Pre)
Hip Abduction Angle (°)	41.2 ± 4.0	44.5 ± 3.7	47.8 ± 3.5	$P < 0.05$ (Post vs. Pre)
Hip Adduction Angle (°)	22.7 ± 3.5	24.9 ± 3.2	26.3 ± 2.8	$P < 0.05$ (Post vs. Pre)
Joint Velocity (m/s)	1.18 ± 0.15	1.25 ± 0.13	1.32 ± 0.12	$P < 0.05$ (Post vs. Pre)
Stride Length (cm)	110.2 ± 8.5	114.8 ± 8.1	118.3 ± 7.8	$P < 0.05$ (Post vs. Pre)
Movement Coordination (%)	78.4 ± 5.3	82.5 ± 4.8	85.6 ± 4.5	$P < 0.05$ (Post vs. Pre)

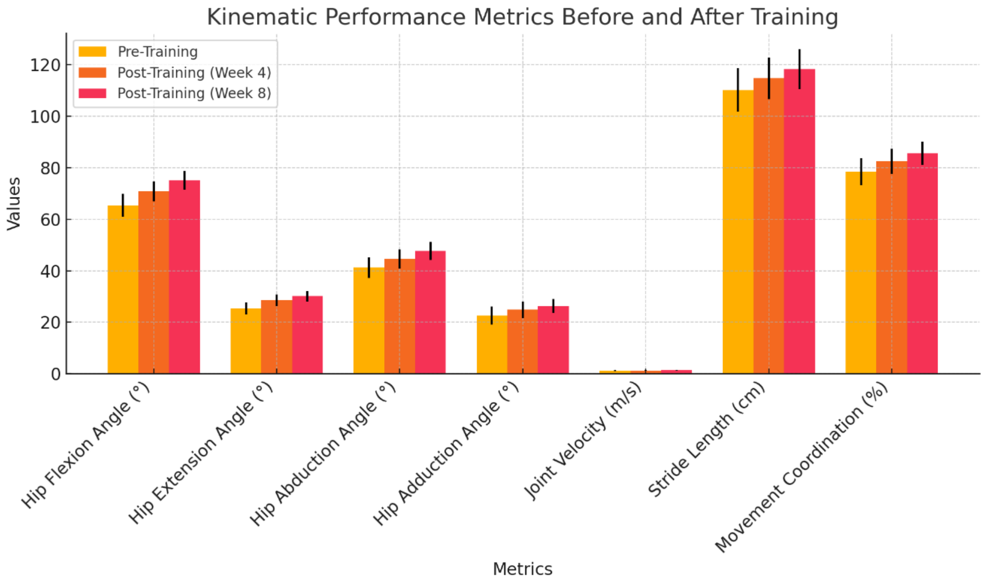

Figure 8. Analysis of kinematic performance metrics.

Table 6 and **Figure 9** show the improvements in performance efficiency and movement symmetry before and after the HFT program. The Stride frequency increased from 90.2 ± 8.1 steps/min pre-training to 95.4 ± 7.5 steps/min post-training the 8 weeks ($P < 0.05$), showing an improvement in the rate of steps during routines. Gait symmetry, which measures the uniformity of leg movements, improved from 84.2 ± 5.4% to 89.6 ± 4.7% post-training ($P < 0.05$). Movement symmetry, representing the coordination of the entire body during dance routines, increased from 81.5 ± 6.2% to 88.3 ± 5.4% by 8 weeks ($P < 0.05$). The efficiency index, which evaluates the overall performance efficiency, improved from 75.6 ± 4.9% to 82.4 ± 4.1% post-training ($P < 0.05$), reflecting enhanced energy use and movement control. Balance control also improved, with the time to regain balance reducing from 1.03 ± 0.08 s to 0.91 ± 0.06 s post-training ($P < 0.05$), indicating faster recovery in maintaining stability during movements.

Table 6. Performance efficiency and movement symmetry metrics.

Variable	Pre-Training	Post-Training (Week 4)	Post-Training (Week 8)	Significant Difference
Stride Frequency (steps/min)	90.2 ± 8.1	92.8 ± 7.9	95.4 ± 7.5	$P < 0.05$ (Post vs. Pre)
Gait Symmetry (%)	84.2 ± 5.4	87.3 ± 4.9	89.6 ± 4.7	$P < 0.05$ (Post vs. Pre)
Movement Symmetry (%)	81.5 ± 6.2	85.0 ± 5.8	88.3 ± 5.4	$P < 0.05$ (Post vs. Pre)
Efficiency Index (%)	75.6 ± 4.9	78.9 ± 4.5	82.4 ± 4.1	$P < 0.05$ (Post vs. Pre)
Balance Control (s)	1.03 ± 0.08	0.97 ± 0.07	0.91 ± 0.06	$P < 0.05$ (Post vs. Pre)

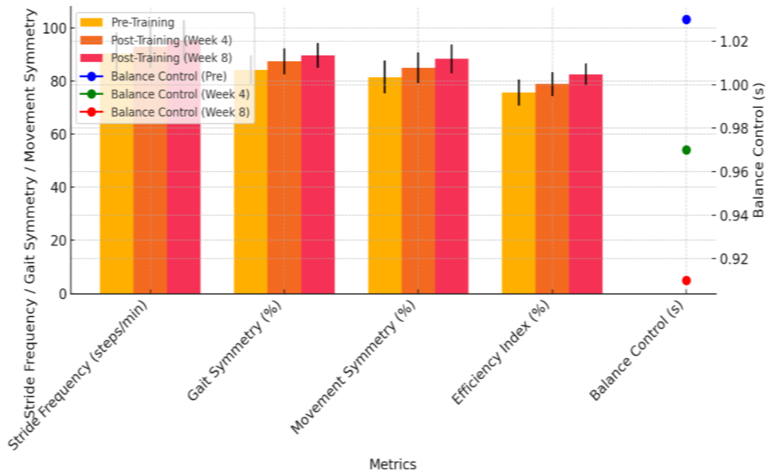

Figure 9. Analysis of performance efficiency and movement symmetry improvements.

Table 7 and **Figure 10** show the Joint Coordination Metrics outcomes before and after the HFT program. Hip-knee coordination increased from 80.2 ± 5.3% pre-training to 86.7 ± 4.5% by 8 weeks ($P < 0.05$), and hip-ankle coordination improved from 78.9 ± 5.8% to 85.5 ± 5.0% during the same period ($P < 0.05$). Knee-ankle coordination also showed improvement, rising from 82.3 ± 4.6% to 87.1 ± 4.1% post-training ($P < 0.05$). In terms of joint angles, the knee flexion angle increased from 95.3 ± 6.2° to 101.4 ± 5.6°, and the knee extension angle improved from 15.4 ± 2.9° to 19.6 ± 2.5° by the end of the program ($P < 0.05$). Ankle flexion showed a significant increase from 110.8 ± 5.9° to 117.6 ± 5.4°, and ankle extension improved from 35.2 ± 3.2° to 40.4 ± 2.8° post-training ($P < 0.05$). These metrics demonstrate enhanced coordination between the hip, knee, and ankle joints and increased flexibility in knee and ankle movements.

Table 7. Joint coordination metrics.

Variable	Pre-Training	Post-Training (Week 4)	Post-Training (Week 8)	Significant Difference
Hip-Knee Coordination (%)	80.2 ± 5.3	83.5 ± 4.9	86.7 ± 4.5	$P < 0.05$ (Post vs. Pre)
Hip-Ankle Coordination (%)	78.9 ± 5.8	82.1 ± 5.4	85.5 ± 5.0	$P < 0.05$ (Post vs. Pre)
Knee-Ankle Coordination (%)	82.3 ± 4.6	84.7 ± 4.3	87.1 ± 4.1	$P < 0.05$ (Post vs. Pre)
Knee Flexion Angle (°)	95.3 ± 6.2	98.7 ± 5.9	101.4 ± 5.6	$P < 0.05$ (Post vs. Pre)
Knee Extension Angle (°)	15.4 ± 2.9	17.8 ± 2.7	19.6 ± 2.5	$P < 0.05$ (Post vs. Pre)
Ankle Flexion Angle (°)	110.8 ± 5.9	114.1 ± 5.7	117.6 ± 5.4	$P < 0.05$ (Post vs. Pre)
Ankle Extension Angle (°)	35.2 ± 3.2	37.9 ± 3.0	40.4 ± 2.8	$P < 0.05$ (Post vs. Pre)

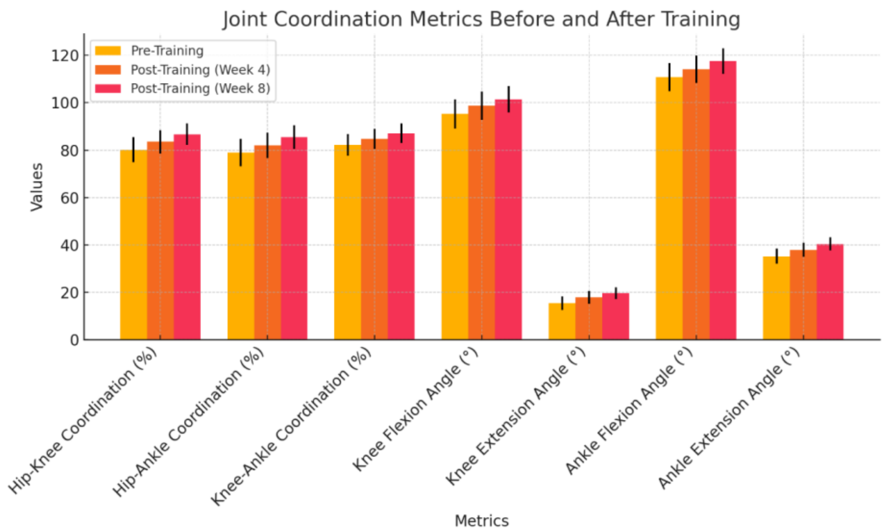

Figure 10. Analysis of joint coordination metrics.

Table 8 and **Figure 11** compare numerous video analysis models used in the study, focusing on key performance metrics. The proposed RFB-ResNET model achieved the highest accuracy at 92.4%, with a precision of 94.0%, recall of 93.4%, and an F1-score of 93.7%. It also had the lowest training loss (0.12) and validation loss (0.14), indicating effective learning and generalization. The inference time per sample was 0.45 s, and the Area Under the Curve (AUC) was the highest at 0.96. In comparison, InceptionV3 reached an accuracy of 89.7%, precision of 90.4%, recall of 89.2%, and an F1-score of 89.8%, with training and validation losses of 0.15 and 0.17, respectively. Its inference time was 0.52 s per sample, and the AUC was 0.91. VGG-16 showed lower performance, with an accuracy of 87.3%, precision of 88.5%, recall of 87.0%, F1-score of 87.7%, and higher losses (training loss 0.18, validation loss 0.19). The inference time for VGG-16 was the longest at 0.60 s per sample, and the AUC was 0.89. The ResNET-50 model performed better than VGG-16 and InceptionV3, achieving an accuracy of 90.8%, precision of 91.2%, recall of 90.5%, and an F1-score of 90.8%. Its training and validation losses were 0.14 and 0.16, respectively, with an inference time of 0.50 s per sample and an AUC of 0.93. The Efficient Net showed competitive performance, with an accuracy of 91.2%, precision of 92.0%, recall of 91.0%, F1-score of 91.5%, training loss of 0.13, validation loss of 0.15, inference time of 0.48 s per sample, and an AUC of 0.94. The 3D-CNN model had an accuracy of 88.1%, precision of 88.9%, recall of 87.6%, F1-score of 88.2%, training loss of 0.17, validation loss of 0.18, and an inference time of 0.58 s per sample. Its AUC was 0.90. Overall, the RFB-ResNET model outperformed all other models across all key metrics, demonstrating superior accuracy and efficiency in analyzing video data for detecting improvements in hip flexibility and movement patterns in dancers.

Table 8. ML model performance comparison.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Loss	Validation Loss	Inference Time (s/sample)	AUC
RFB-ResNET	92.4	94.0	93.4	93.7	0.12	0.14	0.45	0.96
InceptionV3	89.7	90.4	89.2	89.8	0.15	0.17	0.52	0.91
VGG-16	87.3	88.5	87.0	87.7	0.18	0.19	0.60	0.89
ResNET-50	90.8	91.2	90.5	90.8	0.14	0.16	0.50	0.93
EfficientNet	91.2	92.0	91.0	91.5	0.13	0.15	0.48	0.94
3D CNN	88.1	88.9	87.6	88.2	0.17	0.18	0.58	0.90

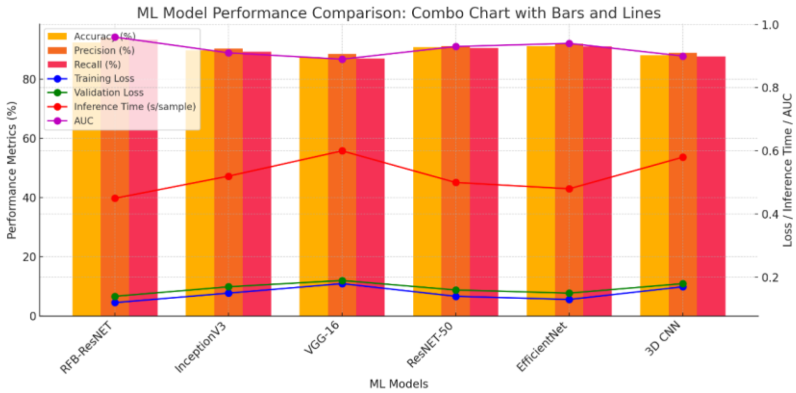

Figure 11. Analysis of ML model performance.

5. Conclusion

This study challenges to recognize the performance optimization level achieved in dancesport through Hip Flexibility Training (HFT). The study used Paso Doble as the model and employed 12 professional dancers as subjects. To understand the effectiveness of the HFT program, the dancers' performance was captured using 3D capturing hardware. After this, the dancers underwent an 8-week training program crafted with more focused stretches that could help movements in Paso Doble dance. After training again, their performance was captured. The dancer's movements were recorded using reflective markers to capture the kinematics behind the movements. The data collected was analyzed using RFB-ResNET, in which the RFB block extracts key features, and the ResNET trains using this feature to identify the key performance optimization aspects. The study analysis has revealed that the HFT program has provided better performance enhancement through metrics such as hip flexion, which increased from 65.4 ± 4.5° to 75.2 ± 3.7° ($P < 0.05$), and hip extension, which improved from 25.3 ± 2.4° to 30.1 ± 2.1° ($P < 0.05$). Joint velocity and stride length also show enhancements and the Oxygen Consumption (OC) and Energy Cost (EC) decreased significantly. The ML model RFB-ResNET has proven its efficiency by outperforming other video analysis methods, achieving the highest accuracy of 92.4% and precision and recall rates exceeding 93%. The study thus confirms the importance of targeted HFT in optimizing performance for competitive dancers, especially in styles that demand high hip control and coordination levels, such as Paso Doble.

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