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Article

Optimization research on biomechanical characteristics and motion detection technology of lower limbs in basketball sports

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Abstract: In basketball, the biomechanics of the lower limbs play a significant role in executing specific movements like sprints, jumps, and directional changes. Optimizing the performance of these movements is necessary for enhancing overall athletic performance and reducing injury risks. The objective of the research is to generate and execute a motion detection algorithm focusing on lower limbs in basketball utilizing a deep learning (DL) based approach. The study proposes the Refined Harries Hawks optimized Intelligent Long-Short Term Memory (RHH-ILSTM) method to improve the accuracy of detecting and analyzing biomechanical characteristics of lower limb movements. Data collection involved basketball players equipped with wearable sensors on their lower limbs to gather on-time data throughout dynamic movements to train the method. The data is pre-processed to remove noise, normalize values, and segment movements into discrete time intervals. Principal Component Analysis (PCA) is utilized to extract characteristics by reducing the dimensionality of the data while maintaining significant biomechanical aspects. The RHH-ILSTM system combines the exploration capabilities of the RHH optimization algorithm with ILSTM's capacity to handle time-series data, leading to improved detection accuracy of lower limb biomechanics. The model efficiently captures crucial lower limb biomechanics, achieving a higher accuracy (94.58%) and recall (95.62%) in detecting movement phases and joint stresses. The proposed RHH-ILSTM method provides a robust solution for monitoring and analyzing lower limb movements in basketball.

Keywords: basketball sports; motion detection; biomechanical characteristics; refined harries hawks optimized intelligent long-short term memory (RHH-ILSTM)

1. Introduction

Basketball is an intelligent team sport where two teams try to gain points by leading the ball into another team's hoop. It involves not only physical qualities such as swiftness, power, and agility but also a mixture of skills that involve passing, dribbling, shooting, and defensive moves [1]. The lower limbs play an essential role in many basketball movements, including jumping, running, and changing direction. Such biomechanical characteristics as joint angles, force production, and muscle group organization are significant. It becomes easier to identify ideal movement patterns, enhance performance, and prevent injuries with such an understanding. Some of them include vertical leap height, sprint time, and handiness as factors that define the lower-body performance of basketball [2]. Biomechanical traits of the lower limbs of basketball players are highly essential because they directly affect skill development, injury prevention, and maximization of performance. It helps in understanding physical attributes like strength, power, and quickness to facilitate the development of training methods and customization of training plans and performance statistics. These qualities also play a role in influencing game plans as well as treatment plans, which finally lead to player development and contribute to overall performance within the team in the sport while reducing the possibility of injuries and optimizing competence [3]. **Figure 1** shows the biomechanical characteristics and movement of the lower limbs.

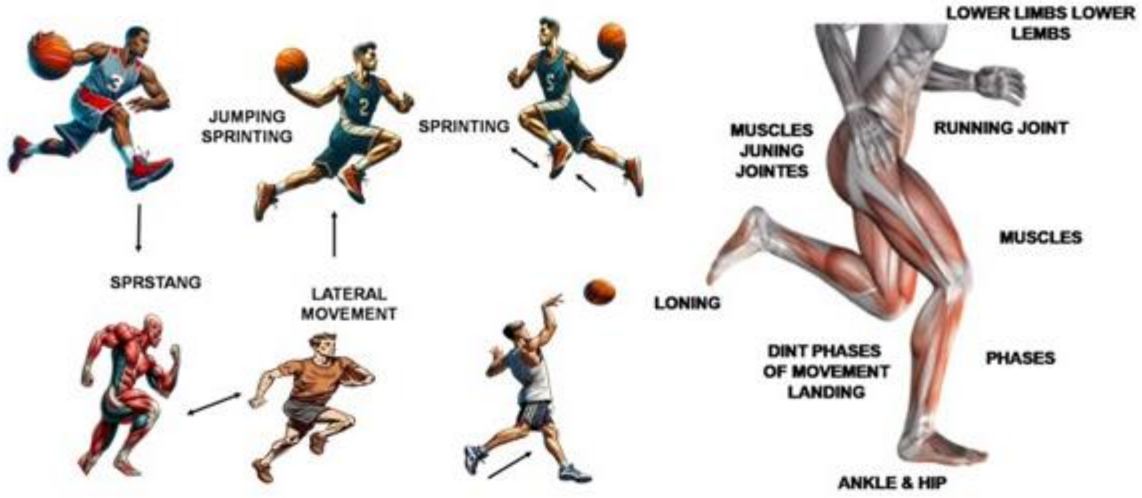

Figure 1. Biomechanical characterises and movements.

Motion detection is the process of recording and analysing athletes' movements with a spectrum of technology, including wearable sensors and video analysis systems. Such technologies are quite capable of measuring force, acceleration, and velocity generated by movements. In basketball, there are several advantages for utilizing motion-detecting technology, where perfect motion detection plays a crucial role in the evaluation of immediate performance and biomechanics, which aids in providing rapid feedback and adjustments [4]. It gives coaches objective information about an athlete's performance, and it is easier to outline the advantages and disadvantages of an athlete. Furthermore, it enables training plans customized by the players stress, enhances techniques for preventing injuries by tracking biomechanical stress, and helps in developing focused analysis plans for injured athletes. Everything measured, including motion detection, supports training and performance development using an evidence-based methodology [5]. Every advantage of motion-detecting technology comes with a limitation. Environmental factors that can influence the accuracy of data in video analysis include light and camera angles. Restrictions on wearable sensors that impact performance due to comfort and battery life also have limits on athletes' performance. Complexity in interpreting the data also requires expertise and sometimes creates challenges in translating findings into appropriate coaching applications. This means there are specific limitations that have to be addressed to explore the utility of motion-detecting systems in basketball [6]. The study's objective is to generate and implement a motion detection framework focused on the biomechanics of lower limb movements in basketball using a deep learning-based approach. By proposing the Refined Harries Hawks Optimized Intelligent Long Short-Term Memory (RHH-ILSTM) model, the purpose of the study is to enhance the accuracy of detecting and analyzing the biomechanical characteristics of lower limbs. The study aims to optimize athletic performance and reduce the risk of injuries through improved understanding and analysis of lower limb biomechanics.

Contribution of the study

The contribution of the study is given below:

- The paper discusses a novel motion detection framework tailored toward applications on lower limb biomechanics in basketball by using state-of-the-art deep learning methods to improve performance analysis.
- The biomechanical data for basketball players during dynamic movements are collected using wearable sensors.
- The RHH-ILSTM system is one of the significant developments in the line, as the optimization algorithms are merged highly efficiently with DL capability for time series data analysis.
- An algorithmic analysis of the biomechanics of the lower limbs could provide valuable insight in planning training and injury prevention tactics, which in turn could lead to better protection of the athlete and performance.

The rest of the study is as follows: Literature review is presented in Section 2. Methodology forms Section 3. Section 4 provides findings from the study. Section 5 and Section 6 summarize the study discussion and conclusion.

2. Related works

This section summarizes some research conducted to assess lower limb biomechanics in basketball with advanced motion detection technologies.

Jiang et al. [7] developed a hardware module using inertial sensors for data gathering and proposed a classification approach with regard to basketball stance recognition. An improved Principal Component Analysis with a Conventional Neural Network (PCA+CNN) advanced PCA+CNN algorithm was proposed, which provided excellent accuracy and speed for the improvement of basketball training with a low discrimination error rate and recognition accuracy rate.

Zhang [8] suggested a new human motion recognition (HMR) method that combines multidimensional feature fusion (MFF) and the kernel extreme learning machine (KELM) to overcome the shortcomings of conventional HMR systems in large-scale datasets and micro motions. The results of simulation trials showed that the KELM-MFF-based algorithm performs better in recognition rates than the current approaches. Ji [9] suggested a method for recognizing basketball shooting gestures using machine learning and image feature extraction. Multi-dimensional characteristics were retrieved from motion posture data collection. Accurate classification was made possible through feature selection and Gaussian hidden variables. The method’s success was validated by a case analysis, which provided insightful information for the advancement of contemporary basketball instruction. Xu and Tan [10] developed a superior Q-learning technique based on ML to plan the paths of intelligent robots training to play basketball. Through the use of ultrasonic signals and a fuzzy controller, the robot was able to avoid obstacles as it approached its targets.

The method generated smoother obstacle-avoidance pathways, as demonstrated by the simulation. Chen and Xu [11] presented the instance-aware feature extraction network Siamese Region Proposal Network (SiamRPN++), which guards against tracker drift from related objects. During motion tracking, variations in target morphology were addressed using a Projected Gradient Descent (PGD) based template update technique. According to experimental results, SiamRPN++ has a success rate of 12.24% and an accuracy improvement of 14.41%; the PGD method yielded improvements of 9.67% and 14.61%. Cheng et al. [12] investigated the use of four algorithms and gesture recognition to enable AI-based movement recognition in basketball training. The results of the experiments indicated that the Back-propagation Artificial Neural Network (BP-ANN) algorithm was employed best, with upper limb accuracy (93.3%) and lower limb accuracy of 99.4%. With a recognition efficiency of above 95%, the technology aids coaches in developing athletes' talents.

Zhao [13] suggested a deep learning (DL) approach for predicting hit probability and recognizing basketball free throw poses. Joint point extraction and pose detection were done with DetectNet and Open Pose. Free throw results were predicted by a support vector machine (SVM). The technique outperformed Open Pose in pose identification and hit probability prediction, with 98.55% accuracy. Zhang [14] provided a dual-stream architecture founded on the Slow-Fast system and an area screening technique for dynamic as well as static detail identification. It used 3D attentive feature fusion to produce a 50% reduction in calculation time and an accuracy improvement of 16.35% to 60.36% in RGB image identification. Zhao et al. [15] suggested an approach to assess four important activity indicators of basketball shooting using a Bayesian-optimized Light Gradient Boosting Machine (GBM). Smart basketballs and wrist sensors with Internet of Things (IoT) capabilities were used to collect motion data. When the model predicted these variables for individual players, it generated significant relationship evaluations, varied from 97.6% to 99.3%. Bo [16] proposed a 94% accurate activity detection method fora basketball player that used the Multi-Path Long Short-Term Memory (MP-LSTM) algorithm in combination with a sensing module. The Deep Q-Network (DQN) learning reinforcement algorithms are integrated into the system to optimize sampling frequency and maintain 90% accuracy while consuming 76% less energy, thus increasing system efficiency. Zhang [17] presented a precise shaking transformation and simplified complexity for a unified global motion model with a quadratic term. Its efficacy in basketball semantic event identification was demonstrated by experimental results, which combined local and global motion patterns to enhance group behavior recognition, particularly in National Collegiate Athletic Association (NCAA) events.

Liang [18] developed an enhanced Efficient Object Detection (EfficientDet) based action trajectory recognition system that was suggested to improve basketball players' training. For improved feature extraction, Laplace pyramid fusion was used together with the addition of a spatial attention mechanism. In upper limb positions, the model achieved 95.6% accuracy, and it took 5.34 seconds to perform 1000 tests. Khobdeh et al. [19] suggested a strategy that combined a deep fuzzy long short-term memory (LSTM) algorithm for classification with You Only Look Once (YOLO) for player detection. According to the results, the integration enhanced the accuracy and the prediction capability by solving the uncertainty limits of LSTM. The results presented in this work indicated that presented model is effective in recognizing basketball actions as it differentiated from other competing baseline models based on Space Jam and Basketball-51 datasets. Front Luo et al. [20] adopted YOLO and CBAM for the target identification of basketball players and Open Pose for the construction of the jump shot prediction model. Internal testing showed its performance at a 71% accuracy and 86% memory, while its external test result established an 89% accuracy and a 77% recall making its usability plausible as an application for basketball coaching. Lan and Dong [21] tried to enhance the precision and stability of the Q-learning by integrating data obtained from various sensors. It examined how the technology automatically created refined Q-learning algorithms and provided comprehensive environmental information for developing a model that profoundly enhanced the precision and reliability of the robots' motions. Gong [22] evaluated the effects of therapy on upper limb motor abnormalities and suggested a ML strategy to predict injuries to the spinal cord in basketball players. The results showed the predictive efficacy of the methodology by showing that players with a Functional Movement Screen (FMS) level of 14 or higher have a greater injury rate.

Guo et al. [23] employed data gathered by a tri-axial inertia device placed on one's wrist during free throws to categorize the talent levels of basketball athletes. It was able to differentiate between amateur and professional players with 88% accuracy and utilized a fully connected CNN, opening the door for the design of a biofeedback device to improve shooting mechanics. Li et al. [24] recognized the hybrid YOLO-LSTM system for basketball player movement identification. For multi-feature extraction, it leveraged an improved Yolo method that integrates Visual Geometry Group (VGG16), VGG19, and Residual network (ResNet50) with LSTM and fuzzy logic. Eight basketball actions were identified by the model with a 99.3% accuracy rate. Zheng et al. [25] provided a DL approach to use sparse inertial sensors to reconstruct human posture. To translate low-dimensional motion data into full-body posture, it made use of a bidirectional recurrent neural network (Bi-RNN). To improve motion reconstructing performance in particular applications, key difficulties were optimized for data collection and sensor positioning. Hao et al. [26] suggested monitoring athlete body parts with corner characteristics and multi-target tracking. For connected component labelling, a sequential approach was utilized. The algorithm's efficient recognition and effective performance were demonstrated through experimental analysis, which also offered important new information.

3. Methodology

The study gathers biomechanical data from basketball players using wearable sensors. It employs discrete wavelet transform (DWT) for noise reduction and signal enhancement, followed by principal component analysis (PCA) to extract significant features for efficient model training. The RHH-ILSTM model is then applied to detect motion patterns, facilitating a comprehensive analysis of player biomechanics. **Figure 2** explains the methodological flow.

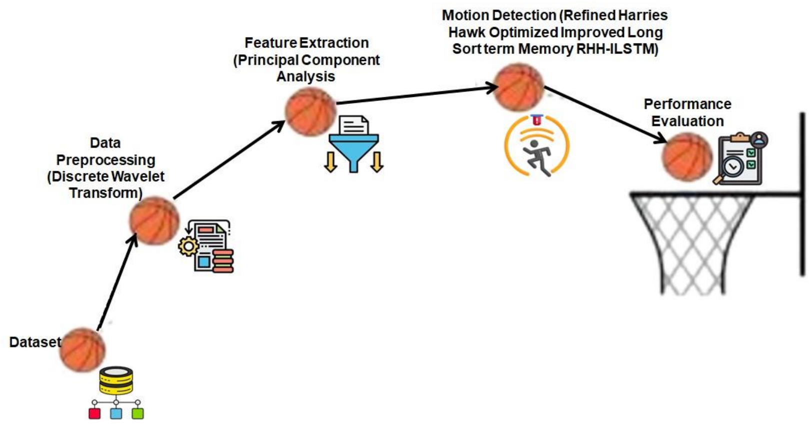

Figure 2. Methodological flow.

3.1. Data collection

This study gathers comprehensive biomechanical data from basketball players using wearable sensors positioned on their lower limbs. The sensors comprising gyroscopes, accelerometers, and pressure sensors record essential biomechanical metrics during dynamic actions like jumps, sprints, lateral direction changes, and other movement patterns typical of basketball play. To capture a variety of real-world movement dynamics, data is collected from multiple players across various time intervals, ensuring a high resolution of time-dependent motion sequences. Key data points include joint angles, acceleration, velocity, and force, particularly during phases such as lift-off, flight, landing, and lateral movement. All the movement phases and phase transitions are well delineated with regard to pointed biomechanical peculiarities that imply the further achievement of the main goal of the supervised learning. These annotate derived data bring the strength to learning and training the RHH-ILSTM model to identify three different movement patterns accurately and effectively. By extending the information about the kind of data retrieved the variability of joint angles or max acceleration elicited in participants, and the data range for different kinds of movements the learning and analysis possibilities of our model will be more apparent and dissected.

3.2. Data pre-processing

Biomechanical data is pre-processed utilizing Discrete Wavelet Transform (DWT). A discrete signal can be represented by wavelets, which are minute waves with conversion and scaling capabilities, by utilizing the statistical method DWT. It is particularly valuable for evaluating non-stationary signals while it captures both incidence and chronological data, in contrast to typical Fourier transforms that assess signals in terms of sine and cosine functions.

The DWT of a discrete signal $y[m]$ can be defined as wavelet decomposition (Equation (1)).

$$d_{i,l} = \sum_{m} y[m]\psi_{i,l}[m] \tag{1}$$

$d_{i,l}$ is the wavelet coefficients, $\psi_{i,l}[m]$ is the wavelet function, $[\sum m]$ and $y[m]$ is the original signal that is scaled and translated. The wavelet coefficients data to reconstruct the original signal data utilized as in Equation (2).

$$y[m] = \sum_{i,l} d_{i,l}\psi_{i,l}[m] \tag{2}$$

DWT effectively separates noise from the signal by decomposing it into different frequency components. By thresholding the wavelet coefficients, high-frequency noise can be diminished while preserving significant signal features, leading to cleaner data. It retains time information, which is crucial for analysing transient events in motion data. This enables the detection of specific movement phases and changes in biomechanical characteristics over time.

3.3. Feature extraction

The noise-removed normalized data features are extracted utilizing principal component analysis (PCA). The procedure transforms data into an entirely novel coordinate system where the highest variance in the data is represented by the first coordinate. The second coordinate denotes the variance that is second from the top, and so forth. This modification lowers the dimensionality of the data while aiding in the identification of its underlying structure. Consider an array of m training images that are $N \times M$ in size. Combining every row into a lengthy vector, where $1 \leq j \leq m$ in an NM-dimensional space, yields a 1-D column vector J_j for each data. The definition of the set's average data is given in Equation (3).

$$n = {}^{1}\!/_{m} \sum_{j=1}^{m} J_j \tag{3}$$

Every signal data deviates from the mean by vector$y_j = ji - n$, where $j = 1, \ldots\ldots, m$. A matrix of dimension $NM \times m$, denoted by $Y = [Y_1, Y_{2,} Y_3 \ldots]$, is used to arrange the shifted data. The training image set's covariance matrix D_Y is determined by Equation (4).

$$D_Y = YY^S \tag{4}$$

Equation (5) is imperative that the eigenvalue problem be resolved.

$$D_Y V = VA \tag{5}$$

Here V is the eigenvectors of λ that are associated with Y, and Y^S is a diagonal matrix defined by the eigenvalues λ of matrix D_Y. The new data space is currently represented by these eigenvectors. The image vector Y has NM potential projections given in Equation (6).

$$X_i = V_i^S Y \qquad\qquad i = 1, \ldots., NM. \tag{6}$$

where the projected values of Y are denoted by the X_i, which are the main components (sometimes referred to as eigenfaces) and the x_i, which are the eigenvalues of the covariance matrix D_Y. From the projections V_i^S, the initial data vector Y can be precisely recreated as Equation (7).

$$Y = Vx = \sum_{i=1}^{NM} v_i\, x_i \tag{7}$$

One way to minimize the dimensionality is to eliminate the small variance eigenvectors by keeping just the first m'/NM eigenvectors. After m terms, the extension of Equation (7) can be truncated to derive the image matrix $\hat{y}$ in the following Equation (8).

$$\hat{y} = \sum_{i=1}^{m} v_i\, x_i \tag{8}$$

For motion detection, a small number of eigenvectors provide enough information. It improves computational performance and makes visualization easier by lowering dimensionality while maintaining variance, which greatly improves data analysis. Exploratory data analysis applications in a variety of domains are vital since it reduces noise, finds important characteristics, and reveals underlying correlations in complex datasets.

3.4. Motion detection using refined harries hawks optimized intelligent long short-term memory (RHH-ILSTM) model

The RHH-ILSTM model combines the exploration capabilities of the RHH in optimization with the time-series processing power of ILSTM.

3.4.1. Intelligent Long Short-Term Memory (ILSTM)

The dimension-reduced biomechanical data is utilized to detect the motion using ILSTM. It enhances the modelling of sequential data and is a more sophisticated version of the conventional LSTM network. When it comes to capturing high-range province time-series data, LSTM is one kind of neural network (NN) that succeeds. By including clever methods that maximize learning and adaptively manage memory, ILSTM expands on the possibilities of LSTM. The ILSTM with forward propagation in the s^{th} period is explained following the information state (Equation (9)).

$$net_{ds} = X_d \times \begin{bmatrix} k_{s-1} \\ Y_s \end{bmatrix} + a_d = X_{dk} \times k_{s-1} + X_{dy} \times Y_s + a_d \tag{9}$$

net_{ds} Represents the net input to a particular neuron. X_d is the input vector for the specific dimension$d$. k_{s-1} is the variable that denotes the weights associated with the input vectorX_d. Y_s Represents an additional input vector at the current time step$s$. a_d is a biased term. $k$is the variable that likely represents a scaling factor. Shared hate is calculated using Equation (10).

$$d_s = \tanh\,(net_{ds}) \tag{10}$$

$d_s$is the output of the activation function, net_{ds} is the variable that denotes the net input to the activation function, and tanh is the hyperbolic tangent activation function. Cell memory was updated using Equation (11).

$$d_s = (1 - v_{s-1}) \times\, d_{s-1} + d_s \times v_s \tag{11}$$

d_{s-1} denotes the value of d from the previous iteration, $s-1$, v_{s-1} is a weighting factor that applies to the previous value d_{s-1},andv_s is another weighting factor for the current value d_s. Output gates are computed by Equations (12) and (13):

$$net_{ps} = X_p \times a_p = X_{pk} \times k_{s-1} + X_{pk} \times y_s + a_p \tag{12}$$

net_{ps} represents the net input to a processing unit, X_p is a vector associated with a particular processing unit p, a_p represents the activation function, X_{pk} denotes a specific input feature k associated with processing unit p, y_s represents another input feature at time step s.

$$p_s = \sigma(net_{ps}) \tag{13}$$

p_s represents the output of a particular node, σ the sigmoid activation function. The output hidden layers calculated by Equation (14).

$$k_s = p_s \times \tanh\,(d_s) \tag{14}$$

tanh $(d_s)$is the hyperbolic tangent function applied to the variable d_s. Equations (15 and 16) are used to calculate the predicted value of output layer.

$$w_s = X_z \times k_s + a_x \tag{15}$$

$$z_s = \sigma(ws) \tag{16}$$

w_s represents the output variable. X_z is a variable that often signifies an input feature, k_s can be interpreted as a scaling factor, $a_{nd\ ax}$ is a term that typically denotes a constant bias value. z_s represents the output of a neuron, and ws represents the input to the activation function. $tanh\,(y)$ is the initiative function y, while $\sigma(y)$ is the activation function y. The detailed Equation (17) calculated is as:

$$\begin{cases} \sigma(y) = z = \dfrac{1}{1 + f^{-y}} \\ tanh\,(y) = z = \dfrac{f^{y} - f^{-y}}{f^{y} + f^{-y}} \end{cases} \tag{17}$$

It provides a host of benefits for precisely recording and interpreting dynamic movements. ILSTM is the best choice for tracking intricate motion patterns over time since it efficiently handles long-range dependencies. The attention mechanism enables the method to focus on important phases of motion, while its adaptive learning capabilities improve model performance by improving responsiveness to changing movement dynamics. Better detection accuracy and noise resistance are the outcomes, which are crucial for real-time applications like monitoring, sports performance analysis, and rehabilitation.

3.4.2. Refined Harries Hawks (RHH) Optimization

Motion-detected data were optimized using RHH to enhance the detection accuracy and reliability. The sophisticated optimization process known as RHH optimization is motivated by the way Harris Hawks hunt. By improving the exploration and exploitation tactics, this approach improves the original Harris Hawks Optimization (HHO) to more successfully address challenging optimization issues.

Initialization phase: This step involves specifying all parameter values, generating the initial population of chaotic maps, and defining the goal function and search space. Hawks are initially positioned at random inside the boundaries delineated by the upper (UL) and lower limits (LL) using Equation (18).

$$Y_I^0 \sim uniform(LL, UL) \tag{18}$$

Y_I^0 is the random variable, $\sim$ signifies that the variable on the left is distributed according to the distribution specified on the right, $uniform(LL, UL)$ specifies a uniform distribution of $LL\ and\ UL$.

Exploration phase: Hawks are considered candidate solutions during this phase. Using two rules that produce new hawk placements based on average positions and random solutions, each hawk's fitness is calculated based on the prey's position. The following Equation (19) provides the mathematical expression for hawk movement.

$$Y_j^{s+1} = Y_j^s + q_3 \times \left(Y_{rabbit}^s - Y_j^s\right) + f \tag{19}$$

Y_j^{s+1} represents the new position of the j^{th} hawk after the update in the s^{th} iteration. Y_j^s is the current position of the j^{th} hawk, q_3 is a scaling factor, $and\ f$ represents additional stochastic factors. The prey position is represented by Y_{rabbit}^s, and random perturbations are used to ensure exploration.

Transition from exploration to exploitation: The target energy, E, is used to represent the transition as it steadily drops and is computed by Equation (20).

$$F = 2F_p \times \left(1 - \frac{s}{S}\right) + F_p \times [1,1] \tag{20}$$

F represents the resultant force, $and\ s$ represents a specific state in the system. Here$S$ is the total number of iterations and F_p is the beginning energy.

Exploitation phase: The exploitation strategy is defined by four methods based on the energy E and the escape probability s of the victim. The Equation (21) for the mild besieges strategy, where $s > 0\ F > 0$ and$s < 0.5\ s < 0.5$, is as follows:

$$Y_j^{s+1} = Y_j^s + I \times \left(Y_{rabbit}^s - Y_j^s\right) \times F \times IY_{rabbit}^s \tag{21}$$

I is a scaling factor that modifies the impact of the disparity between the target location and the hawk's present location.

Hard besiege: In this scenario, where $s < 0.5$ and $F < 0.5$ are both smaller than 0.5 is given in Equation (22).

$$Y_j^{s+1} = Y_{rabbit}^s - F \times Y_j^s \tag{22}$$

In soft surroundings with progressive rapid dives, the hawk approaches the prey with intelligence estimating Using Equation (23).

$$X = Y_{rabbit}^s - F \times Y_{rabbit}^s - Y_j^s \tag{23}$$

X is the variable that indicates the resulting vector that represents the difference in position between the rabbit and the hawk-modified position based on the scaling factor. Fitness comparisons are used to make the decision to dive, which results in the following updated Equation (24).

$$W = X + T \times c(Dim) \tag{24}$$

W is the updated position vector after applying the levy flight (LF). T is a scaling variable that controls the extent of the movement from the current position X. $c(Dim)$ indicates the number of dimensions in which the optimization is taking place, affecting the behavior of the LF.

Fitness evaluation: One important performance metric, the classification accuracy is calculated using Equation (25).

$$fitness = \frac{R \times D}{R \times N} \tag{25}$$

In the above instance$R.D$ is the detection error rate of the chosen classifier, $R$is the subset's cardinal number, and $R.N$ is the overall number of attributes in the data. Its adaptive balance between exploration and exploitation, which resembles hawk hunting techniques to effectively find the best answers, makes it noteworthy. It is ideal for optimization since it can manage multifaceted, high-dimensional search intervals with relief due to its probabilistic movement and dynamic energy modification. This allows for earlier convergence and enhanced accuracy while preventing local optima.

Algorithm 1 Refined Harries Hawks Optimized Intelligent Long Short-Term Memory (RHH-ILSTM) algorithm

1: **Start**

2: **Step 1: Initialization**: Initialize parameters LL, UL, for j from 1 to population size, $Y_1^0 \sim uniform(LL, UL)$to initialize hawk.

3: **Step 2:** Update cell memory using ILSTM

- Train ILSTM method: Initialize weights and biases for ILSTM for epoch from q to max-epochs:
- $net_{ds} = X_d \times \begin{bmatrix} k_{s-1} \\ Y_s \end{bmatrix} + a_d = X_{dk} \times k_{s-1} + X_{dy} \times Y_s + a_d$

4: **Step 3: RHH Optimization**

5: Fitness evaluation for s from 1 to number of iterations

- Update position using exploration phase: $Y_j^{s+1} = Y_j^s + q_3 \times \left(Y_{rabbit}^s - Y_j^s\right) + f$
- Transition from exploration to exploitation: $F = 2F_p \times \left(1 - \frac{s}{S}\right) + F_p \times [1,1]$
- Exploitation phase for j form 1 to population size: $Y_j^{s+1} = Y_j^s + I \times \left(Y_{rabbit}^s - Y_j^s\right) \times F \times IY_{rabbit}^s$
- For s from 1 to max iterations
- For j from 1 to population size: update hawk position: $Y_j^{s+1} = Y_{rabbit}^s - F \times Y_j^s$

6: **Step 4:** Return ds final output for motion detection.

7: END

The RHH-ILSTM system combines the ILSTM method with optimizing the model using the hawk RHH strategy to enhance motion detection. Through intelligent parameter regulation, the system improves the effectiveness and accuracy of the system by capturing complicated motion patterns in sequential data. Suggested for applications in human-computer connection and surveillance, the RHH algorithm efficiently explores the hyper-parameter space while ensuring strong performance in certain conditions. Algorithm 1 shows the RHH-ILSTM algorithm.

4. Results

This section provides a detailed analysis of joint stress during basketball movements, emphasizing stress levels at the knee and ankle, the correlation between movement patterns and the performance analysis of the RHH-ILSTM model, including detection time and training accuracy. The study highlights the model's capability in motion detection and its implications for training and injury prevention.

Joint stress analysis: It revealed significant insights into the biomechanical forces acting on key lower limb joints during basketball movements, focusing on the knee, ankle and hip. The joint stress analysis during different movement phases take-off, landing, and sprinting. It lists stress levels on the knee, ankle, and hip joints, highlighting peak and normal stress percentages. During take-off, the knee experiences 72% peak stress, while the hip peaks at 73%. Landing results in higher stress levels, with the knee reaching 88% and the hip 91%. Sprinting shows relatively lower stress, with the knee at 60% and the hip at 82%. This data illustrates the different activities impose varying stress on joints, emphasizing the importance of monitoring joint health during high-impact movements. Overall, the analysis underscores the importance of real-time biomechanical monitoring to inform injury prevention strategies, allowing for tailored training programs that mitigate joint stress and reduce injury risk in basketball players. **Table 1** and **Figure 3** show the analysis of joint stress levels a) peak and b) normal.

Table 1. Joint stress analysis for lower limb movements.

Movement phase	**Joint**	**Stress level (%)**	
		Peak	**Normal**
Take-off	Knee	72	48
	Ankle	70	50
	Hip	73	50
Landing	Knee	88	72
	Ankle	85	65
	Hip	91	68
Sprinting	Knee	60	52
	Ankle	60	50
	Hip	82	64

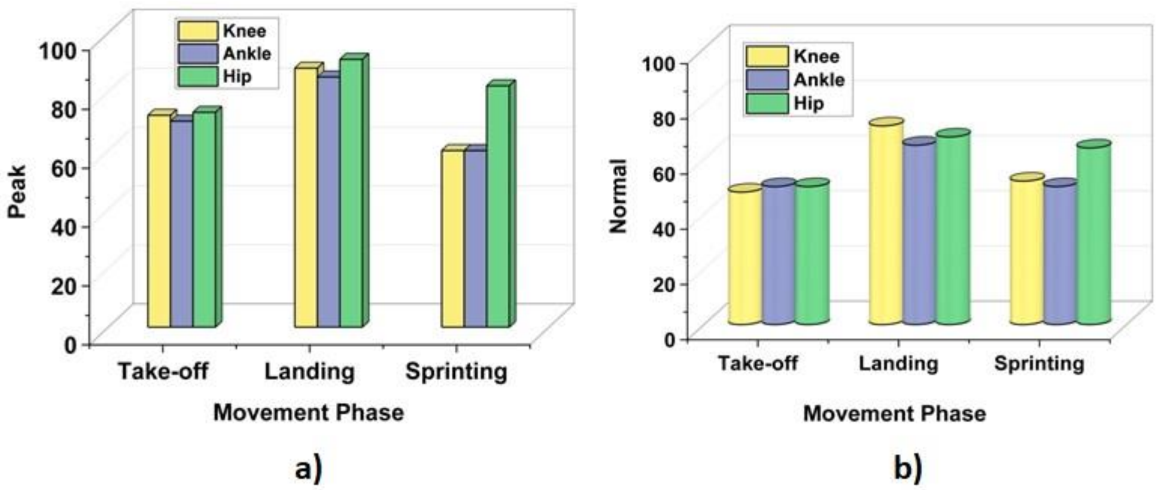

Figure 3. Analysis of joint stress. (a) peak; (b) normal.

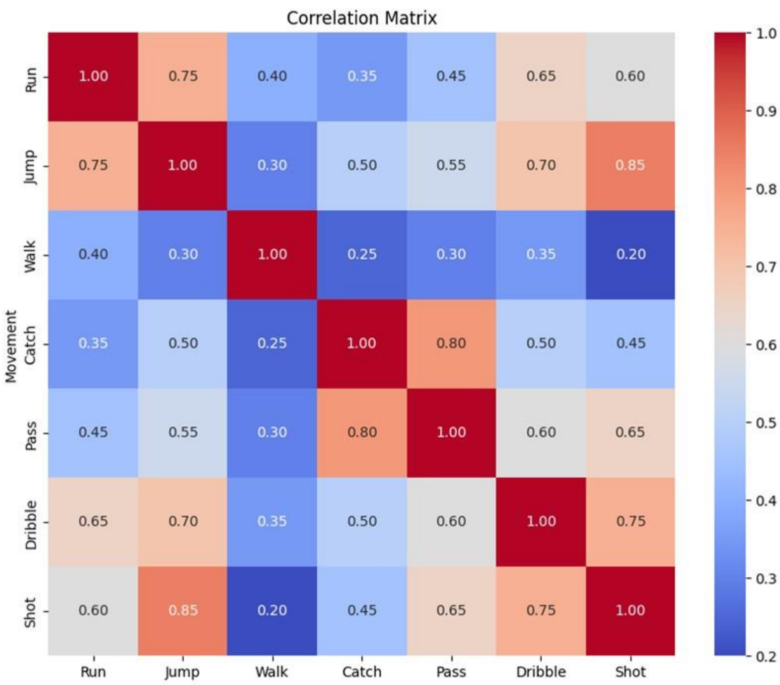

Figure 4. Correlation coefficient.

Correlation analysis: A correlation matrix provides statistical measures of how closely different variables are to each other. In this study, the variables are various basketball movements like running, jumping, walking, catching the ball, passing, dribbling, and shooting. Each value in the matrix represents the correlation between pairs of movements, ranging from -1 to 1. A strong positive correlation (0.75) indicates that players who run frequently also engage in jumping movements. This suggests that the biomechanics of running support the mechanics involved in jumping, making them complementary in performance. A very high correlation suggests that the mechanics of jumping are closely tied to the action of shooting. Athletes who have effective jumping techniques can also have better shooting capabilities, highlighting the importance of verticality in basketball shooting. Walking shows lower correlations in running (0.40), jumping (0.30) and shooting (0.20). This indicates that walking is less biomechanically intense compared to running and jumping. Adding these interpretations enhances understanding of the practical implications of the correlations for training and gameplay, particularly the importance of integrated movement skills. **Figure 4** illustrates the correlation between the variable's motions.

Detection time: This parameter is essential for evaluating how well the model performs in real-time motion detection during gameplay and making sure it can withstand the rigors of fast-paced sports contexts. The detection times for different action categories measured in milliseconds (ms). Offensive actions have an average detection time of 81.67 ms, indicating a relatively quick recognition of aggressive movements. Defensive actions take slightly longer, averaging 87.50 ms, suggesting that recognizing defensive makeovers requires more processing time. General movements, which encompass a broader range of activities, have the shortest detection time at 67.50 ms, reflecting the speed at which everyday actions are identified. Overall, this data highlights the type of action influences the speed of detection, with general movements being recognized most swiftly. Monitoring detection times is also useful for fine-tuning the RHH-ILSTM system for best performance in a diversity of situations, which ultimately has a positive influence on basketball player improvement during targeted training. **Figure 5** and **Table 2** provide the detection time for different action strategies.

Table 2. Comparison of detection times by action category.

Action category	Detection time (ms)
Offensive action	81.67
Defensive action	87.50
General movements	67.50

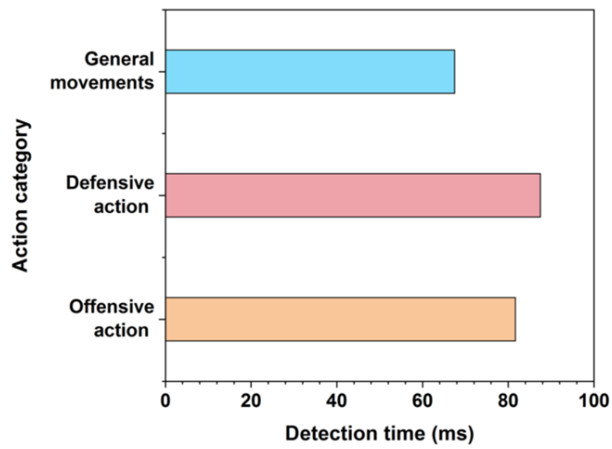

Figure 5. Detection time.

Performance analysis: An analysis of joint stress level and performance analysis of the RHH-ILSTM technique is conducted across diverse movement phases in basketball, with the starting, initiation, executive, follow-through and recovery phases The performance analysis across five movement phases are Starting, Initiation, Executive, Follow-through, and Recovery. It includes joint stress levels, accuracy, and recall percentages for each phase. The joint stress level ranges from 10% to 25%, with the Recovery phase experiencing the least stress and the Executive phase the most. Accuracy scores are generally high, with the Executive phase achieving the highest at 96.15%. Recall rates are also impressive, peaking in the Follow-through phase at 98.89%. The average joint stress level is 17.60%, with overall accuracy and recall at 94.58% and 95.62%, respectively, indicating strong performance. This information can be utilized to inform basketball training tactics and injury avoidance techniques, as well as provide insightful information about biomechanical performance. The effectiveness study of the suggested method employing different basketball movement phases is presented in **Figure 6** and **Table 3**.

Table 3. Performance analysis.

Movement phase	Joint stress level (%)	Accuracy	Recall
Starting phase	15	94.87	97.83
Initiation phase	20	93.75	93.75
Executive phase	25	96.15	97.22
Follow-through phase	18	94.66	98.89
Recovery phase	10	95.65	93.70
Average	17.60	94.58	95.62

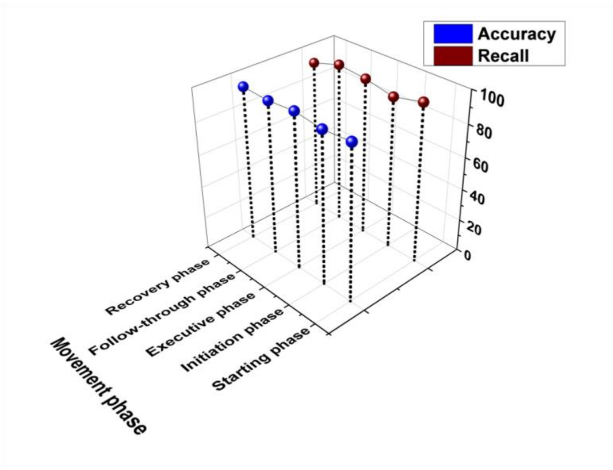

Figure 6. Performance analysis using movement phases.

Training accuracy and loss: The proportion of accurate predictions made by a method on the training data is calculated as training accuracy, which shows how well the method can detect data. Training loss uses a loss function to quantify the difference between expected and actual outputs, with reduced loss indicating better predictions. When taken as a whole, these measures offer valuable insights into how the model learns, pointing out possible problems like overfitting and directing the necessary modifications to improve training success. It effectively captures complex temporal dependencies through its intelligent architecture, allowing for adaptive learning. By refining parameter adjustments based on performance feedback, the model enhances its predictive capabilities. This results in superior generalization across various datasets, making RHH-ILSTM a powerful tool for applications requiring accurate forecasting and robust learning in dynamic environments, ultimately leading to more reliable outcomes. **Figure 7** shows the a) training loss and b) training accuracy of the proposed method.

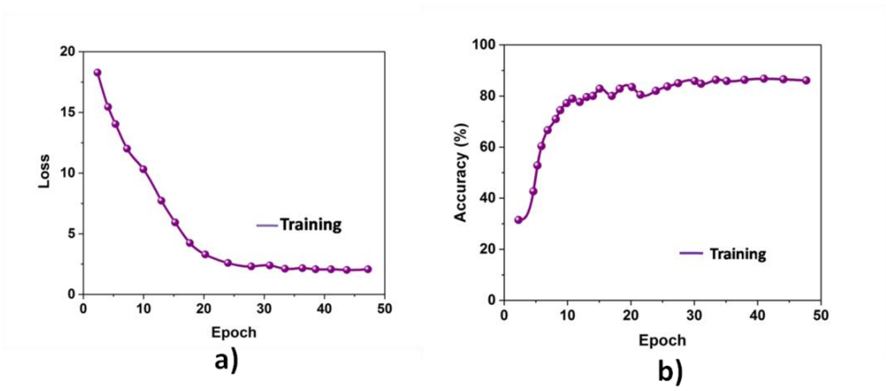

Figure 7. Training. **(a)** Loss; **(b)** accuracy.

5. Discussion

The results of the study show that basketball players face serious biomechanical difficulties, especially when it comes to joint tension during crucial motions. The variations in stress levels across different phases of lower limb movements. During take-off, the hip joint experiences the highest peak stress (73%), closely followed by the knee and ankle. Landing significantly increases stress, particularly at the knee (88%) and hip (91%), indicating a critical risk for injuries. In contrast, during sprinting, stress levels decrease, suggesting more efficient movement mechanics. The data highlights the importance of strengthening and conditioning programs targeting these joints, especially in high-stress phases, to mitigate injury risk and enhance athletic performance. Further research could explore intervention strategies to optimize joint health. Running and jumping have a substantial positive association (0.75) according to correlation matrix, suggesting that athletes who are good at one will probably be good at the other. The relationships between walking and other movements were weaker, indicating a lower level of biomechanical effort. The detection times across action categories reveal notable differences. Offensive actions are detected fastest (81.67ms), suggesting a quicker response due to their dynamic nature. Defensive actions take longer (87.50ms), likely reflecting the need for more complex decision-making. General movements have the shortest detection time (67.50ms), indicating they are processed with less cognitive load. The performance analysis shows a relationship between joint stress levels and metrics of accuracy and recall across different movement phases. Notably, the executive phase, with the highest stress (25%), maintains high accuracy (96.15%) and recall (97.22%). Conversely, the recovery phase has the lowest stress (10%) but still achieves respectable metrics. The effective movement strategies are critical for maintaining performance despite varying stress levels. The system's learning efficiency is established by training accuracy and loss outcomes, which also recognize probable issues like over fitting. These results highlight the significance of meticulous training methods for basketball athletes to lower joint stress and injury hazards and develop overall performance.

6. Conclusion

In this study, the RHH-ILSTM method significantly enhances the detection and analysis of lower limb biomechanics in basketball, achieving high accuracy and recall rates. The biomechanical data for basketball players during dynamic movements are collected. By integrating advanced motion detection with deep learning and optimizing data processing, this approach not only improves athletic performance but also plays a crucial role in injury prevention, making it a valuable tool for athletes and coaches. It discusses a motion detection framework tailored toward applications on lower limb biomechanics in basketball by using state-of-the-art deep learning methods to improve performance analysis. Joint stress analysis indicates significant peak stress levels during landing, particularly at the hip (91%) and knee (88%) it has highlight critical areas for injury prevention and performance optimization in lower limb movements. The detection times reveal that general movements are identified fastest (67.50ms), followed by offensive (81.67ms) and defensive actions (87.50ms), indicating varying complexity in action recognition. The performance analysis indicated that the system could correctly identify major movement phases and measure the stress experienced at the joints during the executive phase, having good accuracy of 94.58% as well as recall of 95.62%. The proposed RHH-ILSTM method provides a robust solution for monitoring and analysing lower limb movements in basketball. This discovery gave athletes and coaches the information they need to modify their strategies of training to improve output. However, this approach has the potential drawback of being highly focused on basketball and reliant on accurate wearable sensors, which limits the applicability of the results to other sports. Future studies should study the inclusion of other factors like upper limb biomechanics and exhaustion thresholds to provide a complete framework for motion analysis and can thus be applied in several sports.

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