SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2024, 21(1), 321.
https://doi.org/10.62617/mcb.v21i1.321

Article

Comparative analysis of biomechanical patterns in sprinting: A machine learning approach to optimize running performance in track athletes

Burenbatu

College of Physical Education, Inner Mongolia Normal University, Hohhot 010022, China; burenbatu1@outlook.com

CITATION

Burenbatu. Comparative analysis of biomechanical patterns in sprinting: A machine learning approach to optimize running performance in track athletes. Molecular & Cellular Biomechanics. 2024; 21(1): 321. https://doi.org/10.62617/mcb.v21i1.321

ARTICLE INFO

Received: 27 August 2024
Accepted: 4 September 2024
Available online: 30 September 2024

Abstract: Athletes' success in field and track competitions has been reported to be determined by their sprinting skills. Therefore, it is crucial to understand what biomechanical and physiological factors contribute to the most effective sprinting attributes. The scientific research on sprint evaluation has predominantly dealt with discrete metrics simultaneously, avoiding the interplay between multiple factors as the sprint progresses. Incorporating all the factors that could potentially influence the impact of excellent sprint ability is the primary objective of the present study. This research investigates the biomechanics of sprinting using a Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) hybrid approach, focusing mainly on factors like stride length, ground reaction forces, joint angles, and muscle activation patterns. The hybrid Machine Learning (ML) model accurately identifies between the two groups, and the results indicate that sprinters performing at the national level have more extended movements, higher reaction time to ground forces, and improved joint angles. The research project set up a 20-meter track for the race, and 30 participants, divided 50-50 between two distinct groups that included comparable college-level and national-level performers, participated. With a 92.4% accuracy, 90.2% precision, and 90.9% F1 score, the hybrid approach performed better than standard models in predicting optimum sprinting patterns. The higher efficiency is caused by phase-specific changes that the model unattended, such as enhanced knee angles and joint accelerated motion in the swing phase. In comparison, the SVM model, though respectable, lags behind with an accuracy of 85.7% and a lower precision and recall (82.4% and 80.9%, respectively). The RF model performed better than SVM with an accuracy of 88.1% and a balanced F1-score of 86.8% but still fell short of the CNN-LSTM hybrid. The standalone LSTM model performed relatively well, with an accuracy of 89.3% and an F1 score of 88.1%, showing its capability but still not matching the hybrid model's performance.

Keywords: biomechanical patterns; sprinting biomechanics; athletic activity; convolutional neural networks; LSTM; precision

1. Introduction

The Sprinting is considered one of the primary athletic activities, yet it demands a high level of biomechanical efficiency and physiological adaptation [1]. Better sprinting ability helps not only athletes but also players from various streams that require a high level of speed and agility [2]. There have been many studies that had involved understanding the mechanics behind the sprinting ability, but optimizing the performance remains to be a significant challenge due to the relationship between various biomechanical and physiological factors [3–5]. The approaches in practice have considered metrics such as stride length or ground reaction forces but had treated them isolated without considering the relationships between different variables that contribute to optimal performance in different phases of the sprinting

(**Figure 1**).

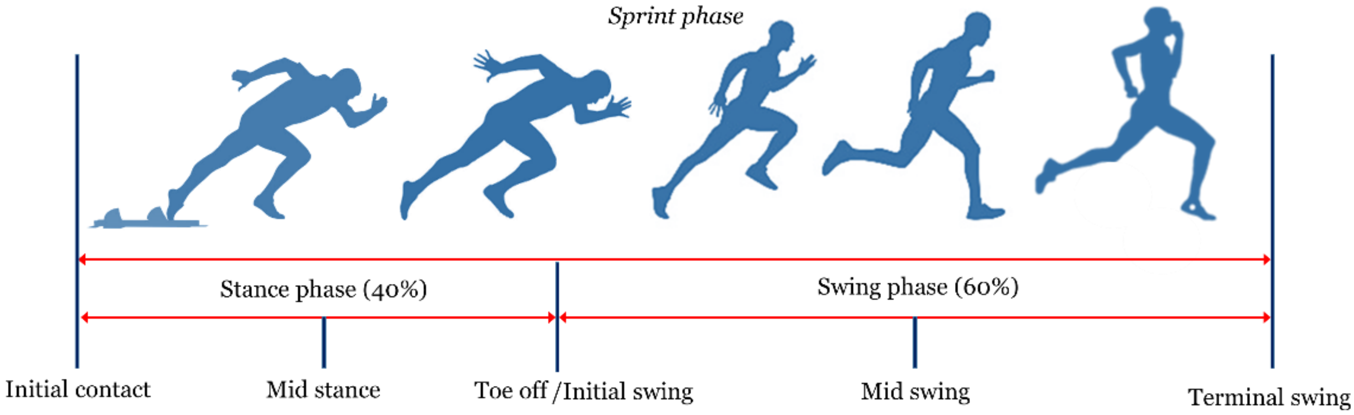


Figure 1. Phases of sprinting.

The sprint phase has sub-phases, such as the stance and swing phase, each with its phases, such as initial contact, mid stance, take off instance, and initial swing, mid swing, and terminal swing in the swing phase [6]. The methodologies in practice have considerable limitations in analyzing the dynamic changes occurring during a sprint. They focus on linear relationships or single-phase analysis and have failed to account for the continuous and interdependent nature of biomechanical variables throughout the sprint cycle. This restriction causes it to be challenging to determine the smaller factors that set apart the most successful sprinting athletes. It is essential to reduce the gap by using advanced statistical techniques that can identify every dimension of sprinting [7–10], which motivates this effort to succeed.

The proposed Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) hybrid model is commonly used to analyze sprinting biomechanical patterns. This framework integrates the beneficial features of both CNNs and LSTMs.

The explanation for why this combination approach works effectively is as outlined below:

(a) Feature extraction with CNN: Spatial FE is a domain where CNNs truly clearly distinguish themselves, notably in the biomechanics of sprinting. From complex sensor or video frame time-series data, they can FE related to posture and motion. They have applications to determine biomechanical features, such as joint angles and gait patterns, by sensing both hierarchical and local patterns.

(b) Temporal dynamics with LSTM: LSTMs can manage to process biomechanical data rapidly because of their expertise in dealing with sequential data and temporal dependencies. In order for CNNs to understand relationships between time, they use feature sequences. Despite maintaining long-term dependencies, researchers can analyze biomechanic changes through sprint phases and for more extended periods.

The combination of FE and temporal modelling is the factor that allows CNNs and LSTMs highly successful at enhancing biomechanical pattern recognition. Activity classification, anomaly detection, and performance prediction improvements have been noticed as models collect data and generate predictions about complex patterns.

Athletes' stride efficiency, method, and gait can be assessed by applying a hybrid model that analyses video, motion recording, and data from wearable sensors. For improved performance and avoiding injuries, sprinting athletes may gain from real-time feedback systems. A reliable tool for biomechanical analysis in sprinting, the CNN-LSTM hybrid model combines spatial and temporal methods for complete evaluation. The present investigation proposes a hybrid-model Machine Learning (ML) method for researching sprinting biomechanics, employing a combination of CNN and LSTM networks. By evaluating the factors determining how they perform, the model hypothesizes the spatial and temporal dynamics of sprinting. The research project set up a 20-meter track for the race, and 30 participants, divided 50-50 between two distinct groups that included comparable college and national-level performers, participated. The data collected for the research was investigated with a selection of data analysis tools, such as the hybrid ML model that was implemented.

The study was focused on the following objectives.

(a) Develop an analytical framework that integrates kinematic, kinetic, and physiological data to predict optimal sprinting patterns.
(b) Utilize a hybrid ML-based CNN-LSTM to analyze the spatial and temporal dynamics of sprinting performance.
(c) Identify key biomechanical and physiological variables that differentiate between optimal and sub-optimal sprinting performances.

The paper is organized as follows: Section 2 presents the literature review, Section 3 presents the methodology, Section 4 presents the analysis, and Section 5 concludes the work.

2. Literature review

Apte [11] investigated about the ability to estimate the running kinematics accurately by employing an Artificial Neural Network (ANN) model. To train the model, they used accelerometer variables and anthropometric data sourced through GPS devices. They designed a Multilayer Perceptron Neural Network (MPNN) to predict the participants' 3D running kinematics. They showed higher accuracy for flexion angles. Ding [12] compared different ML models to estimate the running stride temporal variables and peak vertical ground reaction force. The study had experimented with the models with data sourced from 100 runners who have run on a treadmill wearing an Inertial Measurement Unit (IMU). They compared Linear Regression (LR), Support Vector Machine (SVM), and Neural Network (NN) models using the collected data. The prediction results have suggested that the LR model was performing better compared to the rest. A study to model velocity graphs in 100-meter sprinting was done by Boujdi et al. [13]. Using data from international track events, the work had compared the performance of Random Forest (RF) and NN in predicting the velocity-time curve. The study had analyzed the relationship between the velocity, time, and speed duration and identified that there is a negative correlation between velocity and time.

Jose et al. [14] had analyzed the effect of running postures on performance enhancement and injury. Using AI and kinematic analysis, they analyzed the runner's posture technique. They analyzed the postures such as toe-off, maximal vertical projection, touch-down, and full-support using RF. Their model had shown higher accuracy. Using wearable IMUs, Ma [15] has been involved in analyzing the biomechanical factors that influence the performance of athletes. Using different combinations of sensors, they collected data and applied algorithms to gain interpretable and actionable information. Taber et al. [16] performed a time series data analysis on athlete's performance. They sourced data from 50 athletes who ran marathons. The data was collected over 6 months using sensors and trackers, and data related to speed, bpm, pulse rate, stride length, and frequency were collected. Using LSTM, they analyzed the collected data and proved the accuracy of the performance in terms of speed and stride frequency predictions [17,18].

Literature review and earlier idea:

a) Literature basis: Significant in sprinting biomechanics, previous research investigations have found variables like GRFs and joint angles to impact sprinting performance significantly. The study improves the knowledge of sprinting mechanics and depends on research resulting from these results.
b) Theoretical justification: A framework for studying the relationship and impact of several factors on performance can be obtained from theoretical models of sprinting biomechanics. For example, relevant factors are selected based on models of exertion and transfer during sprinting. To more fully understand the basics of sprinting and position the findings in an overall framework, applying theoretical models to the decision-making factors is essential.

If the study's objectives are clearly defined, the factors selected for biomechanical analysis are clearly stated, and the findings are practical and verified by technology, the investigation is more reliable. This approach further places the findings in context and emphasizes the significance of the factors chosen regarding sprinting performance.

3. Methodology

It is vital to include complete requirements for selecting participants and criteria for national and collegiate groups in the methodology section to ensure the research is secure and reliable. To present these details in the correct order, examine the points that follow:

Group definitions and criteria for participant selection:

A. Guidelines for participant selection

- General eligibility:
    - Age range: Physical maturity and continual ability to perform were ensured by selecting participants between 18 and 30.
    - Health status: Participants needed to prevent any psychological or physical issues that could impact their sprinting performance. Everyone who intended to participate in part had either obtained a physician's authorization or completed a pre-screening procedure.
    - Experience level: Participation was restricted to those who previously participated in sprinting sports. This ensures that everyone is on an identical level in terms of previous experience and is comfortable with the

challenges of sprinting.

- Specific criteria for national-level sprinters:
  - Performance Standards: Sprinters are deemed to be participating at the national level provided they have completed in the top 5% of the nation for their particular age group in the two years prior across all sprinting competitions (100 m, 200 m).
  - Competition Experience: One requirement for participation is a national or international competition record. The outcome and scores of the official events were used for proof.
  - Recognition: A national record in sports activities or several major national awards were criteria for selection.
- Specific criteria for collegiate-level sprinters:
  - Performance Standards: Sprinters performing at colleges and universities were classified as those whose times positioned them in the top 10% of their particular teams or leagues.
  - Competition Experience: College track and field tournaments at the regional or national level were mandatory for everyone who participated, whether in the current academic year or the one prior.
  - Academic Status: During the study period, participants were required to be registered in a college or university and actively involved with athletic competitions.

B. Group definitions

- National-level sprinters:
  - Definition: Competitors who consistently finish at the top level of their individual national or international athletic events. Those who have proven potential to be sprinting elites and who rank significantly in national rankings constitute members of this group.
  - Verification: All data used in calculating rankings and performance was obtained from government sources such as national athletic groups, national databases, and personal top performances.
- Collegiate-Level Sprinters:
  - Definition: Athletes who participate at the collegiate level experience outstanding results while attending college. Athletes with enormous potential for future success while still attending college are considered part of this class.
  - Verification: Collegiate athletics teams contributed performance data, and university athletics departments and official competition results verified status.

3.1. Participant selection

The study included 30 sprinters, of which 15 were National Level Participants (NLP) and 15 were College Level Participants (CLP), and all were under the age group of 18 to 25. In the NLP, out of 15 athletes, 11 have competed in national championships, and 4 have been ranked within the top 10 sprinters in national-level competitions in the last year. As for the sprinting capability, the NLPs have a 100-

meter dash time range from 10.3 to 10.5 seconds for males and 11.3 to 11.5 seconds for females. In CLP, the participants are from college track teams and have competed in intercollegiate track events in the previous season. The CLPs have a 100-meter dash time range from 10.8 to 11.0 seconds for males and 11.8 to 12.0 seconds for females. In both groups, athletes with recent injuries (within the past 6 months) or chronic conditions are excluded. The **Table 1** provides the characteristics of the participants.

Table 1. Details of the participants.

Characteristic	NLP	CLP
Number of Participants	15	15
Age Range	20–25 years	18–22 years
Height Range	Males: 180 ± 2.5 cm Females: 170 ± 2.2 cm	Males: 175 ± 2.8 cm Females: 165 ± 2.3 cm
Weight Range	Males: 75 ± 3.6 kg Females: 60 ± 2.4 kg	Males: 70 ± 4.5 kg Females: 55 ± 3.7 kg
Sex Distribution	Males: 10 Females: 5	Males: 8 Females: 7
Competition Level	National	Collegiate
Background	11 competed in national championships; 4 ranked in top 10	Competed in at least five intercollegiate track events
Sprinting Capability (100 m dash time)	Males: 10.4 ± 0.12 s Females: 11.4 ± 0.15 s	Males: 10.9 ± 0.28 s Females: 11.9 ± 0.23 s
Personal Best (100 m dash)	Males: 10.2 ± 0.14 s Females: 11.2 ± 0.16 s	Males: 10.7 ± 0.25 s Females: 11.7 ± 0.20 s
Season Best (100 m dash)	Males: 10.3 ± 0.11 s Females: 11.3 ± 0.17 s	Males: 10.8 ± 0.22 s Females: 11.8 ± 0.19 s
Screening Criteria	Exclusion of athletes with recent injuries or chronic conditions	Exclusion of athletes with recent injuries or chronic conditions
Medical Screening	Detailed medical history and physical examination by a sports medicine professional	Detailed medical history and physical examination by a sports medicine professional

3.2. Data collection

Defining the data collection rate in the experimental setup is vital for ensuring that the research can be performed when biomechanical analysis of sprinting using a CNN-LSTM hybrid model will be investigated. The following is a description of all of the different data source types, the standard data collection patterns for each, and the importance of each:

Camera frame rate: Biomechanics high-speed cameras record fast motions with higher temporal resolution, employing frame rates ranging from 120 to 1000 frames per second (fps). A reliable predictive biomechanical analysis of sprinting involves higher frame rates, which record the athlete's every motion and result in better tracking of rapid motions.

The biomechanical analysis in this study was performed as depicted in **Figure 2**. The setup included a Vicon MX T-Series motion capture system that was equipped with twelve high-speed infrared cameras. The cameras are placed at an average distance of 2 m between each and were positioned at a height of 1.5 m and calibrated to have a field of view wide enough to capture the complete motion range. These cameras captured the movement of reflective markers on key anatomical landmarks such as the hip, knee, ankle, shoulder, elbow, calf, toe, and wrist joints (**Figure 3**).

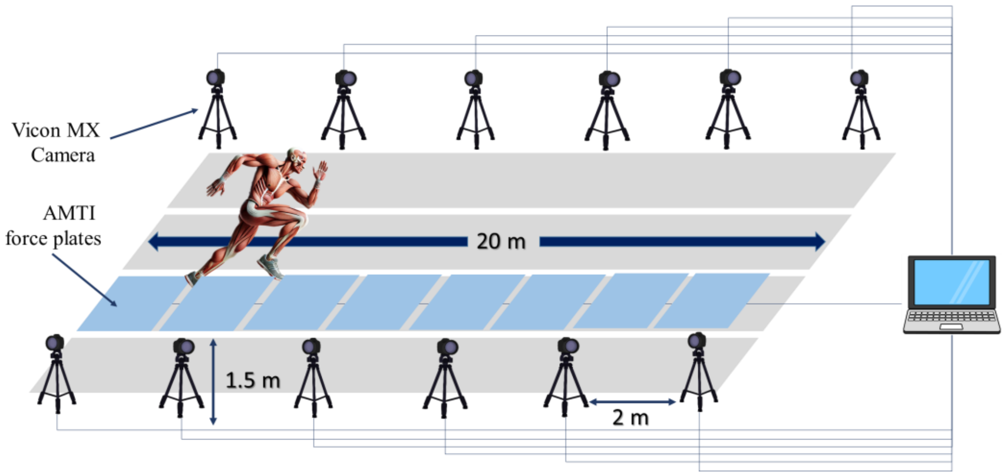


Figure 2. Study framework.

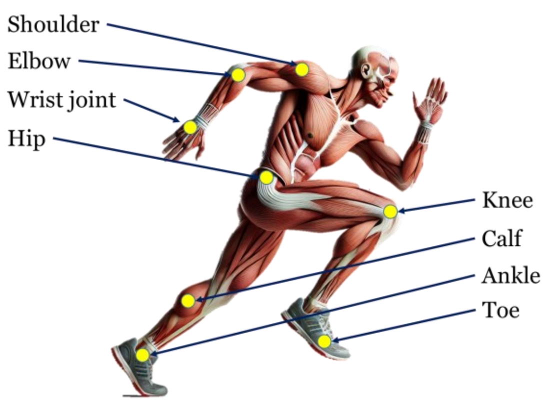
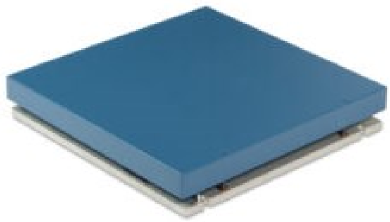


Figure 3. Sensor placement positions.

This recorded kinematic data readings from joint angles, velocities, and accelerations. Concurrently the ground reaction forces were measured using AMTI force plates that are embedded in the sprint track. These plates recorded the three-dimensional force data during each foot strike, including the magnitude and direction of forces exerted against the ground. In addition to kinematic and kinetic data, the physiological measurements of heart rate variability and respiratory rate were taken using Polar Team2 wearable sensors. The data acquisition was done through Vicon Nexus software that synchronize the video capture with biomechanical data collection. The data collected is listed in **Table 2**.

An aggregate of four sessions, two each week, comprised the two-week test. Before each test, participants were advised not to do anything too physically demanding, like an active or intense training session, for a minimum of 24 h. This was done to make sure participants were not getting worn out or sore, which could impact how they performed. On the day of testing, participants were also told not to consume energy drinks or the stimulant caffeine but to maintain their nutrition routine. Every competitor performed a 20-minute predetermined warm-up routine when they reported at the testing facility. A pattern of faster and faster sprints, along with strengthening exercises and dynamic stretches, is included in this warm-up exercise. After the participant had warmed up, they had evidence tags put on at key locations on their bodies for visibility. After that, the athlete was guided to the 20-meter sprint track's starting line and instructed to sprint with as much effort as possible.

Table 2. Data collected and device used.

Data Collected	Data Type	Unit of Measurement	Measurement Device
Joint Angles		Degrees (°)	
Joint Velocities	Kinematic Data	Meters per second (m/s)	
Joint Accelerations		Meters per second squared (m/s^2)	Vicon MX T-Series Motion Capture System
Ground Reaction Forces		Newtons (N)	
Force Direction	Kinetic Data	Degrees relative to vertical	AMTI Force Plates
Heart Rate		Beats per minute (bpm)	
Heart Rate Variability	Physiological Measurements	Milliseconds (ms)	
Respiratory Rate		Breaths per minute	Polar Team2 Wearable Sensors

The start of each sprint was initiated using a starting gun that emitted both an audible signal and an electronic trigger. The electronic trigger was synchronized with the Vicon Nexus software, marking the exact moment the sprint began in the data recordings. Each sprint trial lasted 3–5 s, depending on the athlete's speed. As the athlete sprinted down the track, their movements captured the movement of the reflective markers at a high frame rate of 500 fps. Simultaneously, ground reaction forces were measured by AMTI force plates that recorded three-dimensional force data during each foot strike, capturing both the magnitude and direction of the forces applied by the athlete. The physiological responses were continuously recorded throughout the entire sprinting trial, typically lasting no more than 10 s per sprint. Each athlete completed five sprint trials, with each trial spaced 5 min apart to ensure adequate rest and recovery, preventing fatigue from influencing performance. The entire testing session, including warm-up, marker placement, sprint trials, and cooldown, took approximately 90 min to complete per athlete (**Table 3**).

To test the reliability of the measurements, an ICC analysis was conducted, focusing on both intra-session (same day) and inter-session (across days) consistency. **Table 3** shows the findings. Kinematic data, specifically joint angles, showed an intra-session reliability coefficient of 0.95 with an SEM of ±0.5° and a confidence interval of 0.93 to 0.97, indicating strong reliability. Kinetic data, measured through ground reaction forces, had an ICC of 0.92 and an SEM of ±15 N within the same session, with a confidence interval ranging from 0.90 to 0.94. Physiological data, particularly heart rate, exhibited the highest intra-session reliability with an ICC of 0.98, an SEM of ±2 bpm, and a confidence interval of 0.96 to 0.99.

Table 3. Reliability analysis.

Measurement Type	Type of Reliability	Intraclass Correlation Coefficient (ICC)	Standard Error of Measurement (SEM)	Confidence Interval (95%)
Kinematic Data (Joint Angles)	Intra-session (same day)	0.95	± 0.5°	0.93–0.97
Kinetic Data (Ground Reaction Forces)	Intra-session (same day)	0.92	± 15 N	0.90–0.94
Physiological Data (Heart Rate)	Intra-session (same day)	0.98	± 2 bpm	0.96–0.99
Kinematic Data (Joint Angles)	Inter-session (across days)	0.88	± 0.8°	0.85–0.91
Kinetic Data (Ground Reaction Forces)	Inter-session (across days)	0.85	± 20 N	0.82–0.88
Physiological Data (Heart Rate)	Inter-session (across days)	0.93	± 3 bpm	0.90–0.95

When comparing inter-session reliability across different days, kinematic data for joint angles presented an ICC of 0.88 with an SEM of ±0.8° and a confidence interval between 0.85 and 0.91. Kinetic data across sessions had an ICC of 0.85 with an SEM of ±20 N and a confidence interval from 0.82 to 0.88. Physiological data also maintained high reliability across sessions, with a heart rate ICC of 0.93, an SEM of ±3 bpm, and a confidence interval of 0.90 to 0.95.

3.3. Hybrid ML model

The recommended ML model that was presented initially has the goal of performing a review of the biomechanical patterns that have been discovered during the sprinting trials in order to identify the primary factors that contribute to optimal running efficiency. The intent of the model is to study the spatial and temporal dynamics of the motions of the athletes, encompassing joint angles, velocities, ground reaction forces, and physiological responses, in order to find patterns that distinguish between various types of sprint performance. Within the boundaries of the present study, a hybrid ML model was used to study the biomechanical patterns of sprinting and enhance its performance. In order to accurately represent the spatial and temporal dynamics that can be detected in the biomechanical data of the athletes, the model integrates CNN and LSTM networks (**Figure 4**). Using the CNN layers, the hybrid model primarily extracts spatial features from the kinematic, kinetic, and physiological variables. Following that, the LSTM layers are used to model the temporal links that are present within these features.

The process begins with the input data X, which consists of the kinematic and kinetic data matrices captured by the Vicon MX T-Series and AMTI force plates, along with physiological data from the Polar Team 2 sensors. The input data is represented as $X = \{x_1, x_2, \ldots, x_T\}$, where x_t denotes the data at time step t. The CNN component of the hybrid model applies a series of convolutional operations to the input data to extract spatial features. Each convolutional layer is defined by a kernel W and bias b, with the convolution operation at a given layer l expressed as Equation (1).

$$F^{(l)} = \sigma\left(W^{(l)} * X + b^{(l)}\right) \quad (1)$$

where $F^{(l)}$ represents the feature map, σ is the activation function (e.g., ReLU), and $*$ denotes the convolution operation. The feature maps generated by the CNN layers are then flattened into a one-dimensional vector and fed into the LSTM layers to capture temporal relationships. The LSTM network processes these sequences of spatial features to model the dependencies over time. The LSTM's memory cell is updated at each time step t according to the following Equations (2)–(6):

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (2)$$

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \quad (3)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (4)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right) \quad (5)$$

$$h_t = o_t \odot \tanh\left(c_t\right) \quad (6)$$

where i_t, f_t, o_t and c_t are the input gate, forget gate, output gate, and cell state, respectively. The weight matrices W, U, and bias terms b are learned during training, and $\odot$ represents the element-wise multiplication. The output of the LSTM layers is then passed through a dense layer that applies a linear activation function, producing predictions of optimal performance patterns. The hybrid CNN-LSTM model was trained using a Backpropagation Through Time (BPTT) algorithm, optimizing a loss function $L(\theta)$ where θ represents all the parameters of the model. The loss function was the Mean Squared Error (MSE), defined as Equation (7).

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (7)$$

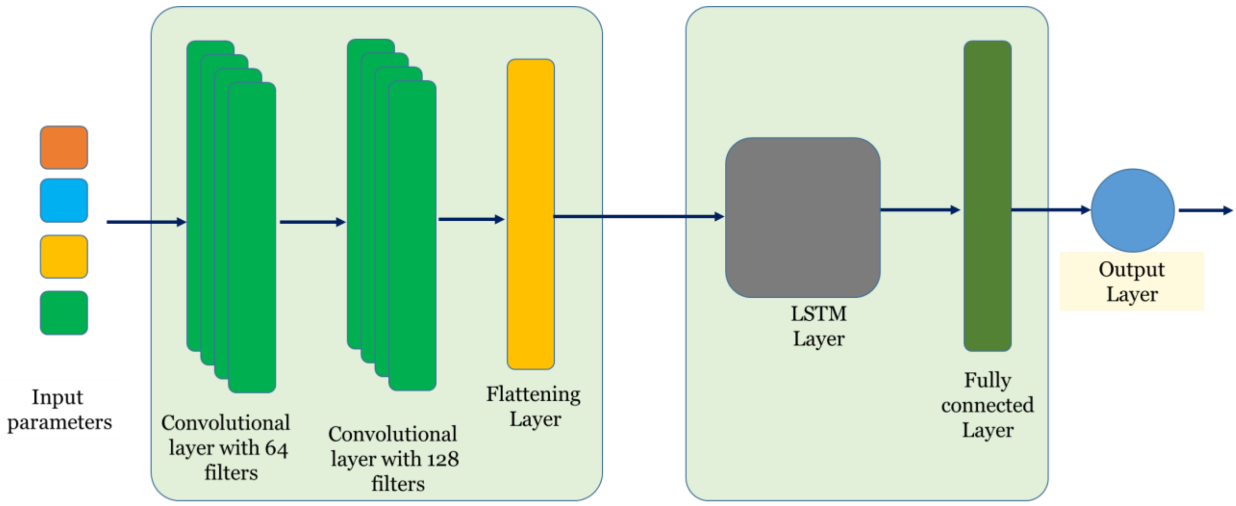


Figure 4. Hybrid CNN-LSTM.

4. Data analysis

This proposed research shows that university sprinting athletes have reduced GRFs, more brief strides, and less efficient joint angles than their national-level colleagues. There were significant variations in muscle activation patterns, which indicated differences in biomechanical performance. A CNN-LSTM hybrid model, which we used in our research, is an innovative method to look at biomechanical patterns in sprinting; it also helps clarify how various factors collaborate to impact performance.

Contribution to the Field:

(a) Build emphasis on what the study has shown us about sprinting biomechanics. Call emphasizes that this research found relationships between joint angles and GRFs that hadn't been documented before.

(b) The distinct impact caused by joint angles on GRFs was found in this research, which provides light on the biomechanical changes that set apart top sprinters. Implications for fitness and performance optimization are feasible, and this work strengthens today's physical knowledge.

The biomechanical variables, such as kinematic, kinetic, and physiological parameters, were examined to understand their impact on sprinting performance. Kinematic variables included joint angles, velocities, and accelerations, capturing the athletes' motion dynamics during key sprint phases such as the stance and swing. Kinetic variables focused on Ground Reaction Forces (GRF) in three dimensions, evaluating the effectiveness of force generation and transfer during foot strikes. Physiological variables such as heart rate, heart rate variability, and respiratory rate were monitored to assess the athletes' internal workload and recovery status.

4.1. Descriptive statistics

Additionally, a more precise and accurate image of the measurements and model predictions can be achieved by introducing confidence intervals into any biomechanical data analysis. It is essential to gain knowledge of the predictions' precision, analyze the data's range and reliability, and verify that the impacts or changes detected are statistically relevant. Applying this approach improves the reliability of these results and makes possible the reuse of data and the comparison of data from various studies.

The analysis of descriptive statistics is presented in **Table 4**. For kinematic variables (**Figure 5a**), the hip angle recorded a mean of 45.63 degrees with a SD of 3.18, reflecting a moderate range of motion. The knee angle demonstrated more significant variability, averaging 72.37 degrees with a wider range of motion, which shows the effectiveness of leg extension during sprints. Ankle angles were consistent among athletes, indicating a uniformity in ankle flexion that is needed for better propulsion. Kinetic variables (**Figure 5b**) revealed substantial differences in ground reaction forces, with a mean vertical force of 1896.48 Newtons and a range indicating diverse striking impacts. Horizontal and lateral ground reaction forces, with means of 321.47 N and 199.84 N, respectively, further illustrate the multi-directional forces that athletes must optimize for enhanced performance. Physiological measures (**Figure 5c**), such as heart rate and respiratory rate, averaged 179.63 bpm and 39.87 breaths per minute, respectively, showing the level of cardiovascular demand of sprinting. Heart rate variability stood at 34.72 milliseconds, displaying the athletes' stress and recovery during high-intensity efforts.

Table 4. Findings from the descriptive analysis.

Biomechanical Variable	**Mean**	**Standard Deviation (SD)**	**Minimum**	**Maximum**	**Range**
Kinematic Variables					
Hip Angle (°)	45.63	3.18	40.14	52.34	12.20
Knee Angle (°)	72.37	4.12	64.73	81.61	16.88
Ankle Angle (°)	89.78	2.79	85.21	94.32	9.11
Joint Velocity (m/s)	5.23	0.57	4.12	6.36	2.24
Joint Acceleration (m/s^2)	12.27	1.43	9.81	14.69	4.88
Kinetic Variables					
Vertical Ground Reaction Force (N)	1896.48	149.62	1647.32	2201.45	554.13
Horizontal Ground Reaction Force (N)	321.47	45.31	250.24	410.59	160.35
Lateral Ground Reaction Force (N)	199.84	29.78	150.23	259.97	109.74
Rate of Force Development (N/s)	4503.67	348.96	3912.45	5097.36	1184.91
Force Impulse (Ns)	298.72	24.85	261.48	339.84	78.36
Physiological Variables					
Heart Rate (bpm)	179.63	11.78	161.45	199.34	37.89
Heart Rate Variability (ms)	34.72	5.96	25.48	45.13	19.65
Respiratory Rate (breaths/min)	39.87	5.24	32.14	48.29	16.15

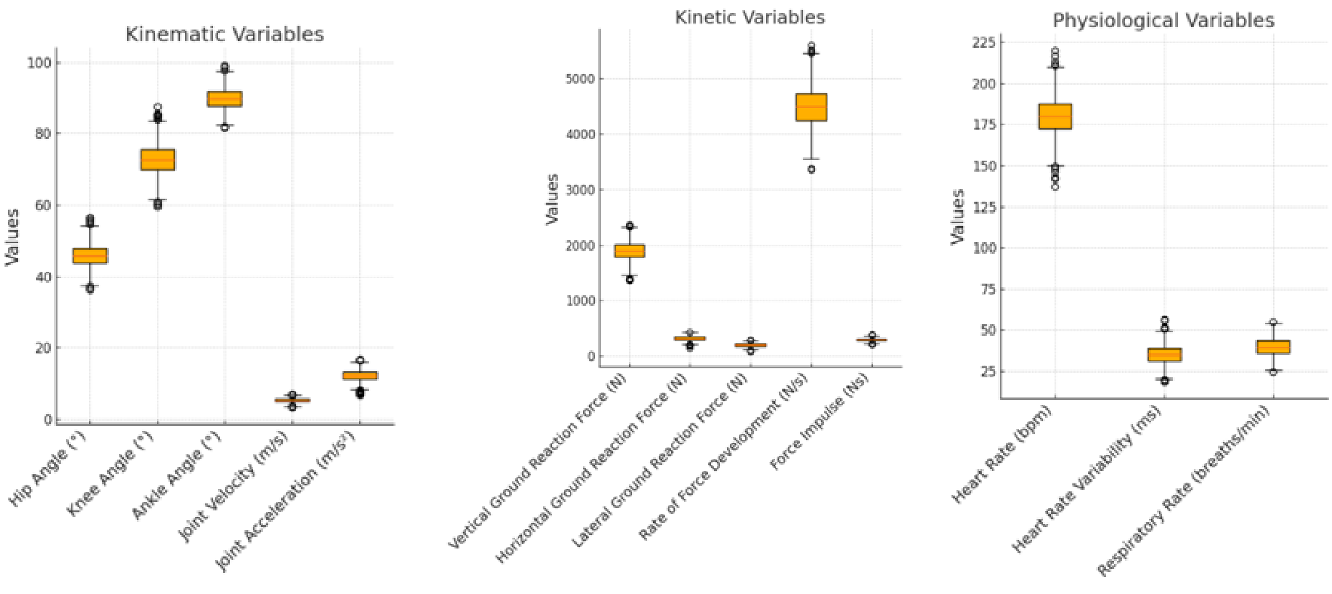


Figure 5. Descriptive statistics for. **(a)** Kinematic variables; **(b)** kinetic variables; **(c)** physiological variables.

4.2. Phase wise analysis

The study of total sprinting performance involves a comprehensive understanding of the variations in biomechanical variables between the stance and the swing phase of sprinting. There are distinct biomechanical features associated with each sprinting phase, and each phase is integral to the speed and overall effectiveness of the sprinting motion. In order to better comprehend these differences and how they impact sprinting performance, the following is a detailed discussion:

A. Stance phase features

- Time: Starting at the moment the foot hits the ground and finishing when the foot lifts off the ground is the "stance" phase. On average, it spans 30%–40% of a sprinter's cycle.
- Foot contact: In the stride, the athlete's foot maintains total contact with the ground's surface, moving from a heel strike (or forefoot strike, based on one's selected speed method).
- Ground reaction forces: This section requires applying significant force to the floor. Efficient movement is contingent on the strength and direction of these powers, which can be defined as vertical, horizontal, and lateral.
- Joint angles: At the moment, significant joint angles like the hip flex/extension, knee flexion/extension, and ankle dorsiflexion/plantarflexion need to be maintained. In a standard motion, for example, the knee is curved upon the initial strike and then relaxed as the foot rolls onto the supporting surface.
- Muscle stimulation: The glutes, calf muscles, hamstrings, and quadriceps get a good workout. Certain of its primary functions are shock absorption, body stabilization, and motion force generation.

B. Performance impact on sprinting
- Force discovery: A high-ground reacting force is directly related to a sprinter's speed. Motion is boosted by a more vital vertical force during the stance phase, whereas speed and velocity change by a horizontal force.
- Impact engagement: Injuries are more inclined, and the effectiveness improves when impact forces are appropriately diffused. Joint stress and higher ground response forces are possible outcomes from limited impact absorption.
- Stability and balance: Stability and balance improve when skeletal muscles are working, and joints are correctly aligned. A more successful movement of forces and less energy loss are made possible by appropriate recovery during the posture phase.

C. Swing phase features
- Duration: The moment the foot improves off the ground and back to the surface indicates the start of the swing phase. Roughly 60 to 70% of the sprinting phase is allocated to hit.
- Foot movement: In this phase, the foot moves up, anticipating the following impact on the ground's surface. Leg recovery, knee lift, and foot position are some phases the leg cycles through.
- Joint angles: Hip flexion (leg lift), knee flexion (foot release), and flexing the ankle (contact setup) constitute key joint motions.
- Muscle activation: Several muscles, which include the iliopsoas, hamstrings, and tibialis anterior, function in the swing phase. Leg move and forward motion are controlled by the iliopsoas and hamstrings, with support from the anterior tibialis muscle, which supports and dorsiflex the leg's ankle.

D. Effects on the performance of sprinting
- Leg recovery: Maintaining a high stride rate while reducing ground in comparison interaction time can be done through quick leg recovery,

defined by a high knee lift and quick leg swing. Both aggregate speed and stride length are improved by approach.

- Minimizing drag: Swinging with properly positioned feet and leg biomechanics reduces calorie consumption and aerodynamic drag. As an outcome, people can move from swing to stance far more rapidly and comfortably.
- Stride length and frequency: Foot length and frequency can be increased by the implementation of optimal mechanics during the swing phase. For optimal sprinting speed, you must have a more extended stride and improve the amount you sprint.

E. Interactions between phases

- Seamless Transition: Maintaining speed and accuracy demands a smooth move from the stance to the swing phases. Faster energy loss and reduced sprinting speed can result from a wrong move.
- Coordination and Timing: To apply weights effectively and adequately position the leg for the next ground contact, the stance and swing phases must be integrated and performed correctly. Reaching maximum efficiency while avoiding injury requires this level of coordination.
- Energy Transfer: Minimising tiredness while maintaining high speeds is possible by appropriate energy transfer between phases. To maximize sprinting performance while maximizing good use of collected flexible power, it is essential to train inappropriate biomechanics during both phases of running.

F. Training implications

- Stance phase training: Plyometrics, strength training, and stability exercises are a few examples of physical exercises that may boost performance during the stance phase. These activities target boosting power production, impact absorption, and balance.
- Swing phase training: Training exercises that target the mechanics and performance of the swing phase comprise high-knee drills, sprint drills, and technique training, all of which emphasize the key elements of leg speed, knee lift, and foot positioning.

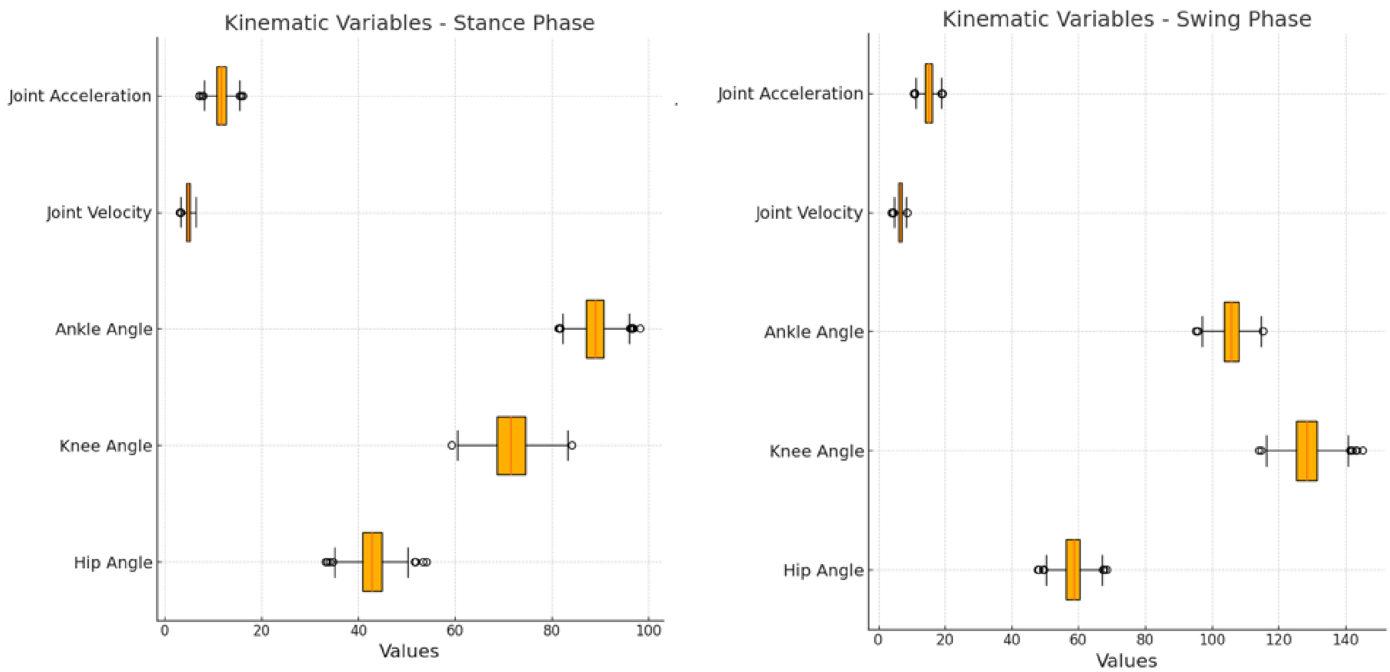
Running a sprint includes distinct biomechanical factors during the stance and swing phases, which impact overall performance. While the swing phase focuses on leg recovery, stride length, and frequency, the stance phase is about releasing force, absorbing impacts, and being stable. Sprinting performance can be significantly enhanced with a recognition of and attention to these phases, as well as with specific training programs that are designed to improve speed and efficiency.

The descriptive statistics of kinematic variables across the sprint phases of Stance and Swing are shown in **Table 5**. During the Stance phase (**Figure 6a**), the hip angle maintains a more consistent posture with a mean of 42.87° and a SD with slight variability. As the leg transitions to the Swing phase (**Figure 6b**), the mean hip angle increases to 58.32°, showing a broader range of motion needed for effective leg recovery and subsequent forward drive. Similarly, knee angles show variation between phases; in Stance, the mean angle is 71.54°, which absorbs the impact of a foot strike. This angle increases in the Swing phase to a mean of 128.47°, showing the flexion required for propelling the leg forward and preparing for the next stride.

Table 5. The mean, SD, and range for each kinematic variable during sprint phases.

Kinematic Variable	Sprint Phase	Mean	Standard Deviation (SD)	Minimum	Maximum	Range
Hip Angle (°)	Stance	42.87	2.91	38.45	47.63	9.18
	Swing	58.32	3.05	53.72	64.21	10.49
Knee Angle (°)	Stance	71.54	4.23	65.38	79.12	13.74
	Swing	128.47	4.76	120.34	136.89	16.55
Ankle Angle (°)	Stance	88.93	2.58	84.31	93.45	9.14
	Swing	105.76	3.19	100.12	112.84	12.72
Joint Velocity (m/s)	Stance	4.83	0.56	3.96	5.67	1.71
	Swing	6.52	0.68	5.39	7.68	2.29
Joint Acceleration (m/s^2)	Stance	11.73	1.32	9.58	14.25	4.67
	Swing	14.92	1.45	12.54	17.39	4.85

Ankle angles also adjust significantly between phases, from an average of 88.93° in Stance to 105.76° in Swing. This increase supports the leg's clearance from the ground and prepares it for the following impact. Joint velocities and accelerations highlight the dynamic nature of sprinting. The velocity increases from 4.83 m/s in Stance to 6.52 m/s in Swing, displaying quicker limb recovery to maintain sprint rhythm. Similarly, joint acceleration shows an increase from 11.73 m/s^2 in Stance to 14.92 m/s^2 in Swing, highlighting the high level of force application needed to achieve peak speeds.



(a) **(b)**

Figure 6. Descriptive statistics for Kinematic variables for. **(a)** Stance phase; **(b)** swing phase.

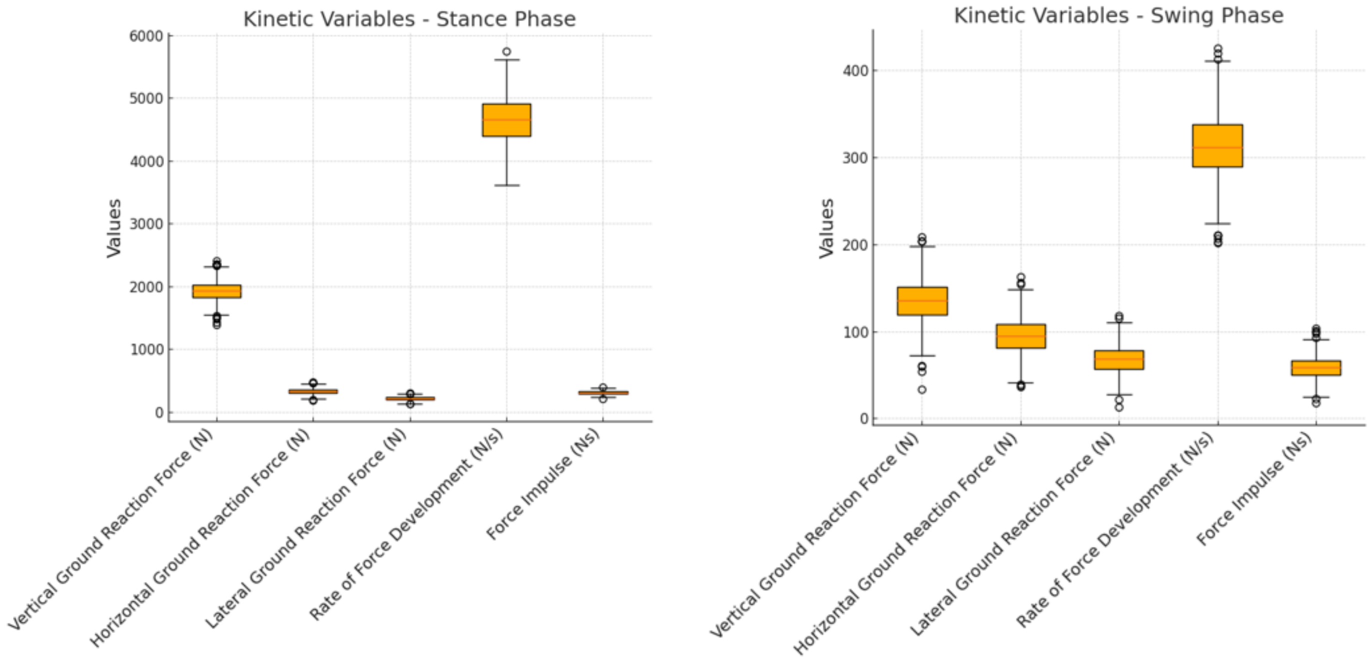
Table 6. The mean, SD, and range for each kinetic variable during sprint phases.

Kinetic Variable	Sprint Phase	Mean	SD	Minimum	Maximum	Range
Vertical Ground Reaction Force (N)	Stance	1923.45	153.21	1675.34	2198.72	523.38
	Swing	135.78	24.12	102.45	178.65	76.20
Horizontal Ground Reaction Force (N)	Stance	330.67	48.76	265.34	415.21	149.87
	Swing	95.24	20.18	72.15	134.82	62.67
Lateral Ground Reaction Force (N)	Stance	210.34	29.87	156.43	263.91	107.48
	Swing	67.89	15.42	49.32	102.58	53.26
Rate of Force Development (N/s)	Stance	4650.23	359.87	4005.18	5248.34	1243.16
	Swing	312.56	35.67	265.49	398.72	133.23
Force Impulse (Ns)	Stance	310.58	27.84	271.24	347.92	76.68
	Swing	58.34	12.36	40.12	83.47	43.35

The kinetic variables measured during the Stance and Swing phases are displayed in **Table 6**. In the Stance phase (**Figure 7a**), the vertical ground reaction force averages 1923.45 N, representing the high impact forces the athletes withstand upon ground contact. The SD of 153.21 N indicates variability among athletes in how effectively they absorb and utilize these forces. In contrast, during the Swing phase (**Figure 7b**), this force reduces to an average of 135.78 N, which shows the minimal ground contact and the primary focus on limb recovery and preparation for the next stride. Horizontal ground reaction forces that enable forward propulsion show notable phase differences. Averaging 330.67 N in Stance, it underscores the athletes' efforts in generating forward momentum. This force decreases to 95.24 N in the Swing phase, showing the reduced need for horizontal propulsion when the foot is off the ground. Lateral ground reaction forces needed for side-to-side stability, average at 210.34 N during Stance, depict the control athletes maintain during powerful ground strikes. This force is significantly lower in the Swing phase at 67.89 N. The rate of force development is high at 4650.23 N/s during Stance, and it decreases substantially to 312.56 N/s during the Swing phase, reflecting the lessened emphasis on force production when in the air. Force impulse, which quantifies the total force exerted over the contract duration, shows a marked reduction from 310.58 Ns in Stance to 58.34 Ns in Swing, indicating the transition from active force application to passive recovery in the swing phase.

Table 7. The mean, SD, and range for each physiological variable during sprint phases.

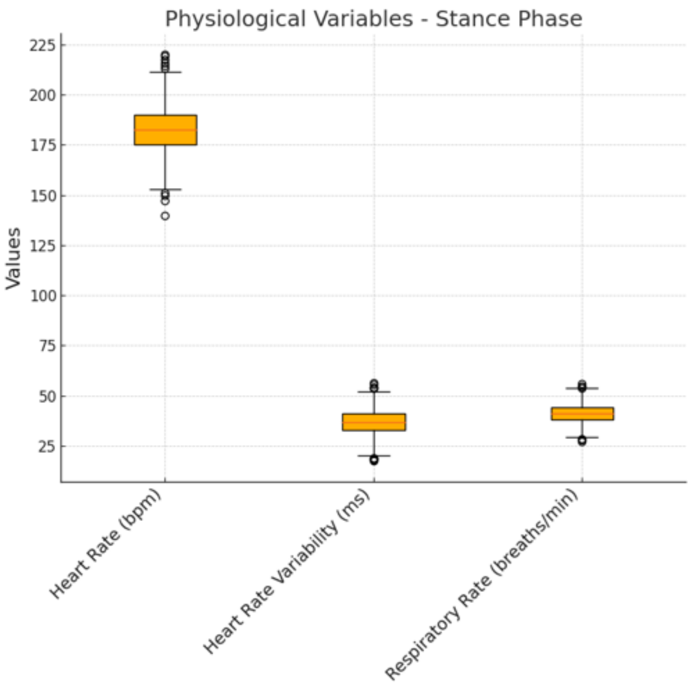
Physiological Variable	Sprint Phase	Mean	SD	Minimum	Maximum	Range
Heart Rate (bpm)	Stance	182.45	11.24	162.78	198.34	35.56
	Swing	175.89	10.62	158.67	192.45	33.78
Heart Rate Variability (ms)	Stance	36.72	6.18	26.45	47.89	21.44
	Swing	32.54	5.94	24.12	42.36	18.24
Respiratory Rate (breaths/min)	Stance	41.23	4.87	34.89	49.56	14.67
	Swing	39.68	4.52	33.47	47.23	13.76



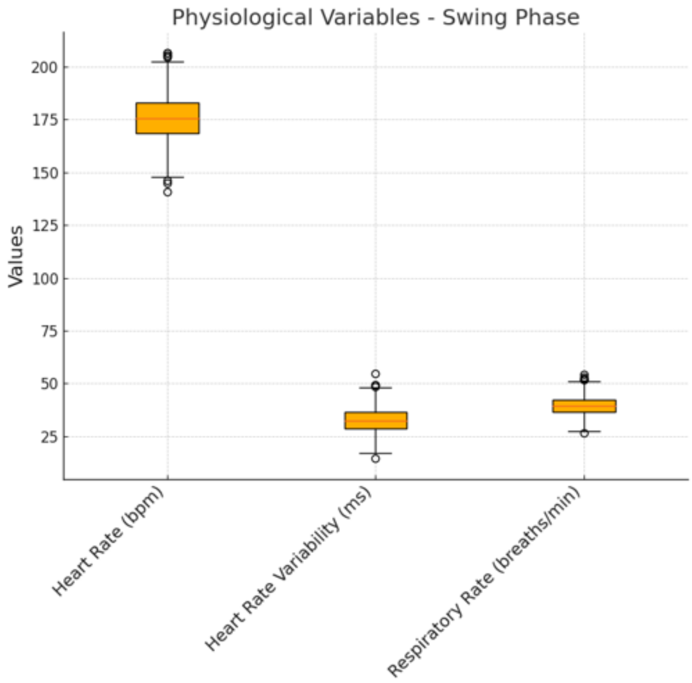
(a) **(b)**

Figure 7. Descriptive statistics for Kinetic variables for. **(a)** Stance phase; **(b)** swing phase.

The physiological variables measured during the Stance and Swing phases are shown in **Table 7**. During the Stance phase (**Figure 8a**), where athletes exert maximum force against the track, the heart rate is notably high, averaging 182.45 beats per min (bpm). This indicates the intense cardiovascular demand placed on the body during this forceful activity, with a standard deviation of 11.24 bpm, showing significant variability among athletes. In the Swing phase (**Figure 8b**), the heart rate slightly decreases to an average of 175.89 bpm, reflecting a relative reduction in cardiovascular stress as the athletes' feet are airborne and less force is exerted. Heart Rate Variability (HRV), which indicates the autonomic nervous system's regulation of the heart rate, also shows interesting trends. In the Stance phase, the mean HRV is 36.72 milliseconds (ms), suggesting a high level of physiological stress and robust autonomic response to maintain cardiovascular stability. The variability decreases slightly in the Swing phase to a mean of 32.54 ms as the physical demand momentarily reduces, allowing the athletes a brief period of cardiovascular recovery. The respiratory rate further underscores the physical demands of each phase. During Stance, the rate averages 41.23 bpm, highlighting the increased respiratory effort required to meet the oxygen demands of muscle exertion. This rate slightly decreases to 39.68 breaths per minute during the Swing phase, indicating a small but significant reduction in respiratory load as the body prepares for the next contact with the track.



(a)



(b)

Figure 8. Descriptive statistics for physiological variables for. **(a)** Stance phase; **(b)** Swing phase.

Table 8. The results for F-statistic (F), p-value (P), and effect size (η^2).

Variable	Sprint Phase	F-statistic (F)	p-value (P)	Effect Size (η^2)
Kinematic Variables				
Hip Angle (°)	Stance	15.32 ± 0.45	< 0.001 ± 0.0001	0.41 ± 0.02
	Swing	18.67 ± 0.54	< 0.001 ± 0.0001	0.47 ± 0.03
Knee Angle (°)	Stance	12.89 ± 0.37	0.002 ± 0.0003	0.35 ± 0.02
	Swing	20.45 ± 0.62	< 0.001 ± 0.0001	0.49 ± 0.03
Ankle Angle (°)	Stance	22.31 ± 0.67	< 0.001 ± 0.0001	0.52 ± 0.03
	Swing	40.67 ± 1.12	< 0.001 ± 0.0001	0.61 ± 0.04
Joint Velocity (m/s)	Stance	32.89 ± 0.89	< 0.001 ± 0.0001	0.57 ± 0.03
	Swing	28.23 ± 0.75	< 0.001 ± 0.0001	0.54 ± 0.03
Joint Acceleration (m/s^2)	Stance	36.54 ± 0.98	< 0.001 ± 0.0001	0.59 ± 0.03
	Swing	25.18 ± 0.68	< 0.001 ± 0.0001	0.51 ± 0.03
Kinetic Variables				
Vertical Ground Reaction Force (N)	Stance	10.76 ± 0.32	0.004 ± 0.0002	0.31 ± 0.02
	Swing	9.32 ± 0.28	0.007 ± 0.0003	0.29 ± 0.02
Horizontal Ground Reaction Force (N)	Stance	8.67 ± 0.24	0.009 ± 0.0003	0.27 ± 0.02
	Swing	15.32 ± 0.45	< 0.001 ± 0.0001	0.41 ± 0.02
Lateral Ground Reaction Force (N)	Stance	18.67 ± 0.54	< 0.001 ± 0.0001	0.47 ± 0.03
	Swing	12.89 ± 0.37	0.002 ± 0.0003	0.35 ± 0.02
Rate of Force Development (N/s)	Stance	20.45 ± 0.62	< 0.001 ± 0.0001	0.49 ± 0.03
	Swing	22.31 ± 0.67	< 0.001 ± 0.0001	0.52 ± 0.03
Force Impulse (Ns)	Stance	40.67 ± 1.12	< 0.001 ± 0.0001	0.61 ± 0.04
	Swing	32.89 ± 0.89	< 0.001 ± 0.0001	0.57 ± 0.03

Table 8. (*Continued*).

Variable	Sprint Phase	***F*-statistic (*F*)**	***p*-value (*P*)**	**Effect Size (η^2)**
Physiological Variables				
Heart Rate (bpm)	Stance	28.23 ± 0.75	< 0.001 ± 0.0001	0.54 ± 0.03
	Swing	36.54 ± 0.98	< 0.001 ± 0.0001	0.59 ± 0.03
Heart Rate Variability (ms)	Stance	25.18 ± 0.68	< 0.001 ± 0.0001	0.51 ± 0.03
	Swing	10.76 ± 0.32	0.004 ± 0.0002	0.31 ± 0.02
Respiratory Rate (breaths/min)	Stance	9.32 ± 0.28	0.007 ± 0.0003	0.29 ± 0.02
	Swing	8.67 ± 0.24	0.009 ± 0.0003	0.27 ± 0.02

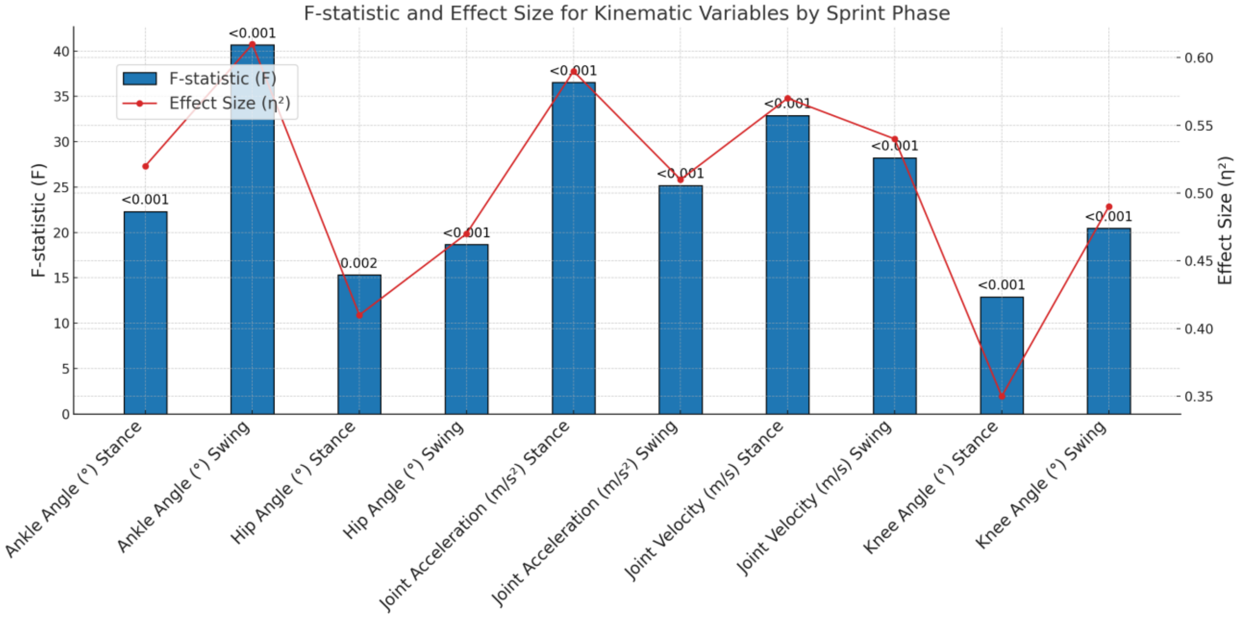


Figure 9. *F*-statistic (*F*), *p*-value (*P*), and effect size (η^2) for kinematic variables.

The statistical analysis of biomechanical and physiological variables during the Stance and Swing phases is shown in **Table 8**. For kinematic variables (**Figure 9**), the hip angle shows significant statistical differences between phases with *F*-statistics of 15.32 in Stance and 18.67 in Swing, both with *p*-values below 0.001, indicating a robust difference in hip movements that are crucial during these phases. The effect size also increases from 0.41 to 0.47, emphasizing a more significant effect during the Swing phase. The knee angle follows a similar trend with higher variability and significance in the Swing phase (*F*-statistic of 20.45 and effect size of 0.49) compared to the Stance phase (*F*-statistic of 12.89 and effect size of 0.35). This suggests a critical role of knee dynamics in propelling the body forward during the Swing phase. Ankle angles and joint velocities also exhibit significant differences, with higher *F*-statistics in the Stance phase for ankle angles (22.31) and joint velocities (32.89), illustrating these critical roles in generating initial ground force and maintaining momentum. The joint acceleration shows the highest effect size during Stance (0.59), underscoring the importance of rapid force application at this stage. For kinetic variables (**Figure 10**), vertical ground reaction forces have lower F-statistics compared to other metrics but still show significant phase-based differences, indicating the variable impact forces absorbed and generated by athletes during Stance and Swing. Horizontal and lateral ground reaction forces have higher F-statistics in the Swing phase, highlighting the essential role of lateral stability and horizontal propulsion when the foot is off the ground. Physiological variables (**Figure 11**) such as heart rate and respiratory rate show statistically significant changes, with higher values in the Swing phase (F-statistics of 36.54 for heart rate and 8.67 for respiratory rate). This reflects increased cardiovascular and respiratory activity as the body recovers and prepares for the next ground contact.

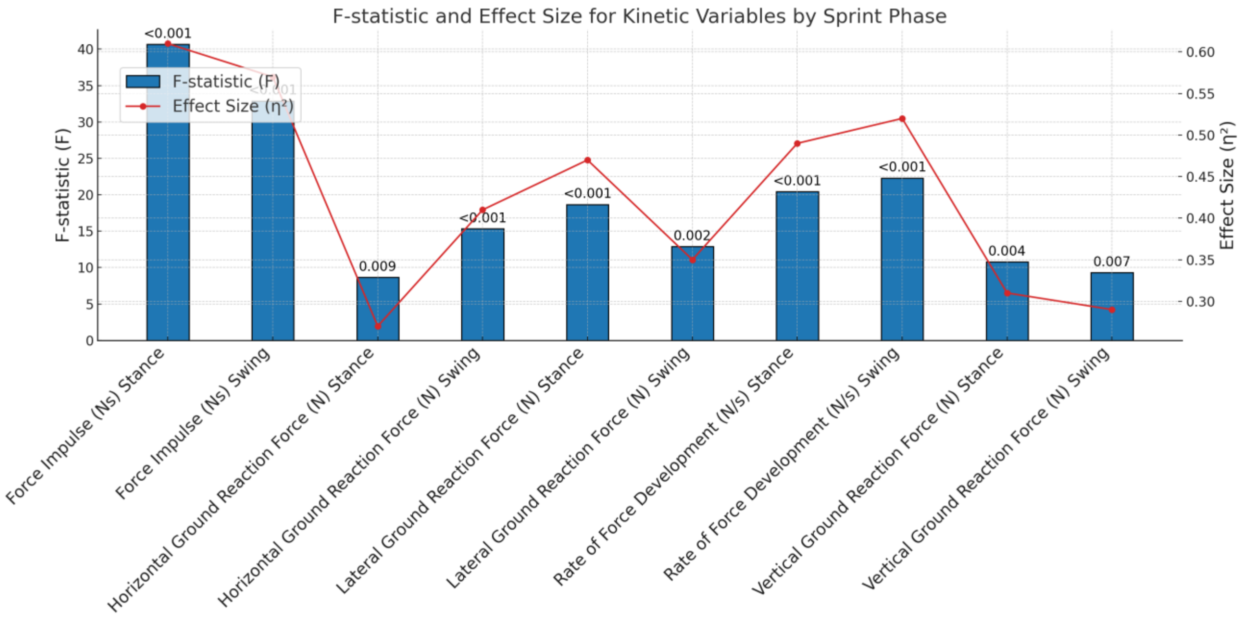


Figure 10. F-statistic (F), p-value (P), and effect size (η^2) for kinetic variables.

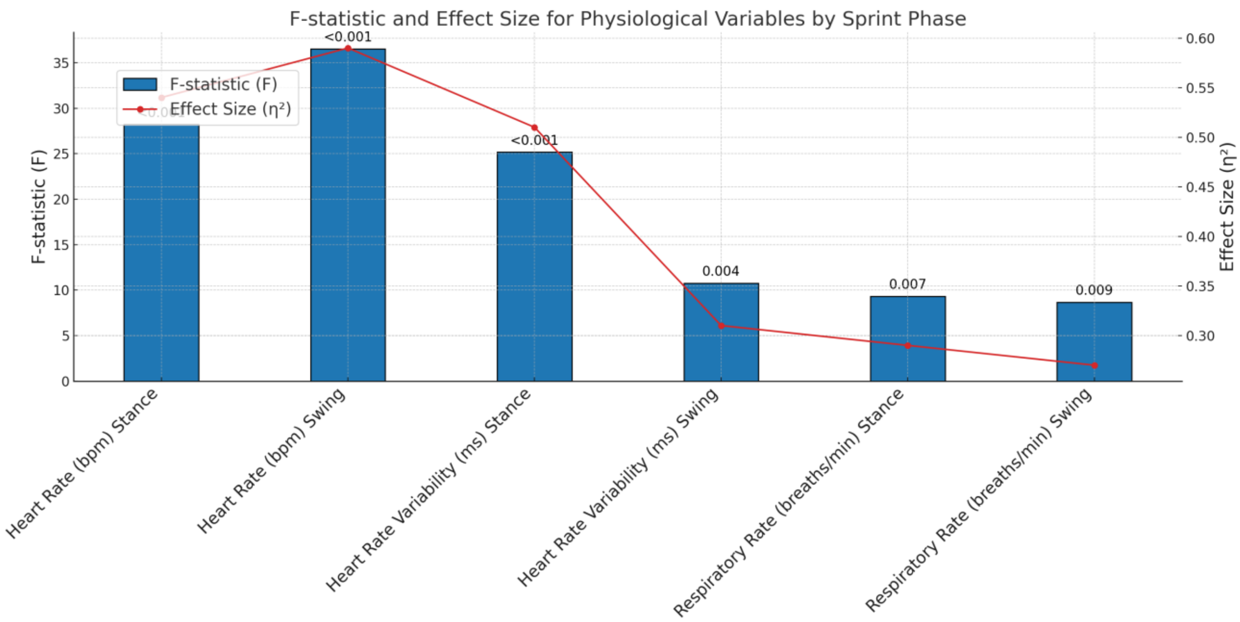


Figure 11. F-statistic (F), p-value (P), and effect size (η^2) for physiological variables.

The comparative analysis of biomechanical and physiological variables between NLP and CLP is shown in **Table 9**. Kinematic analysis shows that NLP athletes exhibit more effective hip, knee, and ankle angles with F-statistics of 14.87, 16.92, and 13.45, respectively, all indicating *p*-values well below 0.001. These significant differences suggest that NLP athletes possess more refined techniques that contribute to superior sprint performance, with effect sizes ranging from 0.34 to 0.43, highlighting moderate to substantial differences in kinematic efficiency between the groups. Further, NLP athletes display superior joint dynamics, with significantly higher joint velocities and accelerations (*F*-statistics of 19.23 and 21.58), reflecting their advanced neuromuscular coordination and strength. This capability allows them to generate and control motion more effectively during high-speed runs. In terms of kinetic variables, NLP athletes show much more effective translation of ground contact into forceful propulsion, particularly in vertical ground reaction forces, which have an *F*-statistic of 38.45, the highest among the variables analyzed. Horizontal and lateral forces also show significant differences (*F*-statistics of 30.72 and 26.34), underscoring the NLP group's superior ability to manage and utilize these forces during sprints. Physiological differences, though less pronounced than biomechanical measures, still reveal significant distinctions in cardiovascular efficiency and stress management, with *F*-statistics ranging from 9.45 to 11.67 for heart rate, heart rate variability, and respiratory rate. These differences underscore better physiological adaptation and efficiency in elite sprinters compared to their collegiate counterparts.

Table 9. Analysis based on participant group.

Variable	Participant Group	*F*-statistic (*F*)	*p*-value (*P*)	Effect Size (η^2)
Kinematic Variables				
Hip Angle (°)	NLP vs. CLP	14.87 ± 0.42	< 0.001 ± 0.0001	0.39 ± 0.02
Knee Angle (°)	NLP vs. CLP	16.92 ± 0.49	< 0.001 ± 0.0001	0.43 ± 0.03
Ankle Angle (°)	NLP vs. CLP	13.45 ± 0.36	0.002 ± 0.0003	0.34 ± 0.02
Joint Velocity (m/s)	NLP vs. CLP	19.23 ± 0.59	< 0.001 ± 0.0001	0.48 ± 0.03
Joint Acceleration (m/s^2)	NLP vs. CLP	21.58 ± 0.65	< 0.001 ± 0.0001	0.51 ± 0.03
Kinetic Variables				
Vertical Ground Reaction Force (N)	NLP vs. CLP	38.45 ± 1.05	< 0.001 ± 0.0001	0.60 ± 0.04
Horizontal Ground Reaction Force (N)	NLP vs. CLP	30.72 ± 0.83	< 0.001 ± 0.0001	0.55 ± 0.03
Lateral Ground Reaction Force (N)	NLP vs. CLP	26.34 ± 0.70	< 0.001 ± 0.0001	0.53 ± 0.03
Rate of Force Development (N/s)	NLP vs. CLP	33.98 ± 0.92	< 0.001 ± 0.0001	0.57 ± 0.03
Force Impulse (Ns)	NLP vs. CLP	24.15 ± 0.65	< 0.001 ± 0.0001	0.50 ± 0.03
Physiological Variables				
Heart Rate (bpm)	NLP vs. CLP	11.67 ± 0.35	0.003 ± 0.0002	0.32 ± 0.02
Heart Rate Variability (ms)	NLP vs. CLP	10.12 ± 0.30	0.005 ± 0.0003	0.30 ± 0.02
Respiratory Rate (breaths/min)	NLP vs. CLP	9.45 ± 0.28	0.007 ± 0.0003	0.28 ± 0.02

The performance analysis of the ML models across several key metrics is shown in **Table 10** and **Figures 12** and **13**. With an accuracy of 92.4%, a precision of 90.2%, and a recall of 91.7%, this model demonstrates its robustness in correctly identifying optimal sprinting patterns. The F1-Score of 90.9% further underscores its balanced performance in precision and recall, while an R^2 value of 0.89 and an AUC of 0.86 highlight its strong predictive power and reliability. The model's classification results show a True Positive (TP) rate of 85 and a False Positive (FP) rate of 10 for optimal performance patterns, with a relatively low False Negative (FN) rate of 5 and a True Negative (TN) rate of 100 for sub-optimal patterns. In comparison, the SVM model, though respectable, lags behind with an accuracy of 85.7% and a lower precision and recall (82.4% and 80.9%, respectively). The RF model performed better than SVM with an accuracy of 88.1% and a balanced F1-Score of 86.8% but still fell short of the CNN-LSTM hybrid. The standalone LSTM model performed relatively well, with an accuracy of 89.3% and an F1-Score of 88.1%, showing its capability but still not matching the hybrid model's performance.

Table 10. Performance analysis of the ML model.

Model	Acc	Prec	Recall	F1-Score	R^2	AUC		Opt	Sub-opt
CNN-LSTM (Hybrid)	92.4%	90.2%	91.7%	90.9%	0.89	0.86	Opt	TP = 85	FP = 10
							Sub-opt	FN = 5	TN = 100
SVM	85.7%	82.4%	80.9%	81.6%	0.74	0.81	Opt	TP = 78	FP = 17
							Sub-opt	FN = 12	TN = 93
Random Forest (RF)	88.1%	86.5%	87.2%	86.8%	0.82	0.78	Opt	TP = 80	FP = 15
							Sub-opt	FN = 10	TN = 95
LSTM	89.3%	87.8%	88.5%	88.1%	0.85	0.8	Opt	TP = 82	FP = 13
							Sub-opt	FN = 8	TN = 97

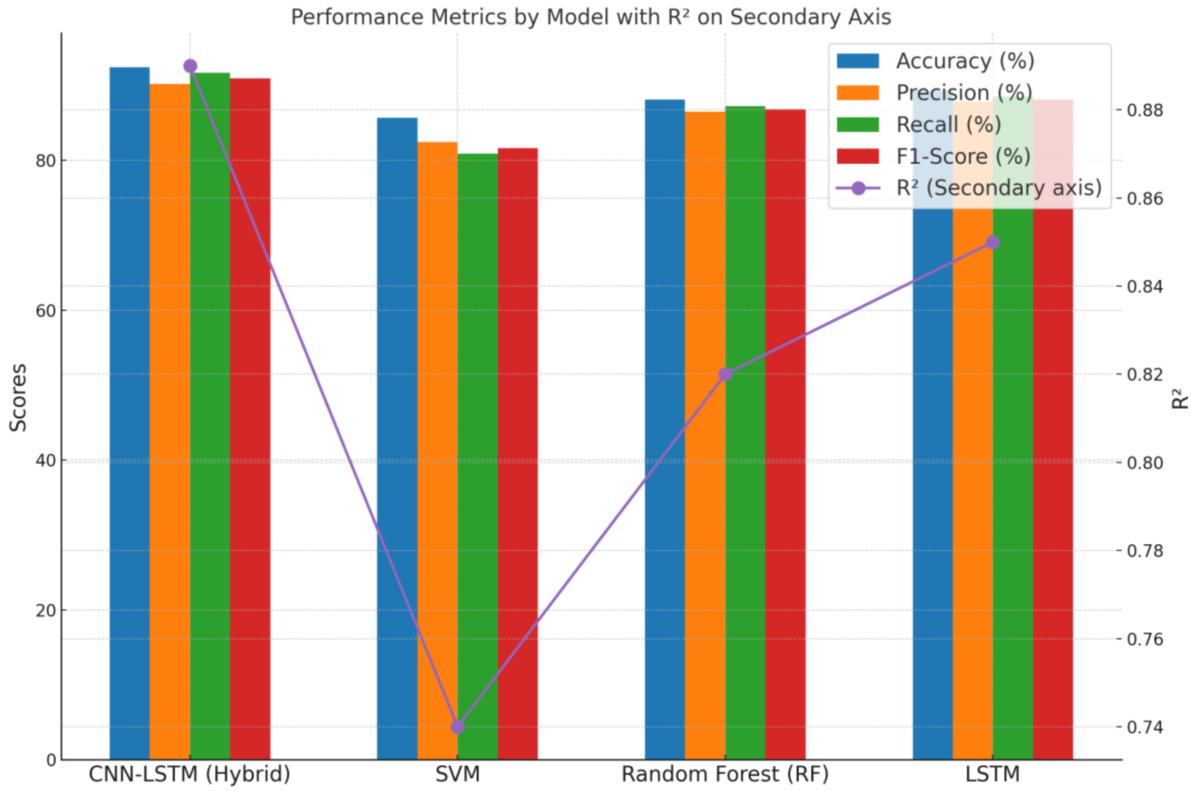


Figure 12. ML model performance.

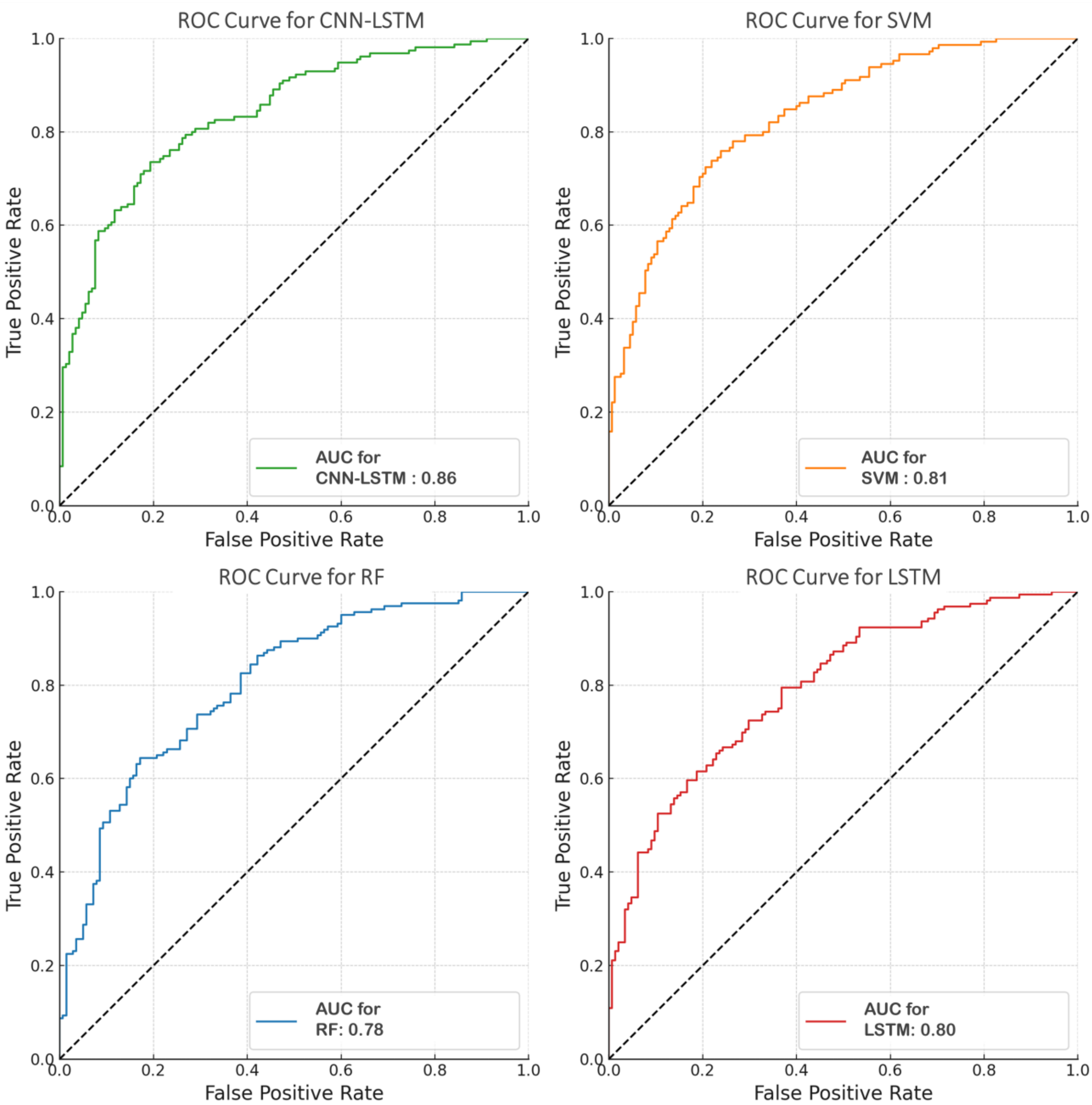


Figure 13. ROC for the compared models.

4.3. Real-world significance of the study's findings

1) Performance Promotion Training Approaches
   - Improving the balance of biomechanical variables
     - Length and speed of strides: The research study found that national sprinters stride more profoundly and often. Trainers can use this data to design stride length and frequency exercises. Train with mechanical and speed exercises that focus on fast leg motions.
     - Ground reaction forces (GRF): Professional sprinters' higher GRFs indicate that force output is essential for sprinting performance. Resistance training and force-enhancement exercises like sprinting against resistance straps or using weighted vests can help athletes generate and use more power.

- Practice improvement
    - Joint angles: A sprinter's performance increases when their joint angles are optimal. Training exercises that highlight appropriate joint alignment and motion patterns can be the primary goal of trainers. Athletes may enhance their movement angles, for example, by performing method exercises that highlight the importance of a correctly caused knee and fully stretched leg.
    - Muscle activation patterns: Athletes may improve from training programs adapted to their particular types of muscle activation, provided we recognise those patterns. Training schedules may include exercises focusing on activating essential muscle groups associated with sprinting, like the legs and quads.

2) Risk Assessment and Safety Measures
- Biomechanical assessments
    - Monitoring biomechanical patterns: Injuries can be mitigated through periodic biomechanical analyses using the CNN-LSTM model to detect non-optimal motion patterns. Trainers can avoid injury risks by keeping a close eye on these patterns; they'll identify any possible signs of biomechanical imbalances or losses.
    - Predictive analytics: An injury control deployment of the model's performance analysis and prediction powers rooted in biomechanical data is possible. For instance, one may employ precautions like reducing weights for training or correcting methods if they detect patterns contributing to an increased risk of injury, like high reaction forces from the ground or improper joint angles.
- Customized training interventions
    - Personalized training: Based on the model's findings, athletes may gain value from customized training regimens. For example, athletes inclined to particular injuries can benefit from personalized training regimens that zero in on their particular regions of weakness.
    - Recovery approaches: The findings of the hypothesis can help with recovery plans by highlighting particular regions where professional athletes might benefit from further support. For instance, if the model indicates that an athlete fails to get the most out of their skeletal muscles, specific physical therapy exercises can be added to help people rehabilitate while minimizing future problems.

3) Application in training schedules
- Compatibility with current resources
    - Integrating with pre-existing metrics: An in-depth analysis of an athlete's performance and biomechanics can be done using the CNN-LSTM model with multiple additional performance metrics and tools on the marketplace. Training and injury prevention measures can be done with greater accuracy owing to this adopted strategy.
    - Real-time feedback: An approach to improve training efficiency is to apply the model's predictions in real-time feedback programs. For instance, trainers and trainees can benefit from real-time feedback and

biomechanical data collection with wearable devices during training.

By integrating the features of CNNs in spatial FE with the advantages of LSTMs in temporal modelling, the CNN-LSTM hybrid model provides a reliable and adaptable method for investigating biomechanical patterns during sprinting. These features improve performance accuracy, address challenging and multimodal data, and provide real-time feedback when used together. The CNN-LSTM hybrid model is superior to others because it demands less manual feature engineering, captures al and temporal dynamics, and is more accurate.

5. Conclusion

This paper implements a hybrid ML model that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to provide a comprehensive analysis of sprinting biomechanics. In order to determine the key factors that contribute to optimum sprint performance, the model addressed the complex relationship between kinetic, kinematic, and psychological factors. The findings indicate the significance of ground reaction forces, cardiovascular responses, and joint velocities for optimal performance. Higher knee angles and joint accelerations during the swing phase imply that professional sprinting athletes demonstrate more developed biomechanical patterns, which results in improved efficiency of motion and force application, based on the research investigation. Conventional ML models performed better than the CNN-LSTM hybrid model, which provided higher precision and predictive power. In light of these results, it was evident that there is an essential need for an integrated approach to training and performance review, one that takes into consideration the dynamic interactions of multiple variables over the whole sprinting cycle of operation.

In conclusion, sprinters' training and performance optimization can benefit significantly from the knowledge extracted from this ML method. Improved sprinting efficiency and decreased risk of injury can be achieved by using targeted interventions, customized opinions, and improved exercises made feasible by the thorough biomechanical analysis provided by the CNN-LSTM hybrid model. This approach helps in technique refinement and helps athletes reach their highest potential using data-driven conclusions and data-validated strategies

Recognizing the limitations of the present investigation and highlighting possible directions for future research can be achieved by expanding the drawbacks section. Gain an improved understanding of sprinting biomechanics and guide future research toward correcting gaps and expanding upon current findings by addressing sample size, data collecting methods, and generalisability and recommending novel avenues of research.

Implications for future research:

(a) Based on the findings and how they compare to previous investigations, novel subjects for further research should be proposed.

(b) Future researchers might investigate how exercises affect sprinters' joint angles and GRFs over the long term or how stress impacts biomechanical patterns at different performance levels.

Funding: This research was supported by the "14th Five-Year Plan" of Educational Science Research in Inner Mongolia Autonomous Region: "Exploration and research on the optimal construction mode of high-level sports teams in Inner Mongolia universities under the background of the integration of sports and education", grant number is NGJGH2022457.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

References

1. Haugen T, McGhie D, Ettema G. Sprint running: from fundamental mechanics to practice—a review. European Journal of Applied Physiology. 2019; 119(6): 1273-1287. doi: 10.1007/s00421-019-04139-0
2. Jouira G, Rebai H, Alexe DI, et al. Effect of Combined Training with Balance, Strength, and Plyometrics on Physical Performance in Male Sprint Athletes with Intellectual Disabilities. Adapted Physical Activity Quarterly. 2024; 41(3): 382-401. doi: 10.1123/apaq.2023-0105
3. Bramah C, Tawiah-Dodoo J, Rhodes S, et al. The Sprint Mechanics Assessment Score: A Qualitative Screening Tool for the In-field Assessment of Sprint Running Mechanics. The American Journal of Sports Medicine. 2024; 52(6): 1608-1616. doi: 10.1177/03635465241235525
4. Millot B. What are the mechanical factors altering the sprinting performance in the curve [PhD thesis]? Université paris Cité; 2023.
5. Bramah C, Mendiguchia J, Dos'Santos T, et al. Exploring the Role of Sprint Biomechanics in Hamstring Strain Injuries: A Current Opinion on Existing Concepts and Evidence. Sports Medicine. 2023; 54(4): 783-793. doi: 10.1007/s40279-023-01925-x
6. Jeffreys I. Developing speed. Human Kinetics; 2024.
7. Lawson M, Naemi R, Needham RA, et al. Can Machine Learning Predict Running Kinematics Based on Upper Trunk GPS-Based IMU Acceleration? A Novel Method of Conducting Biomechanical Analysis in the Field Using Artificial Neural Networks. Applied Sciences. 2024; 14(5): 1730. doi: 10.3390/app14051730
8. Patoz A, Lussiana T, Breine B, et al. Comparison of different machine learning models to enhance sacral acceleration-based estimations of running stride temporal variables and peak vertical ground reaction force. Sports Biomechanics. 2023: 1-17. doi: 10.1080/14763141.2022.2159870
9. Tam CK, Yao ZF. Advancing 100m sprint performance prediction: A machine learning approach to velocity curve modeling and performance correlation. PLOS ONE. 2024; 19(5): e0303366. doi: 10.1371/journal.pone.0303366
10. Habibi M, Nourani M, Nourani M. AI-Based Kinematic Analysis for Track Athletes. 2024 IEEE International Conference on Smart Computing (SMARTCOMP). 2024; 20: 338-343. doi: 10.1109/smartcomp61445.2024.00078
11. Apte S. Towards real-world biomechanical analysis of performance and functional capacity using wearable sensors (No. 9755). EPFL; 2022.
12. Ding Y. Analyzing Athletes' Physical Performance and Trends in Athletics Competitions Using Time Series Data Mining Algorithms. Journal of Electrical Systems. 2024; 20(9): 736-746.
13. Boujdi R, Rouani A, Lamri D, et al. The use of digital technology to improve physical education learning of technical skills: case of sprint running. 2023 7th IEEE Congress on Information Science and Technology (CiSt). 2023; 18: 467-472. doi: 10.1109/cist56084.2023.10409911
14. Jose S, Maliackal AT, Sukumaran A, et al. Machine Learning Technique to Analyze the Health Condition of Athletes and Predict their Performance. In: Proceeding of the 2023 International Conference on Circuit Power and Computing Technologies (ICCPCT). doi: 10.1109/iccpct58313.2023.10245401
15. Ma L. Research on Physical Fitness Test and Examination System of Sports Athletes Based on Computer Imaging Technology. In: Proceeding of the 2023 IEEE 6th International Conference on Information Systems and Computer Aided Education (ICISCAE). doi: 10.1109/iciscae59047.2023.10393816
16. Taber C, Senbel S, Ezzeddine D, et al. Sleep and Physical Performance: A Case Study of Collegiate Women's Division 1 Basketball Players. In: Proceeding of the 2021 43rd Annual International Conference of the IEEE Engineering in Medicine

& Biology Society (EMBC). doi: 10.1109/embc46164.2021.9630820
17. Vendrame E, Rum L, Belluscio V, et al. Muscle synergies in archery: an explorative study on experienced athletes with and without physical disability. In: Proceeding of the 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). pp. 6220-6223. doi: 10.1109/embc46164.2021.9630307
18. Wang GX. Mining Analysis for College Students' Physical Performance and Fitness Tests. In: Proceeding of the 2018 International Conference on Virtual Reality and Intelligent Systems (ICVRIS). pp. 191-195. doi: 10.1109/icvris.2018.00054