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Can BlazePose accurately assess joint angles in outdoor running environments?

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Abstract

Study aim: Accurate measurement of joint angles during running is crucial for performance optimisation and injury prevention. Traditional methods are often expensive or impractical for outdoor settings, making pose estimation techniques a promising alternative. This study aims to validate and evaluate the accuracy of BlazePose for measuring hip, knee, and ankle joint angles at key gait events, initial contact (IC), midstance (MS), and toe-off (TO) in outdoor running.

Material and methods: Sixteen male athletes participated in this study. Joint angles were measured using BlazePose and compared to manual measurements obtained with Kinovea software. Statistical analysis, including paired t-tests, Pearson correlation coefficients (r), Bland-Altman plots, mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE), was performed to assess BlazePose's validity, agreement, and accuracy.

Results: BlazePose demonstrated a strong to very strong correlation with Kinovea (r: 0.70-0.97). Bland-Altman plots indicated good precision with minimal bias (average MAE: 2.11°, MAPE: 1.57%, RMSE: 2.63°). Ankle joint measurements were the most accurate across all joints and events, followed by the hip joint, particularly during midstance. Knee joint measurements had slightly higher errors but remained within an acceptable range.

Conclusions: BlazePose is a valid tool for measuring joint angles during outdoor running, providing an affordable alternative for biomechanical analysis. The findings are specific to the outdoor conditions under which the study was conducted, highlighting the necessity of validating pose estimation techniques in diverse environments and populations for broader applicability.

Keywords: Biomechanical performance – Joint movement – Kinematic – Motion analysis – Sprinting

Introduction

Running is a prevalent recreational and competitive exercise (Souza, 2016), but running injuries are common, with musculoskeletal injury rates ranging from 19% to 78% (Dingenen et al., 2020; Taunton et al., 2002), Faulty kinematics of the ankle (26%), hip (14%), and knee (28%) joints contribute to these injuries (Francis et al., 2019). The recurrence rate of running-related injuries is 85%, emphasising the importance of observing joint angle kinematics for injury-free running (Buck et al., 1987; Folland et al., 2017).

Sophisticated three-dimensional (3D) motion-tracking systems are frequently used in laboratories to estimate joint angle kinematics (Phinyomark et al., 2015). Although these systems are the gold standard for human movement analysis (Zhou & Hu, 2008), they are expensive, non-portable, data-intensive (Simon, 2004), and require extensive user knowledge, making them inaccessible for clinical and outdoor use.

Wearable sensors such as the Inertial Measurement Unit (IMU) offer an alternative but can be costly and intrusive. Two-dimensional (2D) motion analysis systems provide a more cost-effective solution for assessing

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human kinematics in natural settings (Baker, 2006; Littrell et al., 2018). Previous studies have shown promising results using 2D video assessment for measuring joint angles (Balsalobre-Fernández et al., 2014). Approximately 48% (Hensley et al., 2020) of clinical motion analyses utilise 2D systems such as Kinovea (Mathunny et al., 2021), Dartfish (Lu et al., 2020), and ImageJ (Schneider et al., 2012). Conventional 2D video analysis necessitates manual annotation of each video frame's region of interest (anatomical location) to calculate joint angles, a resource-intensive and time-consuming process. This approach limits the amount of data that can be processed and the effectiveness of subsequent analyses (Zult et al., 2019). To measure joint angles with precision, qualified professionals are required.

Automated 2D video analysis using human pose estimation-based methods such as BlazePose (Bazarevsky et al., 2020), Open Pose (Cao et al., 2021), and others have shown satisfactory validity in estimating joint angles (Chung & Wang, 2010). Masafumi Itokazu highlighted the necessity of validating pose estimation technologies across diverse environments and activities (Itokazu, 2022). Analysing dynamic running presents unique challenges due to rapid joint position changes and outdoor factors such as background clutter and varying lighting conditions (Needham et al., 2021). Validating pose estimation techniques for joint angle measurements during outdoor running is crucial for athletes and coaches aiming to improve performance and prevent injuries.

This study aims to validate BlazePose for automated measurement of joint angles during outdoor running, specifically focusing on the hip, knee, and ankle joints at key gait events—initial contact (IC), midstance (MS), and toe-off (TO). Additionally, the study seeks to compare BlazePose measurements with manual joint angle assessments obtained from Kinovea, evaluating the accuracy of BlazePose in outdoor running environments.

Materials and methods

Participants

Sixteen male athletes (age = 20 ± 3 years, body mass = 63.8 ± 11 kg, height = 174.5 ± 12.5 cm) from the Department of Physical Education and Sports voluntarily participated. Inclusion criteria required participants to have a consistent running routine without lower extremity injuries in the preceding three months. The SRM Medical College Hospital and Research Centre's Institutional Ethics Committee (IEC.NO.2841) approved the study and adhered to the Declaration of Helsinki, with written informed consent obtained from all participants ("World Medical Association Declaration of Helsinki Ethical Principles for Medical Research Involving Human Subjects," 2013).

Procedures

Body mass and height were measured using a Digital BMI Machine (SECA 284) with a precision of 0.1 kg and 0.1 cm. Participants underwent a standardised warm-up session, wearing running shoes or barefoot. They completed a 30 m run on a 400 m outdoor track at their preferred speed, recorded with a smartphone camera at 1280 × 720 pixels and 30 frames per second (fps). The camera was mounted on a tripod 5 m from the 25 m mark, perpendicular to the running lane. This setup were meticulously designed to minimise device movement and ensure the reproducibility of the study conditions (van der Kruk & Reijne, 2018).

Since previous research had validated the Kinovea software at a 5 m distance, the same length has been used (Puig-divı et al., 2019). Here, 25 m was selected considering the minimum seven steps required for 2D video analysis in the sagittal plane (Dingenen et al., 2019). To capture the region of interest for participants (from shoulder to toe), the camera lens was positioned 92 cm above the ground, as shown in Fig. 1.

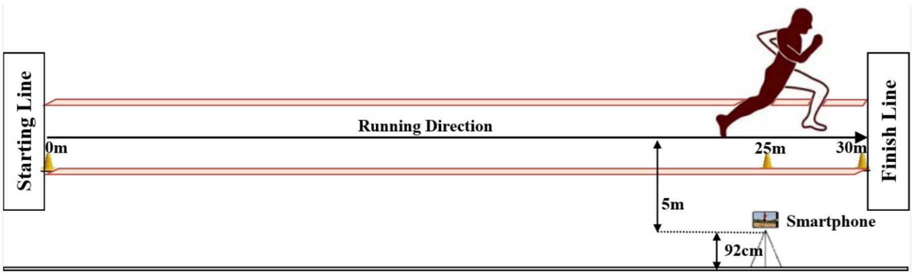

Figure 1. Schematic representation of the experimental setup, providing details of the runway layout and camera positions for capturing the running trials

Environmental and clothing conditions

All recordings were conducted in consistent daytime lighting without significant weather variations. Background elements were present, including people, buildings, and tree structures. However, the clarity of the participant and track was prioritised. While crowd dynamics varied, these fluctuations were not expected to impact pose estimation accuracy significantly. Supplementary Fig. 1 presents sample images illustrating these environmental factors.

Participants wore standard athletic attire that was neither excessively loose nor tight-fitting. While some clothing movements, particularly from untucked shirts, were observed, they occasionally affected the detection of hip landmarks. Additionally, in specific frames, the proximity of hands to the hip region partially obscured joint detection. These considerations were crucial for interpreting the results, especially regarding hip and knee joint angles. Supplementary Fig. 2 presents images demonstrating clothing variability and its influence on landmark detection.

Frame selection for gait analysis

Videos were transferred to a laptop for analysis. An experienced physiotherapist identified frames corresponding to gait events (IC, MS, TO) by advancing frame by frame through the videos. Frames where the runner's foot strike was closer to the centre of the camera's field of view were selected to minimise parallax error (Stephens et al., 2019). The same video was used for both BlazePose and Kinovea, and the joint angles were estimated from the same steps and corresponding frames for consistency in the analysis. The methodology is illustrated in Fig. 2.

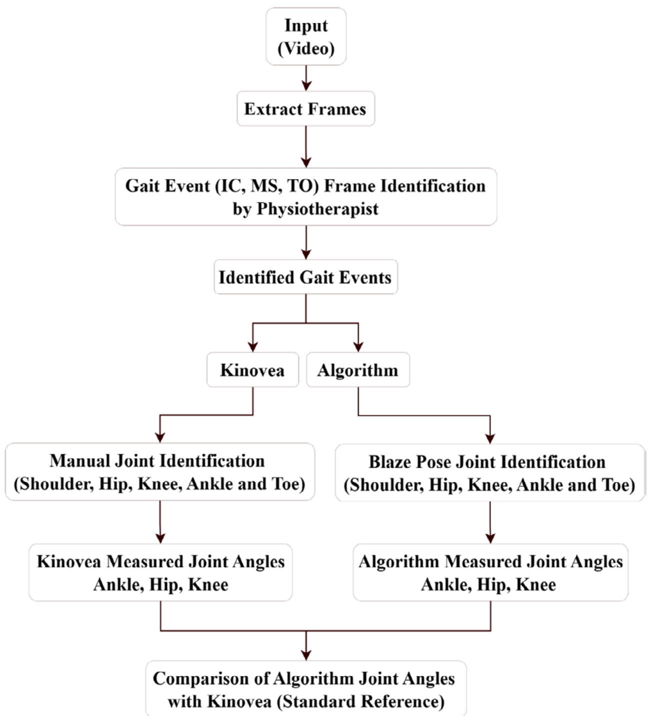

Figure 2. Methodology workflow of the study

Camera setup and participant framing

To ensure optimal framing for accurate joint detection, the height and width of participants within the video frame were analysed. The analysis was based on the subject's pixel height and width relative to the total video frame dimensions (1280 px width by 720 px height). The height ratio of participants ranged from 0.42 to 0.49, with a mean of 0.46, while the width ratio ranged from 0.10 to 0.20, with a mean of 0.16. Furthermore, the overall area ratio, representing the proportion of the frame occupied by the subject, ranged from 4.64% to 9.53%, with a mean of 7.35%. These data indicate that the participants were consistently framed within an optimal range, allowing for accurate joint angle detection using the BlazePose algorithm.

Automated BlazePose joint angle measurement

The algorithm employed in this study enables the measurement of ankle, hip, and knee joint range of motion using 2D videos. The output includes annotated joint angles for each video frame and an Excel spreadsheet containing time frames paired with their corresponding joint angles. For the identification of anatomical landmarks such as the shoulder, hip, knee, ankle, and toe, this study utilised Media Pipe's BlazePose pose estimation algorithm, depicted in Fig. 3. Subsequently, using these landmarks, the hip, knee, and ankle joint angles are computed based on the inverse cosine function as described in Eqs. (1), (5), and (8) respectively. This function takes three side lengths as input, representing the distances between two joints calculated using the Euclidean distance function provided in Eqs. (2), (3), (4), (6), (7), (9), and (10).

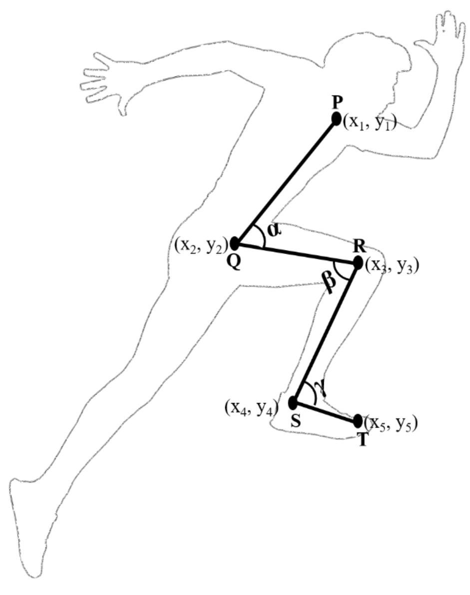

Figure 3. Visual representation for joint angle computation

The computation of joint angles is illustrated visually as follows:

Hip Joint Angle:

$$\alpha = \cos^{-1}\left(\frac{d_2^2 + d_1^2 - d_3^2}{2 \cdot d_2 \cdot d_1}\right) \tag{1}$$

Where

$d_1 = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ is the distance between shoulder joint (P) and hip joint (Q) (2)

$d_2 = \sqrt{(x_3 - x_2)^2 + (y_3 - y_2)^2}$ is the distance between hip joint (Q) and knee joint (R) (3)

$d_3 = \sqrt{(x_3 - x_1)^2 + (y_3 - y_1)^2}$ is the distance between shoulder joint (P) knee joint (R) (4)

Knee Joint Angle:

$$\beta = \cos^{-1}\left(\frac{d_2^2 + d_4^2 - d_5^2}{2 \cdot d_2 \cdot d_4}\right) \quad (5)$$

Where

$d_4 = \sqrt{(x_4 - x_2)^2 + (y_4 - y_2)^2}$ is the distance between hip joint (Q) and ankle joint (S) (6)

$d_5 = \sqrt{(x_4 - x_3)^2 + (y_4 - y_3)^2}$ is the distance between knee joint (R) and ankle joint (S) (7)

Ankle Joint Angle:

$$\gamma = \cos^{-1}\left(\frac{d_5^2 + d_6^2 - d_7^2}{2 \cdot d_5 \cdot d_6}\right) \quad (8)$$

Where

$d_6 = \sqrt{(x_5 - x_4)^2 + (y_5 - y_4)^2}$ is the distance between ankle joint (S) and toe joint (T) (9)

$d_7 = \sqrt{(x_5 - x_3)^2 + (y_5 - y_3)^2}$ is the distance between knee joint (R) and toe joint (T) (10)

Manual Kinovea joint angle measurement

Manual joint angles were annotated using Kinovea Version 0.9.5, a 2D video analysis software freely available at https://www.kinovea.org. Previous studies have validated Kinovea's effectiveness as a markerless tool for analysing joint angles in 2D videos, confirming its suitability for this study analysis (Puig-divı et al., 2019). An experienced researcher proficient in 2D video analysis measured joint angles, specifically angles of the ankle, hip, and knee joints at IC, MS, and TO, using Kinovea. The definitions of joint angles were consistent in both the automated and manual measurement techniques. Both methods used the same anatomical landmarks, and the computation approach for joint angles was identical. However, BlazePose's automated landmark detection differs from Kinovea's manual identification by an experienced researcher. This Kinovea software served as the ground truth against which the joint angles measured by the automated BlazePose algorithm method were compared.

Statistical analysis

The statistical analyses were conducted using SPSS Statistics version 23.0 (IBM Corp., USA) to comprehensively assess the BlazePose algorithm's validity. Descriptive statistics, such as mean and standard deviations, provided an overview of the data. The normality of the distribution for all joint angles across different phases of the gait cycle was assessed using the Shapiro-Wilk test. The results indicated that all distributions were normal ($p > 0.05$), justifying the use of parametric tests for the study. The Shapiro-Wilk statistics table and corresponding histograms and Q-Q plots for visual inspection are provided in Supplementary Table 1, Supplementary Fig. 3, and Supplementary Fig. 4, respectively.

Table 1. Descriptive statistics of the BlazePose algorithm with Kinovea

Joint	Gait Event	Mean (°)		Standard Deviation (°)		Min (°)		Max (°)	
		Kinovea	Algorithm	Kinovea	Algorithm	Kinovea	Algorithm	Kinovea	Algorithm
Ankle	IC	119.38	118.75	7.36	8.67	103.00	102.00	132.00	135.00
	MS	92.69	92.5	6.07	6.81	86.00	83.00	103.00	103.00
	TO	100.13	99.81	6.68	7.84	89.00	86.00	113.00	116.00
Hip	IC	144.06	144.19	3.79	4.25	137.00	136.00	150.00	152.00
	MS	149.81	149.81	4.45	5.60	144.00	141.00	158.00	161.00
	TO	172.81	172.75	3.37	4.12	167.00	165.00	179.00	179.00
Knee	IC	150.00	149.81	5.09	7.18	142.00	136.00	156.00	156.00
	MS	139.94	139.81	3.87	6.97	134.00	128.00	144.00	149.00
	TO	168.69	168.44	4.67	4.69	159.00	162.00	175.00	177.00

Min = minimum, Max = maximum, IC = initial contact, MS = midstance, TO = toe-off

Validity was assessed using Pearson correlation coefficients, which evaluate the correlation strength between measurements obtained from BlazePose and Kinovea. This method was chosen based on the data's confirmed normality and linearity assumptions. The correlation values were interpreted as follows: 0.00–0.19 very weak, 0.20–0.39 weak, 0.40–0.59 moderate, 0.60–0.79 strong, and 0.80–1.0 very strong. Accuracy was evaluated using mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) with a 95% confidence interval considered for significance.

Results

Table 1 presents the descriptive statistics (mean, standard deviation, minimum, and maximum values) for joint angle measurements using the Kinovea software and the BlazePose algorithm.

T-test analysis

Paired t-tests revealed no statistically significant differences between Kinovea and the algorithm for all joint and gait events, demonstrating a strong agreement. Detailed t-test results are presented in Supplementary Table 2.

Pearson correlation coefficients analysis

Table 2 presents the Pearson correlation coefficients, demonstrating BlazePose's strong validity in measuring joint angles. The analysis reveals that ankle joint angles show very strong validity, with coefficients ranging from 0.95 to 0.97 across various gait events. For hip joint angles, strong correlations were found, with coefficients ranging from 0.76 to 0.93, particularly notable during midstance. Knee joint angles also showed strong correlations, with values ranging from 0.70 to 0.95, although the lowest correlation was observed during the TO.

Table 2. Pearson correlation coefficients for joint angle measurements

Joint	Gait event	Pearson correlation
Ankle	IC	0.97
	MS	0.95
	TO	0.95
Hip	IC	0.83
	MS	0.93
	TO	0.76
Knee	IC	0.95
	MS	0.92
	TO	0.70

IC = initial contact, MS = midstance, TO = toe-off

Assessment of agreement

Bland-Altman plots were generated for each joint and gait event (Fig. 4), showing individual data points. The mean difference between the two measurement methods was close to zero (−0.12 to 0.62), indicating minimal systematic bias. The limits of agreement ranged from −7.13 to 7.35, with most measurements falling within this range. The hip joint at the MF gait event showed the narrowest limits of agreement (4.23 to −4.23), indicating high consistency between Kinovea and the algorithm.

Exploratory analysis

The linear regression analysis revealed varying correlation coefficients between the algorithm's joint angle measurements and Kinovea (Fig. 5). For the ankle joint, the coefficients were high, 0.95 at IC, 0.91 at MS, and 0.90 at TO, indicating strong alignment between the methods. In contrast, the hip joint showed moderate correlations, with values of 0.69 at IC, 0.87 at MS, and 0.58 at TO, notably decreasing in the toe-off phase. The knee joint analysis yielded coefficients of 0.89 at IC, 0.85 at MS, and 0.49 at TO, reflecting strong relationships at the IC and MS but a significant drop at TO. These findings affirm the algorithm's effectiveness in measuring joint angles, especially for the ankle, while suggesting caution in interpreting hip and knee results in the toe-off phase.

Accuracy assessment

The MAE, MAPE, and RMSE were computed for each joint and gait event to assess the algorithm's accuracy. The average MAE was 2.11°, the average MAPE was 1.57%, and the average RMSE was 2.63°, indicating the algorithm's high accuracy compared to Kinovea. Detailed results are presented in Table 3.

Table 3. Accuracy metrics of algorithm joint angle measurements of various gait events

Joint	Gait Event	MAE (°)	MAPE (%)	RMSE (°)
Ankle	IC	1.75	1.47	2.29
	MS	1.56	1.71	2.05
	TO	2.06	2.05	2.54
Hip	IC	1.75	1.19	2.29
	MS	1.75	1.16	2.09
	TO	1.94	1.12	2.59
Knee	IC	2.19	1.47	2.77
	MS	3.13	2.24	3.58
	TO	2.88	1.69	3.52

IC = initial contact, MS = midstance, TO = toe-off, MAE = mean absolute error, MAPE = mean absolute percentage error, RMSE = root mean squared error

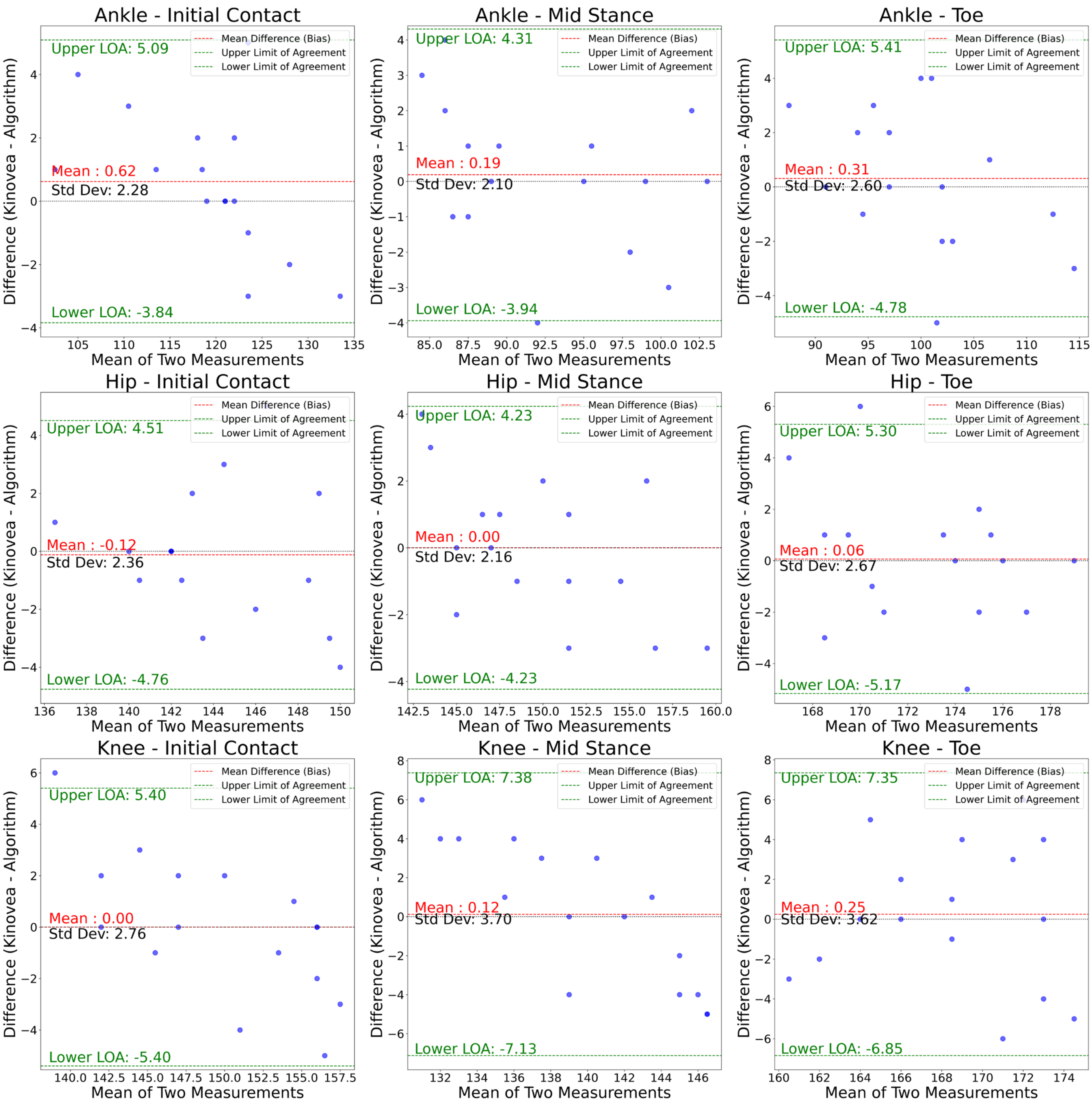

Figure 4. Bland-Altman plots for the agreement between joint angle measurements

Discussion

The study aimed to evaluate the validity of BlazePose, a pose estimation algorithm for measuring joint angles in outdoor running. The primary focus was to assess the hip, knee, and ankle joint angles at key gait events (initial contact, midstance, and toe-off). The need for this validation derived from the prevalence of running-related injuries, often linked to improper joint kinematics. Therefore, the goal was to determine whether BlazePose could offer a cost-effective solution for biomechanical analysis, potentially providing insights for injury prevention and performance enhancement during running in the natural environment.

The results demonstrate a strong relationship between BlazePose and Kinovea, as indicated by the high Pearson correlation coefficients (Table 2) and Bland-Altman plots, which reveal minimal biases. The slightly elevated errors noted during the toe-off phase for the hip and knee joints

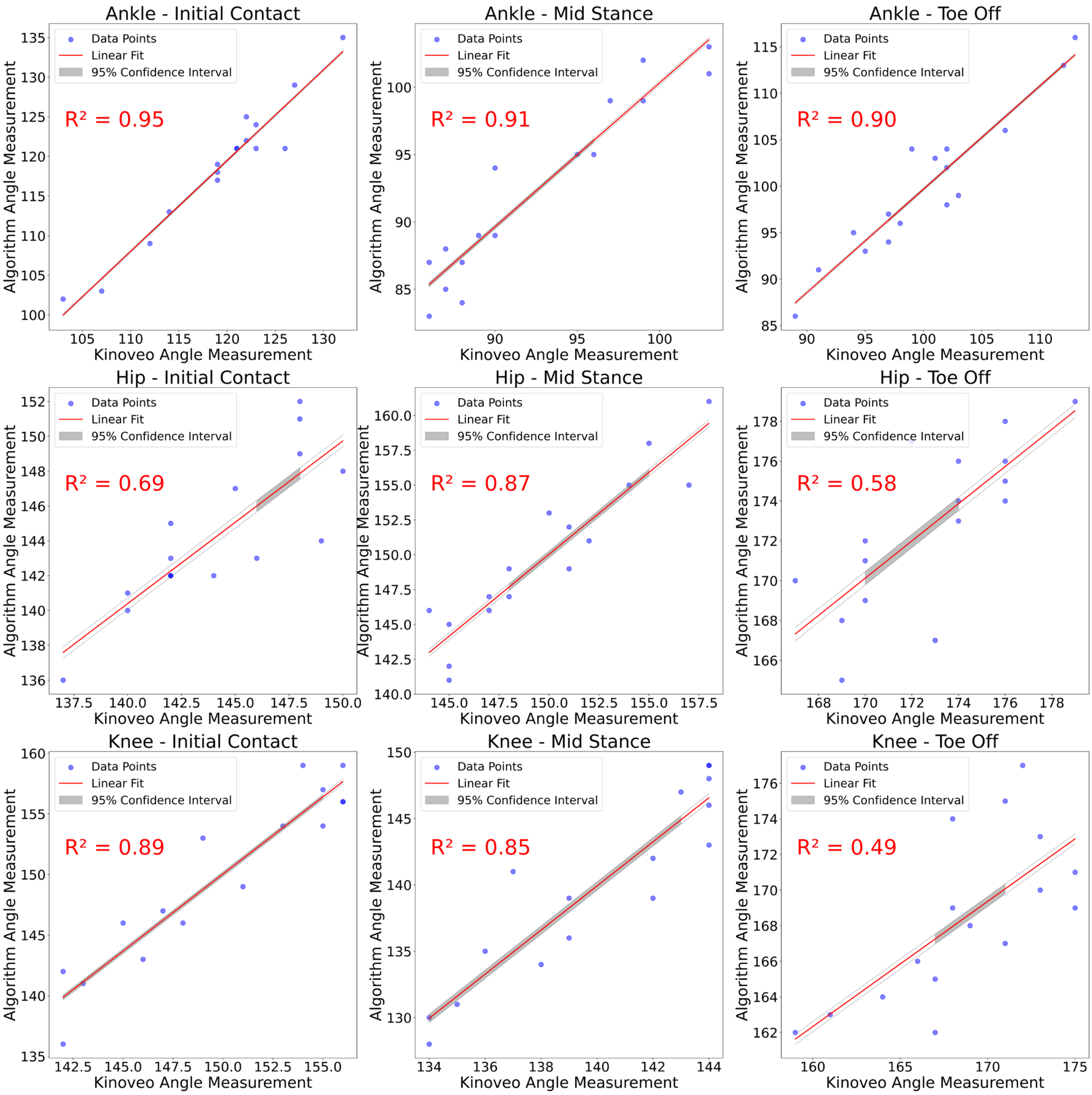

Figure 5. Linear regression analysis of joint angle measurements for algorithm vs Kinovea

may be partially attributed to the constraints of the 30 fps frame rate. While using a 30 fps camera provided a cost-effective and accessible approach, it may limit the accuracy of joint angle measurements during rapid movements, especially at toe-off.

Previous studies indicate that higher frame rates (≥ 120 fps) could yield clearer images, which will give more accurate measurements of running joint kinematics (Cronin, 2021; Souza, 2016)it is now possible to perform such analyses without markers, making outdoor applications feasible. In this paper I summarise 2D markerless approaches for estimating joint angles, highlighting their strengths and limitations. In computer science, so-called "pose estimation" algorithms have existed for many years. These methods involve training a neural network to detect features (e.g. anatomical landmarks. While adopting higher frame rates requires high-speed cameras, which entail increased financial investment, our decision to utilise a 30 fps camera was aimed at balancing accuracy with cost-effectiveness, as supported by prior research findings

(Mathis et al., 2020). Despite the cost-effectiveness of the 30 fps camera, its limitations in capturing rapid movements emphasise the need for higher frame rates (≥120 fps) in future studies.

Performance indicators (Table 3) assess the algorithm's precision and accuracy. The ankle joint showed an average MAE of 1.79°, MAPE of 1.74%, and RMSE of 2.29°, consistently exhibiting higher accuracy than hip and knee joints. These results suggest that BlazePose provides highly accurate measurements for ankle joint angles during running, maintained across all gait events. For the hip joint, BlazePose displayed an average MAE of 1.81°, MAPE of 1.16%, and RMSE of 2.32°, with the highest accuracy during midstance. The knee joint had slightly higher error values, with an MAE of 2.73°, MAPE of 2.14%, and RMSE of 3.62°, particularly during initial contact. Despite these variations, the values fall within an acceptable range, indicating reasonably accurate performance (Gajdosik & Bohannon, 1987; Neal et al., 2020).

Variations in accuracy among different joint angles can be attributed to the BlazePose landmark identification. Notably, the reduced accuracy of hip and knee angles compared to ankle joint angles may be influenced by detecting landmarks associated with the hip. Among athletes wearing jerseys, their movements could affect hip landmark identification, as studies suggest clothing conditions could have an impact (Keller et al., 2022). Ankle angles depend less on the hip landmark, potentially explaining their higher accuracy. The slight decrease in accuracy during toe-off gait events might be connected to the bending of the shoe in the toe region during toe-off gait, which interferes with the detection of toe landmarks.

The study's analysis revealed consistently low errors for the ankle joint across all gait events (MAE=1.79°, RMSE= 2.29°). This accuracy can be attributed to the clarity of ankle landmarks, which are less affected by external factors such as clothing movement, making it suitable for automated measurements for outdoor running. The hip joint also demonstrated commendable accuracy, particularly during midstance. Interestingly, the performance of specific joints varied depending on the gait phase. For instance, the initial contact of the knee joint showed impressive accuracy, while the hip joint achieved its highest precision during midstance. These discrepancies likely stem from challenges in detecting hip landmarks, influenced by clothing dynamics and hand proximity, as well as the rapid movements during toe-off. These findings highlight the nuanced relationship between joints and gait events when using BlazePose.

Compared to prior studies, the enhanced accuracy in joint angle measurement may be primarily attributed to the ground truth data used in this analysis. While this study focused on specific key gait events (IC, MS and TO), as these phases are more commonly associated with running injuries, it is essential to acknowledge that the selection of these events did not contribute to the higher accuracy. Furthermore, unlike previous studies that utilised 3D optical motion capture systems, Kinovea, a 2D analysis software, was employed as the reference standard due to the outdoor setting (Ota et al., 2020). Despite this limitation, the results were consistent with previous indoor studies. Future research could validate BlazePose against advanced motion capture technologies, such as Inertial Measurement Units (IMUs) and hybrid multi-camera setups consisting of 2D and 3D systems integrated with motion analysis software to comprehensively assess the joint angles in outdoor environments (Falbriard et al., 2018).

Limitations and future work

The study sample size of 16 male participants limits the generalizability of our findings. Future studies should aim to include a larger and more diverse participant pool, encompassing female athletes and individuals with varying body types and running styles, to better assess the result's robustness. Although Kinovea is a widely utilised tool, its limitations as a reference standard must be acknowledged. Future research should consider validating measurements with multi-camera setups integrated with motion analysis software. Furthermore, this study did not analyse the effects of lighting conditions and variable weather on measurements in outdoor settings. To improve the applicability of findings, it is crucial to validate pose estimation techniques like BlazePose across diverse environmental conditions and populations. This approach will enhance the reliability of measurements and contribute to a more comprehensive understanding of joint kinematics during outdoor running.

Conclusions

This study utilised BlazePose, a pose estimation algorithm, to accurately measure joint angles during outdoor running. The joint angles extracted were validated against Kinovea, demonstrating BlazePose's high accuracy with low error rates: MAE (2.11°), MAPE (1.57%), and RMSE (2.63°). Unlike previous research focused on indoor activities such as treadmill running, this study provides a unique evaluation of joint angles in dynamic outdoor environments. The findings underscore BlazePose's potential as a robust, affordable tool for biomechanical analysis, with significant benefits for improving running mechanics, aiding in injury prevention, and optimising training protocols. Future research should expand the sample size, incorporate diverse participants, and assess the algorithm's performance under varying environmental conditions. Validation against advanced motion capture technologies could further solidify BlazePose's accuracy in dynamic outdoor settings. Overall, BlazePose shows promise for improving running performance and injury prevention, making it a valuable asset for both athletes and clinicians. It has the potential to bridge the gap between laboratory analysis and field-based applications in sports and rehabilitation.

Ethical approval: The study design was approved by the SRM Medical College Hospital and Research Centre's Institutional Ethics Committee (IEC.NO.2841)

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Conflict of Interest: The author states no conflict of interest.

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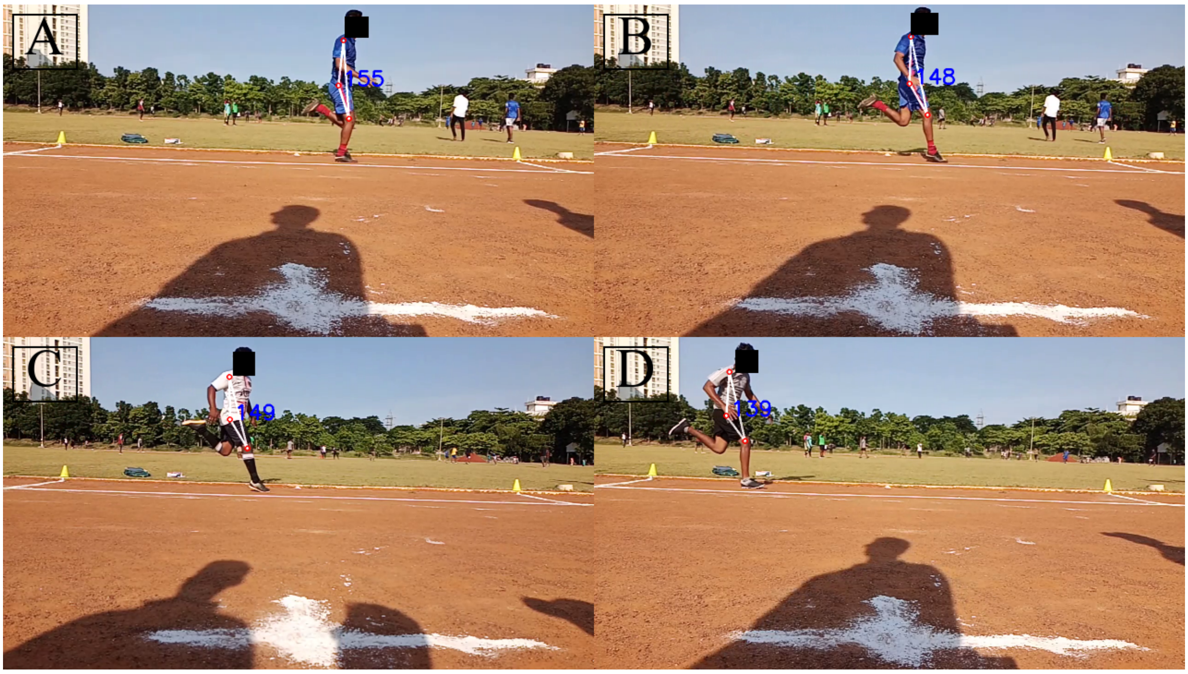
Suplementary

Supplementary Figure 1: Environmental Conditions

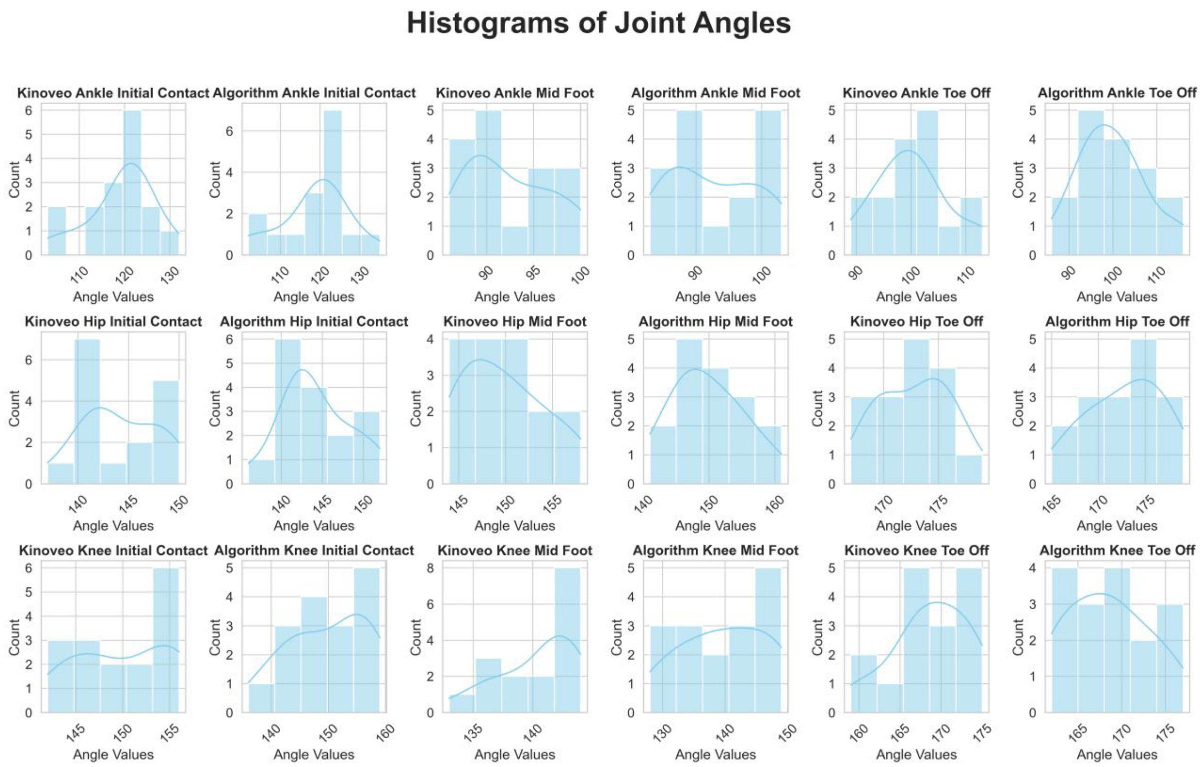


Supplementary Figure 2: Clothing and Appearance

Supplementary Table 1: Shapiro-Wilk statistics

Measurement	Shapiro-Wilk Statistic	p-value	Normally Distributed
Kinovea Ankle Initial Contact	0.9368	0.3114	Yes
Algorithm Ankle Initial Contact	0.9402	0.3510	Yes
Kinovea Ankle Mid Foot	0.9149	0.1397	Yes
Algorithm Ankle Mid Foot	0.9189	0.1618	Yes
Kinovea Ankle Toe Off	0.9615	0.6898	Yes
Algorithm Ankle Toe Off	0.9723	08745	Yes
Kinovea Hip Initial Contact	0.9384	0.3296	Yes
Algorithm Hip Initial Contact	0.9506	0.4985	Yes

Measurement	Shapiro-Wilk Statistic	p-value	Normally Distributed
Kinovea Hip Mid Foot	0.9335	0.3296	Yes
Algorithm Hip Mid Foot	0.9732	0.8878	Yes
Kinovea Hip Toe Off	0.9473	0.4488	Yes
Algorithm Hip Toe Off	0.9706	0.8489	Yes
Kinovea Knee Initial Contact	0.8976	0.0736	Yes
Algorithm Knee Initial Contact	0.9333	0.2753	Yes
Kinovea Knee Mid Foot	0.8930	0.0621	Yes
Algorithm Knee Mid Foot	0.9414	0.3670	Yes
Kinovea Knee Toe Off	0.9510	0.5063	Yes
Algorithm Knee Toe Off	0.9590	0.6432	Yes



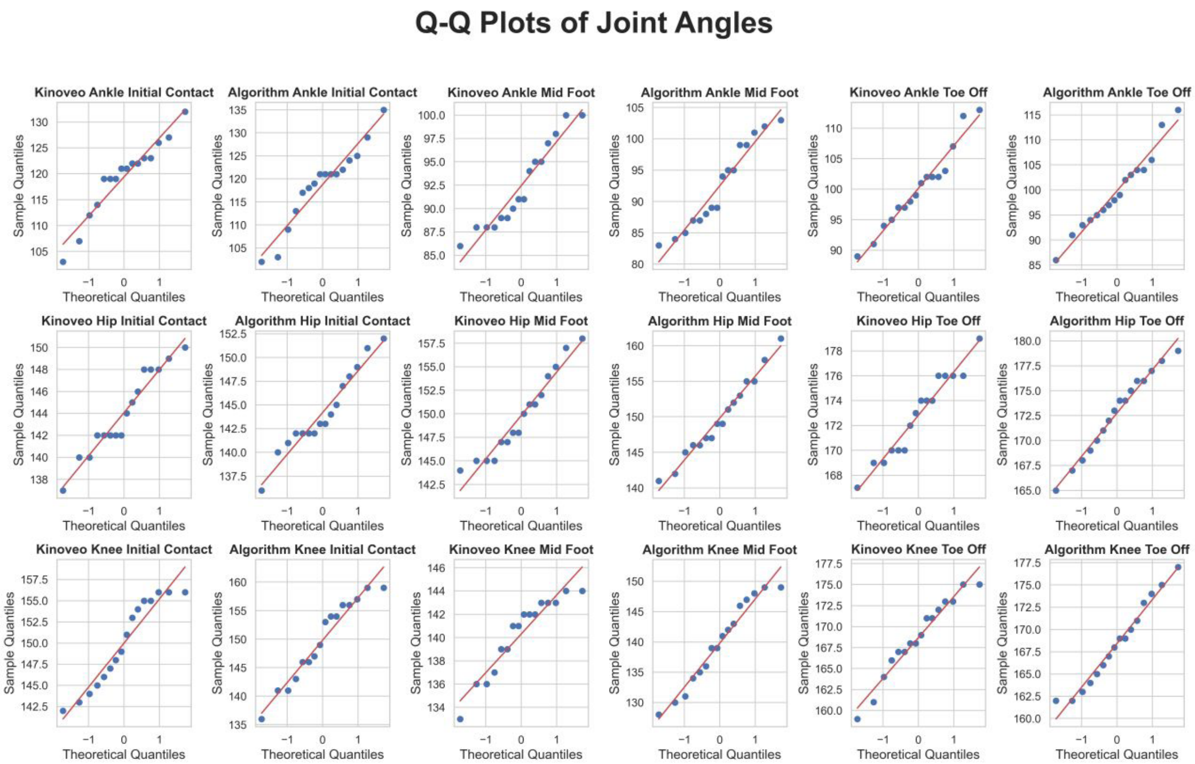
Supplementary Figure 3: Histograms

Supplementary Table 2: T-Test Results for Joint Angle Measurements

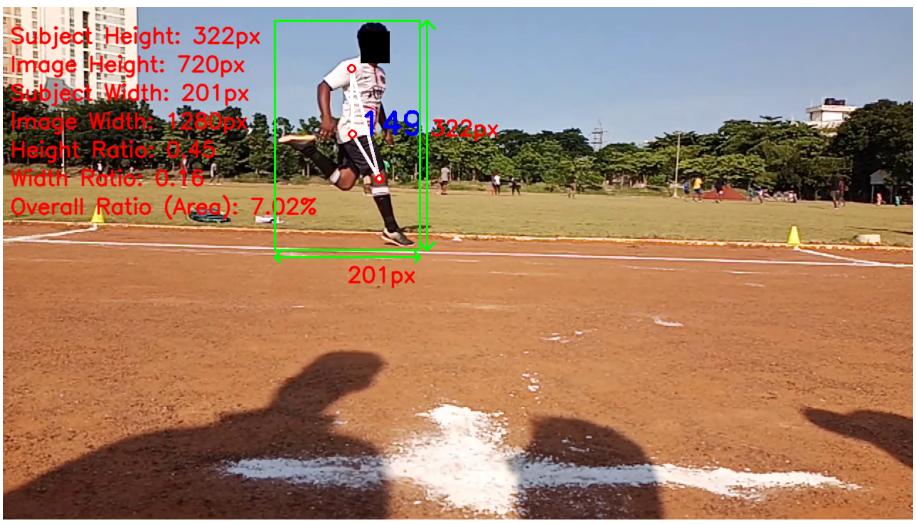
Joint	Gait Event	T-Statistic	P-Value	Confidence Interval (95%)
	IC	0.2199	0.8275	115.46–123.29
Ankle	MS	0.0821	0.9350	89.45–95.92
	TO	0.1213	0.9043	96.56–103.69
	IC	–0.0879	0.9306	142.05–146.08
Hip	MS	0.0000	1.0000	147.44–152.18
	TO	0.0469	0.9629	171.02–174.61

Joint	Gait Event	T-Statistic	P-Value	Confidence Interval (95%)
	IC	0.0853	0.9327	147.29–152.71
Knee	MS	0.0627	0.9505	137.87–142.00
	TO	0.1511	0.8809	166.20–171.18

IC = initial contact, MS = midstance, TO = toe-off



Supplementary Figure 4: Q-Q plots



Supplementary Figure 5: Height and Width Measurements of Subjects