

Strengthening Football Training Through Wearable Embedded Devices To Enhance Skills

Niu Zhirui*

School of Physical Education, Sichuan University of Commerce, Chengdu, Sichuan 61174, China

* Corresponding author. E-mail: niu_zhirui54@outlook.com, selian54680@nit.edu.rs

Received: Oct. 06, 2025; Accepted: Dec. 18, 2025

Wearable embedded devices are a significant innovation in football training, providing real-time physiological and technical data crucial for skill acquisition. This study assessed their efficacy in enhancing training efficiency compared to conventional methods. Thirty amateur and semi-professional players aged 18-30 participated, training while wearing devices equipped with motion and physiological sensors. Quantitative metrics-including sprint speed, passing efficiency, joint angular kinematics, and energy expenditure-were collected over six weeks, with baseline measurements taken before the intervention. Data analysis employed correlation and regression techniques to link wearable metrics with skill improvement. Results showed significant gains, including a 12% increase in passing accuracy and a 15% improvement in sprint speed. High correlation coefficients (above 0.7) indicated strong relationships between wearable-derived data and performance enhancements. The combination of real-time feedback and individualized training schedules proved more effective than traditional approaches. Overall, wearable embedded devices offer a novel, evidence-based, and personalized method for optimizing football training and improving technical, physical, and biomechanical performance.

Keywords: Football training; wearable embedded devices; skill enhancement; motion monitoring; physiological metrics; biomechanics; real-time analytics; performance optimization; IoT in sports

© The Author(s). This is an open-access article distributed under the terms of the [Creative Commons Attribution License \(CC BY 4.0\)](https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are cited.

http://dx.doi.org/10.6180/jase.202608_31.040

1. Introduction

Football training has evolved from traditional methods, which relied on imitation and subjective coach feedback, to more sophisticated approaches incorporating aerobic exercises, agility drills, skill development, tactical practice, and psychological conditioning [1]. Classical methods assess performance, such as dribbling or decision-making, but are limited by subjectivity and the need for manual interpretation, even when supported by video analysis [1]. Modern training is increasingly position-specific, with forwards focusing on scoring and speed, and goalkeepers on reactions and positioning, yet real-time, data-driven feedback remains limited [1, 2].

Wearable embedded devices have transformed training

by integrating sensors, microprocessors, and connectivity to monitor performance metrics such as distance, speed, acceleration, impacts, dribbling speed, shot power, and passing accuracy [2, 3]. Advances in IoT, sensor miniaturization, and cloud computing enable real-time analysis, feedback, fatigue monitoring, and long-term performance tracking [3]. These technologies allow individualized, targeted training programs that improve technical skills, endurance, and decision-making, providing a novel framework for optimizing football performance [3-5].

2. Materials and methods

2.1. Related Works

2.1.1. Motion Tracking Systems and Techniques in Football Training

Early video systems lacked individual precision. Wearable IMUs provide real-time speed, acceleration, and agility data, processed with machine learning and DTW to classify actions and monitor fatigue [5].

2.2. Wearable Physiological Signal Monitoring for Embedded Systems

PPG- and EMG-based wearables monitor cardiovascular fitness and muscle activation, guiding training intensity and preventing overtraining [5, 6]. A multimodal pipeline integrates PPG, EMG, and motion data with calibration and filtering, while EMG and sweat-analysis patches detect muscle imbalances, hydration, and metabolic status for optimized, preventive training.

2.3. Football Training Techniques to Enhance Skills

Technical and tactical drills enhance skills and decision-making, while wearable devices provide real-time, precise feedback on metrics like shot velocity, overcoming traditional training's subjectivity and enabling immediate skill improvement [7].

3. Results and discussion

3.1. Design and Implementation of Wearable Embedded Devices

3.1.1. Architecture of Wearable Devices

The architecture of wearable embedded devices for football training includes hardware sensors, microprocessors, and connectivity modules and software for data acquisition, real-time analysis, and feedback. IMUs, consisting of accelerometers, gyroscopes, and magnetometers, form the core hardware for capturing motion data [8]. See Fig. 1 below.

For instance, inertial measurement unit (IMU) can output linear acceleration (ax, ay, az) and angular velocity ($\omega x, \omega y, \omega z$) for 3D motion capture. The motion state of a player can be represented using Eq. (1);

$$V = \int s(t)dt \quad (1)$$

Velocity (v) and instantaneous acceleration (t) allow precise speed control. Wearables also include PPG and EMG sensors, providing real-time data on heart rate, muscle activity, and player physical condition (Fig. 2). Accelerometer and gyroscope data were recorded at 200 Hz (0.5 – 20 Hz),

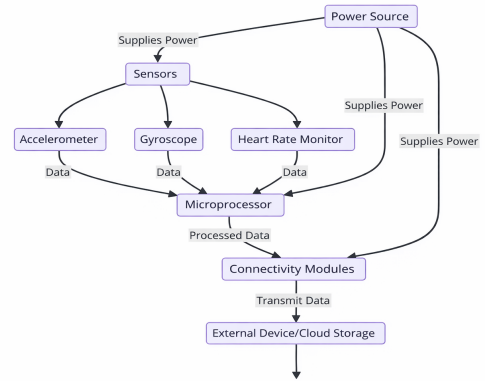


Fig. 1. Architecture of Wearable Embedded Devices

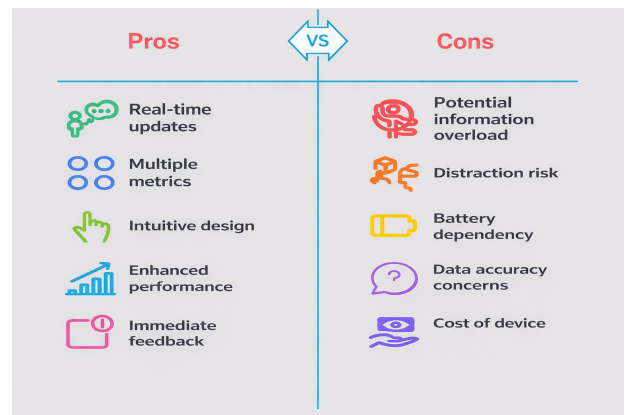


Fig. 2. Real-Time Feedback Display Interface

PPG at 100 Hz (0.7 – 4 Hz), and EMG at 1000 Hz (20 – 450 Hz), with Butterworth filters applied for motion and PPG signals. Microprocessors are the heart of the system, as they are responsible for data processing and applying analysis algorithms [8].

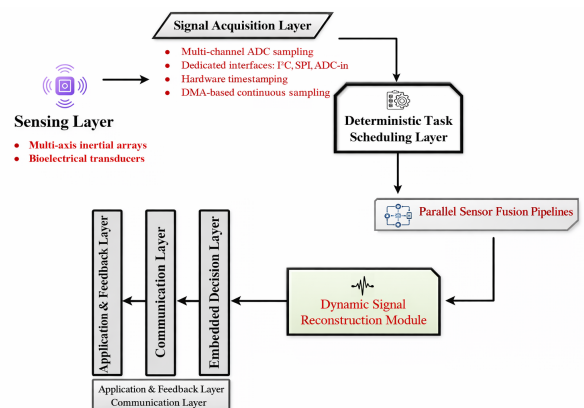


Fig. 3. Modular Cyber-Physical System Architecture for Multisensor Wearable Analytics

Some of the best examples include ARM Cortex-M microcontrollers series that offer high performance with low power consumption to extend battery life. The BLE and Wi-Fi connectivity modules allow transmitting data in real-time to other devices or to the cloud.

The Kalman filter fuses IMU, PPG, and EMG data to estimate movement and physiological states. Extracted features drive decision rules that generate coaching cues and adjust drills automatically. A closed-loop system updates thresholds based on outcomes, improving future training recommendations.

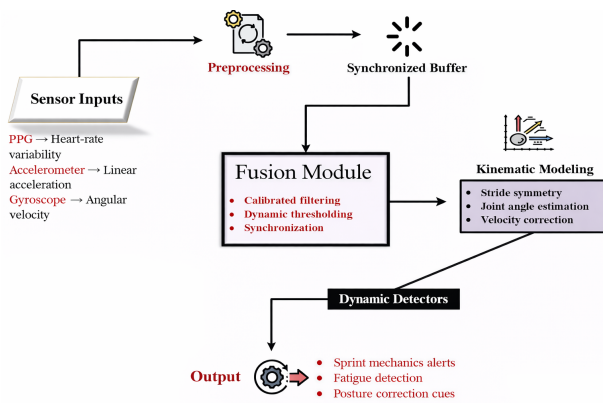


Fig. 4. Low-Latency Embedded Detector Fusion Architecture for PPG, Accelerometer, and Gyroscope Streams

The fusion architecture integrates PPG, accelerometer, and gyroscope data using calibrated filtering, artifact removal, and synchronized buffering, as shown in its entirety in Fig. 4. Dynamic thresholding and real-time kinematic modeling detect fatigue and asymmetry, enabling instant coaching cues and automatic drill adjustments for optimized football skill training.

Fig. 5 shows the closed-loop feedback structure where sensor inputs undergo Kalman estimation, feature extraction, and decision mapping for real-time coaching cues and training adjustments.

3.2. Metrics Measured

Wearable embedded devices in football training are designed to monitor three primary categories of metrics: physical, technical, and biomechanical. Physical metrics such as speed, acceleration, and endurance are crucial for evaluating a player's overall fitness. Speed is derived from positional data, while acceleration is computed using;

$$a = \frac{\Delta v}{\Delta t} \quad (2)$$

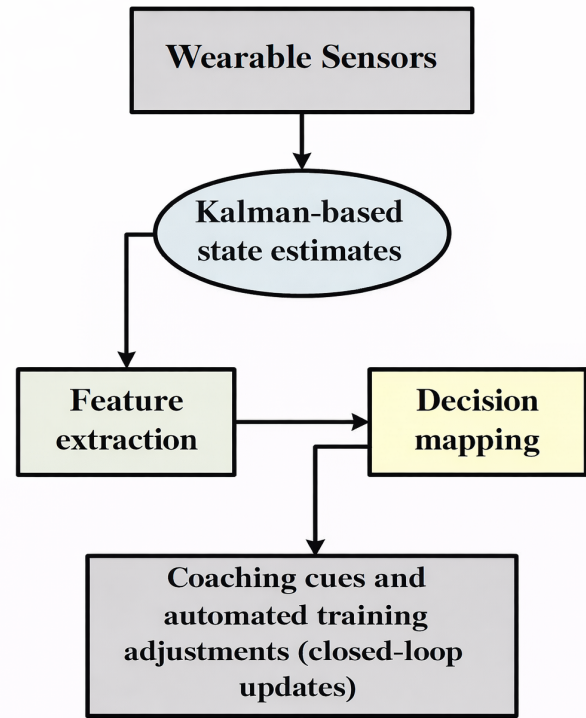


Fig. 5. Kalman Filter-Driven Feedback-to-Coaching Flow Diagram

Endurance metrics track total distance (d total) and high-intensity sprints (v threshold), while technical metrics evaluate ball-handling, passing accuracy, and shot precision, analyzing dribble contact time and velocity changes [8, 9].

A poly-dimensional quantification outlines integrated kinematic reconstruction, dynamic force vector mapping, and spatiotemporal trajectory analytics with algorithmic normalization of velocity, acceleration, and joint angular displacement. Joint angles are measured using gyroscopic data, providing insights into the range of motion. For instance, knee flexion during a sprint is derived using trigonometric calculations based on sensor data.

3.3. Data Transmission and Storage

Wearable devices use IoT for seamless data transmission, acting as network nodes sending information to hubs or the cloud [9]. Bluetooth Low Energy (BLE) enables low-power shortrange communication, with transmission power estimated via the Friis equation (Fig. 6);

$$P_t = P_r \cdot \left(\frac{4\pi d}{\lambda} \right)^2 \quad (3)$$

P_r is the received power. d is the distance between transmitter and receiver, and λ is the wavelength of the signal. Wi-Fi and LoRaWAN are used for transporting data over

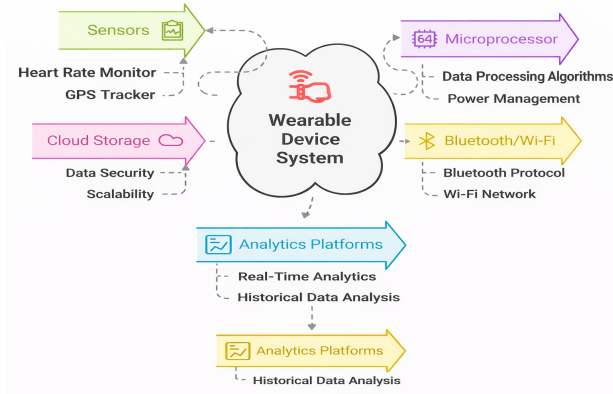


Fig. 6. Data Transmission and Storage Flow

long distances. These systems provide reliable transmission over longer distances while at the same time optimizing on the bandwidth and power usage [9, 10]. Error detection mechanisms such as cyclic redundancy check (CRC) are used to check for corrupted packets and ask for a repeat of the data.

The telemetry system uses adaptive sampling, error correction, wavelet compression, and AES-128 encryption for secure, low-latency (< 80 ms) wearable data transmission, with cloud storage enabling efficient long-term analysis and historical performance tracking.

3.4. Experiment and Analysis

3.4.1. Participants

Thirty semi-professional male footballers (18-30) were grouped by skill level. Training included speed, passing, shooting, and HIIT endurance drills, with wearable devices monitoring acceleration, velocity, heart rate, and recovery [10, 11].

3.4.2. Methodology

The experiment involved baseline testing, six-week wearable-assisted training, and systematic data capture of physical, technical, and biomechanical performance [11, 12]. Synchronized biomechanical framework aligned sensors, calibrated data, establishing baseline metrics [12]. Players used anthropometry-tailored wearables with calibrated, synchronized sensors. Preprocessing—including Butterworth filtering, thresholding, outlier removal, and drift correction—ensured accurate physical, technical, and biomechanical data, enabling reliable realtime feedback during five weekly two-hour training sessions [12, 13].

High-resolution temporal analytics utilize sliding-window spectral decomposition for HRV and obtain joint-angle kinematic derivatives that help in capturing transient fluctuations in sprint, agility, and ball-control drills. As

a result, detection of micro-variations in fatigue, reaction timing, and coordination is enabled. For example, the knee flexion angle (θ_k) was calculated from sensor data as;

$$\theta_k = \arccos \left(\frac{V_1 \cdot V_2}{|V_1| |V_2|} \right) \quad (4)$$

v_1 and v_2 are vectors. Representing thigh and lower leg orientations. Improvements in balance were quantified by analyzing the center of pressure (CoP) trajectory. During dynamic movements, using root mean square (RMS) deviations as a metric [13].

3.5. Data Analysis and Results

Collected data were analyzed using statistical techniques, including correlation and paired t-tests ($p < 0.05$), to assess improvements in football training performance [14].

$$\Delta t_{avg} = \frac{\sum_{i=1}^n (t_{avg}^o - t_{avg}^f)}{n} \quad (5)$$

An embedded statistical engine performs automated feature selection, multivariate regression modeling, and heteroscedasticity correction. Real-time visualization of coefficient confidence intervals supports continuous assessment of wearable-derived performance indicators. As shown in Fig. 7.

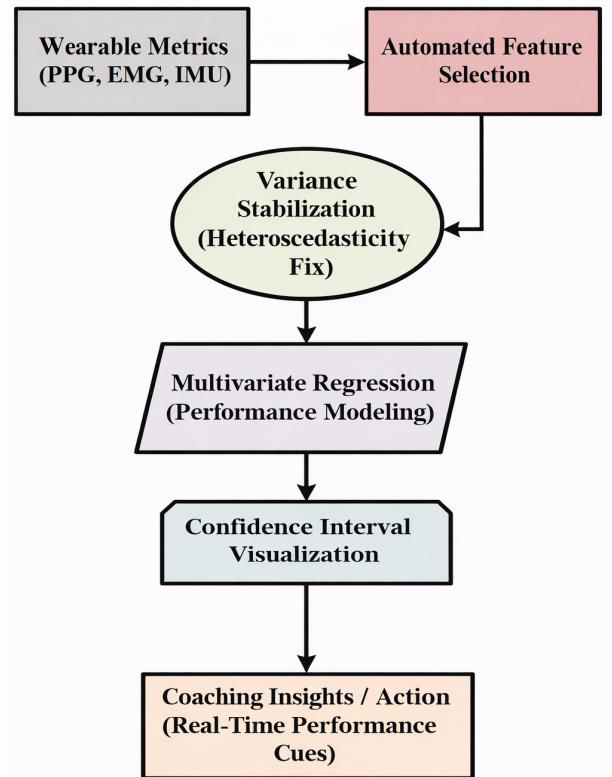


Fig. 7. Statistical Engine Flow for Wearable Data Analysis

3.5.1. Correlation Analysis

Correlation analysis was performed to examine relationships between metrics recorded by the wearable devices and skill enhancement. Metrics such as stride length, passing accuracy, and heart rate variability (HRV) were correlated with performance outcomes using Pearson’s correlation coefficient (r);

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (6)$$

Correlation analysis examined the relationship between wearable device metrics and skill improvement. A multi-gauge fusion background integrates synchronized biomechanical, physiological, and technical streams through precise temporal alignment and covariance-optimized signal weighting. Dynamic outlier filtering removes anomalous signal bursts arising from abrupt impacts or sensor jitter. See Fig. 8 and Table 1)

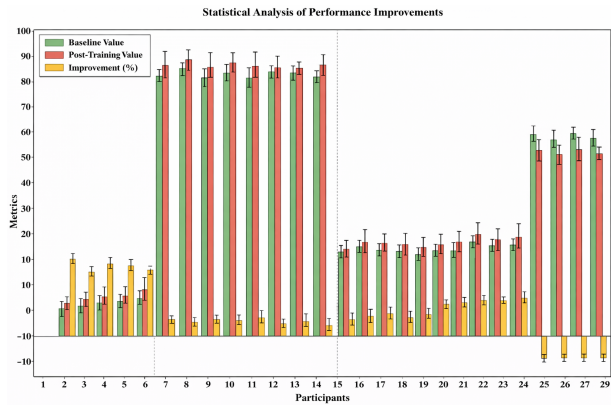


Fig. 8. Statistical Analysis of Performance Improvements

High positive correlations and significant p-values confirm wearable-measured metrics strongly relate to football performance, identifying key indicators for skill development.

Negative correlation between heart rate recovery and endurance improvement reflects the expected inverse relationship. Where faster recovery times correspond to greater endurance gains. High correlations across other metrics further validate the strong association between wearable device data and enhanced performance [14].

3.5.2. Paired t-tests

Paired t-tests in Table 2 demonstrate significant improvements in all measured metrics after incorporating wearable devices into football training. Each metric’s p-value is less than 0.01, indicating that the observed changes are statistically significant and unlikely to have occurred by chance (See Fig. 9).

In every aspect of performance measurement, there was a significant difference attributed to the use of wearable technology in training. The smaller p-values provide strong evidence that the alterations seen were not simply a matter of luck, thus, the advantage of immediate feedback in the training times is being stressed.

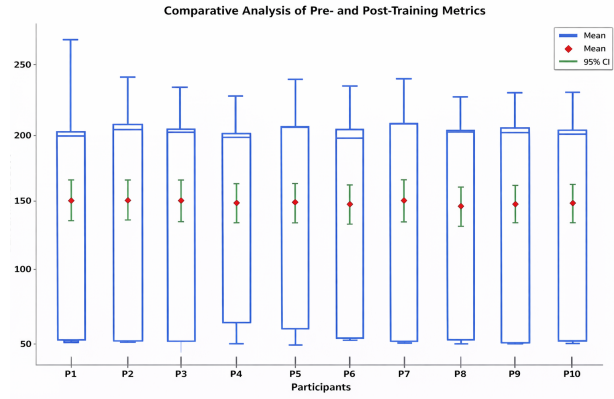


Fig. 9. Comparative Analysis of Pre- and Post-Training Metrics.

3.5.3. Regression analysis

To further analyze the predictive power of wearable metrics, regression models were fitted to assess their impact on skill improvement.

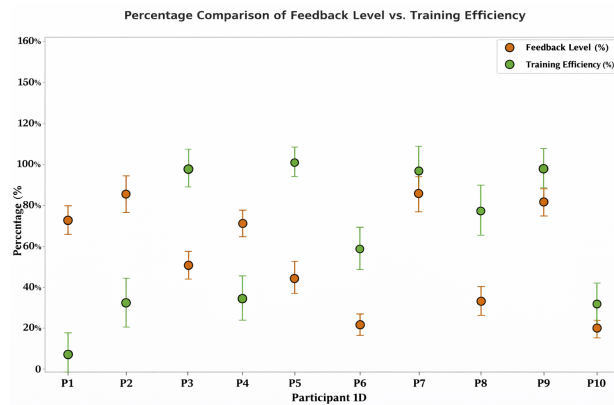


Fig. 10. Impact of Real-Time Feedback on Training Efficiency

Table 3 shows that sprint speed and joint flexion angles positively predict skill improvement, whereas heart rate recovery inversely affects it. See Fig. 10.

Comparative bar chart represented in Fig. 11 is a visual summary of pre- and post-training values for sprint time, passing accuracy, shot precision, endurance score, and heart rate recovery. Moreover, the visual comparison

Table 1. Correlation Between Wearable Metrics and Football Skill Performance

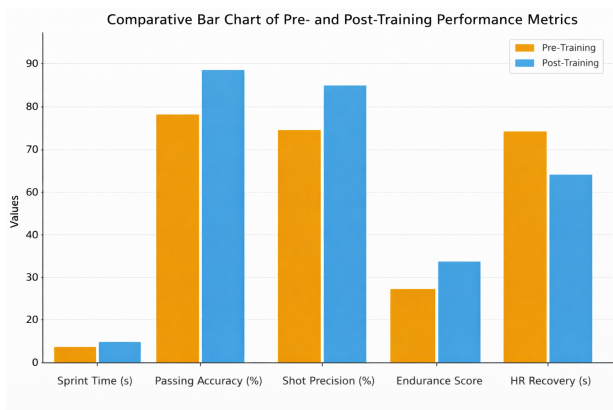
Metric	Skill performance	Correlation coefficient (r)	Significance (p)
Sprint speed (ms)	Passing accuracy (%)	r = 0.78	p < 0.01
Heart rate recovery (s)	Endurance improvement (%)	r = -0.85	p < 0.01
Joint flexion angle (°)	Shot precision (%)	r = 0.69	p = < 0.05
Center of pressure stability (RMS)	Ball control (%)	r = 0.81	p < 0.01

Table 2. Paired t-Test Results Showing Pre- and Post-Experiment Differences in Football Training Metrics Using Wearable Devices

Metric	Mean (baseline)	Mean (post experiment)	t-statistic	p-value
Sprint time (s)	5.48	4.93	t=8.62	p<0.01
Passing accuracy (%)	72.4	85.7	t = 12.31	p < 0.01
Shot precision (%)	68.1	80.9	t = 10.45	p < 0.01
Endurance score (Yo-Yo)	16.5	19.8	t = 14.21	p < 0.01
HR recovery time (s)	63.2	48.7	t = -15.78	p < 0.01

Table 3. Regression Analysis Results for Predicting Football Skill Performance

Predictor	Coefficient (β)	Standard error	t-value	p-value
Intercept (β_0)	5.34	1.23	4.34	p < 0.01
Sprint speed (β_1)	1.48	0.37	4.00	p<0.01
Joint flexion (β_2)	0.95	0.41	2.32	p<0.05
HR Recovery (β_3)	-0.72	0.19	-3.79	p<0.01

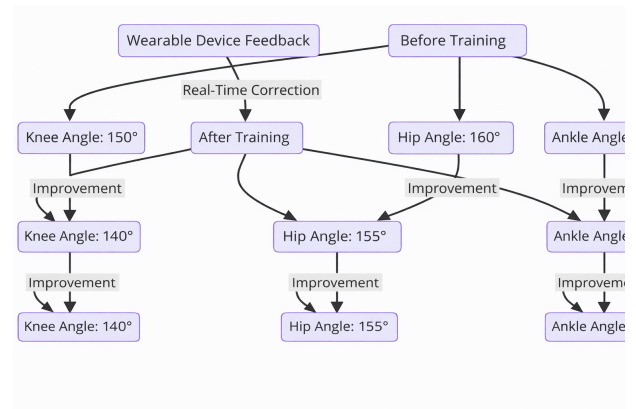
**Fig. 11.** Bar chart of pre and post training

not only illustrates the extent of improvements on all performance indicators, but also supports the statistical results given in Tables 1 and 2.

3.5.4. Discussion

Participants showed 10.04% faster sprints and 20% Yo-Yo endurance improvement, reflecting enhanced speed, acceleration, recovery, and heart health. A p-value < 0.01 for sprint improvement indicates match-level benefits. Enhanced passing, shooting, HR recovery, joint stability, and coordination improve performance, while varied individ-

ual responses emphasize the need for personalized feedback and adaptive training adjustments (shown in Fig. 12).

**Fig. 12.** Biomechanical Improvements in Posture

Technical skill enhancement led to an 85.7% passing accuracy and 18.83% improved shot precision, with strong feedback-performance correlation (r = 0.89) [15]. Biomechanical data improved posture and balance, reducing injury risk. Wearables enhanced ball control, decisionmaking, and reduced turnovers by 12%.

4. Conclusion and future work

Wearable embedded devices improve football training by monitoring speed, endurance, ball control, posture, and biomechanics, providing real-time, individualized feedback, enhancing performance, preventing injuries, though data quality and cost remain challenge. Wearable devices enhance football training with data-driven decisions, personalized feedback, and fatigue monitoring, though challenges like wireless latency, sensor drift, and limited battery life (~ 6 – 7 hours) require future optimization. Future work may integrate AI and cloud systems to predict performance, assess injury risk, and enable adaptive, scalable training.

5. Declarations

Funding: Authors did not receive any funding.

Conflicts of interests: Authors do not have any conflicts.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Code availability: Not applicable.

Authors' Contributions: Niu Zhirui is responsible for designing the framework, analyzing the performance, validating the results, and writing the article.

References

- [1] H. Song, (2021) "Application of embedded wearable devices in football training injury prevention" **Microprocessors and Microsystems** 82: 103915. DOI: [10.1016/j.micpro.2021.103915](https://doi.org/10.1016/j.micpro.2021.103915).
- [2] P. Tierney. "Wearable Technology in Football Further Education Settings in the United Kingdom". (phdthesis). Liverpool John Moores University, 2021. DOI: [10.24377/LJMU.d.00000107](https://doi.org/10.24377/LJMU.d.00000107).
- [3] Y. Wen, (2023) "Research on the Training Model of Engineering Excellence" **Journal of Applied Science and Engineering Innovation** 10(2): 59–63.
- [4] D. He and L. Li, (2021) "A novel deep learning method based on modified recurrent neural network for sports posture recognition" **Journal of Applied Science and Engineering** 24(1): 43–48. DOI: [10.6180/jase.202102_24\(1\).0005](https://doi.org/10.6180/jase.202102_24(1).0005).
- [5] P. Tierney, N. Clarke, and S. Roberts, (2024) "Use and application of wearable technology in football further education settings in the UK" **Sport, Education and Society**: 1–14. DOI: [10.1080/13573322.2024.2404896](https://doi.org/10.1080/13573322.2024.2404896).
- [6] G. Aroganam. "Design of performance data through wearable technology for ankle movement upon football shots". (phdthesis). Brunel University London, 2023.
- [7] F. Chen, (2021) "Athlete muscle measurement and exercise data monitoring based on embedded system and wearable devices" **Microprocessors and Microsystems** 82: 103901. DOI: [10.1016/j.micpro.2021.103901](https://doi.org/10.1016/j.micpro.2021.103901).
- [8] A. Seçkin, B. Ateş, and M. Seçkin, (2023) "Review on Wearable Technology in sports: Concepts, Challenges and opportunities" **Applied Sciences** 13(18): 10399. DOI: [10.3390/app131810399](https://doi.org/10.3390/app131810399).
- [9] M. Cardinale and M. C. Varley, (2017) "Wearable training-monitoring technology: applications, challenges, and opportunities" **International Journal of Sports Physiology and Performance** 12(s2): S2–55. DOI: [10.1123/ijspp.2016-0423](https://doi.org/10.1123/ijspp.2016-0423).
- [10] N. Mateus, J. Exel, S. Santos, B. Gonçalves, and J. Sampaio, (2023) "Effectiveness of wearable technology to optimize youth soccer players' off-training behaviour and training responses: a parallel group randomized trial" **Science and Medicine in Football** 7(4): 384–393. DOI: [10.1080/24733938.2022.2114604](https://doi.org/10.1080/24733938.2022.2114604).
- [11] G. M. Migliaccio, J. Padulo, and L. Russo, (2024) "The impact of wearable technologies on marginal gains in sports performance: An integrative overview on advances in sports, exercise, and health" **Applied Sciences** 14(15): 6649. DOI: [10.3390/app14156649](https://doi.org/10.3390/app14156649).
- [12] A. bin Hamid, (2024) "Advancements in Wearable Technology For Enhancing Athletic Performance And Training" **Revista Multidisciplinar de las Ciencias del Deporte** 24(96):
- [13] R. Lindberg, J. Seo, and T. H. Laine, (2016) "Enhancing physical education with exergames and wearable technology" **IEEE Transactions on Learning Technologies** 9(4): 328–341. DOI: [10.1109/TLT.2016.2557338](https://doi.org/10.1109/TLT.2016.2557338).
- [14] X. Li, D. Fan, J. Feng, Y. Lei, C. Cheng, and X. Li, (2024) "Systematic review of motion capture in virtual reality: Enhancing the precision of sports training" **Journal of Ambient Intelligence and Smart Environments**: 1–23. DOI: [10.3233/AIS-230198](https://doi.org/10.3233/AIS-230198).
- [15] L. Yang, O. Amin, and B. Shihada, (2024) "Intelligent wearable systems: Opportunities and challenges in health and sports" **ACM Computing Surveys** 56(7): 1–42. DOI: [10.1145/3649456](https://doi.org/10.1145/3649456).