

Artificial intelligence in football training: A systematic review

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Abstract:

Background: Although The integration of Artificial Intelligence into football training has expanded considerably. The existing literature predominantly aggregates match analytics, tactical modeling and injury prevention. No systematic review has specifically examined AI applications in training environments dedicated to the development of technical and tactical skills in football environment. **Methods:** In accordance with PRISMA guidelines, five electronic databases (Google Scholar, Scopus, PubMed, EBESCO and SPORTDiscus) were systematically searched. Eight empirical studies satisfied the inclusion criteria and were evaluated using the Mixed Methods Appraisal Tool. **Results:** Studies fell into two clusters: data-driven assessment and classification tools (n = 5) and AI-enhanced feedback interventions (n = 3). Machine learning and deep learning architecture, including Artificial Neural Networks (ANN) and Convolutional neural Networks (CNN), achieved high classification and skill discrimination accuracy in controlled settings. However real-world deployment revealed significant performance degradation: CNN shot detection sensitivity dropped from 75% in laboratory conditions to 45% in field scenarios, while Support Vector Machine (SVM) pass sensitivity reached only 20.9%. Among intervention studies, only one utilized a conventional coaching control group, demonstrating a 2.5fold greater improvement in tackling technique with AI driven 3D visual feedback (23.84%) compared to verbal coaching (9.63%). **Conclusion:** AI driven tools offer significant promise as objective, augmented coaching aids for movement analysis and skill feedback. The use of AI should be positioned as an augmented coaching aid rather than a replacement for coaching expertise, with adoption barriers being largely organizational rather than technical. Future research priorities include large scale RCTs, Longitudinal retention studies, standardized effect size reporting, and geographic diversification beyond the current Asia centric literature.

Key Words: Deep learning; Computer Vision; Motor Skill Development; Augmented Feedback; Soccer Training.

Introduction

Football is the world's most widely practiced team sport, demanding the simultaneous development of technical proficiency (Lee et al., 2023), tactical intelligence (Calster et al., s. d.), and physical capacity across all levels of play (Lampre-Ezquerria et al., 2026). Traditionally, football training has relied on coach-led observation and experiential judgment to assess player performance and guide skill development (Ma, 2024). While this model has proven effective in building foundational competencies, it is inherently constrained by subjective evaluation, inconsistency among assessors, and the practical difficulty of delivering individualized feedback within large-group training environments (Zaharia et al., 2023).

Against this backdrop, the integration of Artificial Intelligence (AI) into sport science has grown substantially over the past decade (Dakwala & Chen, 2025), with football emerging as one of the most extensively studied domains (Liu et al., 2026). Across a growing body of research, AI-driven tools, encompassing machine learning (ML), deep learning (DL), and computer vision, have been applied to a wide

range of football-related problems, including match outcome prediction, injury risk modelling, physiological monitoring, and tactical pattern recognition (Berrar et al., 2024; Claudino et al., 2019; Elstak et al., 2024). These diverse applications reflect the broad versatility of AI as an analytical framework and have generated considerable interest among researchers, practitioners, and governing bodies alike (Liu et al., 2026).

However, the scope of existing literature on AI in football has remained predominantly broad (Yang et al., 2026), with reviews and empirical studies tending to aggregate training applications alongside match analysis, injury prevention, and general performance monitoring without isolating the specific question of how AI tools function within the training environment itself (Elstak et al., 2024; Hewitt & Karakuş, 2023). This breadth, while valuable for mapping the overall landscape of AI adoption in the sport (Weiss & Morales-Ponce, 2026), obscures a more targeted and practically urgent question: to what extent are AI-driven tools being applied specifically within football training to develop technical and tactical skills, and what does the evidence say about their effectiveness?

This distinction matters for both scientific and applied reasons. From a scientific standpoint, the mechanisms through which AI may support skill development are distinct from those underlying match analytics and warrant dedicated investigation (Tian et al., 2024). From an applied perspective, coaches and sport scientists need clear, evidence-based guidance on using AI in training, such as going beyond general capabilities to focus on measurable training outcomes (Gautam et al., 2025; Pillitteri, 2025). Augmented feedback theory provides a relevant conceptual lens: a well-established body of motor learning research demonstrates that characteristics of feedback, such as its modality, timing, and frequency, play a critical role in shaping skill acquisition and learning outcomes (Petancevski et al., 2022). This is further reflected in applied contexts, where feedback interventions including video-based and AI-enhanced approaches have been shown to support skill development and performance improvement (Bridgeman & Giraldez-Hayes, 2024; Harris et al., 2020). The question of whether AI-driven tools can deliver feedback that is more precise (Pollard & Reep, 1997), consistent, and individualized than traditional coaching methods is therefore not only technologically interesting but theoretically grounded (Bouzid et al., 2026).

Within training contexts, two functionally distinct categories of AI application have emerged in the literature (Arocena, 2025; Weiss & Morales-Ponce, 2026; Yu, 2024). The first encompasses data-driven assessment and classification systems i.e. tools that use algorithms such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Convolutional Neural Networks (CNNs) to objectively quantify, classify, and monitor player movement and performance (Abdullah et al., 2016; Stoeve et al., 2021; Zhou et al., 2022). These systems address a longstanding limitation of observational coaching by introducing reproducible, quantitative measures of technical execution. The second category encompasses AI-enhanced feedback and visualization systems. These are tools that use motion capture, computer vision, and three-dimensional animation to deliver structured, individualized feedback to players during or following training sessions (Cao et al., 2023; Mazian et al., 2025; Sami Bouzid et al., 2025). While both categories represent meaningful departures from traditional coaching methods, they address different phases of the coaching process: measurement and intervention, respectively. Moreover, their evidence bases differ in both maturity and depth (Dudek et al., 2025).

Despite the increasing volume of research on artificial intelligence in football, much of the existing literature has focused broadly on performance analytics, match analysis, injury prediction, and decision-making. Comparatively less attention has been given to AI-driven tools used specifically within football training environments to support technical and tactical skill development. To date, no systematic review has clearly isolated these training-focused applications as a distinct body of evidence. This represents an important gap, as practitioners and researchers currently lack a focused synthesis of which AI tools have demonstrated practical value, which remain experimental, and what methodological limitations restrict their wider adoption.

The aim of this systematic review is to examine how AI-driven tools are currently applied in football training contexts and to evaluate the strength and consistency of empirical evidence regarding their effects on technical and tactical skill development. Specifically, the review seeks to identify the main types of AI applications used in training, including assessment-oriented tools that analyse player performance and feedback-oriented systems that support learning, correction, and decision-making. It also aims to critically appraise the methodological quality of existing studies and highlight the key gaps that should guide future research.

The review is guided by the hypothesis that AI-driven tools have strong potential to enhance football training by improving performance assessment, providing individualized feedback, and supporting the development of technical and tactical skills. However, it is also expected that the current evidence base remains inconsistent and methodologically limited, making it difficult to draw strong conclusions about their effectiveness in applied training settings.

Conceptually, this review contributes to the field by distinguishing AI applications in football training from the broader domain of football analytics and by organizing the evidence around their role in skill development. In practice, the findings may support coaches, sports scientists, and practitioners in making more informed decisions about the responsible integration of AI tools into football training programs. By identifying both the demonstrated benefits and current limitations of these technologies, this review also provides guidance for future intervention studies and encourages more rigorous research designs to evaluate the real-world impact

of AI in football training. While existing reviews have mapped AI applications broadly across football, none have isolated the training environment as a distinct evidence base, a gap this review addresses.

Material & methods

This systematic literature review was preregistered and is publicly available on the Open Science Framework (OSF; DOI: 10.17605/OSF.IO/E4CBN).

Inclusion and Exclusion

This systematic review includes empirical studies examining the application of AI-driven tools, specifically data-driven assessment systems and AI-enhanced visual feedback technologies within football training environments, with a focus on their impact on technical and tactical skill development. Eligible participants include amateur and professional football players of all ages and genders. All empirical study designs, including experimental, quasi-experimental, and case studies, published in peer-reviewed English-language journals were considered for inclusion.

Studies were excluded if they focused on outcomes unrelated to the review aims, including match outcome prediction, injury prevention, and physiological analysis. Research examining other football codes, including rugby, American football, futsal, and beach soccer, was excluded. As were studies focused exclusively on the development of coaches or physical education teachers working with AI tools. Non-peer-reviewed sources, including theses, conference abstracts, book chapters, editorials, commentaries, and grey literature, were excluded. Studies lacking human participants or sufficient methodological detail to permit quality appraisal were also eliminated.

Search Strategy

This systematic review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Liberati et al., 2009). A comprehensive literature search was performed across five major electronic databases: Google Scholar, Scopus, PubMed, EBSCO, and SPORTDiscus. Searches were conducted using predefined keywords and Boolean operators combining terms across three conceptual domains: AI tools, sport context, and training application. Wildcard operators were applied where appropriate to capture variant word forms. Full search terms and Boolean combinations are reported in Table 2. The initial screening and selection of studies were conducted independently by both authors following a standardized eligibility procedure. Each author screened titles and abstracts independently against the predefined inclusion and exclusion criteria before proceeding to full-text review. Disagreements between reviewers were resolved through discussion and consensus. Neither reviewer prioritized specific journals or study designs during the selection process.

Search Outcome

Database searches retrieved a total of 110 records: PubMed (n = 10), EBSCO (n = 11), Scopus (n = 8), SPORTDiscus (n = 54), and Google Scholar (n = 27). An additional 31 records were identified through manual reference list screening of retrieved articles. After removing duplicate records, 137 articles were assessed for title and abstract eligibility. Of these, 109 were excluded at the initial screening stage. The remaining 28 articles proceeded to full-text review, of which 20 were subsequently excluded because their primary focus was on technology validation or algorithm development rather than football training outcomes. Ultimately, eight articles met all inclusion criteria and were included in the final synthesis (see Figure 1).

Quality Assessment

The methodological quality of included studies was appraised using the Mixed Methods Appraisal Tool (MMAT; Hong et al., 2018). The MMAT begins with a two-item preliminary screening phase assessing the clarity of the research question (S1) and the appropriateness of the collected data for addressing it (S2). Following this screening, each study is evaluated against five design-specific criteria: (Q1) relevance of the sampling strategy to the research question; (Q2) representativeness of the sample relative to the target population; (Q3) appropriateness of measurement tools; (Q4) risk of non-response bias; and (Q5) suitability of the statistical analysis. Each criterion is rated as Yes, No, or Uncertain, reflecting the methodological rigor and transparency demonstrated by the study (Hong et al., 2018).

Quality appraisal was conducted independently by two authors. Ratings were compared and any discrepancies resolved through discussion until consensus was reached. Appraisal outcomes are reported in Table 3. All eight studies satisfied the two preliminary screening criteria, demonstrating clearly defined research questions and appropriate data collection approaches. Across the substantive quality criteria, six studies were rated Yes across all applicable criteria, reflecting adequate methodological rigor relative to their respective designs. Two studies, however, warranted 'uncertain' ratings on specific criteria, for reasons grounded directly in the studies' own reported methods and acknowledged limitations. Mazian et al. (Mazian et al., 2025) received uncertain ratings on Q2 (sample representativeness) and Q5 (appropriateness of statistical analysis). Regarding Q2, the study recruited only two university football players from a single institution, selected by an AFC-certified coach. While a small purposive sample is appropriate for a system development and validation study, which this explicitly is, it cannot be considered representative of any broader player population. Therefore, findings cannot be generalized beyond proof-of-concept demonstration. Regarding Q5, the study reports no

inferential statistics. Results are presented as descriptive cross-validation percentages (ranging from 50% to 74% Extrinsic Feedback scores) and TRUE/FALSE comparison tables between Motion Template sets and Score Rubric Assessment benchmarks. This approach is appropriate for the study's validation purpose but precludes conclusions about statistical significance or effect magnitude, thereby limiting its contribution to evidence on training outcomes. Nevertheless, to overcome statistical limitation, we have calculated effect sizes for all studies in which the published data permitted it.

Liao & Fu (Liao & Fu, 2025) received uncertain ratings on Q2 (sample representativeness) and Q4 (risk of non-response bias), relating specifically to the qualitative interview component of this mixed-methods study. Regarding Q2, the interview sample comprised 30 sports teachers and five technology companies drawn from a single regional Chinese context. The authors explicitly acknowledge in their limitations section that the number of participating companies and teachers was relatively small and that future research should expand this sample to obtain more comprehensive results. The restricted geographic and institutional scope limits the transferability of findings regarding AI adoption factors to other educational and cultural contexts. Regarding Q4, the study does not report participant recruitment procedures, selection criteria for interviewed teachers and companies, or response rates. The absence of this information makes it impossible to assess whether those who participated differed systematically from those who did not. This introduces potential non-response bias in the qualitative findings. It should be noted that these concerns apply specifically to the interview component; the technical model development and performance evaluation components of Liao & Fu (Liao & Fu, 2025) were assessed as methodologically sound across all relevant criteria. These uncertain ratings do not disqualify the affected studies from inclusion. Both Mazian et al. (Mazian et al., 2025) and Liao & Fu (Liao & Fu, 2025) address research questions of direct relevance to this review, and their findings contribute meaningfully to the evidence base when interpreted within the appropriate scope of each study's design.

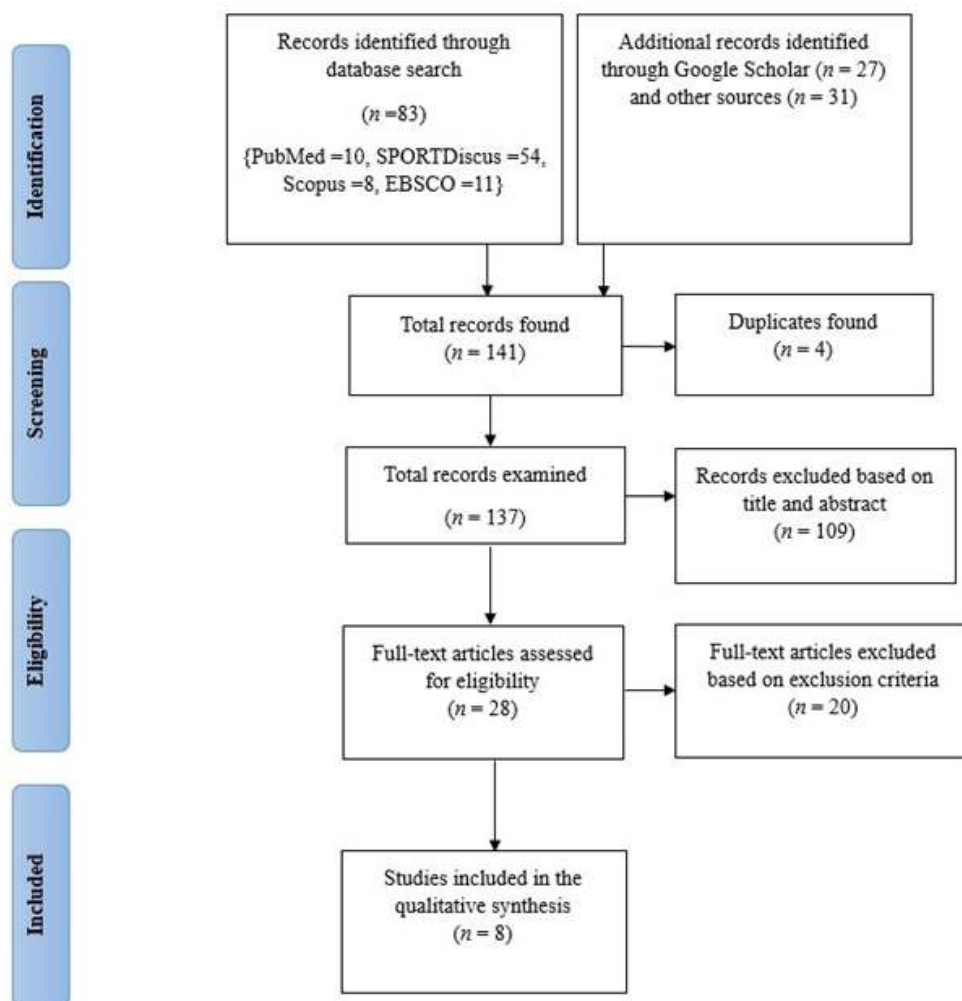


Figure 1. Flow chart of the PRISMA review

Table 1. Inclusion and Exclusion Criteria for Eligible Studies

Inclusion Criteria	Exclusion Criteria
- Articles published in English - All empirical studies and case studies - Articles in peer-reviewed journals - Studies examining AI-based motion capture, video-based feedback, or data-driven assessment tools within football training environments - Studies focused on the development of technical or tactical skills in football players of any age or competitive level	- Abstracts - Books (or chapters) - Conference Proceedings - Dissertations - Editorials, Commentaries - Literature and systematic reviews - Methodological papers - Short reports - Studies on other football codes (Rugby, American football, Futsal, Beach Soccer) - Research on unrelated outcomes (match prediction, injury prevention, physiological analysis)

Table 2. Search Terms and Boolean Operators Used in the Review

AND	AND
'Artificial Intelligence', OR 'Machine Learning', OR 'Deep Learning', OR 'Large Language Model*' OR "Neural Network*" OR "Computer Vision" OR "Vision-Based" OR "Automated Analysis" OR "Algorithm*" OR "Predictive Model*" OR "Classification Model*" OR "Pattern Recognition"	'Football', OR 'Association Football', OR 'Soccer' "Motion Capture" OR "Markerless Motion Capture" OR "Pose Estimation" OR "Human Pose Estimation" OR "Movement Analysis" OR "Performance Analysis" OR "Video Analysis" OR "Video-Based Feedback" OR "Visual Feedback" OR "Augmented Feedback" OR "Real-Time Feedback" OR "Automated Feedback" OR "Tracking System*" OR "Player Tracking" OR "Computer Vision-Based Tracking" OR "Data-Driven" OR "Analytics" OR "Performance Metric*"

Note: The wild card (*) extends the search to any ending of the word trunk

Table 3. Quality Assessment of the Studies Included based on MMAT

	S1-Are there clear research questions?	S2-Do the collected data allow for the research questions to be addressed?	Q1-Is the sampling strategy relevant to address the research question?	Q2-Is the sample representative of the target population?	Q3-Are the measurements appropriate?	Q4-Is the risk of nonresponse bias low?	Q5-Is the statistical analysis appropriate to answer the research question?
Abdullah et al., 2016 (Abdullah et al., 2016)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AbiDiN, 2021 (AbiDiN, 2021)	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Stoeve et al., 2021 (Stoeve et al., 2021)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zhou et al., 2022 (Zhou et al., 2022)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cao et al., 2023 (Cao et al., 2023)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Liao et al., 2025 (Liao & Fu, 2025)	Yes	Yes	Yes	Uncertain	Yes	Uncertain	Yes
Mazian et al., 2025 (Mazian et al., 2025)	Yes	Yes	Yes	Uncertain	Yes	Yes	Uncertain
Sami Bouzid et al., 2025 (Sami Bouzid et al., 2025)	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Results

The characteristics of the eight included studies are summarized in Table 4. Studies originated from Malaysia (Abdullah et al., 2016; Mazian et al., 2025), Turkey (AbiDiN, 2021), Germany (Stoeve et al., 2021), China (Cao et al., 2023; Liao & Fu, 2025; Zhou et al., 2022), and Tunisia (Sami Bouzid et al., 2025). Designs ranged from empirical and experimental studies to case studies and system validation work, reflecting the interdisciplinary nature of the field. Sample sizes ranged from two university players (Mazian et al., 2025) to 836 players across laboratory and field sessions (Stoeve et al., 2021). For synthesis purposes, studies are organized into two functional clusters: (1) data-driven assessment and classification, and (2) AI-enhanced feedback and visualization interventions.

Data-Driven Assessment and Classification Studies

Five studies examined AI as an assessment or classification tool (Abdullah et al., 2016; AbiDiN, 2021; Liao & Fu, 2025; Stoeve et al., 2021; Zhou et al., 2022). Abdullah et al. (Abdullah et al., 2016) applied principal component analysis (PCA) combined with a back-propagation ANN to performance data from 184 male youth players (mean age 15.2 ± 1.6 years) across eight Malaysian academies. PCA reduced 26 variables to 19 significant parameters (71.68% of cumulative variance), and hierarchical agglomerative cluster analysis (HACA) classified players into novice and elite groups. The optimum ANN architecture achieved a validation R^2 of 0.922, RMSE of 0.190, and misclassification rate of 0.065, demonstrating reliable skill-level discrimination from a reduced parameter set.

Abidin (AbiDiN, 2021) applied seven machine learning algorithms, including random forest, to training evaluation data from a U13 academy (Altinordu, Turkey) using the Hit/iT system. Results supported Machine Learning-assisted player selection and team composition decisions. Stoeve et al. (Stoeve et al., 2021) examined SVM and deep learning classifiers for shot and pass detection from inertial measurement units (IMU) sensors worn in football boot insoles, using data from 836 players across 181 sessions (laboratory and real-world). The SVM performed poorly in real-world conditions, achieving a pass sensitivity of only 20.9% and a shot sensitivity of 36.0% in field scenarios. The CNN achieved the highest weighted f1-score of 0.928 in real-world scenarios, substantially outperforming the SVM. Critically, however, even the CNN showed a meaningful drop in shot detection from laboratory (75%) to field conditions (45%), demonstrating that laboratory-trained models do not transfer reliably to real-world environments.

Zhou et al. (Zhou et al., 2022) developed a dual-stream CNN system for functional strength training using 4,800 training videos, achieving action recognition accuracy ranging from 89.8% (starting) to 97.6% (jumping). A small comparison experiment (approximately 10 athletes per group, one week) found AI-assisted training produced higher performance upgrade rates (maximum 25.7%) than traditional training (maximum 19.6%). Liao & Fu (Liao & Fu, 2025) built a CNN keypoint detection model trained on 27,987 annotated images, achieving over 90% accuracy and a mean Intersection over Union of 73.78% on a benchmark dataset, outperforming all comparison models. Environmental robustness was confirmed across a range of conditions (88.7%–92.3%). Notably, practitioner interviews with 30 teachers and five technology companies identified

policy, attitudinal, and infrastructural factors, not technical accuracy, as the primary barriers to AI adoption in training: a finding absent from all other studies in this cluster.

AI-Enhanced Feedback and Visualization Intervention Studies

Three studies examined AI as an active training intervention measuring skill change (Cao et al., 2023; Mazian et al., 2025; Sami Bouzid et al., 2025). Sami Bouzid et al. (Sami Bouzid et al., 2025) conducted a six-week experimental study with 23 male youth players (mean age 16.1 ± 0.4 years), in which the experimental group received 3D-animated visual feedback via the DeepMotion platform, while the control group received conventional coaching. The experimental group improved tackling performance by 23.84% compared to 9.63% in the control group, a 2.5-fold difference with motivation scores also improving. This is the only study in the review with a direct conventional coaching comparator, making it the most relevant source of evidence on comparative effectiveness.

Cao et al. (Cao et al., 2023) used a backpropagation neural network-based image processing model to evaluate kicking posture and provide automated feedback to 116 youth players (aged 8–13 years) across 24 training sessions conducted over one month. The model successfully demonstrated the capability to identify deviations from standard movement patterns which can support feedback for training. Mazian et al. (Mazian et al., 2025) developed Reverse-Gesture Description Language based motion templates for penalty kicks using full-body motion capture data from two university players. The system generated five biomechanical rules per template and differentiated between individual players' movement signatures through cross-validation against coach-evaluated rubric scores. Extrinsic Feedback scores (50%–74%) did not surpass coach benchmarks in any condition.

Effect Sizes

Effect sizes were calculated or extracted for three of the eight included studies where sufficient statistical data was available. Cao et al. (Cao et al., 2023) yielded an estimated average Cohen's $d = 0.58$ (medium), Liao and Fu (Liao & Fu, 2025) reported Cohen's $d = 0.62$ (medium-to-large), and Sami Bouzid et al. (Sami Bouzid et al., 2025) reported Cohen's d values ranging from 1.07 to 2.20 (large to very large). The average Cohen's d across the three studies was 1.13, indicating a large overall effect. For the remaining five studies, the nature of the reported data did not permit effect size calculation.

Table 4. Characteristics of the Studies Included

Author/Year	Country/Study Type	Sample size, Age, Gender	Aim	AI Tool/Approach	Key Findings
Abdullah et al., 2016 (Abdullah et al., 2016)	Malaysia / Empirical Study	184 male youth players; mean age 15.2 ± 1.6 years	To predict technical skill proficiency in Malaysian youth football players using multivariate analysis and Artificial Neural Networks	PCA for variable reduction; HACA for skill-level classification; back-propagation ANN for performance prediction	PCA-ANN model reliably discriminated novice from elite youth players using a reduced parameter set, demonstrating strong predictive accuracy for technical skill proficiency.
Abidin, 2021 (AbiDiN, 2021)	Turkey / Case Study	21 players (U13), Altinordu Football Academy	To apply ML algorithms to combined Hit/it training data and coach evaluations to support player selection and team formation decisions	Seven ML algorithms (including Random Forest, MLP, SVM) applied via WEKA to training performance and coach evaluation data	Random Forest outperformed all other algorithms in player selection and position classification; ML-generated lineups closely matched both the coach's ideal lineup and real match lineups across a full season.
Cao et al., 2023 (Cao et al., 2023)	China / Experimental Study	116 youth players, aged 8–13 years; experimental group $n = 60$, control group $n = 56$; gender not specified	To investigate the impact of functional strength training on the physical capabilities of youth football players and to develop a BPNN-based image processing approach for kicking posture recognition	BPNN applied to high-speed camera images of kicking actions; movement speed, sensitivity, and strength used as input vectors; similarity between player and standard kicking action as output	BPNN-based image processing successfully identified deviations in kicking technique from a standard movement template, demonstrating the system's capability to provide objective, automated feedback on technical execution.

Liao & Fu, 2025 (Liao & Fu, 2025)	China / Mixed-Methods Study (model development + qualitative interviews)	Model trained on 27,987 images (no human participant sample); interviews with 30 sports teachers and 5 technology companies	To develop a CNN-based keypoint detection model for youth football training and to identify factors influencing AI adoption in campus football through practitioner interviews	Deep learning CNN with cascaded detection and heatmap regression networks for player keypoint detection; trained on self-collected football training video images	The CNN keypoint detection model achieved strong technical accuracy and outperformed all comparison models; however, practitioner interviews revealed that policy, attitudinal, and infrastructural barriers, not technical limitations are the primary obstacles to real-world AI adoption in football training.
Mazian et al., 2025 (Mazian et al., 2025)	Malaysia / Experimental study	2 male university football players; Player A aged 23 (right-footed), Player B aged 22 (left-footed)	To develop and validate R-GDL-based Motion Templates for evaluating extrinsic feedback in penalty kick training using full-body motion capture data	R-GDL applied to motion capture data; five biomechanical rules generated per template capturing joint angles and limb trajectories	R-GDL-based Motion Templates successfully differentiated individual players' penalty kick movement signatures across conditions; however, Extrinsic Feedback Scores did not surpass coach-evaluated Score Rubric Assessment benchmarks in any condition.
Sami Bouzid et al., 2025 (Sami Bouzid et al., 2025)	Tunisia / Experimental Study	23 male youth players; mean age 16.1 ± 0.4 years; experimental group $n = 12$, control group $n = 11$	To examine the effects of AI-enhanced 3D animated visual feedback on tackling skill acquisition, biomechanical efficiency, and motivation in youth football players	DeepMotion Animate 3D platform; video footage converted into 3D animated motion capture visualizations delivered as augmented feedback to the experimental group following each tackling attempt	The AI feedback group demonstrated significantly greater improvements in tackling technique and biomechanical alignment compared to the verbal feedback control group, with intrinsic motivation also increasing significantly.
Stoeve et al., 2021 (Stoeve et al., 2021)	Germany / Empirical Study	836 players across 181 sessions (lab and field); youth to adult; 97% male-3% female	To compare SVM and deep learning models for IMU-based shot and pass detection across scenarios ranging from laboratory to real-world conditions	SVM compared against CNN, LSTM, and convLSTM applied to IMU insole sensor data across three evaluation scenarios	CNN achieved the highest classification performance overall, but all models showed meaningful degradation from lab to real-world conditions, underscoring that laboratory accuracy does not reliably transfer to applied training environments.
Zhou et al., 2022 (Zhou et al., 2022)	China / Empirical Study	Dataset of 4,800 training videos; ~20 athletes in comparative experiment	To develop and evaluate a CNN-based intelligent system for functional strength training of football players, and an FCN-based field line detection model for football robots	Dual-stream CNN for action recognition applied to training videos; FCN-based model for robot field line detection	The dual-stream CNN achieved the highest action recognition accuracy; AI-assisted training produced higher performance upgrade rates than traditional training across all five functional strength actions.

Note. PCA=Principal Component Analysis; HACA=Hierarchical Agglomerative Cluster Analysis; ANN=Artificial Neural Network; ML=Machine Learning; MLP=Multilayer Perceptron; SVM=Support Vector Machine; IMU=Inertial Measurement Units; CNN=Convolutional Neural Net; ConvLSTM=Convolutional Long Short-Term Memory; FCN=Fully Convolutional Network; BPNN=Backpropagation Neural Network; R-GDL=Reverse Gesture Description Language

Table 5. Architectural taxonomy of AI technologies Applied in football training

Technical category	Underlying algorithm	Architecture/	Primary Data /Input type	Included Studies	Functional Training Domain
Classical Machine Learning	- Support Vector Machine (SVM)	Vector	- IMU Sensor data	- Stoeve et al., 2021 (Stoeve et al., 2021)	- Shot and pass detection
	- Random forest		- stats and coach evaluation data	- Abidin, 2021 (AbiDiN, 2021)	- Players selection and position classification
Deep learning	- Convolutional Neural Networks (CNN)	Neural Networks	- Video streams and images	- Abdullah et al., 2016 (Abdullah et al., 2016)	- Technical skill prediction
	- Artificial Neural Networks (ANN)	Neural Networks	- Performance metrics	- Sami Bouzid et al., 2025 (Sami Bouzid et al., 2025)	- Action recognition and line detection
	- Backpropagation Neural Networks (BPNN)	Neural Networks	- High speed camera frames	- Liao & Fu, 2025 (Liao & Fu, 2025)	- Kicking posture recognition
	- Dual Stream CNN		- Annotated training videos	- Zhou et al., 2022 (Zhou et al., 2022)	- Key point detection
Expert/ Rule Based Systems	Reverse Gesture Description Language (R-GDL)		Full body motion capture data	- Cao et al., 2023 (Cao et al., 2023)	Biomechanical penalty Kick template

Note: This taxonomy shows literature is heavily saturated with AI Models focusing on computer vision and the current Soccer methodologies

Discussion

This review synthesized eight studies examining AI applications in football training across two functional categories: data-driven assessment and classification, and AI-enhanced feedback interventions. The findings indicate that AI tools are currently more mature as instruments of movement measurement than as instruments of skill development, a distinction with direct implications for research and practice. As the table 5, the taxonomy shows different architectures used by the authors with using the AI in the program trainings.

Unlike prior reviews, which broadly synthesize AI/ML applications in football across match prediction, injury risk, physiological monitoring, talent identification, tactical match analysis, and professional performance analytics, the present review is deliberately narrower. Rico-González et al. (Rico-González et al., 2022) reviewed ML in soccer across injury, performance, and talent forecasting; Teixeira et al. (Teixeira et al., 2025) focused on AI-based tactical behavior and collective dynamics mainly using match datasets; and mapped a broad literature on professional football performance and result prediction. In contrast, this review includes only empirical studies in which AI is applied within football training environments to support assessment, feedback, or the development of technical and tactical skills (Sahli et al., 2026). This distinction reflects a substantively different research question; one oriented toward the pedagogical and motor learning implications of AI, rather than its predictive or analytical capabilities at the match level.

Assessment-oriented studies collectively demonstrate that deep learning and machine learning algorithms can classify football-specific movements with meaningful accuracy. Abdullah et al. (Abdullah et al., 2016) showed that ANN-based models could reliably discriminate between novice and elite youth players using a reduced parameter set and offers an objective complement to traditional talent identification. Liao & Fu (Liao & Fu, 2025) achieved keypoint detection accuracy exceeding 90% with reasonable environmental robustness, representing a step toward practically deployable tools. The most practically significant finding in this cluster, however, comes from Stoeve et al. (Stoeve et al., 2021), whose data directly challenge the assumption that laboratory accuracy translates to real-world utility. Even the best-performing CNN showed shot detection

sensitivity dropping from 75% in laboratory conditions to 45% in field scenarios, while the SVM failed almost entirely under real-world conditions (pass sensitivity: 20.9%). This finding underscores that ecological validity in model development is a prerequisite for applied use, not an optional refinement. This is consistent with broader observations in sport science regarding the limited transferability of laboratory-derived models (Davids, 1988). It is acknowledged that Stoeve et al. (Stoeve et al., 2021) address activity recognition rather than skill development per se; its inclusion is justified by its direct relevance to training contexts and its unique contribution in characterizing real-world classification limits. Zhou et al. (Zhou et al., 2022) include a football robot component and address functional strength conditioning rather than narrowly defined technical or tactical skill development. This study is retained for its methodological relevance, but these boundaries are acknowledged as limitations. With the partial exception of Zhou et al. (Zhou et al., 2022), none of the assessment studies measured skill development as a direct training outcome, instead evaluated the technical accuracy and classification performance of AI tools within training contexts. The practical added value of AI classification tools over existing coaching practice therefore remains largely unevidenced, and bridging this pedagogical gap is the most pressing priority for future research in this cluster.

The three intervention studies provide the most direct evidence on skill development outcomes yet differ considerably in what they can support. Sami Bouzid et al. (Sami Bouzid et al., 2025) is the only study in this review with a conventional coaching control group. The 2.5-fold difference in tackling improvement between the AI feedback group (23.84%) and the control group (9.63%) provides the clearest empirical evidence that AI-enhanced visual feedback can yield superior outcomes compared with traditional coaching methods. This aligns with augmented feedback theory, which identifies feedback precision and format as critical determinants of motor learning (Chiou & Chang, 2016; Meira Junior et al., 2012). However, the small sample ($n = 23$) substantially limits generalizability, and replication in larger randomized trials is necessary. Cao et al. (Cao et al., 2023) strengthen the evidence base through a larger sample ($n = 116$) and 12-week duration, demonstrating that BPNN-based can analyze movement patterns and provide objective, data-driven feedback on technical execution. However, the absence of a conventional coaching control group means observed improvements cannot be specifically attributed to the AI component rather than to the training program more broadly. Mazian et al. (Mazian et al., 2025) contribute methodological infrastructure rather than evidence of interventions. The R-GDL framework successfully characterized individual movement signatures but did not measure skill-acquisition outcomes, thereby limiting its contribution to system validation rather than to training efficacy.

The effect sizes reported in this review should be interpreted with caution. Only three of the eight studies provided data sufficient for effect size calculation, and these differed substantially in design, outcome measures, and participant characteristics. Different AI interventions applied across different skill domains and competition levels are likely to produce meaningfully different effects, making direct cross-study comparison premature. For the five studies where calculation was not possible, this reflects a structural limitation of research designs. Future research should report inferential statistics and effect sizes as standard practice to enable more robust cross-study synthesis.

Limitations and Future Directions

The evidence base is small ($n = 8$), geographically concentrated in Asian contexts, and methodologically heterogeneous. No study employed a fully randomized design, and only one included a conventional coaching comparator. Outcome measures varied widely, precluding quantitative synthesis. Notably, the absence of studies from European elite football contexts represents a gap between applied practice and empirical evidence (Herold et al., 2022). Importantly, Liao & Fu (Liao & Fu, 2025) identify that policy, attitudinal, and infrastructural factors, not technical accuracy, are the primary barriers to AI adoption in training. Hence, highlighting the need for multidisciplinary collaboration among coaches, data scientists, and institutional stakeholders. Future research should prioritize randomized controlled trials, longitudinal designs assessing skill retention and match transfer, standardized outcome measures enabling cross-study comparison, and implementation studies examining the organizational conditions for effective AI adoption across football's competitive.

Conclusions

This systematic review shows that AI-driven tools are a promising yet emerging component of research in football training. Across the included studies, AI was most consistently used for assessment purposes, including movement classification, technical skill prediction, action detection, posture recognition, and player profiling. These findings suggest that AI can provide objective and detailed information about player performance, particularly under well-controlled, as well as varied conditions. This AI feature could be useful for monitoring developmental progress and performance deterioration, signalling health issues or athletic burnout. However, the evidence also shows that strong model accuracy in laboratory or structured settings does not always translate into reliable practical value in real-world training environments.

The most meaningful practical potential lies in AI systems that support feedback and skill learning, such as visual feedback, motion templates, key point detection, and automated technique analysis. Early evidence suggests that these tools may improve technical execution, biomechanical efficiency, and player motivation, but the current evidence base remains limited by small sample sizes, short interventions, narrow geographic

coverage, and few rigorous experimental designs. This review contributes conceptually by distinguishing training-focused AI applications from broader football analytics, and practically by showing that AI should currently be viewed as a complementary coaching aid rather than a replacement for expert judgment. Future research should prioritize larger randomized trials, ecologically valid outcomes, longer-term interventions, and closer collaboration between coaches, sport scientists, and technology developers. Organizations seeking to integrate AI into football training should prioritise platforms that convert motion capture and computer vision data into actionable, real time or post session feedback as the 3D animated pose overlays since these directly enhance motor learning and player engagement, rather than investing in data collection for its own sake. However, technological precision alone does not guarantee successful adoption: organizations surveys consistently show that institutional policy, coach attitudes, and infrastructure constraints, rather algorithmic performance, represent the primary barriers to AI implementation in youth and educational training contexts. Consequently, effective implementation strategies must go beyond technical deployment to emphasize coach education, intuitive and user friendly interface design and close alignment with institutional policy with ensuring that AI tools are not only accurate but also practically embedded within the human and organisational fabric of the coaching environment.

Declaration of Generative AI use: During the preparation of this manuscript/study, the authors used Grammarly and ChatGPT for the purposes of language and grammar checks. The authors also used Consensus AI to identify possible references beyond those yielded by the database searches. Consensus AI returned results that overlapped entirely with those already retrieved via Google Scholar; no additional eligible studies were identified. All suggested references were thoroughly verified against the existing search results. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

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