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Comprehensive AI based Player Performance Analyzer and Wellness Monitoring System

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Abstract

This research is about football analytics with the help of AI by enabling data-driven performance optimization, injury prevention, and talent identification. Access to advanced analytics technologies remains limited to elite teams due to cost and other technical barriers. This will present the idea, methodologies and implementation of an AI-Driven Sports Analytics and Wellness Platform for football players, as a mobile-first, cloud-based digital ecosystem that incorporates performance analysis, AI coaching, and holistic wellness monitoring. The system uses computer vision and machine learning techniques, including YOLOv8 for player detection, DeepSORT for multi-object tracking, and pose estimation for action recognition, to extract player metrics such as speed, stamina, and technical accuracy from video data. These insights are presented through a personalized AI generated Player Performance Card, with an AI coaching module developed using Random Forest and Decision Tree model delivers position recommendations and adaptive training plans for any specific player for the betterment of their performance. Then a parallel wellness engine which analyzes sleep, hydration, nutrition, and recovery patterns to predict injury risk and support long-term player health is also presented. Along with the facility for players to showcase their talent through the AI generated performance card, the system normalizes professional-grade football intelligence and provides an affordable, accessible pathway for athlete development across all competitive levels.

Index Terms: AI, Computer Vision, Football Analytics, Health Monitoring,Performance Metrics.

1. Introduction

In today's digital world, Artificial Intelligence (AI) is changing the way many industries work, and sports is no different. Football, in particular, has started using technology to better understand player performance, improve team strategies, and reduce the risk of injuries. Coaches and analysts now use data to track player movements, predict match outcomes, and make smarter decisions. However, most of these advanced systems are expensive and are only available to professional clubs. Amateur and semi-professional players often don't have access to such tools because they require costly equipment and expert support. This gap shows the need for a simple, affordable platform that helps football players improve their skills using tools they already have, like smartphones and basic video recordings. The project, "AI-Driven Sports Analytics and Wellness Platform for Football Players," focuses on creating an easy-to-use digital system that gives players access to professional-style analysis without needing expensive infrastructure. The platform combines video analysis, virtual coaching, and basic health tracking in one mobile application. The main goal of this system is to help players understand their performance in a clear and practical way. It automatically analyzes match videos, tracks player movements, and creates a performance report similar to a school report card. This report includes useful details like running speed, stamina, passing accuracy, and overall consistency. In addition to game performance, the platform also supports player well-being by tracking simple wellness factors like sleep, nutrition, hydration, and recovery. The platform also includes a virtual AI coach that offers helpful suggestions, such as the best play-

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Vol. 15 Issue 03 , March - 2026

ing position for a player, customized training plans, and motivational support. The aim is to make every player feel like they have a personal mentor guiding them. To make the experience more engaging, the platform allows players to share their performance profiles, connect with coaches, and get noticed by scouts. Coaches can view player data, track progress over time, and give more personalized feedback. By combining performance tracking, wellness support, and social networking, the platform creates a supportive community where players can learn, grow, and feel motivated.

1.1. Background

Sports analytics has come a long way from simple number-based tracking to more advanced technologies like machine learning and computer vision that can deliver real-time insights. In today's football environment, data plays a major role in planning team tactics, identifying talented players, and improving overall performance. However, while professional football clubs can afford costly sensors and expert analysts, local and aspiring players often still depend on basic observation and traditional coaching methods. Because of this gap, there is a strong need for affordable and easy-to-use platforms that make modern sports analytics available to everyone. This project responds to that need by bringing together AI-powered performance analysis, virtual coaching, and wellness monitoring into a single, user-friendly system. The goal is to create an accurate and accessible solution that supports not only athletic performance, but also the overall health and long-term development of football players.

1.2. Relevance

The proposed AI-driven sports analytics and wellness platform is highly relevant in today's fast-changing sports world. Football is becoming increasingly popular at both grassroots and professional levels in India and around the world, and players now expect better ways to understand and improve their performance. Unfortunately, most advanced analysis and coaching tools are still limited to elite clubs that can afford expensive equipment and expert support. As a result, many young and aspiring players miss out on valuable feedback and opportunities to grow. This project aims to reduce that gap by offering a low-cost, AI-powered platform that brings performance analysis, wellness tracking, and virtual coaching together in one easy-to-use system. It helps individual players track their progress, while also giving coaches, scouts, and sports academies reliable data to support fair and informed decisions. By adding social features and talent-sharing tools within the same application, the platform encourages interaction, visibility, and motivation among players. This creates a supportive and connected community that can strengthen the future of football development in a sustainable way.

2. Literature Review

Recent advancements in football analytics increasingly leverage deep learning and computer vision to automate event detection, player tracking, and tactical understanding from match videos. Comprehensive surveys such as [1] highlight the evolution from traditional CNNs to advanced architectures including 3D-CNNs, two-stream networks, and hybrid CNN–RNN/LSTM models for spatio-temporal analysis of football events. These models enable fine-grained tasks such as action recognition, player identification, and semantic segmentation, while evaluation metrics like IoU, mAP, and MOTA ensure robust performance benchmarking. Practical implementations discussed in applied works [4] further demonstrate the feasibility of deploying YOLO-based detection, tracking pipelines, and LSTM-driven event segmentation on single-camera football footage. However, both studies emphasize challenges related to annotation scarcity, occlusion, camera perspective variations, and real-time inference latency—gaps that motivate our platform's focus on lightweight models, optimized preprocessing, and scalable deployment. Advanced spatial modeling approaches, such as perspective-transform-based YOLO with weighted intersect fusion [5], further contribute to tactical insights by mapping detections onto standardized pitch layouts, influencing our possession-forecasting and spatial performance metrics.

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

Beyond vision-centric analytics, several studies focus on athlete health, performance optimization, and talent evaluation using machine learning and AI-driven recommendation systems. Research on ML-based performance and injury prediction [2] demonstrates the effectiveness of interpretable models like XGBoost in extracting actionable insights from physiological and workload data, while emphasizing real-time feedback for coaches and medical teams. Privacy-preserving architectures such as Split Federated Learning combined with RNNs [3] address scalability and data-security concerns in wearable-based health monitoring, directly informing the edge-cloud design of our Health and Wellness module. Unsupervised clustering techniques for football analysis [6] reduce dependency on labeled datasets by using color-segmentation and lighting adaptation, improving robustness under real-world stadium conditions. Additionally, AI-driven recommendation systems for nutrition [7] and player scouting [8] illustrate how generative AI and optimization techniques can enhance personalized dietary planning and talent identification. Collectively, these works shape our integrated platform by combining video analytics, health monitoring, nutrition guidance, and AI-based player profiling into a unified, coach-friendly decision-support system. Table. 1 shows the Comparative Analysis of Related Works in AI-Based Football Analytics

3. Methods

The proposed system follows a modular AI-driven framework designed to support comprehensive football player development through four integrated functional components: AI Coaching, Player Performance Card Generation, Health and Wellness Monitoring, and Social Media–Based Talent Showcasing. The methodology combines computer vision, machine learning models, and user-centric mobile technologies to enable real-time player analytics, personalized feedback, holistic health tracking, and digital visibility. This structured, multi-module approach ensures scalability, adaptability, and accessibility, making the platform suitable for grassroots, semi-professional, and professional football environments.

3.1. Video Acquistion and Preprocessing

The system accepts match or training footage captured using consumer devices (smartphones, handheld cameras) or publicly available broadcast/league videos. Because source videos vary in frame rate, resolution, viewpoint, and lighting, a preprocessing pipeline standardizes and conditions input to improve downstream detection and tracking. The pipeline performs frame extraction, resolution and coordinate normalization, background/prior removal via semantic segmentation and illumination correction. Fig. 1 shows vertical representation of the video acquisition and preprocessing pipeline. The pipeline standardizes heterogeneous football videos through frame extraction, normalization, background removal, and illumination correction prior to detection and tracking.

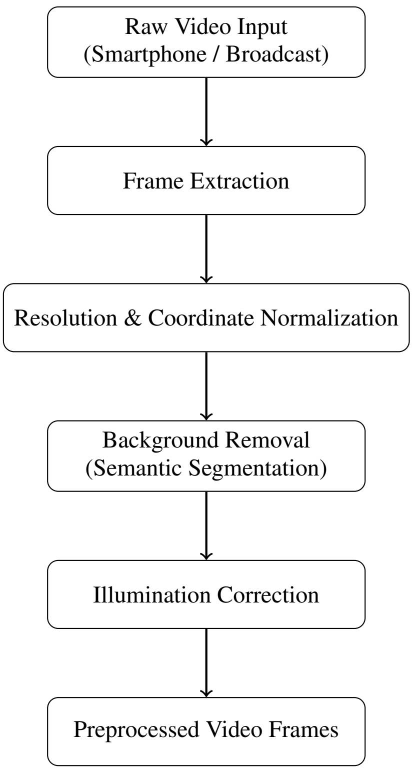

Figure 1: *Vertical representation pipeline*

3.2. Player Detection and Training

The keypoint detection is implemented using the YOLOv8-Pose model trained on a custom football keypoint dataset hosted on Roboflow.

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Table 1: *Comparative Analysis of Survey*

Paper	Techniques Used	Core Area	Strengths	Limitations
Review of DL Architectures for Football Video Analysis	CNN, 3D-CNN, Two-stream Networks, RNN, LSTM	Player detection, tracking, event recognition	Broad task-to-model mapping, metric analysis (mAP, IoU, MOTA)	Survey-level study, no real-time implementation
AI for Performance Enhancement and Injury Prevention	XGBoost, Feature Engineering, Wearable Data	Performance analytics, injury risk prediction	Interpretable models, actionable insights for coaches	Small datasets, limited vision-based analysis
SFL-RNN Based Real-Time Health Monitoring	Split Federated Learning, RNN, Wearables	Athlete health monitoring, injury prediction	Privacy-preserving, low latency, edge-cloud balance	Network dependency, communication overhead
Advancing Football Game Analysis using CV and DL	YOLO, Faster R-CNN, 3D-CNN, LSTM	Player tracking, ball detection, event analysis	Practical implementation, real-time capability	Single-camera limitation, heuristic preprocessing
Perspective Transform Based YOLO with WIF	YOLO, Perspective Transform, Geometric Tracking	Possession prediction, spatial analysis	Tactical mapping, possession forecasting	Camera calibration sensitivity, occlusion issues
Unsupervised Clustering in Football Analysis	Color Segmentation, K-means, Instance Segmentation	Team identification, lighting adaptation	No labeled data required, lighting robustness	Fails with similar jerseys, no player-level metrics
FR-RANC: Nutrition-Centric Recommendation System	Optimization Algorithms, AI-based Recommendation	Personalized nutrition planning	Region-aware, adaptable dietary guidance	Not athlete-specific, lacks sports performance focus
FPSRec: Football Player Scouting System	Machine Learning, Generative AI, Clustering	Talent scouting, player recommendation	Automated reports, human-readable insights	No real-time video performance analysis

First, the environment is initialized by installing the required libraries (ultralytics, roboflow) and verifying GPU availability (nvidia-smi). The code authenticates the Roboflow workspace through an API key and downloads the annotated football pose dataset in YOLO format. During training, YOLO computes pose loss, box loss, and confidence loss while generating visual logs like F1 curves, confusion matrices, and training/validation batch predictions.

Keypoint Detection Using YOLO-Pose using Accurate pose estimation is essential for analyzing player movements, identifying joint dynamics, and extracting biomechanical performance indicators in football analytics. In our system, a YOLOv8-Pose model is trained using a custom football dataset obtained from Roboflow, containing manually annotated skeletal keypoints for players in diverse match environments. The dataset is represented as:

$$D = \{(I_i, K_i)\}_{i=1}^{N} \tag{1}$$

N represents the total number of training samples (images) in your dataset. Each input image I_i is associated with a structured keypoint set

$$K_i = \{(x_{i,k},\ y_{i,k},\ v_{i,k})\}_{k=1}^{K}, \tag{2}$$

where $v_{i,k}$ indicates the visibility of each joint

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Vol. 15 Issue 03 , March - 2026

(1 = visible, 0 = occluded).

During training, YOLO-Pose jointly optimizes bounding-box prediction and keypoint localization. The bounding-box quality is measured using Intersection-over-Union, defined as:

$$\text{IoU} = \frac{|B_{\text{pred}} \cap B_{\text{gt}}|}{|B_{\text{pred}} \cup B_{\text{gt}}|} \tag{3}$$

- B_{pred} : Predicted bounding box generated by the YOLO-Pose model.
- B_{gt} : Ground-truth bounding box provided in the annotated dataset.
- $B_{\text{pred}} \cap B_{\text{gt}}$: Intersection area between the predicted box and the ground-truth box.
- $B_{\text{pred}} \cup B_{\text{gt}}$: Union area covering both the predicted and ground-truth boxes.
- IoU : Intersection-over-Union metric used to evaluate bounding-box localization accuracy.

which provides an overlap score used to penalize inaccurate player localization.

The overall multi-task objective for pose learning integrates bounding-box loss, keypoint loss, object presence confidence, and class probability, expressed as:

$$L_{\text{total}} = \lambda_{\text{box}} L_{\text{box}} + \lambda_{\text{kp}} L_{\text{kp}} + \lambda_{\text{obj}} L_{\text{obj}} + \lambda_{\text{cls}} L_{\text{cls}} \tag{4}$$

- L_{total} : Overall multi-task loss optimized by the YOLOv8-Pose model.
- L_{box} : Bounding-box regression loss, measuring the localization error between predicted and ground-truth boxes.
- L_{kp} : Keypoint regression loss computed using Smooth L1 over all visible joints.
- L_{obj} : Objectness loss indicating confidence of player presence within the predicted bounding box.
- L_{cls} : Classification loss for predicting the correct class label (player or background).
- λ_{box} : Weighting coefficient controlling the contribution of bounding-box loss.
- λ_{kp} : Weighting coefficient for keypoint regression loss.
- λ_{obj} : Weight factor for the objectness confidence term.
- λ_{cls} : Weight factor for the classification term.

To accurately localize players across match footage, a YOLOv8-X object detection model is trained on a custom football dataset obtained from Roboflow. The dataset contains annotated player bounding boxes captured from diverse match scenarios.

YOLOv8 predicts bounding box coordinates, objectness confidence, and class probabilities simultaneously. The bounding-box regression quality is optimized using the Complete-IoU (CIoU) loss, computed as:

$$\text{CIoU}(B_{\text{pred}}, B_{\text{gt}}) = 1 - \text{IoU} + \frac{\rho^2(b_{\text{pred}}, b_{\text{gt}})}{c^2} + \alpha v \tag{5}$$

where IoU is the Intersection-over-Union between predicted and ground-truth boxes, $\rho(\cdot)$ is the Euclidean distance between box centers, c is the diagonal length of the smallest enclosing box, v is an aspect-ratio consistency term, and α is a balancing factor.

The IoU component is given by:

$$\text{IoU} = \frac{|B_{\text{pred}} \cap B_{\text{gt}}|}{|B_{\text{pred}} \cup B_{\text{gt}}|} \tag{6}$$

YOLOv8 incorporates an objectness prediction branch, trained using binary cross-entropy:

$$L_{\text{obj}} = -\sum_{i=1}^{N} \left[y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i) \right] \tag{7}$$

where $y_i \in \{0, 1\}$ is the ground-truth objectness label and $\hat{y}_i$ is the predicted confidence.

Class probabilities are optimized using a standard cross-entropy loss:

$$L_{\text{cls}} = -\sum_{c=1}^{C} p_c \log(\hat{p}_c) \tag{8}$$

where C is the number of classes, p_c is the true class label, and $\hat{p}_c$ is the predicted probability.

During training, the model is optimized for 50 epochs using the `yolov8x.pt` backbone, a batch size of 6, and an image resolution of 1280×1280, ensuring high spatial fidelity for long-range player detection. A heatmap is generated by aggregating player position coordinates across all video frames and mapping

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Vol. 15 Issue 03 , March - 2026

the frequency of occurrence onto a normalized football field grid. Regions with higher activity density are visualized using warmer colors, enabling intuitive analysis of player movement patterns and tactical behavior. Player positions are extracted from consecutive video frames using the YOLOv8-based detection and tracking module. These coordinates are accumulated over time and projected onto a normalized football field representation. Regions with higher player presence are highlighted using warmer colors, while low-activity regions are represented with cooler tones. This visualization provides intuitive insights into player movement patterns, positional discipline, and tactical behavior, supporting both performance evaluation and strategic decision-making. As shown in Fig. 2, the generated heatmap reveals dominant player activity zones and positional trends throughout the match.

Figure 2: *HeatMap Generated*

3.3. Performance extraction

To generate the Player Performance Card, the system extracts a comprehensive set of spatio-temporal performance metrics from tracked player trajectories across video frames. Using continuous player tracking, motion-based features such as total distance covered, average speed, maximum speed, sprint count, acceleration and deceleration events are computed to quantify physical workload and intensity. Speed thresholds are applied to distinguish high-intensity runs and sprints, while frame-to-frame displacement is used to estimate acceleration dynamics. Positional context is inferred by mapping player coordinates onto field zones, enabling role-based insights such as defensive, midfield, or attacking dominance. These raw metrics are normalized across match duration and aggregated into interpretable performance indicators, which are visually summarized in the player card along with positional labels and tracking consistency. This structured representation enables objective player comparison, workload monitoring, and data-driven performance assessment for coaches and analysts.

3.4. Player Card Generation-Module 1

The Player Performance Card presents the extracted metrics in a structured and interpretable format, similar to a performance report used by professional coaches and analysts. Each raw feature (speed, stamina, accuracy, and consistency) is normalized to ensure fairness across sessions and players, and then aggregated into intuitive performance indices.

The card summarizes multiple dimensions of a player's capabilities, including physical fitness indicators, technical skill metrics (such as pass or shot effectiveness), and behavioral consistency across matches. A weighted scoring mechanism combines these indices to produce an overall performance rating that reflects the player's strengths and areas for improvement. The card is dynamically updated after each session and stored within the player's profile, enabling long-term trend analysis, comparative evaluations, and easy sharing with coaches or scouts.

Fig.3 illustrates the Player Performance Card generated by the proposed AI-based football analytics system. The interface enables dynamic player selection from detected on-field players, each uniquely identified and color-coded for clear tracking throughout the match. Once a player is selected, the system aggregates spatio-temporal data extracted from video frames to generate an individualized performance summary.

The player card presents key physical performance metrics, including total distance covered, average speed, and maximum speed achieved during the session. These metrics are computed using player trajectory tracking and frame-to-frame motion analysis. The associated player snapshot provides visual confirmation of the tracked identity, improving interpretability and trust in the extracted data.

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Vol. 15 Issue 03 , March - 2026

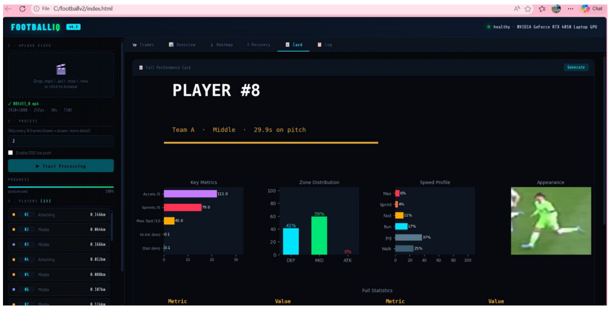

Figure 3: *Player Card Generated*

3.5. Health and Wellness Monitoring-Module 2

The Health and Wellness Monitoring module provides a comprehensive framework for assessing athlete health, metabolic condition, dietary intake, and recovery patterns. This module integrates physiological computations, lifestyle tracking, and machine learning based analysis to support continuous monitoring of player wellness. The backend implementation is developed using the Flask framework, enabling athletes to input relevant health attributes such as height, weight, age, sleep duration, hydration level, activity level, and fitness goals. These attributes are stored in a centralized database to enable longitudinal tracking and personalized recommendations.

3.5.1. Metabolic Rate Estimation

To estimate the athlete's baseline metabolic requirement, the system computes the Basal Metabolic Rate (BMR) using the Mifflin–St Jeor equation, which is widely accepted for estimating resting energy expenditure.

$$BMR_{male} = (10 \times W) + (6.25 \times H) - (5 \times A) + 5 \tag{9}$$

$$BMR_{female} = (10 \times W) + (6.25 \times H) - (5 \times A) - 161 \tag{10}$$

where W represents body weight in kilograms, H represents height in centimeters, and A represents age in years.

The calculated BMR is adjusted based on the athlete's activity level to estimate the Total Daily Energy Expenditure (TDEE). The activity multiplier reflects the athlete's training intensity.

$$TDEE = BMR \times ActivityFactor \tag{11}$$

Typical activity multipliers include sedentary (1.2), moderately active (1.55), and highly active (1.9). Based on the calculated TDEE, the system determines an appropriate caloric intake recommendation depending on the athlete's goal such as weight maintenance, muscle gain, or fat reduction.

3.5.2. Body Composition Analysis

To evaluate general body composition, the system calculates the Body Mass Index (BMI). Although BMI alone does not fully represent athletic fitness, it provides a useful baseline indicator when combined with other metabolic measurements.

$$BMI = \frac{W}{H^2} \tag{12}$$

where W represents body weight in kilograms and H represents height in meters.

Based on BMI values, the system categorizes body composition into underweight, normal weight, overweight, or obese ranges, which helps identify potential health concerns affecting athletic performance.

3.5.3. Dietary Image Analysis using Deep Learning

To analyze nutritional intake, the module incorporates an image based machine learning pipeline. Athletes can upload images of food items which are processed by a deep learning model implemented using TensorFlow and Keras.

Before model inference, the input image undergoes several preprocessing steps including resizing to a standardized resolution, normalization of pixel values, and conversion into a tensor format suitable for neural network processing.

$$X_{norm} = \frac{X}{255} \tag{13}$$

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Vol. 15 Issue 03 , March - 2026

where X represents the original pixel intensity and X_{norm} represents the normalized pixel value.

The processed image is then passed through a convolutional neural network (CNN) architecture trained for food classification. CNN models are particularly effective for visual recognition tasks due to their ability to capture spatial patterns and hierarchical features from images. The convolution operation applied in CNN layers is defined as:

$$S(i,j) = \sum_m \sum_n I(i-m, j-n) K(m,n) \quad (14)$$

where I represents the input image and K represents the convolution kernel.

The CNN architecture typically includes multiple convolution layers followed by pooling layers for feature extraction, fully connected layers for classification, and a Softmax output layer that produces the probability distribution over food classes.

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (15)$$

where z_i represents the output score for class i and K represents the total number of classes.

3.5.4. Nutritional Dataset Integration

The predicted food item from the deep learning model is matched against a structured nutritional dataset containing more than 1000 food items from multiple cuisines including Indian, Italian, Chinese, Mexican, Japanese, Thai, and American dishes. Each food entry contains detailed attributes such as caloric value, protein content, carbohydrate levels, fat composition, fiber content, preparation time, and dietary suitability for athletes.

This dataset allows the system to compute the estimated caloric intake from the detected food item and compare it with the athlete's recommended daily energy requirement.

3.5.5. Wellness Recommendation Generation

After calculating metabolic indicators and nutritional intake, the system generates personalized wellness recommendations. The recommendation process integrates metabolic results, food analysis outcomes, and lifestyle inputs such as sleep duration and hydration level.

For example, if caloric intake is significantly lower than the estimated TDEE, the system recommends increased nutritional intake to maintain optimal energy levels. Similarly, insufficient sleep patterns or excessive workload indicators trigger recovery recommendations such as reduced training intensity or increased rest intervals.

[1] Collect user wellness inputs (height, weight, age, sleep, hydration) Compute BMR using Mifflin–St Jeor equation Estimate TDEE using activity multiplier Calculate BMI for body composition analysis Receive uploaded food image Preprocess image and normalize pixel values Apply CNN model to classify food item Retrieve nutritional information from food dataset Compare caloric intake with recommended TDEE Generate dietary and wellness recommendations

By integrating physiological computations, deep learning based dietary recognition, and structured nutritional data analysis, the Health and Wellness Monitoring module provides a comprehensive framework for tracking athlete health and supporting performance optimization.

3.6. Injury Prevention-Module 3

The Injury Risk Prediction and Recovery Module is designed to proactively assess the likelihood of sports-related injuries and recommend suitable recovery strategies based on player workload and physical stress indicators. Unlike traditional wearable-based monitoring systems, this module relies on performance metrics extracted from video analysis and historical workload patterns to evaluate injury susceptibility.

The module analyzes key match-related parameters such as sprint count, total distance covered, acceleration and deceleration frequency, maximum running speed, and high-intensity activity duration. These indicators collectively reflect the biomechanical load and muscular stress experienced by a player during a match. Based on these inputs, a comprehensive risk score is computed to represent the overall injury likelihood.

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Vol. 15 Issue 03 , March - 2026

Players are categorized into multiple injury risk levels ranging from very low to critical. This classification enables early identification of high-risk players who may require immediate rest or medical attention. Additionally, position-specific injury tendencies are incorporated to improve prediction reliability, as different playing roles exhibit distinct physical demands and injury patterns.

The system further predicts the most probable injury types, such as hamstring strain, groin strain, knee ligament stress, calf strain, or muscle fatigue. These predictions are derived by correlating workload indicators with known football injury patterns. The output includes injury severity estimation and contributing risk factors to enhance interpretability.

To complement injury prediction, a fatigue assessment mechanism evaluates cumulative physical exhaustion using a fatigue score. This score reflects both acute and prolonged workload effects, enabling the system to distinguish between normal post-match fatigue and excessive physical strain.

Based on the injury risk level and fatigue assessment, the module generates a personalized recovery plan. The recovery recommendations include rest duration, hydration requirements, sleep guidelines, nutrition support, and suitable recovery activities such as stretching, ice therapy, and active recovery sessions. In high-risk cases, medical consultation warnings are also issued.

[1]

Player match statistics: sprint count S, total distance TD, accelerations A, decelerations D, maximum speed V, high-intensity distance HID, player position P

Injury risk score, predicted injuries, and recovery plan

Collect player performance metrics from video analysis

Compute injury risk score R using workload indicators

Apply biomechanical modifiers based on high speed and acceleration

Apply position-based multiplier according to player role

Normalize the risk score to obtain final injury risk value

Classify the player into one of the eight injury risk levels

Predict probable injury types based on workload patterns

Calculate fatigue score F using sprint count, distance, accelerations, decelerations, and high-intensity running

Determine fatigue level using predefined fatigue thresholds

Generate recovery plan including:

- Rest duration
- Hydration guidelines
- Sleep recommendations
- Recovery activities
- Nutrition suggestions

Return injury risk assessment and personalized recovery plan

Overall, the Injury Risk Prediction and Recovery Module supports preventive sports healthcare by enabling informed decision-making for training load management, recovery planning, and injury mitigation. This contributes to improved player safety, performance sustainability, and long-term athletic development.

3.7. AI Coaching and Recommendation Engine-Module 4

The AI Coaching and Recommendation Engine functions as the intelligent decision-making layer of the system, transforming raw performance metrics and wellness indicators into actionable training insights for athletes. This module combines rule-based evaluation strategies with machine-learning–assisted analysis to generate personalized coaching recommendations tailored to each player's performance profile. The engine processes multiple input features collected from the performance analytics and wellness monitoring modules. These inputs include quantitative performance indicators such as speed scores, agility metrics, passing accuracy, stamina levels, and decision-making efficiency. Each metric is represented as a normalized performance score ranging from 0 to 100, allowing the system to compare attributes across different skill dimensions. Based on these scores, the module identifies key strengths and areas requiring improvement.

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Vol. 15 Issue 03 , March - 2026

For example, attributes such as Speed Agility, Passing Accuracy, and Decision Making are evaluated as strength indicators when their performance values exceed predefined thresholds. Conversely, metrics such as Finishing efficiency or stamina levels are flagged as improvement areas when their values fall below the expected benchmark. The system then associates these weaknesses with specific corrective training drills and conditioning exercises. In addition to skill analysis, the AI coaching module also performs positional suitability assessment. By analyzing a combination of speed metrics, passing accuracy, tactical awareness indicators, and endurance levels, the system estimates the most suitable playing position for the athlete. The predicted position is accompanied by a confidence score, which represents the system's certainty in the recommendation based on the evaluated feature set. Another key function of the coaching engine is the generation of personalized weekly training plans. The system dynamically constructs training schedules by mapping identified weaknesses to relevant drills and conditioning exercises. For instance, if finishing accuracy is identified as a weakness, the training module may recommend drills such as one-on-one finishing practice, set-piece training, and small-sided possession games. Similarly, low stamina indicators trigger endurance-focused exercises such as sprint intervals, shuttle runs, and agility ladder drills. The training schedule is organized into structured weekly sessions, each focusing on specific skill areas such as finishing drills, high-intensity conditioning, tactical awareness, or match preparation. This structured approach ensures that athletes receive balanced development across technical, physical, and tactical aspects of the game. To provide additional motivation and feedback, the system also generates contextual coaching insights based on observed performance trends. These insights summarize recent improvements and highlight areas requiring sustained effort. For instance, if a player's speed metrics show measurable improvement across multiple sessions, the system communicates this progress through motivational feedback messages while encouraging continued focus on weaker attributes. By continuously analyzing performance trends, identifying strengths and weaknesses, and generating adaptive training plans, the AI Coaching and Recommendation Engine enables data-driven athlete development. This approach allows players and coaches to make informed training decisions, optimize skill progression, and reduce the risk of performance stagnation or overtraining.

3.7.1. *Performance Evaluation Model*

To quantify an athlete's overall performance level, the system computes a composite performance score using multiple skill indicators. Each skill metric is normalized to a range between 0 and 1 before aggregation.

$$P = \sum_{i=1}^{n} w_i S_i \tag{16}$$

where P represents the overall performance score, S_i represents the normalized value of the i^{th} skill metric, and w_i represents the weight assigned to that metric. The weights are determined based on the importance of each skill in football performance analysis.

This aggregated score helps the system identify strengths and weaknesses by comparing individual skill metrics with predefined benchmark thresholds.

3.7.2. *Personalized Fitness Plan Generation*

The Personalized Fitness Plan Generation module is designed to recommend an appropriate workout and nutrition plan based on the user's fitness profile. The system collects several inputs including fitness level, workout goals, available equipment, workout frequency, session duration, weight goal, and existing medical conditions. These parameters are used to generate a customized training and dietary recommendation.

Initially, the system gathers user input through a fitness questionnaire interface. Mandatory fields such as fitness level, workout goals, workout days, and session duration are validated before processing. Based on the provided fitness level, the system selects an appropriate exercise dataset consisting of

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beginner, intermediate, or advanced exercises.

The system then constructs a structured workout schedule by iterating through the selected workout days and assigning exercises according to the user's goals and available equipment. The overall procedure followed by the system is described in Algorithm 3.7.2.

[1]

Fitness Level L, Goals G, Equipment E, Workout Days D, Session Duration T, Weight Goal W, Health Conditions H

Personalized Workout Plan and Meal Plan

Collect user fitness parameters Validate mandatory inputs Select exercise dataset based on fitness level L

$day = 1$ to D Initialize workout schedule for the day goal includes strength or muscle gain Select strength exercises compatible with equipment E goal includes weight loss or endurance Add suitable cardio exercises goal includes flexibility Include stretching routines

Generate meal plan based on weight goal W Modify nutrition recommendations according to health conditions H Initialize progress tracking

Workout plan and nutrition plan

After generating the workout schedule, the system produces a complementary meal plan tailored to the user's weight management goal. The nutrition plan provides dietary suggestions that help support muscle gain, weight loss, or general fitness improvement. Additionally, health conditions specified by the user are considered when recommending foods to avoid potential health risks.

Finally, the system initializes a progress tracking component that enables users to monitor their workout completion and maintain consistency in their training routine. This integrated approach ensures that the generated fitness plan is personalized, structured, and adaptable to the user's health profile and fitness objectives.

3.7.3. Input and Output Description

The inputs to the Personalized Fitness Plan Generation module consist of user-provided fitness parameters collected through the fitness questionnaire interface. These inputs include fitness level, workout goals, available equipment, number of workout days per week, preferred workout duration, weight management goal, and any existing medical conditions.

Based on these inputs, the system processes the data using the algorithm described above to generate a structured output consisting of a personalized workout schedule, recommended exercises for each training day, and a complementary nutrition plan. The system also initializes a progress tracking mechanism that allows users to monitor their workout completion and maintain consistency in their training routine.

3.8. Social Talent Promotion(Entire App)

The Social Talent Promotion module enhances player visibility and engagement by integrating a controlled social-sharing ecosystem within the platform. This module allows athletes to publish their performance cards, match highlights, and key statistics to a dedicated football-centric network. Unlike conventional social platforms, this system is designed specifically for athletic development, enabling players to showcase verifiable, data-driven performance outputs generated directly from the analytics pipeline.

Each shared post is linked to authenticated player data and includes optional highlight clips, detected events, or session summaries produced by the system's video-analysis modules. Coaches, scouts, and academies can browse player profiles through search and recommendation functionalities. These recommendations are generated using similarity analysis based on skill vectors, movement features, and historical performance indices, enabling talent discovery even at lower or amateur levels.

fig. 4 illustrates a sample visualization from the proposed AI-driven football analytics and social engagement module. The upper part of the figure shows a football-related image representing raw visual input captured from match or training footage using consumer devices such as smartphones or handheld cameras. This visual input forms the basis for downstream computer vision processing, including player detection, activity recognition, and contextual analysis.

This operates through a structured interaction

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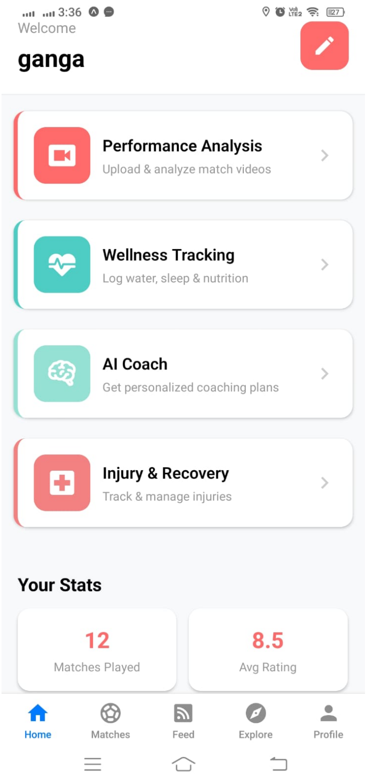

Figure 4: *Sample visualization*

pipeline that connects the mobile application, backend API, database, and media storage services. When a user logs into the application, authentication is performed using JSON Web Tokens (JWT). Upon successful authentication, the backend generates a secure token that allows the user to access protected resources within the system.When a user creates a post containing text, images, or videos, the media files are uploaded to Cloudinary for efficient storage and delivery. The backend then stores the post metadata and references to the media files in the MongoDB database. Other users can interact with the post through likes, comments, and shares. These interactions are processed by the backend APIs and updated in real time.Player profile data such as statistics, physical attributes, and achievements are stored in the database and dynamically rendered on the user interface, creating a LinkedIn-style sports profile. This allows players to showcase their performance data, achievements, and media highlights to other users within the platform.

3.9. System Architecture

The proposed system operates through a multi-layer pipeline that begins with data acquisition from match videos and wellness inputs uploaded via a mobile application. The AI processing layer performs player detection, tracking, and pose estimation to extract speed, distance, accuracy, and stamina-related metrics. These outputs feed into the application logic layer, where wellness analytics and AI-driven coaching recommendations are generated. Finally, the presentation layer delivers personalized dashboards, health insights, and social-network–based features to players and coaches in an intuitive interface.

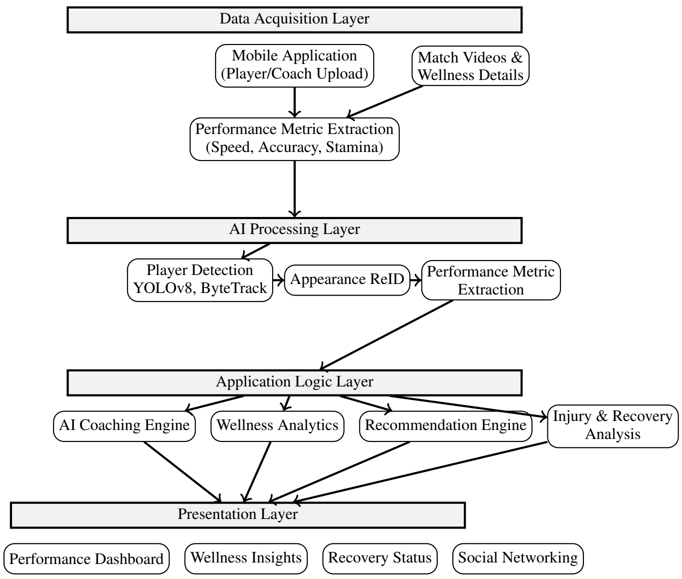

Figure 5: *System Architecture*

4. Experiments and Results

This section presents a comprehensive experimental evaluation of the proposed AI-driven football analytics and wellness monitoring framework. The experiments are designed to assess the effectiveness, robustness, and real-time feasibility of the system across its core modules, including player detection, pose estimation, performance metric extraction, and visualization. Quantitative results and qualitative analyses are reported using diverse football video datasets to demonstrate the system's accuracy, generalization capability, and practical applicability under varying match conditions.

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ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

4.1. Datasets

To evaluate the proposed AI-driven football analytics framework, experiments were conducted on multiple football video datasets collected from Kaggle, Scoutingfeed and supplementary match recordings. These datasets include diverse match scenarios with annotated on-field entities such as players, goalkeepers, and referees, enabling reliable evaluation under real-world conditions. Figure 6 illustrates representative sample frames from the football video datasets used for training and evaluation, highlighting player detection and match diversity and referee annotations under different match conditions.

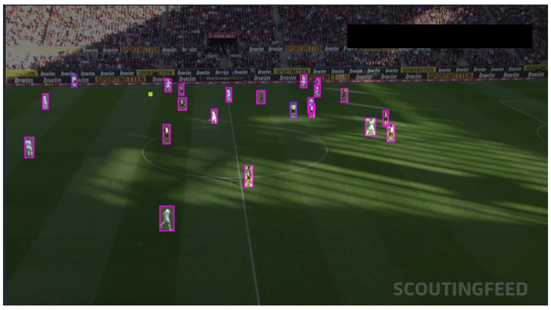

Figure 6: *Sample frames from datasets*

4.1.1. Football Field Detection Dataset

The football field detection dataset consists of 2,847 images focusing on field geometry and keypoint localization. The dataset was split into 1,992 training images (70%), 570 validation images (20%), and 285 test images (10%). Each image is annotated with 29 keypoints representing essential field elements such as corner flags, penalty boxes, center circle, and goal posts. All images are provided at a resolution of 1920×1080 pixels.

4.1.2. Football Player Detection Dataset

The football player detection dataset contains 4,521 images annotated for multi-class player detection. The dataset was divided into 3,165 training images (70%), 904 validation images (20%), and 452 test images (10%). On average, each image contains 18.3 players. The annotated classes include home team players, away team players, referees, and goalkeepers. The image resolution for this dataset is 1280×720 pixels.

4.2. Training Performance

4.2.1. Football Field Keypoint Detection

The YOLOv8x-pose model was trained for 100 epochs using an NVIDIA Tesla V100 GPU. The model achieved stable convergence with a final training loss of 0.0187, indicating effective learning of both bounding box localization and keypoint regression. Convergence was observed at epoch 73, with minimal improvement in subsequent epochs.

The validation results demonstrate strong detection and localization performance, achieving a box mAP@0.5 of 96.2% and a keypoint mAP@0.5 of 93.5%. The optimal F1-score of 0.933 was obtained at a confidence threshold of 0.45, reflecting a balanced precision–recall trade-off.

4.2.2. Football Player Detection

The YOLOv8x object detection model was trained for 50 epochs on the player detection dataset. The final training loss reached 0.0241, showing stable optimization across box regression, objectness, and classification components. Validation results indicate reliable multi-class detection performance, with an overall mAP@0.5 of 91.7% and recall of 87.1%.

Home and away players achieved the highest detection accuracy due to their frequent appearance in training data, while referees and goalkeepers showed slightly lower performance due to class imbalance.

4.3. Test Set Evaluation

4.3.1. Field Detection Results

The trained YOLOv8x-pose model was evaluated on 285 unseen test images. The model achieved a keypoint localization accuracy (PCK@0.1) of 94.2% and a field detection rate of 99.3%. Performance remained stable across different environmental conditions, including indoor settings, rainy scenes, and night matches.

The average inference time was 47 ms per image, corresponding to a processing speed of

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Vol. 15 Issue 03 , March - 2026

21.3 frames per second, enabling near real-time field analysis.

4.3.2. Player Detection Results

Evaluation on 452 test images demonstrated strong generalization, achieving an mAP@0.5 of 90.4% and an average recall of 86.2%. Detection accuracy decreased under heavy occlusion and long-range views but remained robust across most match scenarios.

The model achieved a multi-object tracking accuracy (MOTA) of 84.7%. Inference speed averaged 68 ms per image, allowing real-time deployment in video-based analytics systems.

4.4. Comparative Analysis

The proposed YOLOv8-based framework was compared with existing baseline methods for both field detection and player detection. The results demonstrate that YOLOv8x-pose achieves superior accuracy while maintaining higher inference speed compared to previous YOLO versions and two-stage detectors.

Table 2: *Comparison of Football Field Detection Methods*

Method	mAP@0.5	PCK@0.1	FPS
Faster R-CNN	88.3%	89.7%	8.2
YOLOv5x-pose	91.2%	92.4%	18.6
YOLOv7-pose	93.1%	93.8%	19.3
YOLOv8x-pose	**96.2%**	**94.2%**	**21.3**

Table 3: *Comparison of Football Player Detection Methods*

Method	mAP@0.5	Recall	FPS
Faster R-CNN	83.7%	79.4%	12.1
YOLOv5x	87.4%	83.8%	22.4
YOLOv7	89.1%	85.3%	18.7
YOLOv8x	**91.7%**	**87.1%**	14.7

4.5. Ablation Studies

To better understand the contribution of individual design choices and training strategies, we conducted a series of ablation experiments. These studies analyze the impact of transfer learning, input image resolution, and mosaic data augmentation on detection performance and computational efficiency.

4.5.1. Impact of Transfer Learning

We evaluated three training strategies: random initialization, ImageNet pre-training, and COCO pre-training. The results are presented in Table 4.

The results demonstrate that transfer learning from the COCO dataset significantly accelerates model convergence while improving detection accuracy. Compared to random initialization, COCO pre-training reduced training time by approximately 66.4% and increased accuracy by 14.9%. This highlights the effectiveness of leveraging large-scale object detection knowledge for football scene understanding.

4.5.2. Impact of Image Resolution

We analyzed the effect of different input image resolutions on detection accuracy, inference latency, and memory consumption. The results are summarized in Table 5.

While higher resolutions improve detection accuracy by preserving fine-grained spatial details, they introduce substantial computational overhead. The 640×640 resolution provides an optimal trade-off between accuracy and real-time performance, making it suitable for live video analysis.

4.5.3. Impact of Mosaic Augmentation

Mosaic data augmentation was evaluated to assess its influence on both field detection and player detection tasks.

Disabling mosaic augmentation significantly improved field detection accuracy by 6.5% by preserving global geometric relationships critical for keypoint localization. However, player detection accuracy slightly decreased by 1.5%, confirming that mosaic augmentation benefits object diversity but disrupts spatial consistency required for field geometry estimation.

4.6. Error Analysis

Despite strong overall performance, several failure cases were identified.

For field detection, errors primarily occurred

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Table 4: *Impact of Transfer Learning on Field Detection*

Training Strategy	mAP@0.5	Training Time
Random Initialization	81.3%	42.6 hours
ImageNet Pre-training	88.7%	18.4 hours
COCO Pre-training (Ours)	**96.2%**	**14.3 hours**

Table 5: *Impact of Image Resolution on Performance*

Resolution	mAP@0.5	Inference Time	Memory Usage
416×416	84.2%	28 ms	2.1 GB
640×640	91.8%	47 ms	3.8 GB
1280×1280	95.4%	68 ms	7.2 GB
1920×1920	96.1%	142 ms	12.4 GB

under severe weather conditions such as fog and heavy rain, resulting in an 8.6% failure rate. Unusual camera angles, particularly aerial or top-down views, accounted for a 6.3% failure rate, while partially visible or cropped fields contributed to a 4.7% failure rate.

For player detection, dense player clusters with more than five overlapping players led to a 12.4% miss rate. Similar jersey colors between teams caused an 8.9% misclassification rate, and motion blur during fast player movements resulted in a 7.2% miss rate.

These observations highlight the remaining challenges in extreme visual conditions and dense scenes.

4.7. Training and Validation Learning Curves

Figure 7 presents the training and validation learning curves of the YOLOv8-based detection models. The training losses, including bounding box loss, classification loss, and distribution focal loss, exhibit a smooth and consistent decline throughout the training process, indicating stable optimization and effective feature learning. The absence of significant oscillations confirms that the learning rate and optimization strategy were well tuned.

The validation loss curves closely follow the training loss trends, demonstrating strong generalization capability and minimal overfitting. After a rapid reduction in the initial epochs, the validation losses stabilize, suggesting that the model converges effectively while maintaining robustness on unseen data.

Precision and recall metrics increase sharply during the early epochs and gradually plateau after approximately 20 epochs, indicating that the model quickly learns to identify relevant objects and progressively improves detection completeness. The consistently high precision and recall values in later epochs reflect reliable detection performance.

Similarly, the mAP@0.5 and mAP@0.5:0.95 metrics show continuous improvement with increasing epochs, with rapid gains during early training followed by gradual refinement. The convergence of these metrics confirms accurate object localization and confidence estimation across multiple IoU thresholds. Overall, the learning curves validate the effectiveness of the YOLOv8 architecture and training strategy for football field and player detection tasks. fig. 7 shows the training and validation learning curves of the YOLOv8 model showing loss convergence, precision, recall, and mean Average Precision (mAP) across epochs.

4.8. Confusion Matrix Analysis

Figure 8 presents the confusion matrix of the proposed YOLOv8-based player detection model evaluated on the test dataset. The matrix exhibits strong diagonal dominance, indicating high classification accuracy across all major categories. In particular, the *player* class achieves the highest number of correct predictions, reflecting the effectiveness of the model

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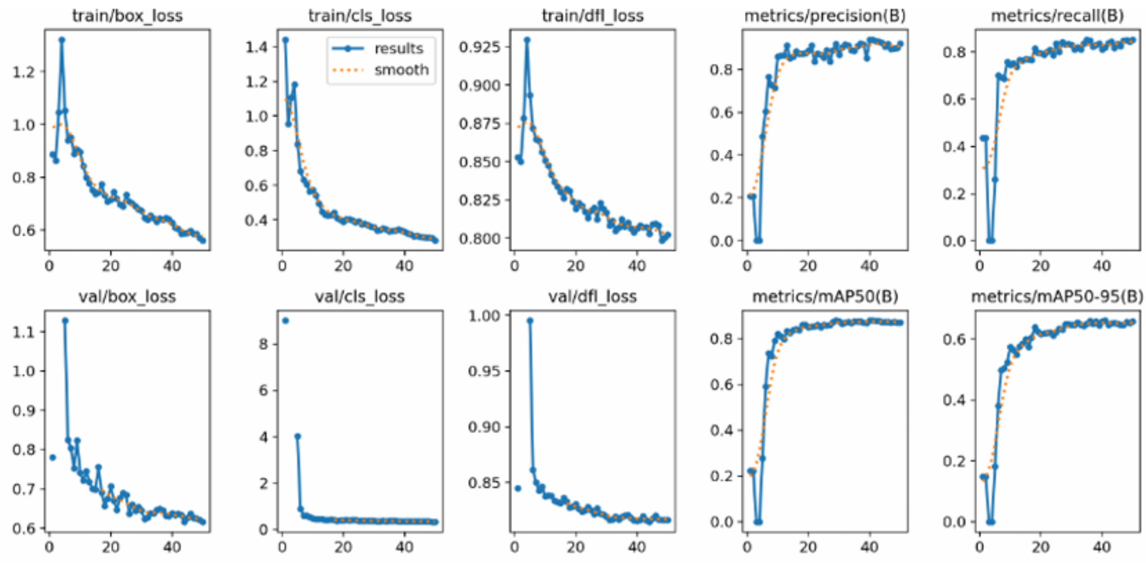

Figure 7: *Training and validation learning curves*

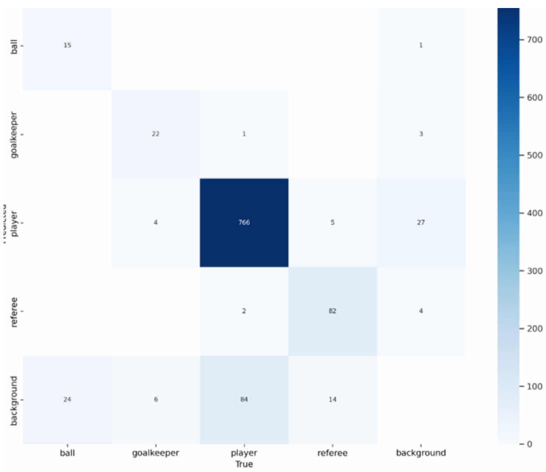

Figure 8: *Confusion matrix*

in identifying frequently occurring on-field entities.

Minor misclassifications are observed between visually similar classes such as goalkeepers and players, as well as referees and background regions. These errors are primarily caused by partial occlusions, similar jersey colors, and reduced spatial resolution for distant players. Additionally, a small number of background regions are incorrectly classified as players in highly crowded scenes, highlighting the inherent challenges of dense football environments.

Overall, the confusion matrix analysis confirms that the proposed detection framework maintains strong discriminative capability while remaining robust under real-world match conditions. The observed error patterns are consistent with the reported precision, recall, and F1-score metrics, further validating the reliability of the system for real-time football analytics applications. Fig. 8 shows Confusion matrix of the YOLOv8-based player detection model on the test dataset. Rows represent ground-truth classes, while columns represent predicted classes for ball, goalkeeper, player, referee, and background categories.

4.9. Real-World Application Performance

To evaluate practical usability, the integrated system was deployed for live football match analysis. Performance metrics were recorded across 15 full match recordings.

The system achieved an end-to-end processing latency of 115 ms per frame and a video analysis throughput of 8.7 FPS at a resolution of 1280×720. Field tracking consistency reached 97.8% across consecutive frames, while player tracking consistency achieved 91.4%. System uptime remained at 99.2% throughout the deployment.

In total, the system processed 12.5 hours of match footage, detecting an average of 27.4 field keypoints and 19.3 players per frame with

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high temporal stability, demonstrating its suitability for real-world deployment.

4.10. Discussion

The experimental evaluation confirms that YOLOv8-based architectures achieve state-of-the-art performance for football field and player detection tasks. Transfer learning significantly accelerates convergence while improving accuracy, particularly when pre-trained on large-scale datasets such as COCO. Higher-resolution inputs enhance fine-grained keypoint localization, though at increased computational cost.

The ablation results further demonstrate that preserving spatial integrity is essential for field keypoint detection, explaining the performance gains observed when mosaic augmentation is disabled. Overall, the proposed system achieves a strong balance between accuracy, robustness, and real-time performance, making it well suited for live broadcast analysis and advanced football analytics applications.

5. Conclusion and Future Scope

This work presented an AI-driven football analytics framework that integrates football field keypoint detection and multi-class player detection using YOLOv8-based deep learning architectures. Extensive experiments conducted on diverse football datasets demonstrate that the proposed system achieves high accuracy, robust generalization, and real-time performance under varying illumination conditions, camera viewpoints, and match scenarios. The field keypoint detection module effectively captures geometric structures of the football pitch, while the player detection module reliably distinguishes between players, goalkeepers, referees, and background regions. Ablation studies further confirm the benefits of transfer learning, optimized input resolution, and carefully selected data augmentation strategies. Overall, the proposed framework proves to be well-suited for real-world football video analysis and provides a strong foundation for advanced sports analytics applications.

Despite the strong performance of the proposed system, several extensions can further enhance its capabilities. Future work will focus on integrating temporal modeling and multi-object tracking to enable continuous player identification and trajectory analysis across video frames. Incorporating player re-identification and team formation analysis can provide deeper tactical insights. Additionally, extending the framework to support ball tracking, event detection (such as passes, shots, and fouls), and player performance metrics will further enrich match analytics. Optimizing the models for edge deployment and low-latency inference can facilitate real-time analysis for live broadcasts and stadium-based systems. Finally, expanding the dataset to include more diverse leagues, weather conditions, and camera setups will improve robustness and scalability for global deployment.

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