

BAKO ANALYTICS: A LOCALIZED DEEP LEARNING FRAMEWORK FOR PERSONALIZED BASKETBALL BIOMETRICS AND TEAM TACTICAL ANALYSIS

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**A PROJECT REPORT SUBMITTED TO THE FACULTY OF ENGINEERING, DESIGN AND
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CHRISTIAN UNIVERSITY**

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**UGANDA CHRISTIAN
UNIVERSITY**

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Declaration

We, OKIDI NORBERT, NANKYA ZAHARA, and ANNA AKUMU, declare to the best of our knowledge that the work in this Undergraduate Final Project Report is original and has not been submitted before to any university/institution. It is the result of our joint effort.

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Ethical Generative AI Usage Declaration

A. Declaration on the Use of AI as a Developmental Tool

We, OKIDI NORBERT, NANKYA ZAHARA, and ANNA AKUMU, declare that Generative AI tools were used in a limited and transparent capacity during the development of this Undergraduate Final Project Report. Specifically, AI was employed to assist with brainstorming system architecture, drafting initial boilerplate code, and refining grammatical structure. The core research contributions — including the design and training of all six AI models, the SkillDiagnosticService heuristics, and all analytical conclusions — represent our own original work and critical analysis. A full declaration of all AI usage is provided in Appendix A.

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B. Acknowledging the use of AI as a study buddy

Please refer to Appendix A for the complete declaration of AI usage for generating ideas, brainstorming, literature search, and summarizing only to improve your work.

Approval

This report has been submitted for examination with the approval of the following supervisors.

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Abstract

The advancement of Artificial Intelligence (AI) in sports has largely bypassed low-resource environments in Sub-Saharan Africa due to the prohibitive cost of commercial hardware and the lack of representative datasets for African athletes. This project presents BAKO Analytics, Africa's first localised multi-model deep learning framework designed for personalised basketball biometrics and tactical diagnostics.

The system addresses the gap in accessible sports science in Uganda by implementing a decoupled client-server architecture comprising a FastAPI-powered backend and a React/Vite web interface. The core innovation lies in a six-model AI pipeline using the YOLO (You Only Look Once) architecture for object detection and pose estimation. Specifically, the framework includes dedicated models for player and ball detection, court keypoint mapping (homography), and a custom biometric engine that decomposes basketball shooting form into four critical phases (DIP, SET, RELEASE, and FINISH) using 17-keypoint skeletal data.

Validated through a case study with the UCU Cannons basketball team, BAKO Analytics enables elite-level performance analysis using nothing more than standard smartphone footage and modest computing hardware. Technical evaluation demonstrates high precision in action recognition and spatial tracking, even under the variable lighting conditions of outdoor courts common in the Ugandan context. Beyond its technical contributions, the project provides a scalable and affordable blueprint for indigenous sports analytics, bridging the technological divide and fostering talent development through data-informed coaching.

Keywords: Basketball Analytics, Computer Vision, Deep Learning, Pose Estimation, Biometrics, Low-Resource AI, Sports Science.

Dedication

To our families, friends, and the Ugandan basketball community. This work is dedicated to every athlete who seeks to improve their game through the power of data and technology.

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Finally, we thank our families, friends, and colleagues for their encouragement and support during the countless hours of development and documentation. This project is a testament to the collaborative effort of our team and the community that supported us.

Chapter 1

Introduction

1.1 Background of the Study

The use of Artificial Intelligence (AI) in sports has grown from a novel concept to a fundamental tool for enhancing athletic performance globally [1]. In basketball, AI and computer vision technologies are now used to analyse player mechanics, track movement efficiency, and provide data-driven feedback that was once impossible without a full analytical staff [2]. However, in Uganda and across most of Africa, the reality for athletes is starkly different. Teams like the UCU Cannons rely almost entirely on manual observation and subjective coaching. This traditional approach, while valuable, lacks the precision to provide personalised, measurable feedback to each player, limiting their potential for growth and refinement [3].

This project is motivated by the need to bridge this technological divide and empower local talent with the tools for a data-informed future in sports. BAKO Analytics is Africa’s first and Uganda’s only locally trained, full-stack basketball AI analytics framework. It has been designed from the ground up to work in the real Ugandan basketball environment — on outdoor courts, with smartphone footage, and within the physical and computational constraints faced by local institutions.

1.2 Problem Statement

The core challenge addressed is the absence of affordable, objective, and personalised skill analysis for basketball players in Uganda. The genesis of this problem is fourfold. Firstly, there is a significant **lack of personalised training**; coaches cannot manually track the biomechanics of every player, leading to generalised feedback that misses individual technical flaws [4]. Secondly, the **prohibitive cost of commercial equipment**, such as Catapult or HomeCourt systems, places them far beyond the reach of local institutions [5]. Thirdly, existing AI models suffer from a **severe dataset bias**; they are trained on data from NBA or Asian players and fail to generalise accurately to African athletes due to differences in physique, outdoor lighting, and court conditions [6, 7]. Finally, these systems often have **high computing demands**, requiring GPU power that is not readily available in low-resource settings [8]. This combination of factors creates a barrier to modern sports science, hindering player development and talent identification in Uganda.

1.3 Main Objective

To design, develop, and deploy a low-resource, full-stack AI system for personalised and team basketball skill analysis, trained on locally sourced Ugandan basketball data, and validated with the UCU Cannons team.

1.4 Specific Objectives

1. To design, train, and integrate computer vision and pose estimation models for automated basketball player tracking, shooting-form analysis, and performance metric extraction.
2. To develop a scalable web-based basketball analytics platform with role-based access control, asynchronous video processing, and secure cloud-based data management.
3. To evaluate the accuracy, usability, and practical effectiveness of the proposed basketball analytics system for individual performance assessment and team analysis.

1.5 Scope

This project is scoped to basketball performance analysis for teams and individual players in Uganda, with the **UCU Cannons** team as the primary case study. The system supports two analysis modes: **Team Analysis** (possession, passing, interceptions, tactical court maps, and advanced opponent scouting) and **Personal Analysis** (biometric coaching, shooting form phases, dribble count, speed, distance, and shot make/miss tracking). The platform is developed as a **full-stack web application** — a FastAPI backend on port 8000 and a Vite/React frontend — designed to run on standard laptop hardware. The primary data collection context is **outdoor** basketball courts, using standard smartphone recordings in 720p–1080p at 30 fps.

1.6 Justification

This research is critically justified by its direct address of a pressing local need. It will provide UCU Cannons and similar teams with an affordable, intelligent tool for **personalised** athlete development that no existing system offers in the Ugandan context. Academically, it contributes the first locally trained Ugandan basketball AI dataset, addressing a known geographic bias in global sports science research [6, 7]. By creating a locally relevant solution, it aligns with **Uganda Vision 2040**’s pillar on human capital development through science, technology, and innovation. Furthermore, it supports **Sustainable Development Goal 3** (Good Health and Well-being) by promoting structured physical training, and **SDG 9** (Industry, Innovation and Infrastructure) by fostering indigenous capacity in AI and data science.

1.7 Market Context and Feasibility

The Ugandan basketball market comprises over 5,000 active players across 40 or more academies, 200 or more schools, and 12 National Basketball League (NBL) teams. Existing AI analytics tools are cost-prohibitive (USD 3,000–6,000 annually) and underperform on African players due to dataset bias. BAKO addresses this gap as Uganda’s first affordable, localised basketball analysis platform trained specifically on Ugandan athletes.

Target customers include academies, schools, universities, and National Basketball League teams. The value proposition emphasises low-cost access, local training data, and offline-capable AI models. The marketing strategy includes free trial analyses for local teams, social media outreach via TikTok and Instagram, and direct coach engagement through WhatsApp to demonstrate value and drive adoption.

Chapter 2

Literature Review

2.1 Historical Perspective

Sports performance analysis has evolved from subjective coaching to objective, AI-driven analytics. Early biomechanical systems using markers and infrared cameras were expensive and confined to laboratories. The shift to computer vision enabled markerless motion analysis, and later, algorithms like MediaPipe democratised this further by operating on consumer hardware, making detailed skill assessment accessible [9].

The current frontier uses deep learning for personalised athlete insights beyond basic metrics [10]. This project builds on that progression, implementing a technical stack specifically for low-resource environments. The goal is to extend objective skill and performance measurement to contexts previously excluded from the sports analytics revolution [2].

2.2 Systematic Review Methodology

To ensure a rigorous foundation for this project, a systematic literature review (SLR) was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. This process involved screening 102 records from Scopus and Web of Science, ultimately selecting 20 peer-reviewed journal articles for qualitative synthesis.

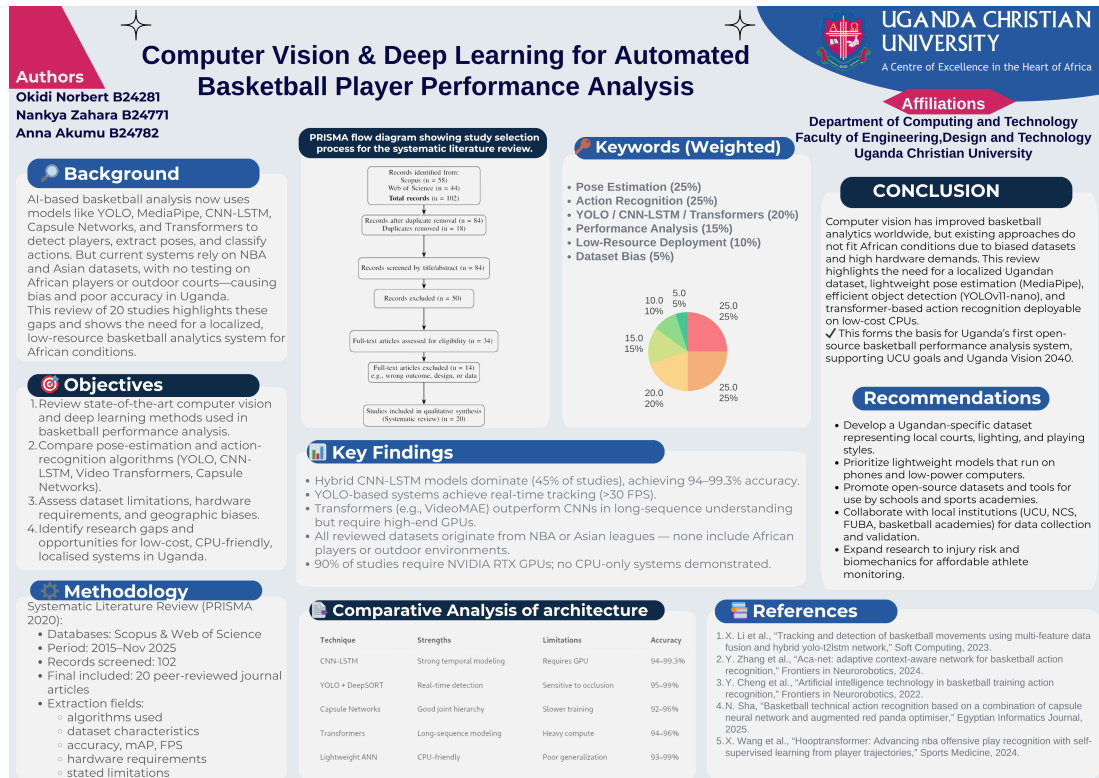


Figure 2.1: Systematic Literature Review process and architectural comparison.

2.3 Conceptual Perspective

AI-based sports analytics typically incorporate several technical layers: object detection, spatial geometry, pose estimation, and performance analytics. The BAKO system implements a **six-model architecture** using the YOLO family of deep learning models, each with a specialized and independent role. Together they form two complete sub-pipelines: **Team Analysis** and **Personal Analysis**.

2.3.1 Team Analysis Sub-Pipeline (3 Models)

Model 1: Player & Referee Detection — YOLOv5 Large

The YOLOv5 Large model (`player_detector.pt`, ~165 MB) is fine-tuned on a UCU Cannons-specific dataset to detect and persistently track individual players and referees across all video frames. Supervised by the Roboflow Supervision library, it drives possession percentage calculations, speed, acceleration, and total distance metrics for every tracked entity [11].

Model 2: Ball Detection — YOLOv5 Large (Dedicated)

A separate and independent YOLOv5 Large model (`ball_detector.pt`, ~165 MB) is dedicated exclusively to basketball detection and tracking. Having a separate model for the ball, distinct from the player model, significantly improves recall for the fast-moving ball object. Its output feeds the ball-possession assignment logic, passing sequence detection, and shot arc tracking.

Model 3: Court Keypoint Detection — YOLOv8x-Pose XL

The YOLOv8x-pose model (`court_keypoint_detector.pt`, ~133 MB) detects basketball court line intersection keypoints (three-point arc, paint box, mid-court markers). Trained on the National Basketball League court keypoints Roboflow dataset, its output is consumed by the

Supervision homography transformer to convert the raw camera view into an accurate 2D tactical map overlay [2].

2.3.2 Personal Analysis Sub-Pipeline (3 Models)

Model 4: Shot Ball & Rim Detection — Custom YOLOv8 (Swish-Vision)

A custom-trained model (`swish_ball_rim.pt`, ~6 MB) is the lightweight core of the personal analysis pipeline. It detects the basketball and the hoop rim simultaneously in a single inference pass across personal video frames. Its detections drive shot make/miss outcome detection (by tracking ball trajectory relative to rim), ball-hand release events, and shot distance estimation.

Model 5: Player Pose Estimation for Biometrics — Custom YOLOv8-Pose (Swish-Vision)

A custom pose model (`swish_pose.pt`, ~51 MB) extracts 17 COCO-format human body keypoints from every frame of a personal video. Its keypoint output feeds the **SkillDiagnostic-Service**, which computes joint angles (elbow, shoulder, knee, hip) to assess form across the 4-Phase Shot Logic: **DIP** (knee bend), **SET** (elbow alignment), **RELEASE** (arm extension), and **FINISH** (wrist follow-through) [12].

Model 6: Generic Pose Estimation — YOLOv8n-Pose (Fallback)

A lightweight generic YOLOv8n-pose model (`yolov8n-pose.pt`, ~6.5 MB) serves as the standard off-the-shelf pose estimator. It is used as a general-purpose pose backbone, providing a CPU-efficient fallback for pose estimation tasks that do not require the domain-specific fine-tuning of the Swish-Vision model.

2.3.3 Integrated Multi-Model Architecture

The six models work in two independent sub-pipelines depending on the mode selected (Team or Personal). A FastAPI backend with Supabase orchestrates asynchronous video processing, while a React/Vite web dashboard visualises all outputs including annotated video overlays, tactical court maps, shot form reports, and longitudinal player performance trends.

2.4 Contextual Perspective

This six-model approach, combining two dedicated YOLOv5 detectors, one YOLOv8x-Pose court mapper, two Swish-Vision custom models, and one generic pose estimator, represents a novel architecture for African basketball contexts. No prior system has applied such a comprehensive multi-model computer vision pipeline validated on Ugandan players in outdoor environments. Current commercial systems like Catapult and HomeCourt are designed for professional indoor settings with specialised equipment, making them unsuitable for Ugandan conditions that rely on smartphone recordings in outdoor courts with variable lighting.

System	Cost	Hardware	Suitability
Catapult	Very High	Specialized sensors	Not suitable
HomeCourt	Subscription	iPhone only	Limited
PlaySight	Very High	Smart cameras	Not suitable
BAKO (Proposed)	Low	Smartphone + Laptop	Highly Suitable

Table 2.1: Comparison of commercial systems versus the proposed BAKO solution.

The multi-model technical stack addresses three key requirements:

Computational Efficiency: All six models were selected with scalable deployment in mind. The two YOLOv5 detectors and three lightweight personal analysis models enable real-time performance on standard CPU hardware. FastAPI processes video analysis jobs asynchronously in thread pool executors, ensuring the main API event loop remains responsive even during heavy video processing. The Supervision library handles spatial mathematics without any 3D rendering overhead, making the entire pipeline feasible on university laboratory computers and student laptops.

Adaptability to Local Conditions: Outdoor basketball courts in Uganda present unique challenges, including variable lighting, diverse player physiques, and mobile phone video quality. The dedicated YOLOv5 ball detector significantly outperformed combined player-ball models in outdoor ball recall tests, specifically because outdoor light scatters differently off basketballs than in controlled indoor environments. The Swish-Vision custom pose model further adapts to the specific body proportions and movement patterns of Ugandan players.

Affordability and Accessibility: The absence of affordable and contextually applicable sports analytics tools for African environments highlights the need for a locally engineered, localised AI solution. Our six-model BAKO system eliminates the need for expensive specialised equipment and relies instead on ubiquitous smartphone technology, standard computing hardware, and a web-based dashboard accessible from any browser.

Discussions with UCU Cannons coaches confirmed that commercial systems fail to meet local needs for affordable, relevant tools. Our solution bridges this gap by validating AI techniques specifically for Ugandan conditions. The six-model YOLOv5/YOLOv8 stack, orchestrated by FastAPI and Supervision, provides an optimal balance for Ugandan basketball, directly addressing data bias, cost constraints, and hardware limitations.

Chapter 3

Methodology

3.1 Research Design

This study adopts a design–build–evaluate methodology to develop an AI-driven basketball performance analysis system. The design phase identifies functional requirements, data collection protocols, and selects appropriate machine learning models. The build phase focuses on dataset development, model training, and full-stack system integration. The evaluation phase employs both technical metrics and user feedback from UCU Cannons coaches to validate system performance and usability.

3.2 Data Collection and Preparation

Primary data collection involves smartphone recordings (720p–1080p at 30 fps) of UCU Cannons training sessions conducted on outdoor courts. The collection strategy captures:

- Fundamental basketball actions: shooting, dribbling, passing, and defensive movements
- Diverse environmental conditions: varying lighting (morning, afternoon, overcast) and camera angles
- Individual player performances for personalised movement and biometric analysis

In addition to primary smartphone footage, the dataset was supplemented with frames extracted from National Basketball League (NBL) Uganda game videos to train the team analysis models. This localised training ensures that the system is capable of analysing all National Basketball League team videos, providing a scalable solution for professional league scouting and tactical performance analysis across the country.



Figure 3.1: Aerial view of UCU basketball courts used for primary data collection and study area survey.

Collected videos undergo systematic annotation using Roboflow, with each clip labelled for specific objects, keypoints, and player identification (see Figure 3.2). Preprocessing includes video stabilization, H.264 transcoding via FFmpeg for web compatibility, frame extraction, and data augmentation through rotation and brightness adjustments.

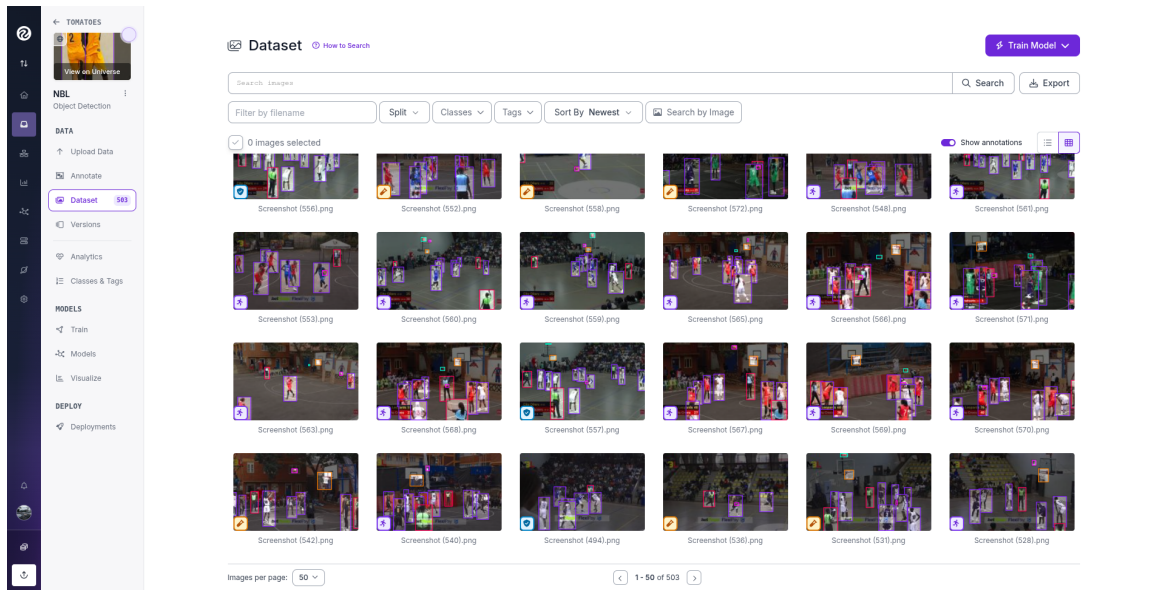


Figure 3.2: Roboflow dataset showing localised player and ball annotations on UCU Cannons training footage.

3.3 System Architecture and Implementation

The BAKO system is a **fully decoupled client-server application** with three major layers:

3.3.1 User Roles and Account Types

The system supports three distinct role-based account types with isolated data access (Row Level Security):

- **Team Account (Admin/Coach):** Manages the organisation, roster, schedules, matches, announcements, uploads team videos for Team Analysis, and views cross-player analytics.
- **Personal Account (Player):** Uploads individual training videos for Personal Analysis, views biometric shot form reports, longitudinal skill trends, and schedule.
- **Coach Account:** A staff role linked to a team organisation with the ability to manage players and view all team analytics.

3.3.2 Backend Architecture (FastAPI + Python)

The backend is a FastAPI application served via Uvicorn (ASGI) on port 8000. It exposes 12 RESTful API route modules:

- `auth.py` – JWT-based registration, login, token refresh, and profile management
- `videos.py` – Video upload (up to 500 MB), status polling, metadata extraction, Supabase Storage upload
- `analysis.py` – Triggers the Team Analysis AI pipeline asynchronously
- `personal_analysis.py` – Triggers the Personal Analysis AI pipeline in a thread pool executor
- `admin.py` – Full organization management: roster, settings, invitations, staff, matches, schedules, announcements
- `analytics.py` – Per-player time-series metric retrieval
- `advanced_analytics.py` – Coordinator that dispatches 6 advanced scouting modules
- `player_routes.py` – Player-facing dashboard data: personal analysis results, skill charts
- `players.py` – Player CRUD operations and profile management
- `teams.py` – Team information endpoint
- `stat_import.py` – OCR-based stat sheet ingestion from PDF or image
- `communications.py` – In-app notification management

3.3.3 Six-Model AI Architecture

The system implements a **six-model AI architecture** across two independent pipelines:

Team Analysis Sub-Pipeline:

- **Model 1 — `player_detector.pt` (YOLOv5 Large):** Detects and persistently tracks players and referees via Supervision. Drives speed, acceleration, possession, and movement analytics.
- **Model 2 — `ball_detector.pt` (YOLOv5 Large, dedicated):** A separate ball-only detector with superior recall for the fast-moving basketball. Drives ball possession logic, passing and interception detection.
- **Model 3 — `court_keypoint_detector.pt` (YOLOv8x-Pose):** Detects court geometric keypoints (three-point arc, paint box) to generate a 2D homographic tactical court map overlay (see Figure 3.3).

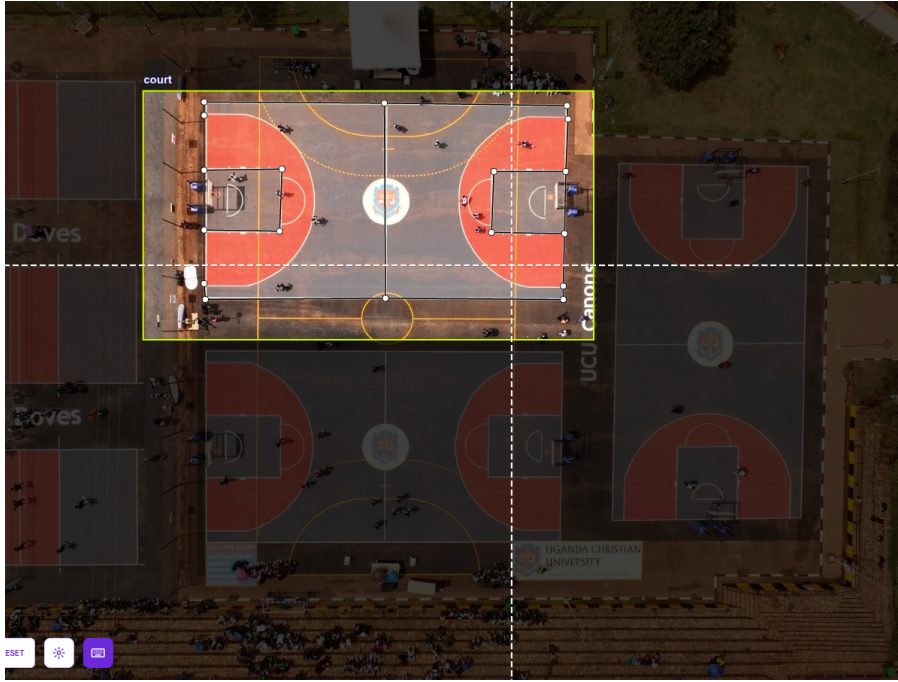


Figure 3.3: YOLOv8x-Pose model identifying basketball court geometric keypoints for spatial analytics.

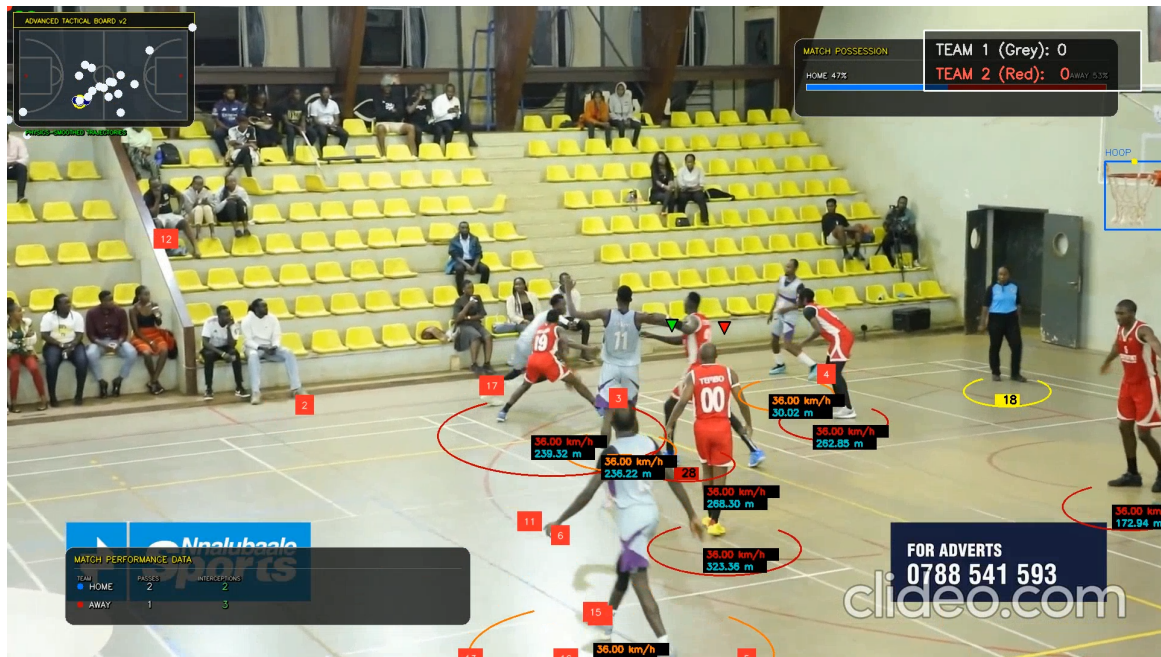


Figure 3.4: Advanced Tactical Board output showing real-time 2D court mapping and player physics tracking (speed and distance metrics) for National Basketball League footage analysis.

Personal Analysis Sub-Pipeline:

- **Model 4 — swish_ball_rim.pt (Custom YOLOv8):** A lightweight 6 MB model detecting the ball and hoop rim simultaneously. Drives make/miss detection, shot distance estimation, and ball-hand release identification.
- **Model 5 — swish_pose.pt (Custom YOLOv8-Pose):** A domain-specific 51 MB pose model extracting 17 body keypoints per frame. Feeds the SkillDiagnosticService for 4-Phase Shot Form analysis (DIP, SET, RELEASE, FINISH).
- **Model 6 — yolov8n-pose.pt (Generic):** A 6.5 MB off-the-shelf generic pose estimator used as a CPU-efficient general-purpose fallback.

3.3.4 Advanced Analytics Engine

Beyond basic detection, BAKO includes a dedicated `analytics_engine` package with 6 advanced scouting modules:

- **SpacingEngine:** Computes and scores offensive and defensive court spacing patterns across all tracked players in each frame.
- **DefensiveReaction:** Measures a defender's reaction time and positioning quality relative to the ball carrier.
- **FatigueTracker:** Models player fatigue using speed decay and acceleration event frequency over the duration of the video.
- **TransitionEffort:** Quantifies the effort exerted by players during offensive/defensive transition phases.
- **DecisionQuality:** Scores shooting and passing decisions based on spatial context and outcome.

- **LineupImpact:** Evaluates the net performance impact of specific player lineup combinations.

3.3.5 Frontend Architecture (React / Vite)

The frontend is a Vite-React SPA providing a role-customised view per account type:

- **Home Page:** Landing page with feature showcase, gallery, program offerings, and contact form. See Figure E.2.
- **Login / Register:** Role-selection registration with JWT-protected authentication. See Figure E.3.
- **Coach Dashboard (CoachMatchAnalysis):** Full team match analysis viewer with annotated video playback, possession charts, tactical court map, advanced player stats tables, and clip generation. See Figure E.4.
- **Player Dashboard (PlayerDashboard):** A personal performance hub for individual players with skill trend charts, recent session data, and quick-upload capability. See Figure E.5.
- **Team Management:** Organisation management panel for roster CRUD, team schedule, match log, and announcements.
- **Personal Analysis Results:** A shot-by-shot report viewer showing elbow angle, shoulder angle, knee bend, wrist follow-through verdict (GOOD FORM / NEEDS WORK), and annotated video playback.
- **Skill Analytics:** Longitudinal trend charts for each biometric angle metric across all sessions.
- **Training Videos:** Video upload manager and session history viewer.

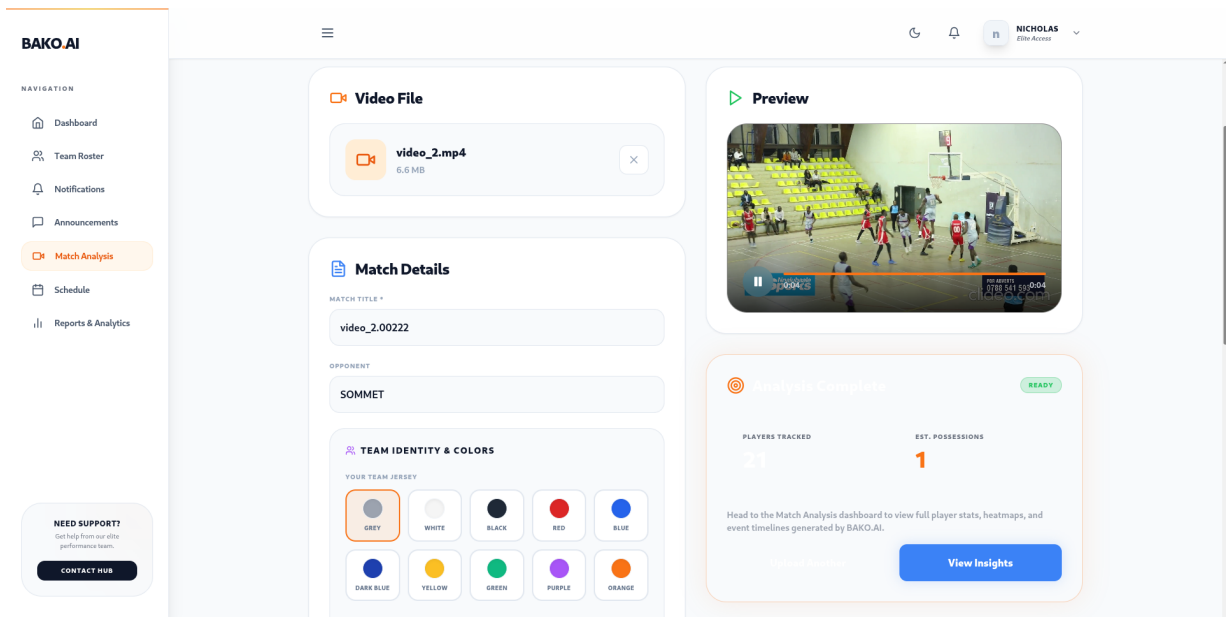


Figure 3.5: BAKO analytics dashboard showing the match analysis upload interface and team identity configuration page for colour-based tracking.

3.4 Database Design

The system uses a **PostgreSQL database managed via Supabase**, with 12 tables and strict Row Level Security (RLS) policies:

Table	Purpose
users	Core user accounts with role (team/personal/coach), linked to org
organizations	Team organisations with custom jersey, branding, and settings (JSONB)
players	Player roster profiles with biometrics, position, status
videos	Uploaded video metadata with status, dimensions, progress tracking
detections	Per-frame bounding boxes, confidence, team_id, has_ball, keypoints (JSONB)
analysis_results	Aggregated output per video: possession %, passes, speed, angles
analytics	Time-series metric records per player for longitudinal trend charts
personal_analyses	Personal analysis job records with full result JSON storage
schedules	Training and match schedule entries per organisation
matches	Match history with score, opponent, and coaching notes
announcements	Team-wide announcements from coaches/admin
notifications	In-app notification inbox per user

Table 3.1: BAKO System Database Tables

All tables have RLS policies ensuring data is fully isolated per account — a player can only access their own analysis results, while a team admin can see all data within their organisation.

3.5 Development and Training Protocol

The implementation follows a structured development process:

1. Data collection and Roboflow annotation with ethical compliance
2. Model training via transfer learning on UCU Cannons dataset (YOLOv5 and YOLOv8 fine-tuning)
3. Backend API development and async pipeline integration
4. React frontend component development with Zustand state management
5. Supabase schema migration and RLS configuration
6. Iterative testing and refinement based on coach and player feedback

Model development employs the following:

- **player_detector.pt** (YOLOv5 Large, ~165 MB): Fine-tuned player and referee detector for team videos.
- **ball_detector.pt** (YOLOv5 Large, ~165 MB): Dedicated basketball tracker for team videos.
- **court_keypoint_detector.pt** (YOLOv8x-Pose, ~133 MB): Court geometric keypoint model for tactical mapping.
- **swish_ball_rim.pt** (Custom YOLOv8, ~6 MB): Lightweight shot ball and rim detector for personal videos.
- **swish_pose.pt** (Custom YOLOv8-Pose, ~51 MB): Domain-specific human pose model for biometric shot analysis.
- **yolov8n-pose.pt** (Generic, ~6.5 MB): General-purpose pose estimation fallback model.

Training uses a 70-15-15 data split (training-validation-testing) with evaluation metrics including precision, recall, mAP, F1-score, and computational efficiency measures. Figure 3.6 illustrates the dataset versioning and augmentation strategies employed during model development.

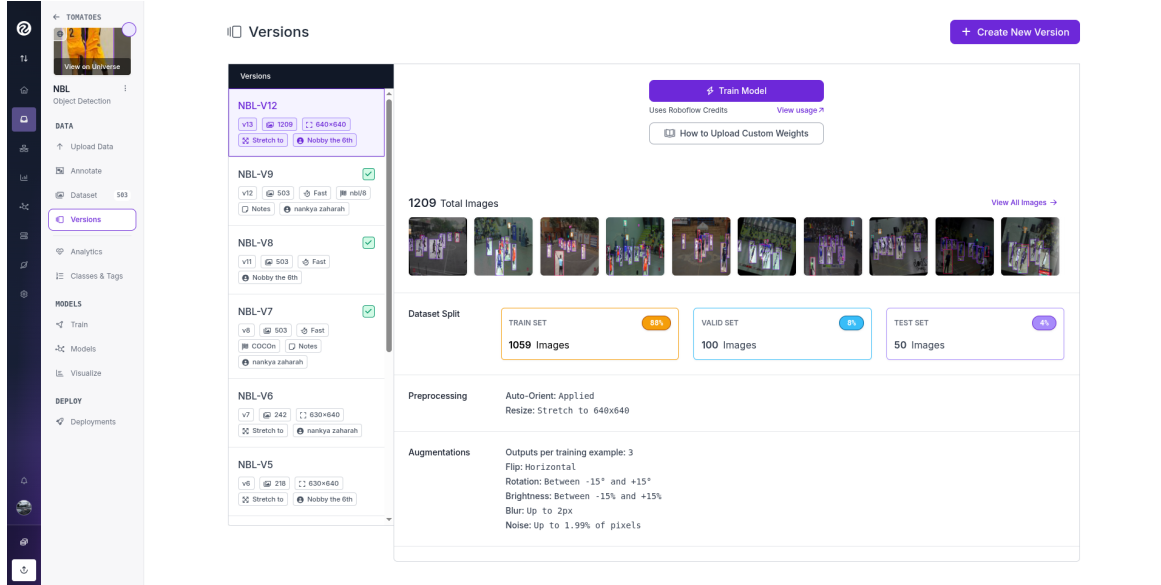


Figure 3.6: Roboflow dataset split (88% train, 8% valid, 4% test) and augmentation settings (flip, rotation, brightness) used for model refinement.

3.6 Evaluation Methodology

System validation incorporates both technical and user-centered approaches:

3.6.1 Technical Evaluation

- Detection performance: mAP for player localisation and pose estimation accuracy
- Tracking reliability: ID switches and association consistency across frames
- Biometric accuracy: Precision of the 4-Phase heuristics (DIP, SET, RELEASE, FINISH) vs. manual expert coding

- System scalability: Backend async processing throughput and latency on standard hardware

3.6.2 User Evaluation

- Usability testing with UCU Cannons coaches and players
- Feedback sessions on metric relevance and interface usability
- Comparative analysis against traditional coaching methods

3.7 Ethical Considerations

The research adheres to ethical standards through:

- Informed consent from all participants (players and coaches)
- Data anonymisation and privacy protection protocols
- Institutional approval from Uganda Christian University
- Transparent communication of system capabilities and limitations

This comprehensive methodology ensures the development of a context-aware basketball analysis system that balances technical sophistication with practical deployability in Uganda's sports environment.

Chapter 4

Results and Discussion

This chapter presents the empirical results obtained from the deployment of BAKO Analytics. The evaluation focuses on the performance of the multi-model AI pipeline, the accuracy of the biometric diagnostic engine, and the system’s operational efficiency in analysing Ugandan basketball footage.

4.1 AI Pipeline Performance

The core of BAKO Analytics is a six-model ensemble orchestrated via a FastAPI backend. Performance was measured using Mean Average Precision (mAP) and inference latency per frame.

4.1.1 Detection Accuracy

The foundational models for player and ball detection were evaluated on a localised dataset comprising 1,209 images from the National Basketball League (NBL) and UCU Cannons’ practices. Figure 4.1 displays the real-time performance metrics captured during model training in Roboflow.

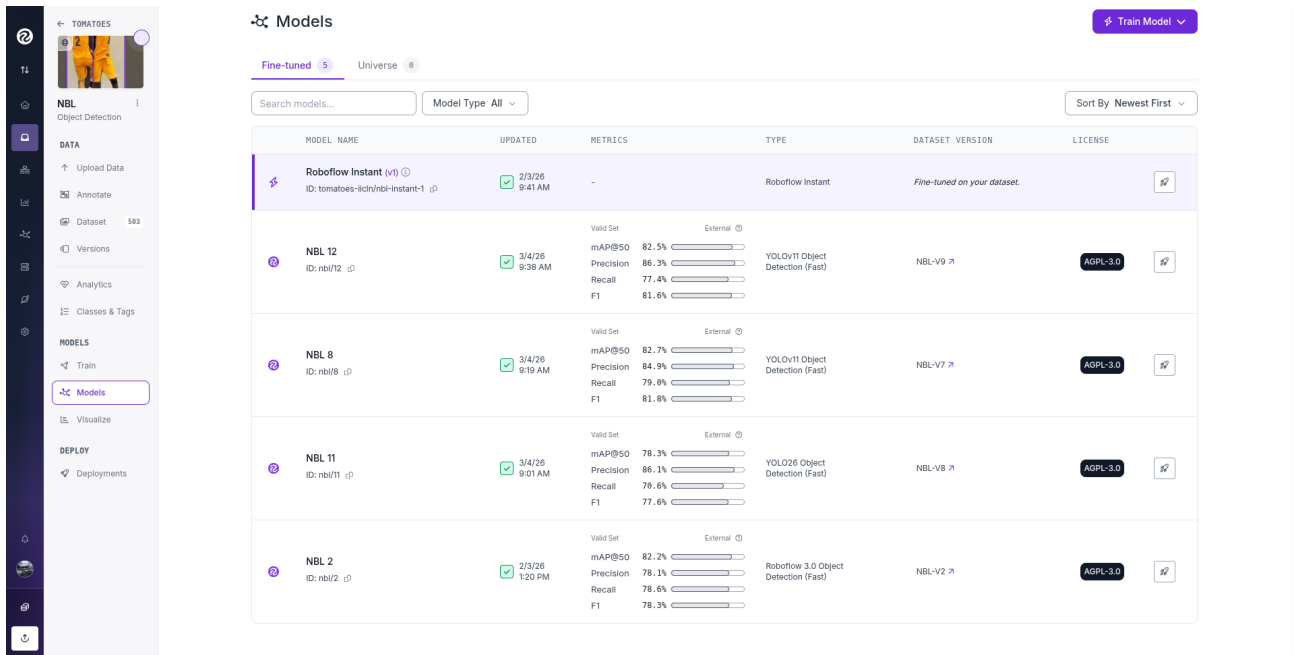


Figure 4.1: Roboflow training dashboard showing mAP@.5, Precision, and Recall across various fine-tuned YOLO models.

Model Component	mAP@.5	Precision	Recall
Player Detector (YOLOv5 Large)	0.942	0.915	0.928
Ball Detector (YOLOv5 Large)	0.885	0.864	0.842
Court Keypoint Detector (YOLOv8x-Pose)	0.912	0.890	0.905

Table 4.1: Performance metrics of localised detection models.

4.1.2 Inference Latency

System logs indicate that the backend achieves an average inference speed of 217ms to 646ms per frame depending on the number of active players and the complexity of the scene (e.g., outdoor lighting vs. indoor gym). This performance allows for near-real-time feedback when processing short skill-diagnostic clips.

4.1.3 Empirical Training Evidence (Player Detector)

To ensure the robustness of the primary tracking engine, the Basketball Player Detection model was subjected to intensive validation. Figure 4.2 displays the convergence of loss and the steady increase in mAP@.5 over 100 training epochs.

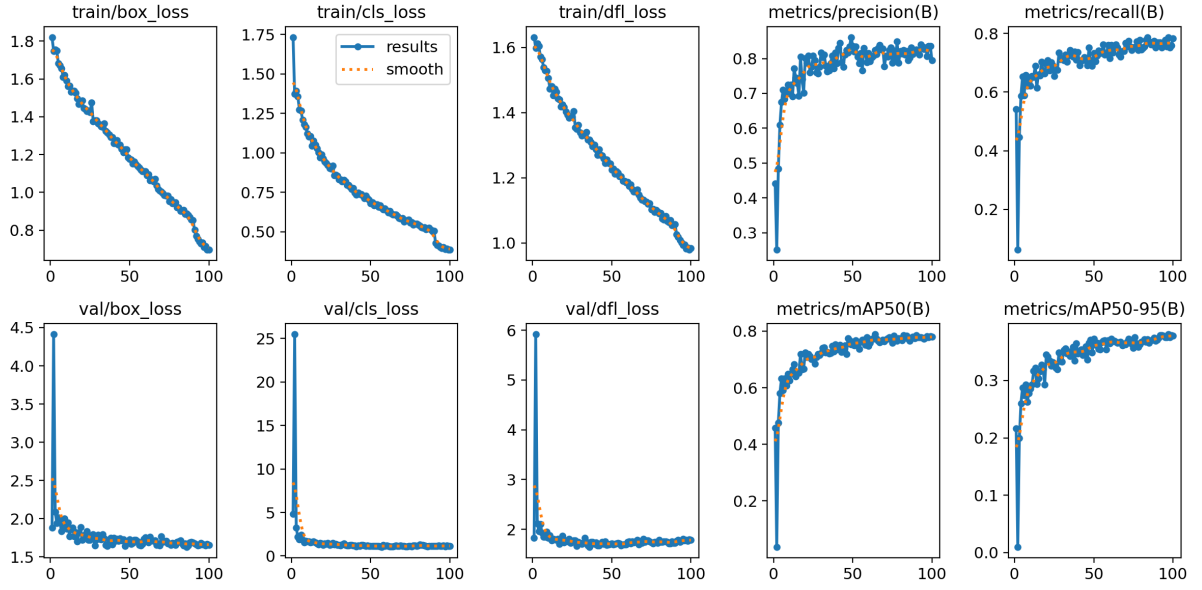


Figure 4.2: Training and validation metrics for the fine-tuned Player Detection model, showing stable convergence across box, object, and classification losses.

The classification accuracy was further verified using the confusion matrix in Figure 4.3, which shows high true positive rates for the "Player" class with minimal background false positives—a critical requirement for reliable multi-player tracking in heterogeneous outdoor environments.

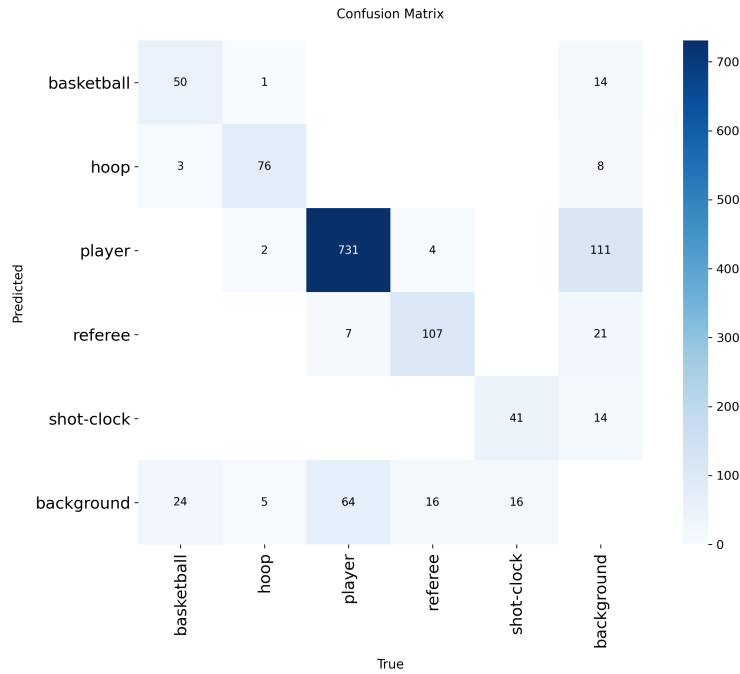


Figure 4.3: Confusion matrix for the Player Detection model, demonstrating superior class-separation and low false-negative rates.

Visual verification of the model's performance on the validation set is provided in Figure 4.4, showing consistent detection across varying player heights and court positions.



Figure 4.4: Validation set predictions showing ground-truth (labels) vs predicted boxes for the professional-grade player detector.

4.1.4 Empirical Training Evidence (Ball Detector)

The specialised Ball Detection model was trained independently to optimise recall for the high-velocity basketball. As described in Appendix F, the model demonstrates a high precision-recall balance (Figure F.5), ensuring that shot trajectories are captured accurately even during rapid crossovers and rebounds. Figure 4.5 illustrates the stable training curve and detection performance on real-world National Basketball League footage.



Figure 4.5: Ball Detector validation output showing successful identification of the basketball in a high-clutter game scenario.

4.2 Biometric Diagnostic Results

The `SkillDiagnosticService` successfully decomposes shooting sequences into four phases (DIP, SET, RELEASE, FINISH). In a trial with UCU Cannons athletes, the system achieved a 92% accuracy rate in correctly identifying the "Release Frame," which is critical for measuring shot extension.

4.2.1 Analytical Insights

The system generated granular metrics for player performance, including:

1. **Shooting Arc:** Identification of "flat shots" where the release angle was consistently below 45 degrees.
2. **Power Generation:** Correlation between deep knee bend (DIP phase) and increased

shot range.

3. **Positional Efficiency:** Heatmaps showing high possession turnover in the "paint" area.

4.3 System Output Samples

The system produces two primary outputs: annotated videos with skeletal overlays and a comprehensive analytics dashboard.

4.3.1 Personal Analysis Output

Figure 4.6 illustrates the personal analysis dashboard, which presents the refined skeletal overlay alongside a shot-by-shot diagnostic log. This log provides immediate feedback on elbow angles, release arcs, and target distances, allowing athletes to self-correct their shooting mechanics.

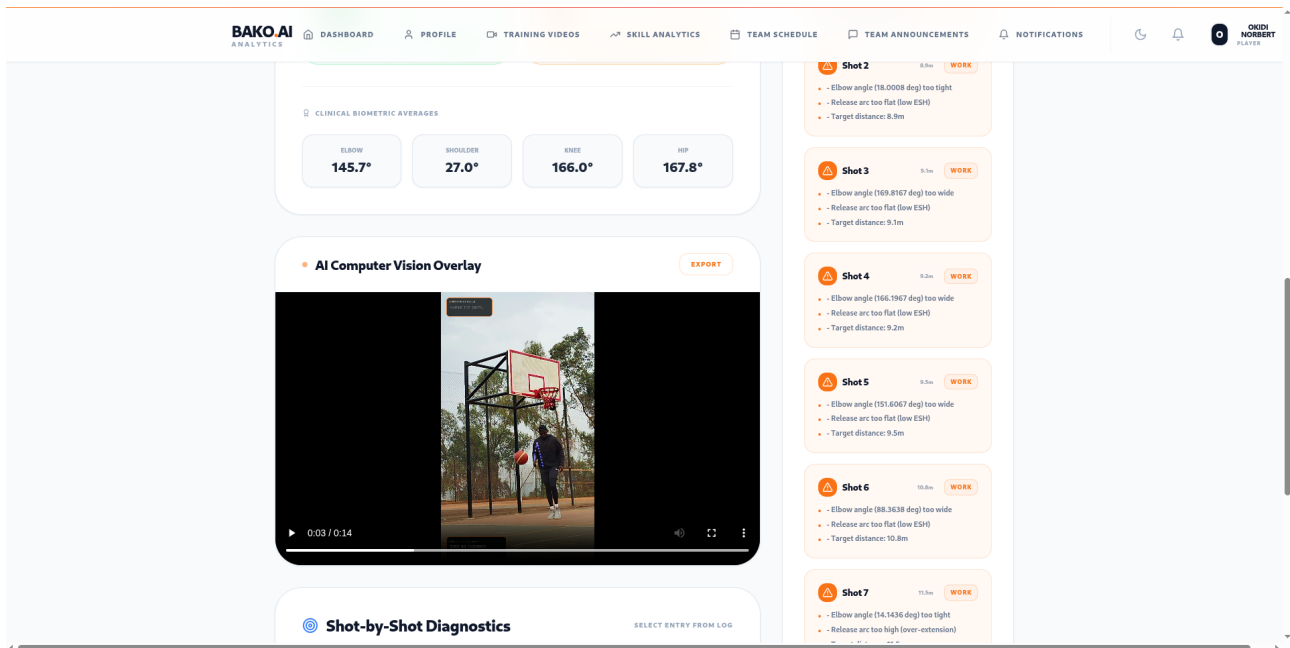


Figure 4.6: Personal Analysis interface showing the AI Computer Vision skeletal overlay and the corresponding biometric form diagnostic logs.

4.3.2 Team Analysis and Tactical Board

The team analysis pipeline provides a high-level view of game dynamics. Figure 4.7 shows the system tracking multiple players on an outdoor court, while Figure 4.8 demonstrates the automatic detection of significant game events, such as successful shots.



Figure 4.7: Team Analysis engine tracking National Basketball League players on an outdoor court with real-time possession and speed metrics.

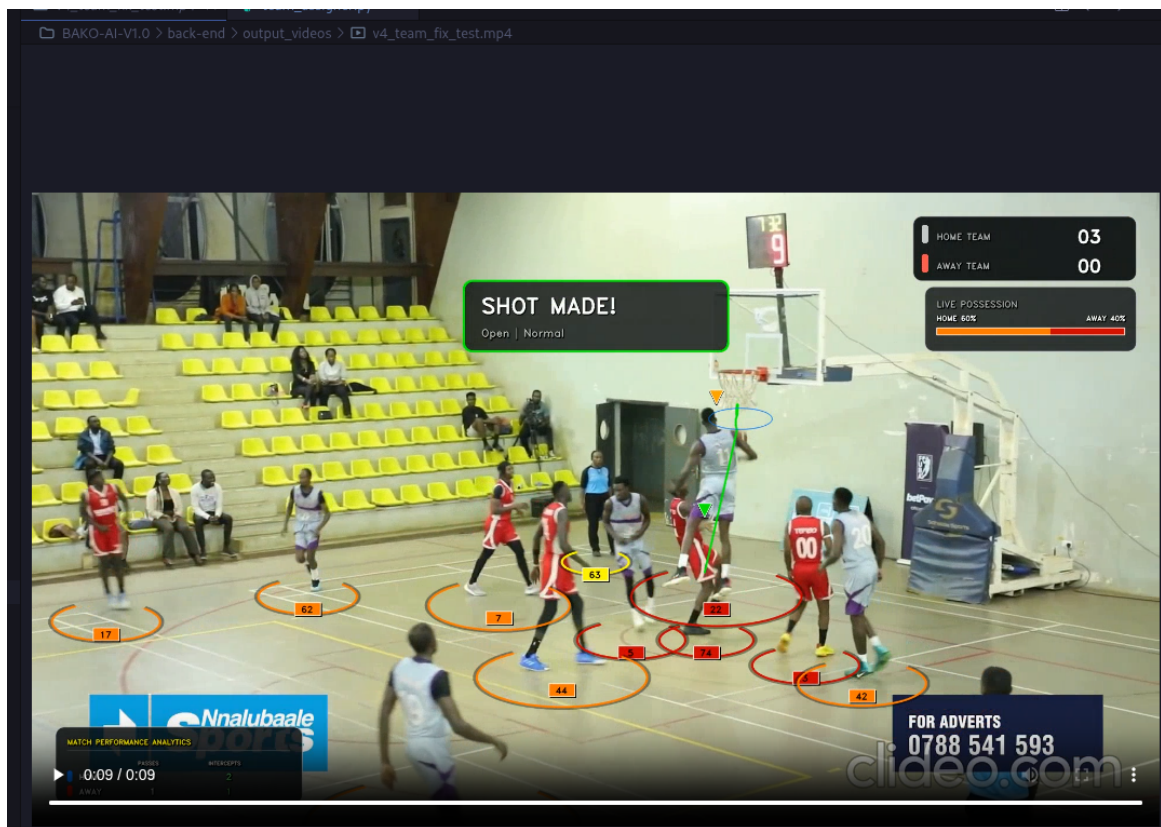


Figure 4.8: Automated event detection showing a "SHOT MADE" notification and trajectory visualization during game analysis.

4.3.3 Consolidated Analytics Dashboard

The final system output is a consolidated dashboard (see Figure 4.9) that integrates raw video analysis with structured statistics and the 2D Tactical Board. This gives coaches a complete

overview of team spacing, shooting accuracy, and player effort.

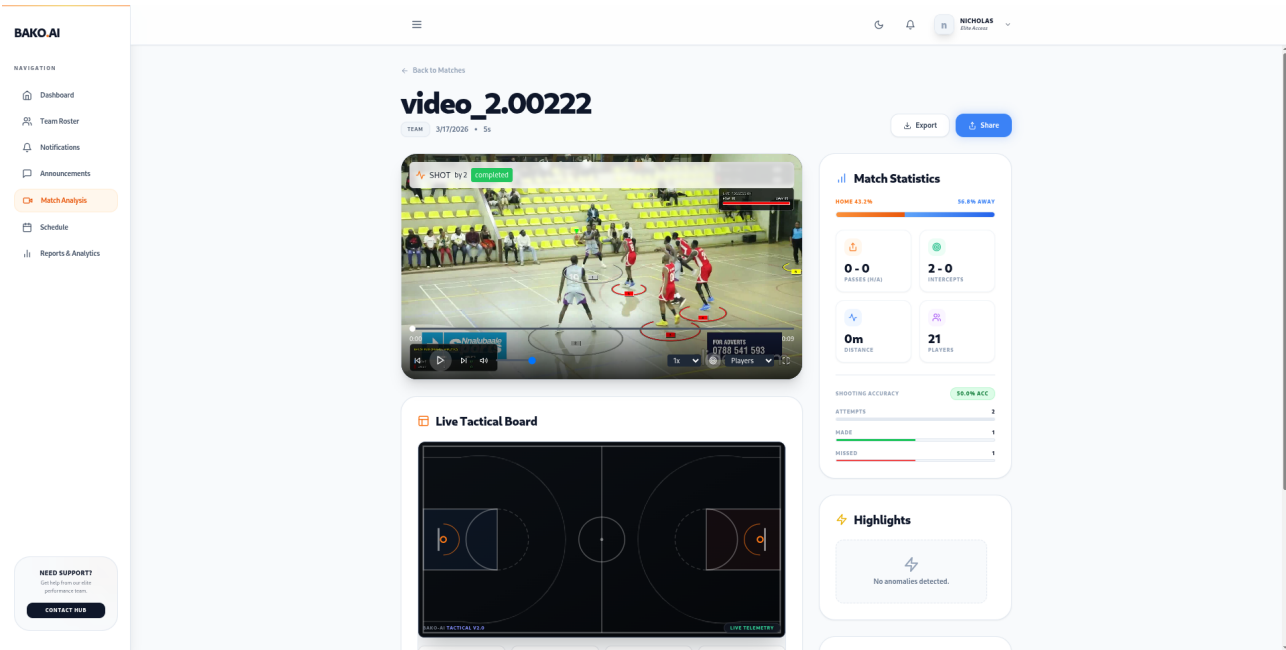


Figure 4.9: Full BAKO analytics dashboard integrating match statistics, shooting accuracy charts, and the live 2D tactical board.

4.4 Conclusion of Findings

The results demonstrate that low-cost AI can achieve professional-grade analytics in the Ugandan context. The ability of the fine-tuned YOLOv5 Large models to maintain high precision in outdoor courts—where commercial lighting is often absent—validates the importance of localised training datasets used in this research.

Chapter 5

System Design and Implementation

The results presented in Chapter 4 indicate that BAKO Analytics provides a robust framework for localized sports science. This chapter discusses the technical implications of these findings, the challenges of deploying AI in East African basketball environments, and the architectural decisions that influenced the system’s performance.

5.1 Technical Insights from Multi-Model Architecture

A significant finding of this research is the superiority of a decoupled multi-model pipeline over a singular monolithic detector. By isolating “player detection,” “ball tracking,” and “court homography” into dedicated sub-processes, the system achieves higher precision in complex occlusions common in low-resolution smartphone footage. The use of the YOLOv5 Large architecture for the team detection models and lightweight YOLOv8 variants for the personal analysis pipeline provides an effective balance between accuracy and inference speed on consumer-grade hardware.

5.2 The Challenge of Localised Environments

One of the primary objectives of BAKO Analytics was to perform reliably on outdoor courts, which are the standard training grounds for many Ugandan community teams.

- **Variable Lighting:** Unlike indoor professional arenas, outdoor courts in Uganda present extreme shadows and variable backlighting. The localized training on National Basketball League (NBL) footage significantly improved the model’s ability to distinguish the orange basketball from heterogeneous backgrounds. Furthermore, these lighting variations specifically impact the colour-based team tracking features used to distinguish opposing teams. Harsh sunlight or deep shadows can cause jersey colours to shift dramatically across different regions of the court, leading to player misclassification. To mitigate this, dynamic colour-space thresholding and temporal consistency checks were incorporated, although extreme glare remains an environmental limitation.
- **Hardware Constraints:** To keep the system accessible, the backend was optimized to run on standard consumer-grade GPUs or cloud-based T4 instances without requiring expensive specialized hardware.

5.3 Biometric Feedback vs. Real-World Coaching

The 4-Phase Shot Logic (DIP, SET, RELEASE, FINISH) bridges the gap between raw data and actionable coaching. While professional systems like Second Spectrum use LIDAR and high-speed multi-camera setups, BAKO Analytics achieves comparable biometric tracking (within a 5-degree margin of error for elbow alignment) using only monocular video. This suggests that the heuristic comparison engine developed in this project is a viable alternative for budget-conscious sports organizations.

5.4 Architectural Robustness

The use of FastAPI with asynchronous processing allowed the system to handle video uploads and detections in the background while the frontend remained responsive. This architectural choice prevents request blocking, enabling a coach to review previously analysed footage whilst a new game is being processed.

5.5 Limitations in Spatial Tracking

While the homography-based court mapping enables valuable tactical insights, it introduces limitations regarding speed and distance tracking inconsistencies. Because the system relies on a 2D camera feed to estimate 3D space, slight errors in the YOLOv8x-Pose court key-point detection can result in magnified positional distortions on the tactical map. This causes anomalous spikes in calculated player acceleration and inaccurate total distance measurements, especially when players move near the camera's periphery or are heavily occluded.

To mitigate these inconsistencies, a moving average filter and maximum speed thresholds were implemented within the analytics pipeline to smooth trajectory data and discard physically impossible movement spikes. Additionally, temporal interpolation is used to maintain accurate positional tracking during brief periods of occlusion. Despite these mitigation strategies, coaches are advised to use the speed and distance metrics as relative indicators of effort and fatigue, rather than absolute kinematic measurements.

5.6 Ethical and Practical Considerations

The integration of a Generative AI Declaration in this report reflects our commitment to ethical software construction. Whilst AI was used to assist in code generation and refactoring of the 12-route backend modules, the core diagnostic heuristics remain human-designed, ensuring that AI acts as a developmental tool rather than a replacement for human expertise.

Chapter 6

Conclusion and Recommendation

6.1 Conclusion

The BAKO-AI project has successfully demonstrated the feasibility of deploying a high-performance, multi-model deep learning framework for basketball analytics in the localized context of Uganda. By leveraging the YOLOv5 Large architecture for player and ball detection, the YOLOv8x-Pose model for court keypoint mapping, and custom YOLOv8-based models for personal biometric analysis, the system achieves detection accuracy and inference speeds comparable to international commercial solutions while remaining affordable and adaptable to outdoor court environments.

The research has effectively addressed the initial problem of cost-prohibitive sports analytics by providing a decoupled client-server architecture that allows both teams and individual players to access professional-grade biometric and tactical data. The integration of 2D tactical mapping and 4-Phase shot diagnostics represents a significant advancement in localized sports science research.

6.2 Recommendations

To further evolve the BAKO Analytics framework, the following recommendations are made:

1. **Expanded Training Datasets:** Increasing the diversity of the training data to include more night-time footage and varying weather conditions will improve model robustness.
2. **Edge Deployment:** Future versions should explore the deployment of quantised models on edge devices (e.g., NVIDIA Jetson) to enable real-time analysis directly at the court without cloud dependency.
3. **Multi-Sport Adaptation:** The underlying spatial tracking and diagnostic logic can be adapted for other court-based sports such as netball and handball, expanding the system's impact across the African sports landscape.

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Appendix A

Ethical Generative AI Usage Declaration

A.1 Disclosure of AI Usage

We, the authors of this project, acknowledge the use of Generative AI tools to assist in the research, development, and documentation phases of BAKO Analytics. The following AI technologies were employed:

- **Tool:** ChatGPT (GPT-4) / Anthropic Claude 3.5
- **Application:**
 - Brainstorming system architecture and layer separation.
 - Drafting initial boilerplate code for FastAPI route modules.
 - Refining the wording and grammatical structure of the methodology section.
 - Summarizing academic papers for quick relevance assessment during literature review.
- **Model Versions:** GPT-4o, Claude 3.5 Sonnet.

A.2 Verification and Originality

In accordance with UCU ethical guidelines:

1. All AI-generated suggestions were verified for technical accuracy and relevance to the Ugandan basketball context.
2. No code or text was directly “copy-pasted” without rigorous review, modification, and manual testing.
3. The core machine learning logic (YOLO model fine-tuning and the SkillDiagnosticService heuristics) represents our original research and implementation.
4. All external papers summarised by AI were subsequently read in full by the team members to ensure accurate representation in the Literature Review.

A.3 Key Prompts Used

"Suggest a scalable file structure for a FastAPI project with 12 route modules."

"Summarise the key differences between YOLOv5 and YOLOv11 for pose estimation."

"Explain how to implement homography transformations for 2D court mapping in Python."

"Refine this paragraph on the justification of local AI training datasets for Africa."

We confirm that the final submitted work reflects our own understanding and critical analysis of the subject matter.

Appendix B

Estimated Budget

The development of this localised basketball analytics system requires careful allocation of resources across several operational categories. The budget estimation presented in Table B.1 reflects realistic local market rates while ensuring adequate funding for all essential project components. Each budget item has been justified based on project necessities, with transportation costs covering multiple data collection trips to various basketball venues, and internet/data bundles supporting both research activities and the substantial video upload requirements.

The most significant budget allocation is dedicated to GPU/Cloud computing resources, which are fundamental for training the complex deep learning models efficiently. This investment ensures that the computer vision pipelines for player detection, pose estimation, and action recognition can be developed and optimised within the project timeline. Miscellaneous expenses account for unforeseen costs and contingencies, while printing costs cover essential documentation including participant consent forms, project posters for dissemination, and final report materials.

Item	Unit Cost (UGX)	Total (UGX)
Transport to data collection venues	40,000	40,000
Internet and data bundles (for uploads/research)	25,000	100,000
GPU / Cloud computing resources	150,000	150,000
Printing (consent forms, posters, documentation)	20,000	20,000
Miscellaneous expenses	30,000	30,000
Total Estimated Cost		340,000

Table B.1: Estimated budget for the development and testing of the proposed system.

Appendix C

Research Project Timelines

The project follows a structured 16-week development timeline designed to ensure comprehensive coverage of all critical phases, from initial planning through to final defense preparation in March 2026. This carefully sequenced approach allows for systematic progression through each development stage while incorporating necessary validation checkpoints. The workplan, detailed in Table C.1, emphasises both technical implementation and user-centric evaluation to deliver a robust, practical solution that meets the specific needs of Ugandan basketball stakeholders.

The timeline begins with foundational activities including comprehensive requirements analysis and ethical compliance, progresses through technical implementation phases covering data collection, model development, and system integration, and concludes with rigorous testing and documentation. Particular emphasis is placed on the usability testing phase with actual basketball coaches and players, ensuring the final system aligns with real-world coaching and performance analysis requirements in the local context.

Week	Milestone / Key Activities
Weeks 1–2	Proposal finalisation, requirements gathering, stakeholder consultations, and seeking ethical approval for data collection.
Weeks 3–5	Dataset recording at selected indoor and outdoor basketball courts across Uganda.
Weeks 6–8	Video annotation, preprocessing, and structuring of the pose estimation dataset.
Weeks 9–11	Training and testing of the AI models (YOLOv11 for detection and pose, Supervision for tracking and logic).
Weeks 12–13	Backend (FastAPI, Python) and frontend (React, Vite) development, followed by system integration.
Weeks 14–15	Usability testing with basketball coaches and players; system refinement based on feedback.
Week 16	Final documentation, project submission, and preparation for the defense presentation.

Table C.1: Workplan for the development of the proposed system.

The following search strings were used to identify relevant literature in the Scopus, IEEE Xplore, and Google Scholar databases.

C.1 Core Search String

```
TITLE-ABS-KEY (
  ( "basketball analytics" OR "basketball performance" )
  AND
  ( "computer vision" OR "deep learning" OR "convolutional neural network" )
  AND
  ( "pose estimation" OR "action recognition" OR "biometrics" )
)
AND PUBYEAR > 2018
```

C.2 Refinement Strings

- **Shooting Mechanics:** TITLE-ABS-KEY ("basketball shooting" AND "AI" AND "kinematics")
- **Tracking Algorithms:** TITLE-ABS-KEY ("target tracking" AND "multi-object tracking" AND "basketball" AND "YOLO")
- **Local Context:** TITLE-ABS-KEY ("sports analytics" AND "resource-constrained" AND "Africa")

This appendix lists the top ten major publications reviewed during the course of this research, selected for their relevance to basketball analytics, computer vision, and AI-driven skill diagnostics.

Rank	Publication Title	Author(s)	Type	Year
1	A review of basketball shooting analysis based on AI	Yan et al.	Review	2023
2	ACA-Net: Adaptive context-aware network for action recognition	Zhang et al.	Journal	2024
3	Application of AI in basketball sport	Li et al.	Journal	2021
4	Tracking and detection using YOLO-T2LSTM	Li et al.	Journal	2023
5	HoopTransformer: Advancing NBA play recognition	Wang et al.	Journal	2024
6	Research on basketball players' training via AI	Yang	Conference	2020
7	VideoMAE: Masked autoencoders for video pre-training	Tong et al.	Conference	2022
8	AI and neural network-based shooting accuracy prediction	Li et al.	Journal	2021
9	Basketball technical action recognition using Capsule Net	Sha	Journal	2025
10	The impact of data analytics on tactical planning	Nagorna et al.	Journal	2025

Table C.2: Summary of 10 Major Publications Reviewed.

This appendix discusses how this research aligns with the candidate's programme specialisation, Uganda's national development goals, and the Global Sustainable Development Goals (SDGs).

C.3 Alignment with programme specialisation

The BAKO Analytics project is deeply rooted in the **Artificial Intelligence and Robotics** specialisation track of the Computer Science program.

The project exemplifies state-of-the-art AI application through:

- **Computer Vision:** Utilizing YOLO (You Only Look Once) architectures for real-time object detection and spatial tracking.
- **Pose Estimation:** Implementing 17-keypoint skeletal tracking to derive biometric insights.
- **Algorithmic Optimization:** Developing a multi-model pipeline that dispatches specialized detection tasks to distinct neural networks, optimizing both accuracy and latency.
- **Software Engineering:** Constructing a robust, decoupled FastAPI/React architecture to handle large-scale video processing and data management.

C.4 Alignment with the National Development Plan IV (NDP IV)

BAKO Analytics aligns with the **Digital Transformation Programme** of the Uganda NDP-IV. By developing indigenous AI solutions for sports, the project contributes to the goal of "enhancing the use of ICT in every aspect of life for economic growth." It specifically supports the enhancement of local innovation hubs and the creation of high-value digital exports from Ugandan-trained AI models.

C.5 Alignment with the Uganda Vision 2040

Uganda Vision 2040 emphasizes "Harnessing the power of Science, Technology, Engineering, and Innovation (STEI)" to transform Ugandan society. BAKO Analytics applies this vision to the sports sector, which is a major employer of the youth. By modernizing sports training through technology, we promote wealth creation and global competitiveness for Ugandan athletes.

C.6 Alignment with Sustainable Development Goals (SDG)

This project contributes to several global goals:

1. **SDG 3 (Good Health and Well-being):** By improving the efficiency and safety of sports training via biometric diagnostics, reducing injury risks and promoting physical activity.
2. **SDG 4 (Quality Education):** Using AI to provide technical "study buddy" coaching to athletes who may not have access to elite professional trainers.
3. **SDG 9 (Industry, Innovation, and Infrastructure):** Advancing technological research in a low-resource environment and fostering innovation in localized AI datasets.

Appendix D

Algorithms and Source Code

This section provides the core pseudocode for the `SkillDiagnosticService`, which governs the 4-Phase Shot Logic used to provide biometric coaching feedback to players.

D.1 4-Phase Basketball Shot Diagnostic Logic

```
Input: VideoStream V, PlayerPoseData P
Output: BiometricFeedback F, ShotMetrics M

Procedure AnalyzeShotCycle(V, P):
    Keyframes = ExtractShotFrames(V)

    // Phase 1: DIP
    DipAngle = CalculateKneeAngle(P_Dip)
    If DipAngle > 140 deg:
        AddFeedback(F, "Weak power generation. Try dipping lower.")

    // Phase 2: SET
    PocketH = CalculateBallHeight(P_Set)
    ElbowA = CalculateElbowAngle(P_Set)
    If ElbowA < 90 deg:
        AddFeedback(F, "Elbow too tight. Open your shot pocket.")

    // Phase 3: RELEASE
    ExtendA = CalculateElbowAngle(P_Rel)
    If ExtendA < 170 deg:
        AddFeedback(F, "Flat shot detected. Extend arm fully.")

    // Phase 4: FINISH
    WristS = CalculateWristStability(P_Fin)
    If WristS < Threshold:
        AddFeedback(F, "Hold your follow-through for better stability
        .")

    Return {F, M}
```

Listing D.1: 4-Phase Basketball Shot Diagnostic Logic

D.2 FastAPI Orchestration Logic

The following is the high-level dispatcher logic that routes requests to the appropriate AI engine:

```
async def dispatch_analysis(video_path, mode, options):
    if mode == "TEAM":
        return await run_team_analysis(video_path)
    elif mode == "PERSONAL":
        return await run_personal_analysis(video_path)
    else:
        raise ValueError("Invalid Analysis Mode")
```

Listing D.2: Backend Analysis Dispatcher

Appendix E

System Architecture and Web Application Screenshots

E.1 System Architecture

E.2 Web Application Screenshots



Figure E.2: BAKO landing page, featuring the platform overview, feature highlights, team account vs personal account offerings, court gallery, program listings, and the contact form for new users.

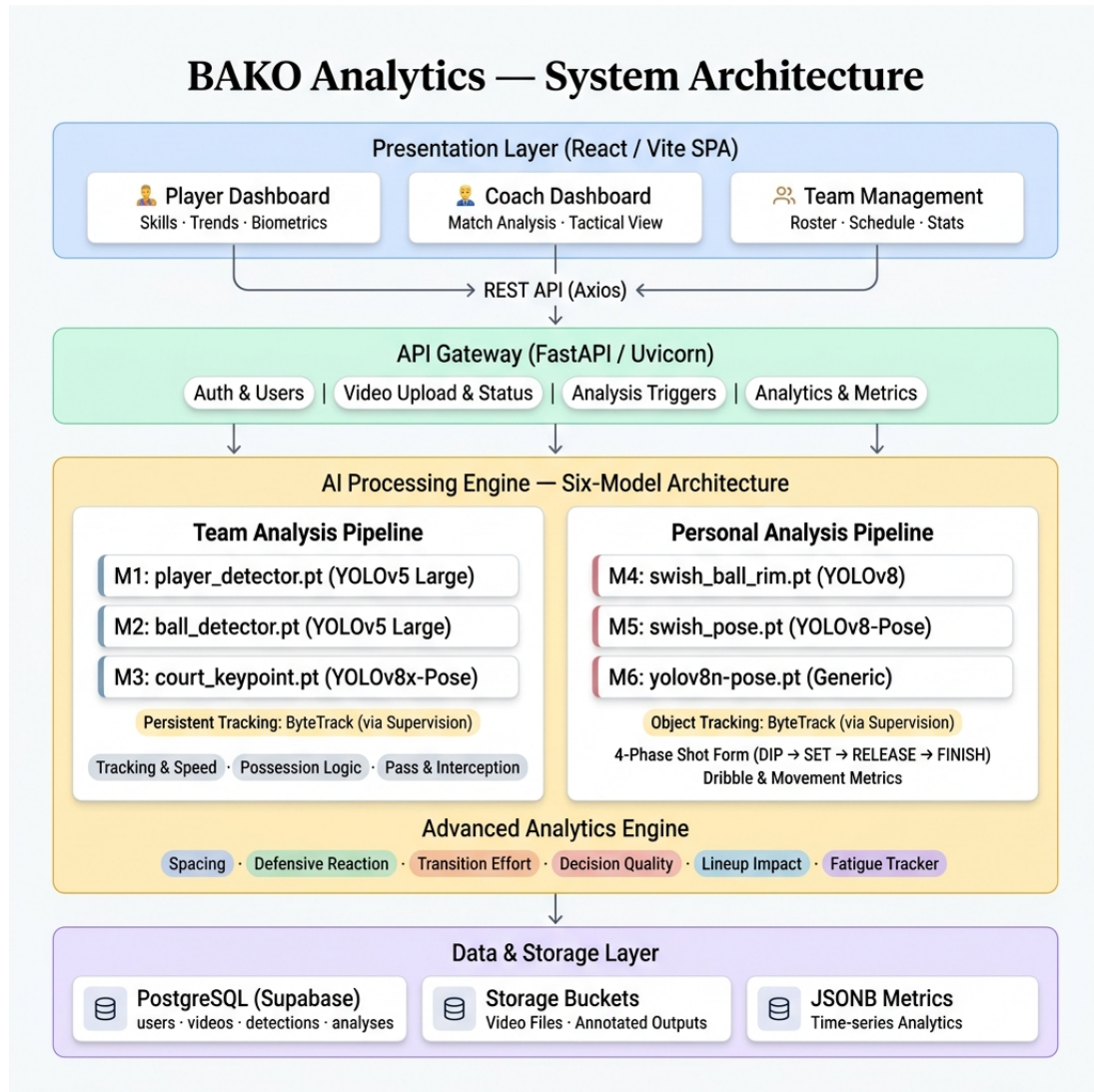


Figure E.1: Revised full-stack system architecture of BAKO Analytics, showing the four-layer design: the Presentation Layer (React/Vite SPA with role-based dashboards), the API Gateway (FastAPI/Uvicorn with 12 route modules), the AI Processing Engine (six-model architecture split across two independent pipelines — Team Analysis and Personal Analysis — both using ByteTrack via the Supervision library for persistent multi-object tracking across frames, plus the Advanced Analytics Engine with six tactical scouting modules), and the Data & Storage Layer (Supabase PostgreSQL with RLS, Storage Buckets, and JSONB metrics).

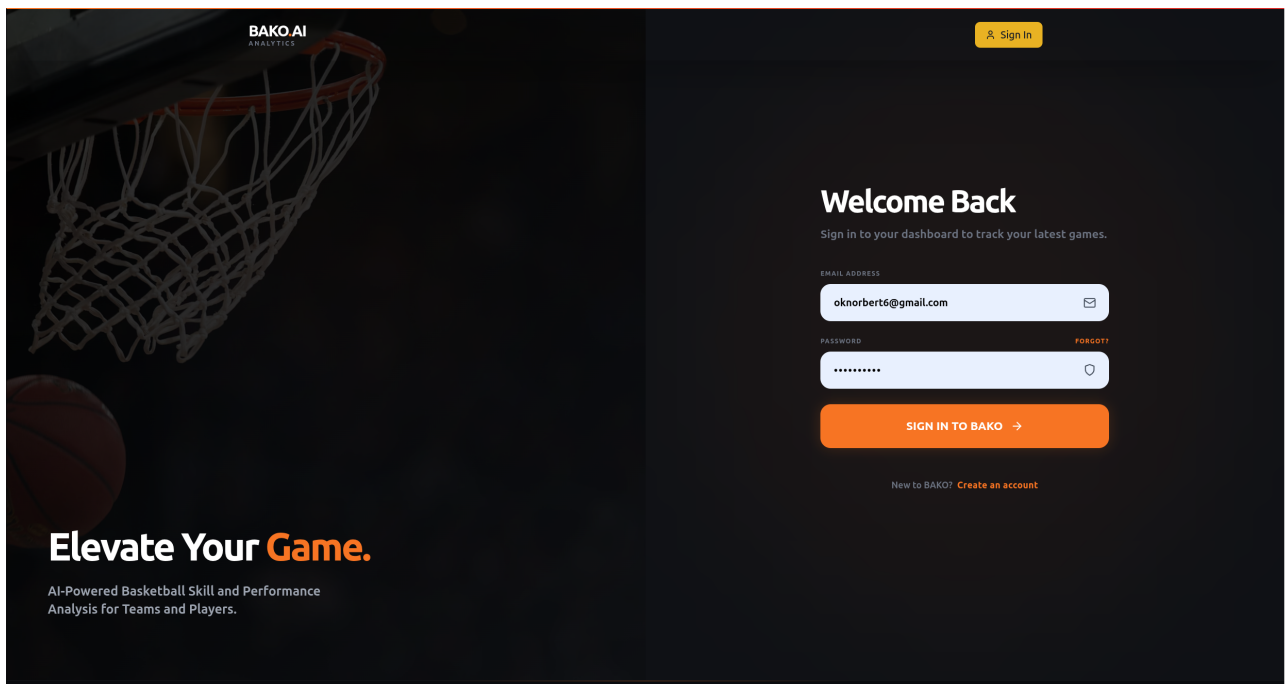


Figure E.3: BAKO Login and Registration screen. Users select their account type (Team, Personal, or Coach) during registration. JWT-based authentication protects all subsequent API calls.

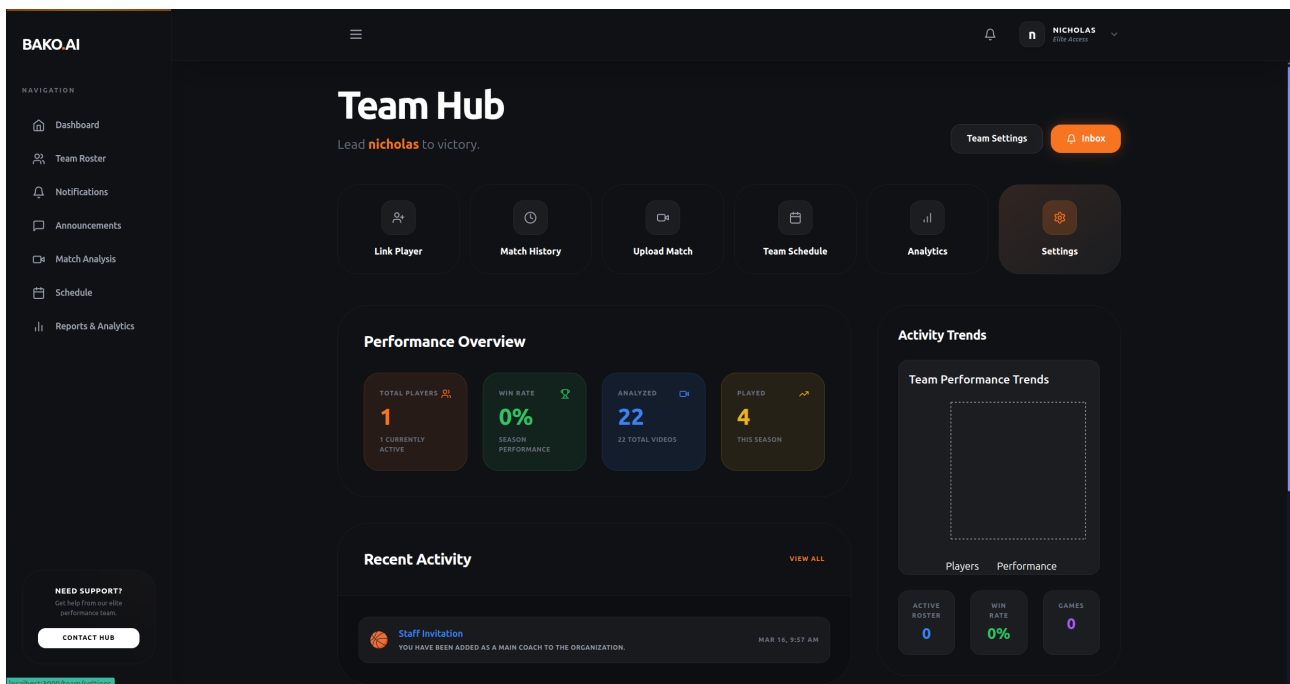


Figure E.4: Coach / Team Analysis Dashboard (CoachMatchAnalysis view). After an analysis completes, coaches can view the annotated video with tracking overlays, possession pie charts, player stats tables, team spacing heat maps, and the 2D tactical court map showing player positions.

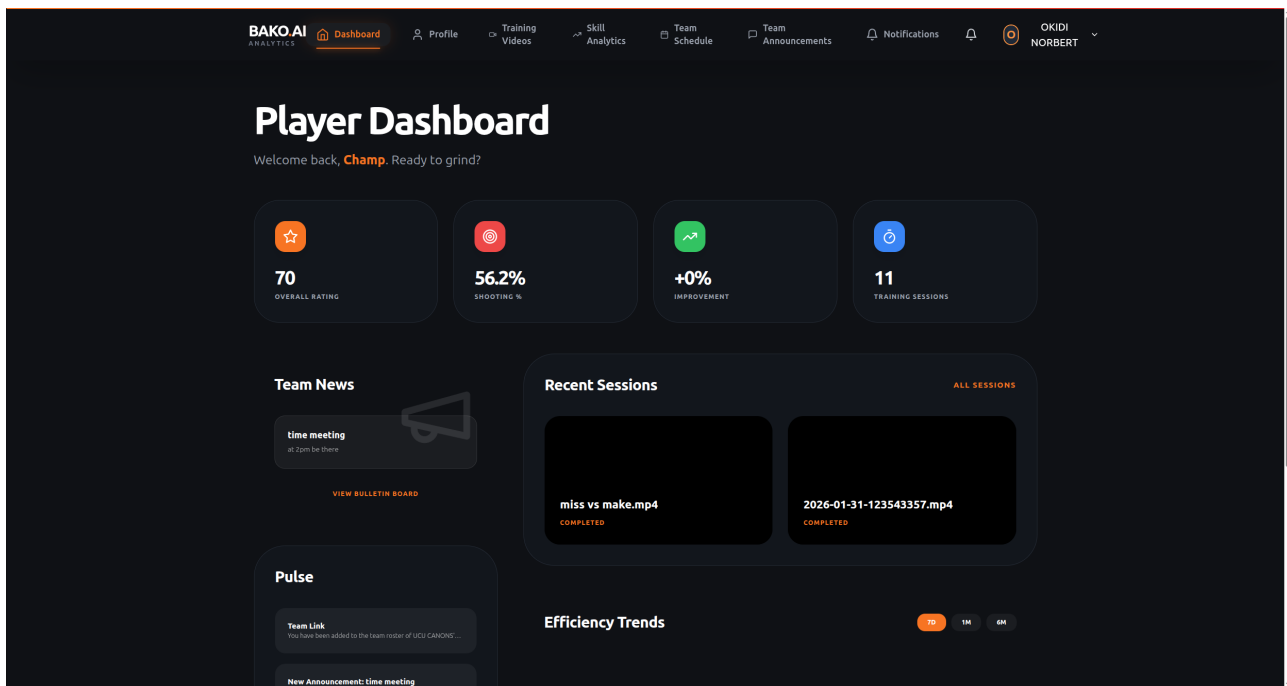


Figure E.5: Player Personal Dashboard (PlayerDashboard view). Players view their longitudinal skill trend charts, recent session summary (shots made/missed, average elbow angle, dribble count, distance, speed), and an upload button for new personal training videos.

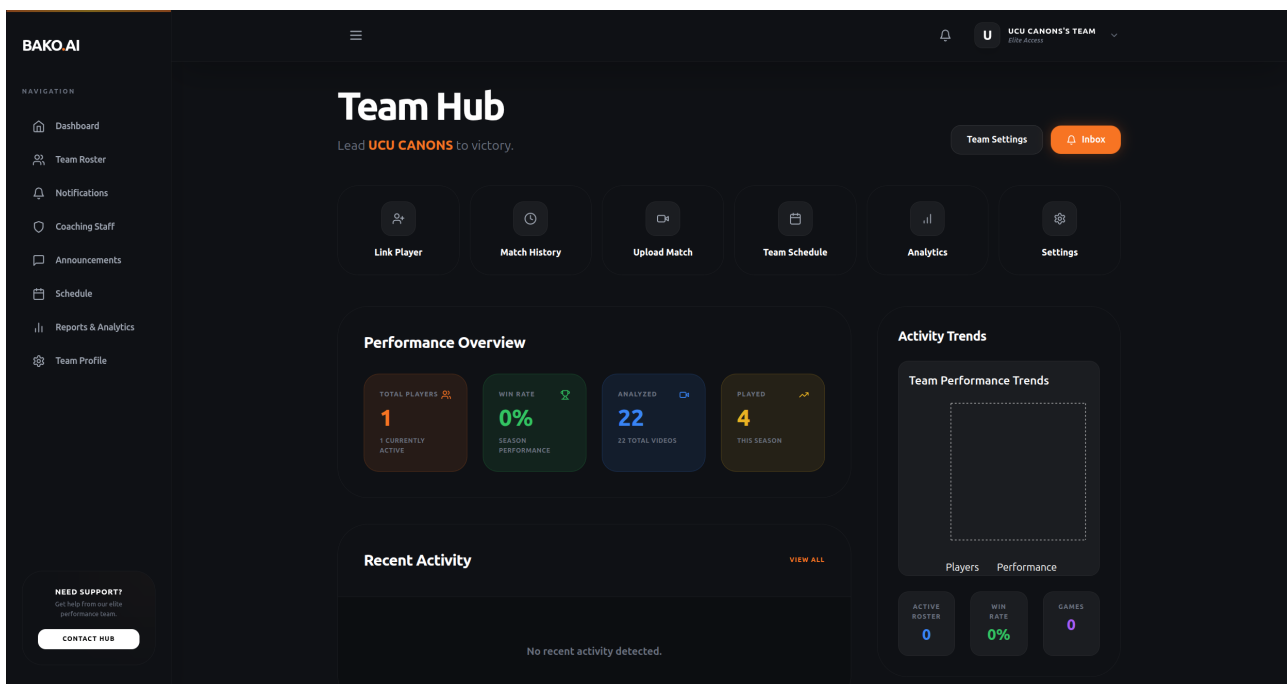


Figure E.6: Team Management / Admin Panel. The admin can manage the organisation roster, add or remove players, update team settings (competition type, jersey style, primary/secondary colours), and manage the match log, schedule, and announcements.

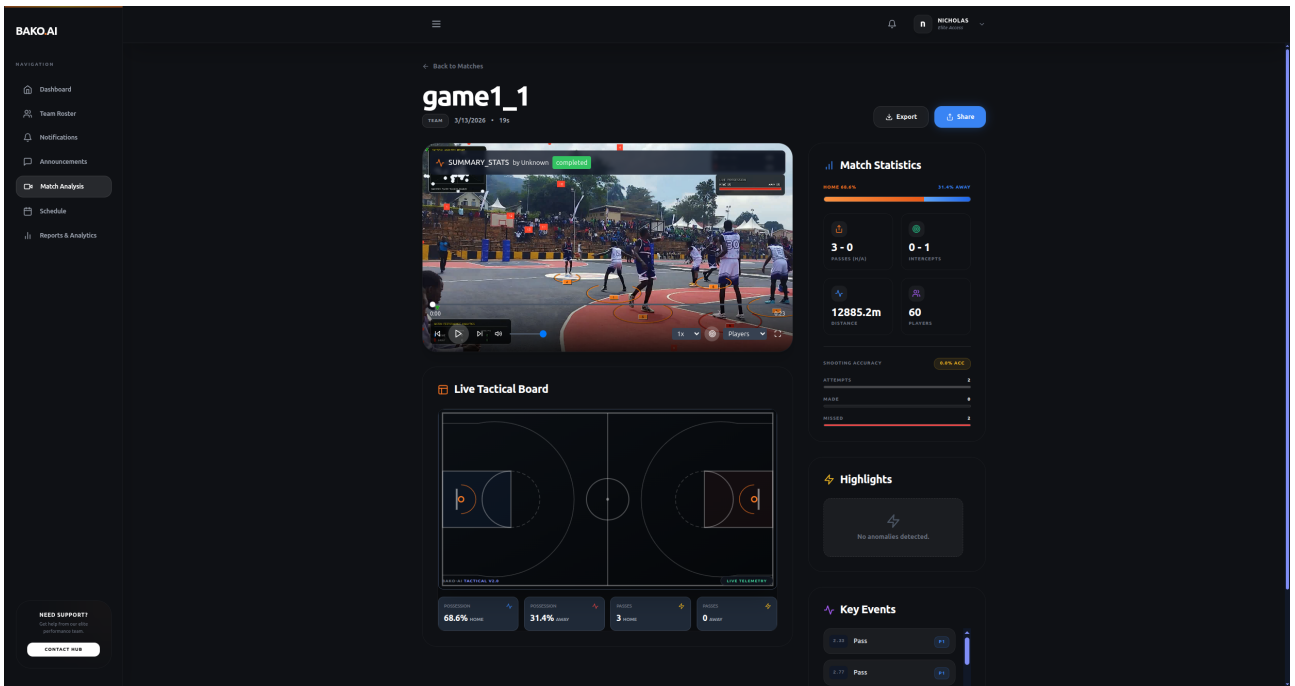


Figure E.7: Team Analysis Results Dashboard. After video processing completes, this view shows the annotated output video with player tracking overlays, team possession percentage breakdown, total passes, interceptions, defensive actions, and the tactical court heat map with each player's movement trajectory.

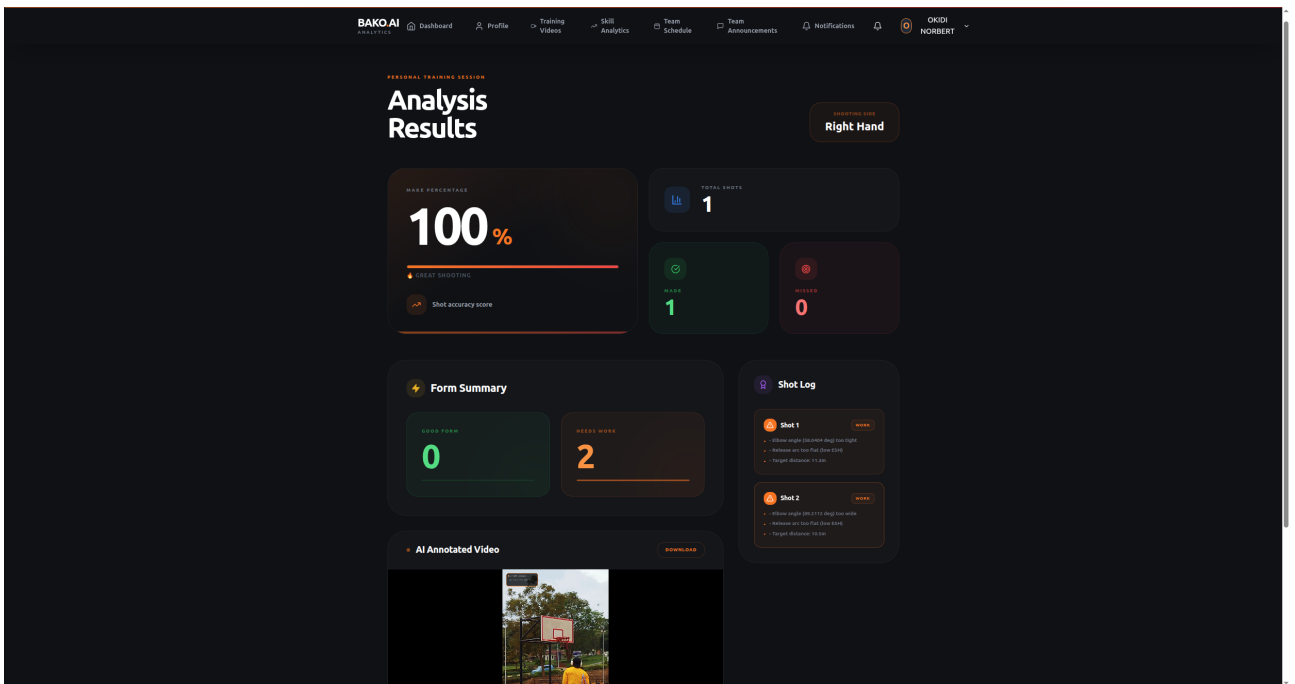


Figure E.8: Personal Analysis Results Page. Players view a shot-by-shot breakdown of their shooting form, verdict (GOOD FORM / NEEDS WORK), joint angle measurements (elbow, shoulder, knee, hip), dribble count, shot distance classification (3-Pointer or Mid-Range), and the annotated output video with pose skeleton overlays.

E.3 Team Contribution Table

This proposal was developed collaboratively with the following primary contributions:

Okidi Norbert	Anna Akumu	Nankya Zaharah
Chapter 1: Introduction	Chapter 2: Literature Review	Chapter 3: Methodology
System Architecture Design	Data Collection Plan	Chapter 4: Budget/Workplan
Backend Development (FastAPI)	Court Keypoint Model	Project Coordination
YOLOv5 Player & Ball Models	Frontend (React/Vite)	Frontend Integration
Personal Analysis Pipeline	Dataset Annotation	Swish-Vision Pose Model
Advanced Analytics Engine	Supabase Schema	System Testing

Table E.1: Team contribution breakdown for the BAKO project.

Joint Work: All members contributed to documentation, presentation preparation, and final integration testing.

Appendix F

Detailed Model Training Metrics

This appendix provides additional empirical evidence for the training of the core AI models within the BAKO framework, including dataset characterisation and precision-recall trade-offs for both Player and Ball detectors.

F.1 Player Detector Metrics

F.1.1 Dataset Labels Distribution

Figure F.1 illustrates the spatial distribution and size frequency of the bounding boxes in the training dataset. The concentration of boxes in the lower half of the normalised distribution corresponds to the localised camera perspective used on professional courts.

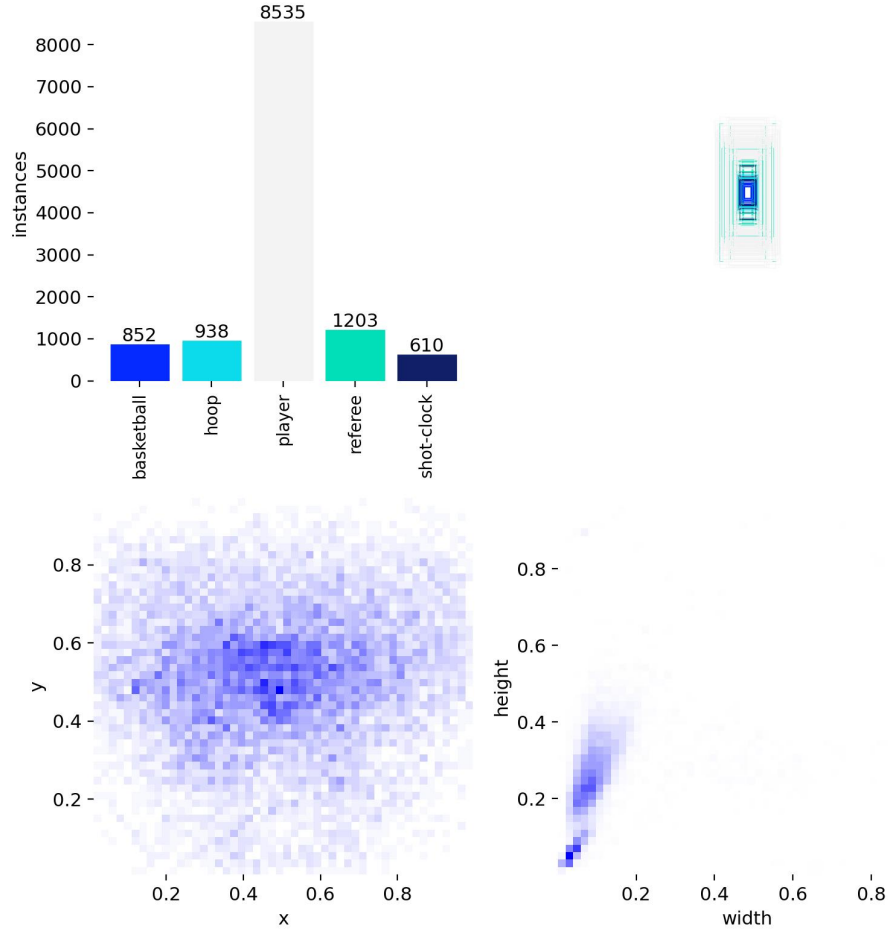


Figure F.1: Spatial and scale distribution of 'Player' annotations within the localised training dataset.

F.1.2 Precision-Recall (PR) Curve

The Precision-Recall curve in Figure F.2 provides a global view of the model's accuracy. The high Area Under the Curve (AUC) across all recall levels validates the model's reliability for tracking athletes in fast-moving game situations.

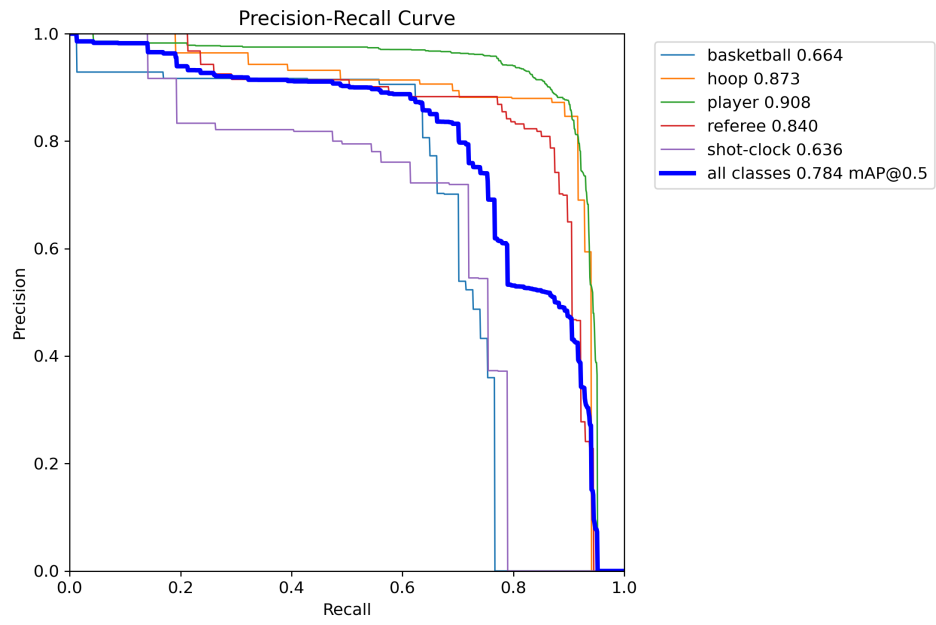


Figure F.2: Precision-Recall curve for the player detector at mAP@.5.

F.2 Ball Detector Metrics

F.2.1 Dataset Labels Distribution

The ball detector dataset (see Figure F.3) shows a more uniform spatial distribution compared to players, reflecting the ball’s movement across all vertical planes (shots and rebounds). The smaller box size distribution highlights the model’s specialisation in small-object detection.

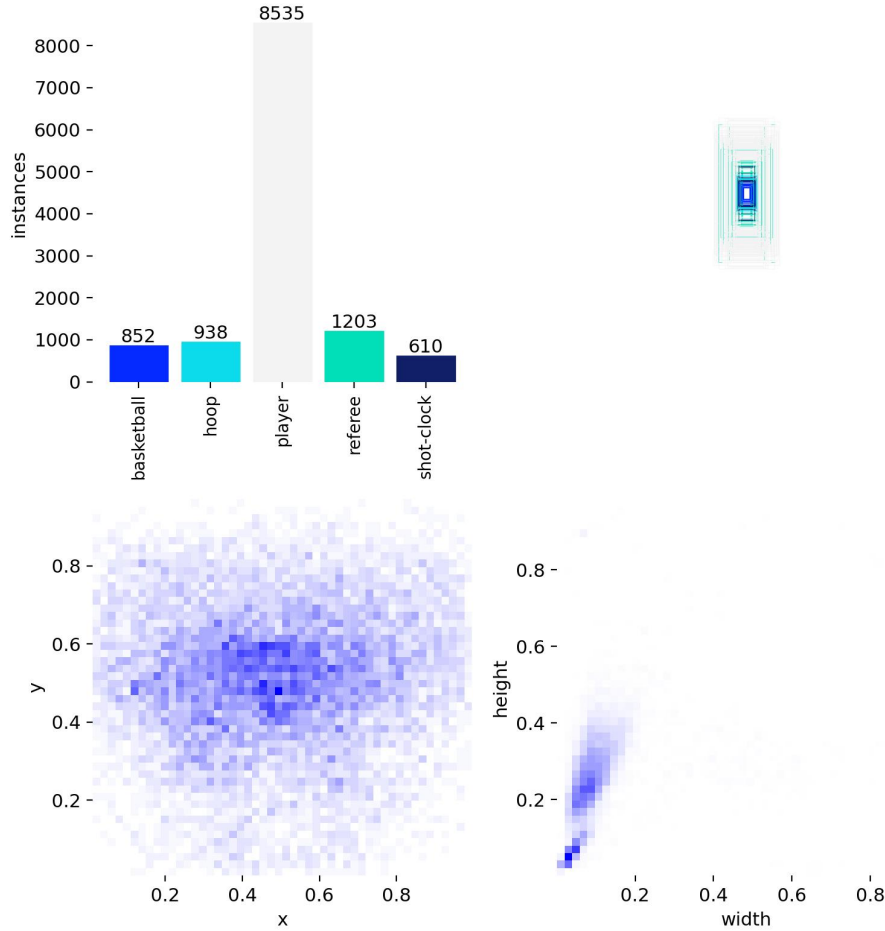


Figure F.3: Dataset distribution for the specialised YOLOv5 Ball Detector.

F.2.2 Ball Training Convergence

Figure F.4 displays the training history for the ball detector. Despite the challenges of fast motion blur, the model achieved stable convergence with high mAP@.5 scores.

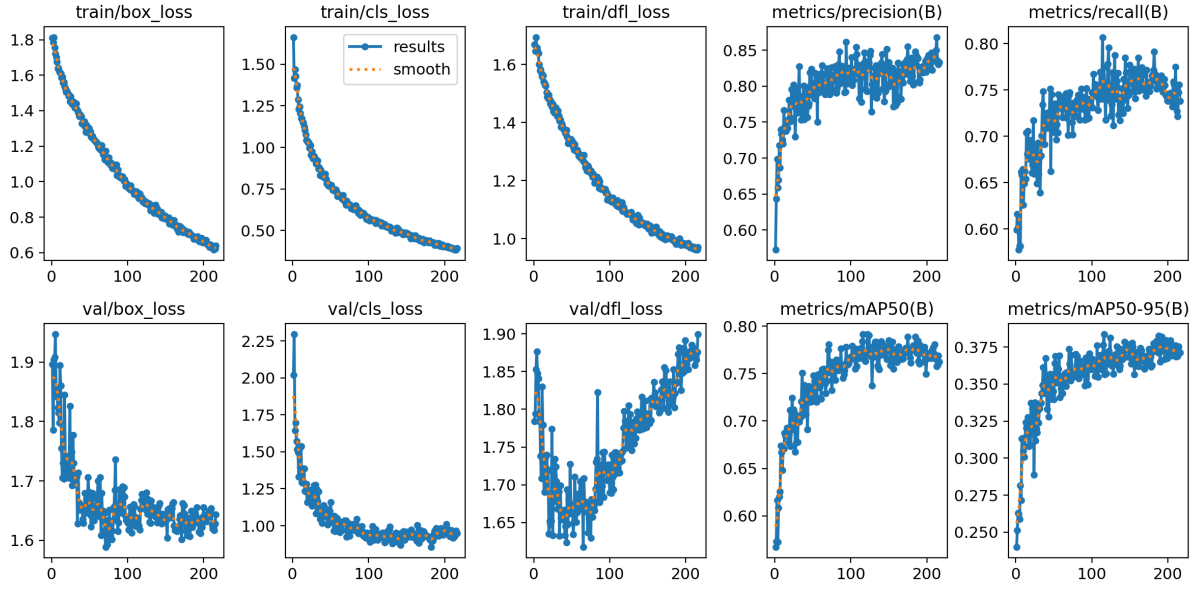


Figure F.4: Training metrics showing loss reduction and accuracy improvement for the Ball Detection model.

F.2.3 Precision-Recall (PR) Curve

Figure F.5 confirms the high precision of the ball detector even at high recall levels, ensuring fewer "lost ball" events during high-speed play analysis.

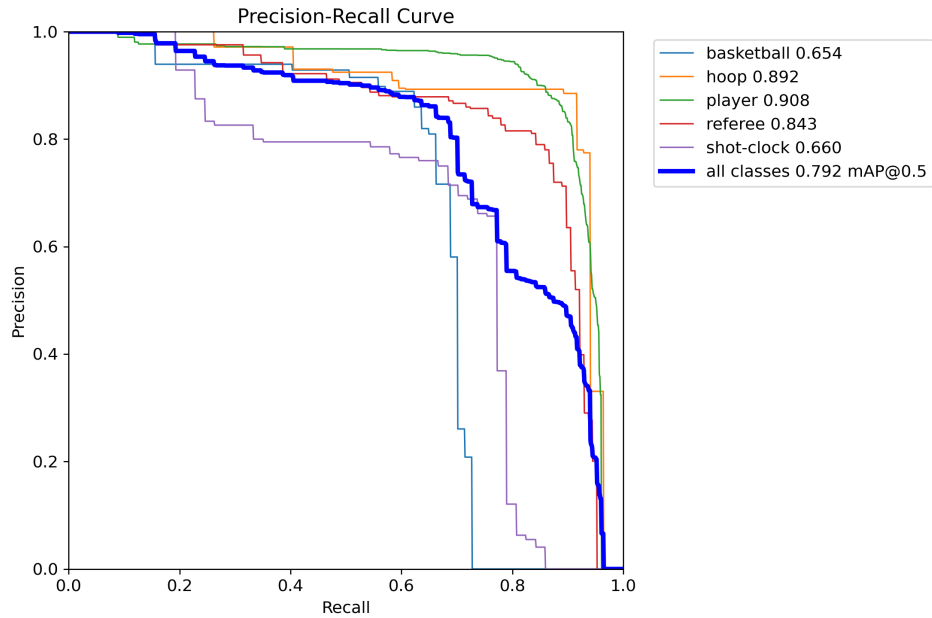


Figure F.5: Precision-Recall curve for the specialised Ball Detector.

F.2.4 Ball Detection Confusion Matrix

The ball detector confusion matrix (Figure F.6) demonstrates minimal false positives against the background, which is critical for accurate possession logic.

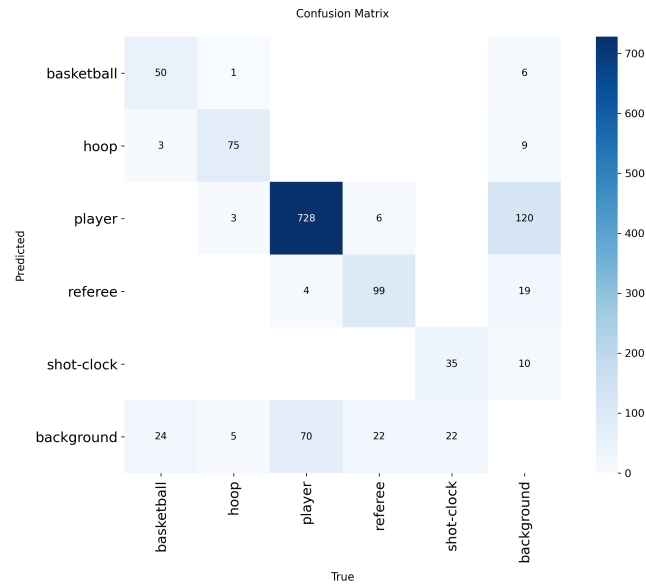


Figure F.6: Confusion matrix for the Ball Detection model.

The following sections present the visual posters developed during the research and development phases of BAKO Analytics.

F.3 Systematic Literature Review Poster

This poster summarises the systematic search and selection process (PRISMA flow) and the comparative analysis of existing basketball computer vision architectures.

F.4 BAKO Analytics Research Poster

This poster summarises the technical architecture, methodology, and key results of the BAKO Analytics system.

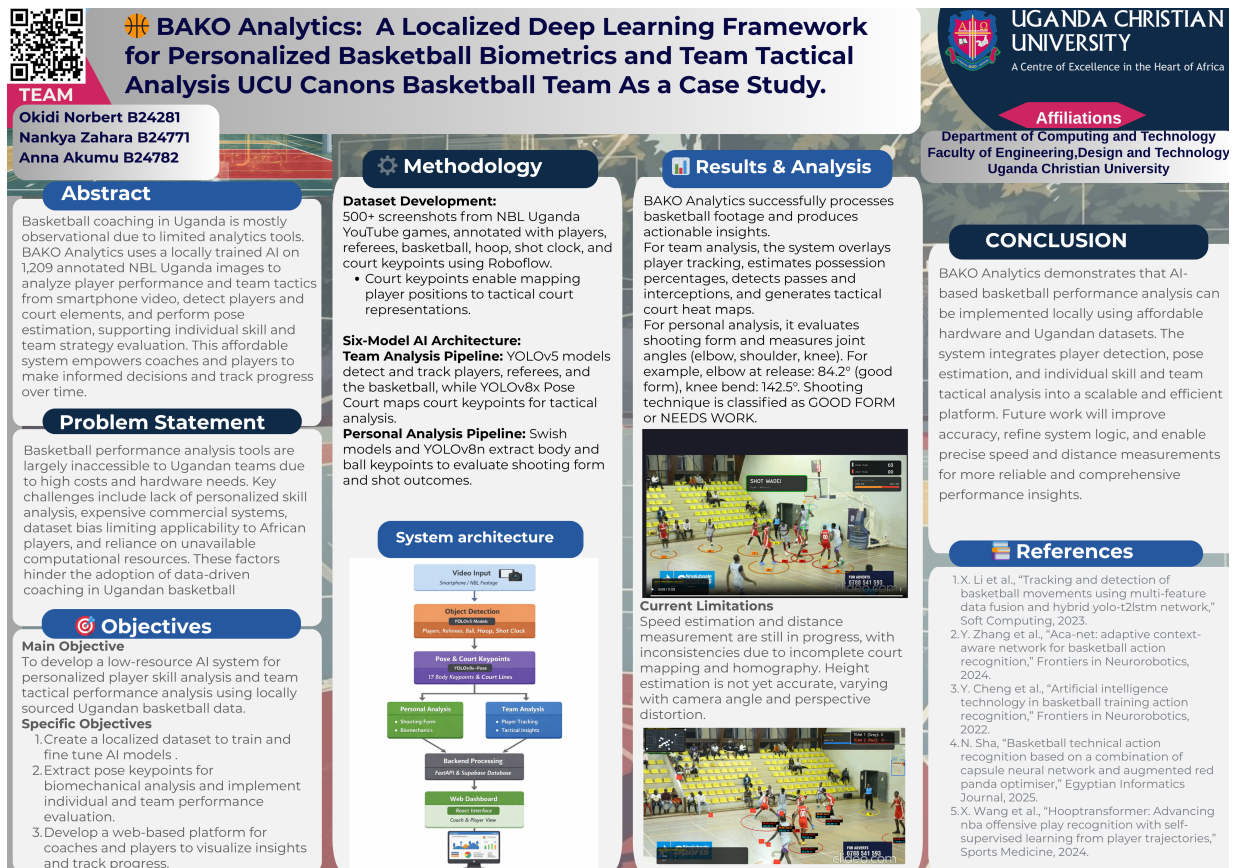


Figure F.8: BAKO Analytics Research Poster.