Real-Time Detection of Volleyball Player Movements with YOLOv8 to Support Rehabilitation

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***Abstract*—This paper presents a computer vision system based on YOLOv8 for detecting and classifying critical volleyball postures, serve, set, pass (bump), and block, alongside ball tracking in real time. Designed to support physiotherapist and coaches, the system enables objective monitoring of biomechanical correctness during rehabilitation, addressing one of the key challenges in injury recovery: ensuring accurate execution of sport-specific movements. The project builds upon previous clinical research on volleyball rehabilitation and was implemented using open source tools, leveraging Google Colab for training on a custom-labeled dataset. Results demonstrate promising detection accuracy, indicating potential for integration into physiotherapy workflows and future augmented reality(AR) rehabilitation systems.**

***Index Terms*—Computer Vision, YOLOv8, Volleyball, Physiotherapy, Posture Detection, Rehabilitation, Sports Analytics**

I. Introduction

Volleyball is a high-intensity sport with a significant incidence of injuries, particularly in the lower limbs, such as knee and ankle joints, due to frequent jumps, landings, and sudden directional changes. During rehabilitation, incorrect execution of movements can delay recovery or lead to reinjury. Ensuring biomechanical precision in exercises is therefore a critical factor for both return-to-play safety and long-term athlete health. [1]

Traditional physiotherapy supervision relies on visual observation, which is subjective, prone to human error, and limited in scalability. The use of computer vision for automated posture detection offers an objective, consistent, and scalable alternative.

This work introduces a lightweight, accessible tool for real-time detection of volleyball-specific postures, optimized for rehabilitation contexts. The selected movements,serve, set, pass, and block, were chosen based on their relevance to injury prevention and rehabilitation protocols, as documented in prior clinical studies on volleyball biomechanics. [1]

The proposed solution combines deep learning with a simple graphical interface to make detection capabilities accessible to professionals without technical expertise, enabling integration into both clinical and sports training environments.

II. Related Work

Deep learning models, particularly YOLO-based architectures, have been widely adopted in sports analytics for tasks such as player detection, ball tracking, and action recognition [2]. Alternative approaches, including OpenPose and MediaPipe, focus on skeletal keypoint estimation but often require high-resolution inputs and controlled environments, limiting their applicability in physiotherapy sessions or amateur sports contexts. [5], [6]

YOLOv8 [7], the latest iteration in the YOLO family, offers improved detection accuracy, streamlined deployment, and optimized inference speed—key features for real-time rehabilitation applications. Studies have demonstrated YOLO's suitability for sports motion analysis, including football, basketball, and tennis, but applications in volleyball rehabilitation remain underexplored.

Previous clinical research in volleyball has emphasized the biomechanical demands of actions such as serve, block, and set, identifying them as both performance-critical and injury-prone. These findings provided the foundation for selecting the target postures in this study, ensuring clinical relevance and direct applicability to physiotherapy practices. [1]

III. Methodology

A. System Architecture

The system follows a modular architecture with four primary components 1:

- Capture Module – acquires frames from either a live webcam feed or uploaded images.
- Detection Engine – executes YOLOv8 [7] inference on the input, returning bounding boxes and class predictions.
- Visualization Layer – overlays detection results on the original frames using OpenCV [12].

- User Interface – built with Tkinter [13], providing a simple, accessible GUI for physiotherapists.

This structure allows future integration with external platforms, such as Unity-based AR systems, via standardized communication protocols.

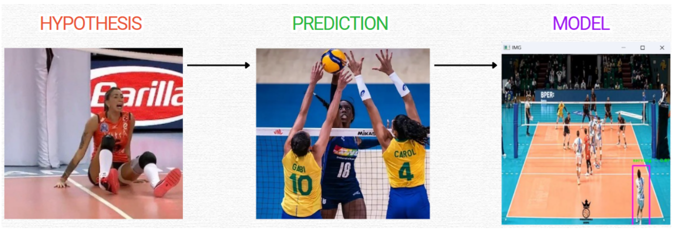

Fig. 1. workflow

B. Dataset

The dataset consists of 1,107 images [11] sourced from volleyball training footage, public repositories, and controlled practice sessions. The images include variations in lighting, camera angle, resolution, and athlete body type to improve model generalization.

The dataset was annotated manually using Roboflow [10], applying the YOLO [7] annotation format. Each bounding box corresponds to one of the five classes: serve, set, pass, block, and ball.

Annotation challenges: *Serve:*often appears in multiple airborne positions, requiring careful selection to ensure consistent labeling.

*Block and Set:*in certain camera angles, these postures appear visually similar, demanding attention to arm positioning and ball trajectory.

Image quality variation: frames extracted from videos often presented motion blur or compression artifacts.

The dataset was split into 80 training, 10 validation, and 10 testing. All annotations were reviewed by at least two team members to ensure label accuracy.

C. Model Training in Google Colab

The YOLOv8 [7] architecture was selected due to its balance between accuracy and inference speed, making it suitable for real-time posture detection on resource-limited hardware. YOLOv8 introduces architectural refinements over previous YOLO versions, including decoupled heads for classification and regression, anchor-free detection, and enhanced CSPDarknet backbones, which collectively improve generalization and robustness in small datasets.

Model training was performed entirely in Google Colab [8], leveraging NVIDIA Tesla T4 GPUs [14] for accelerated computation. The Colab environment allowed rapid prototyping by enabling on-demand GPU allocation, seamless integration with cloud storage for dataset access, and version control through linked GitHub repositories. This workflow reduced hardware dependency and eliminated the need for local high-performance computing infrastructure.

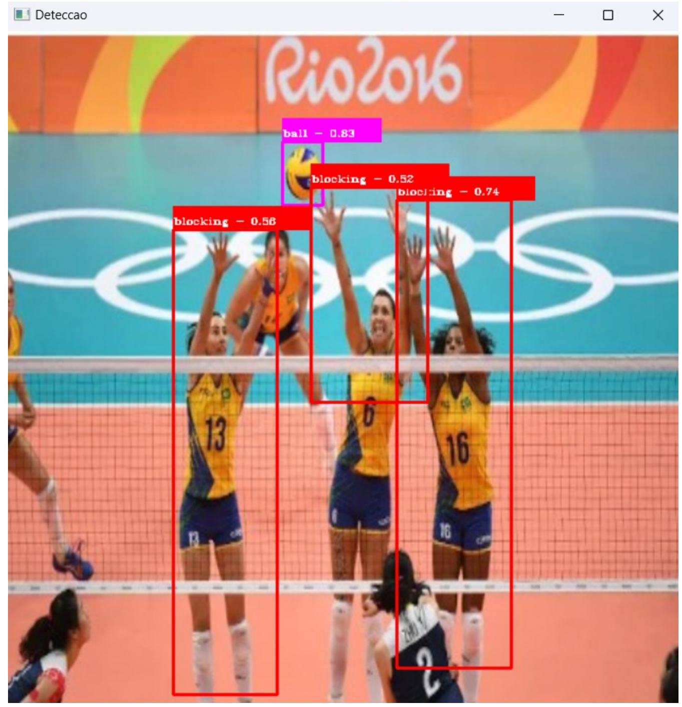

Fig. 2. Output with bounding boxes

Training scripts were adapted from the official Ultralytics [**?**] implementation, enabling easy customization of hyperparameters, automated logging, and integrated metric tracking. The combination of YOLOv8's modern design and Colab's [8] accessible cloud infrastructure was essential to achieving an optimal model within constrained development timelines. [8], [9]

Training configuration:

Model: YOLOv8s (Ultralytics implementation) *Epochs:*100 *Image size:* 640×640 *Optimizer:*SGD *Environment:* Python 3.10, Visual Studio Code, OpenCV, Roboflow, Tkinter *Annotation Format:* YOLO (.txt files)

The use of Colab facilitated experimentation with multiple hyperparameter configurations, checkpoint saving to Google Drive, and easy sharing with collaborators.

D. User Interface Specifications

The Tkinter interface includes:

- Image Upload – allows physiotherapists to test static images.
- Live Detection – activates the webcam for real-time classification.
- Results Display – overlays bounding boxes and labels directly on the video feed or uploaded image.

The design prioritizes minimalism 3 to ensure compatibility with low-spec computers often found in clinics or training centers.

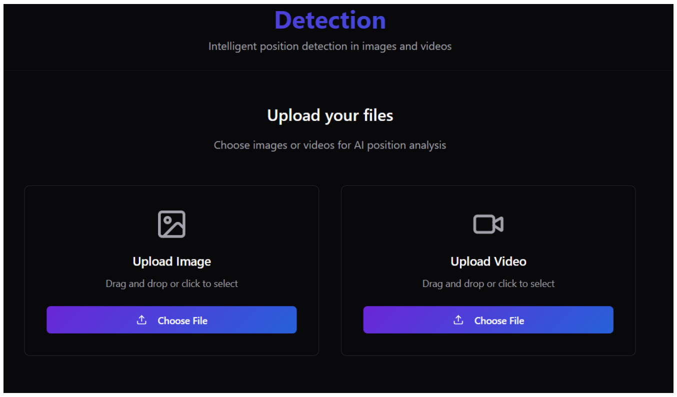

Fig. 3. Example of GUI interface

E. Clinical Considerations

The selection of target postures aligns with physiotherapy protocols for volleyball athletes, focusing on movements with high biomechanical demand and injury risk. Detecting incorrect execution during rehabilitation sessions allows early intervention, potentially reducing recovery time and preventing chronic injury recurrence.

IV. RESULTS AND DISCUSSION

The YOLOv8 model was evaluated on a held-out test set composed of 206 images, totaling 416 labeled instances across the five target classes: serve, set, pass(bump), block, and ball. Evaluation metrics followed the COCO standard, including precision(P), recall(R), mean Average Precision at an IoU threshold of 0.5 (mAP@50), and the averaged mean Average Precision across IoU thresholds from 0.5 to 0.95 (mAP@50–95). The results are presented in Table 1.

Class	Precision	Recall	mAP@50	mAP@50-95
All	0.607	0.608	0.647	0.327
Ball	0.877	0.877	0.896	0.438
Block	0.489	0.605	0.573	0.237
Pass	0.444	0.474	0.491	0.268
Serve	0.642	0.607	0.706	0.399
Set	0.582	0.478	0.569	0.292

TABLE I
PERFORMANCE METRICS BY CLASS

Bounding box examples for each posture demonstrate consistent detection 4 even under challenging conditions such as partial occlusion or non-uniform lighting. The explicit inclusion of the ball as a fifth detection class was a deliberate design choice aimed at improving movement recognition efficiency for actions that involve multiple impulses and coordinated motion of several body segments, particularly the serve. By detecting the ball alongside the player's posture, the system can better infer the temporal phases of a movement — initiation, execution, and follow-through — thereby reducing false positives in visually similar scenarios. For instance, differentiating between a player preparing to serve and a player in a static upright position becomes more reliable when the ball's position and interaction with the athlete's hands are tracked concurrently.

Fig. 4. Training and validation

A. Error Analysis

Confusion between setting near the net and blocking was the most common misclassification, particularly when the camera angle was limited to the upper body. Improvements in dataset diversity and possible incorporation of temporal information from short video clips are expected to mitigate this issue.

B. Clinical Relevance

Insights from physiotherapy research indicate that blocking and serving are among the most biomechanically demanding volleyball actions. The system's ability to detect these movements accurately provides a foundation for clinical applications in injury prevention and rehabilitation monitoring.

V. POTENTIAL APPLICATIONS AND IMPACT

The system offers value for:

- Physiotherapist: enabling objective posture assessment during rehabilitation;
- Coaches: monitoring technical execution during training;
- Athletes: receiving visual feedback for technique improvement.

Beyond volleyball, the methodology can be adapted to other sports where biomechanical precision is crucial.

VI. PROOF OF CONCEPT(POC)

A controlled evaluation with professional physiotherapists is planned, involving real-time detection during rehabilitation exercises in a sports clinic environment.

VII. Future Technical Extensions

Planned developments include:

- Integration with AR for real-time feedback during rehabilitation exercises.
- Implementation of a performance analytics dashboard for physiotherapists:
- Longitudinal tracking of posture accuracy.
- Graphical summaries of athlete progress.
- Integration with FastAPI for API data management.

VIII. Conclusion

This work presented a lightweight, clinically-oriented posture detection system for volleyball based on the YOLOv8 family. The implemented pipeline, dataset curation and consensus-driven annotation, YOLOv8 training on Google Colab, and a Tkinter/OpenCV GUI for real-time inference, demonstrates a pragmatic path from research prototype to clinical aid. Empirical evaluation on a held-out test set (206 images) produced competitive per-class performance for ball and serve detection, while revealing limitations for visually similar classes (set vs. block) due to viewpoint and occlusion challenges. These results indicate the approach is already useful for high-level monitoring (e.g., confirming execution of targeted gestures), but further refinement is required for precise biomechanical assessment.

Technically, immediate next steps are: (1) integrate keypoint estimation or a light-weight pose regressor to complement bounding-box outputs and enable joint-angle computation; (2) expand the dataset focusing on underrepresented viewpoints and augmentations that simulate motion blur and variable lighting; (3) add temporal models (short sliding-window 3D-CNN or sequence models such as TCN/LSTM) to smooth per-frame predictions and reduce instantaneous misclassifications caused by mid-air poses; and (4) conduct controlled usability and validation studies with physiotherapists to quantify clinical utility (sensitivity/specificity for clinically-relevant movement faults) and to collect human factors feedback.

From an engineering perspective, the modular architecture allows two practical extensions: (a) streaming detection results to a Unity-based AR overlay to provide immediate visual feedback in rehabilitative trials, and (b) integration with CI/CD pipelines for automated retraining when new annotated data become available. Ethically and operationally, future clinical validation should follow institutional review standards and include repeated-measures designs to compare conventional assessment vs. combined human+vision workflows. In summary, the proposed system bridges computer vision and rehabilitation practice, providing an extensible foundation for objective, low-cost monitoring of volleyball-specific gestures in clinical settings.

IX. Acknowledges

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