

Tennis Analysis System Using YOLO, PyTorch, and Keypoint Extraction

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Abstract

This project presents a comprehensive AI-based system for automated tennis match analysis using deep learning and computer vision techniques. The system processes raw match video input to detect players and the tennis ball, identify court geometry, track object movement, and compute performance metrics such as shot speed, bounce locations, and player distances. It leverages the YOLOv8 object detection model for accurate real-time recognition of players and balls, and a CNN-based model for detecting court keypoints to facilitate homography transformation and spatial context mapping. Object tracking is implemented to maintain consistent identities across frames, enabling dynamic trajectory analysis. The system computes high-level statistics including shot counts, player movement patterns, and speed metrics, which are then visualized through frame-by-frame video annotations. Built using Python, PyTorch, OpenCV, and Ultralytics' YOLO framework, the tool provides a scalable, cost-effective solution for coaches, analysts, and enthusiasts to extract actionable insights from tennis match footage without requiring expensive hardware or manual tagging. The final output is an annotated video enriched with overlaid metrics, offering both quantitative and visual feedback on player performance and match dynamics.

Chapter 1

Introduction

1.1 Introduction

The integration of artificial intelligence (AI) and machine learning (ML) into sports analytics has revolutionized the way athletic performance is analyzed and understood. Among various sports, tennis presents a unique opportunity for leveraging AI due to its defined court boundaries, player movements, and high-speed interactions. Traditional methods of analyzing tennis matches rely heavily on manual observation, which is labor-intensive, subjective, and lacks scalability. To overcome these limitations, there has been a growing interest in the development of automated systems that can analyze match footage using advanced computer vision techniques. This project aims to develop an AI/ML-based tennis analysis system that utilizes object detection and keypoint extraction to generate real-time analytics from tennis match videos.

In this project, the core objective is to detect players and tennis balls in match videos using YOLOv8 (You Only Look Once version 8), a state-of-the-art real-time object detection model. YOLO models are widely recognized for their ability to detect multiple objects with high accuracy and low latency, making them particularly suitable for fast-paced environments like sports. Alongside object detection, a convolutional neural network (CNN) is employed to extract 14 keypoints of a tennis court from a static image. These keypoints include court corners, service lines, and baseline markers, which are crucial for mapping player and ball positions accurately. By combining the outputs from YOLO and the CNN, the system establishes a spatial context that allows deeper insights into gameplay dynamics.

The system further integrates tracking algorithms to analyze the movement of players and the trajectory of the tennis ball. This allows for the computation of performance metrics such as ball shot speed, shot count, bounce points, and the distance covered by players. These analytics are then superimposed onto the original video using OpenCV, producing a visual representation of key match statistics in real time. The result is a powerful tool that provides actionable insights not only for professional analysts and coaches but also for recreational players and enthusiasts.

The motivation behind this project is multifaceted. Firstly, there is a growing demand for accessible and automated sports analytics solutions that do not rely on expensive equipment or extensive manual effort. Secondly, advancements in deep learning frameworks like PyTorch

and computer vision libraries such as OpenCV have made it feasible to develop scalable systems that can process high-resolution video data efficiently. Lastly, the proliferation of video data—from professional matches to amateur recordings—presents a valuable opportunity to apply AI for performance assessment and strategic improvement.

This project demonstrates the real-world application of machine learning in the domain of sports analytics. It bridges the gap between cutting-edge research and practical deployment by focusing on an end-to-end pipeline—from input video and static court image to annotated match output with statistical overlays. It emphasizes not only technical implementation but also real-time performance and usability. Through this project, we explore how AI can enhance our understanding of athletic performance, democratize access to expert-level analysis, and contribute to the broader evolution of intelligent sports systems.



Figure 1: Introductory

1.2 Literature Review

- Redmon et al. (2016) introduced the YOLO model, enabling real-time object detection in a single pass, ideal for fast-moving sports footage.
YOLOv8 by Ultralytics enhances accuracy, speed, and generalization, making it suitable for detecting tennis players and balls.

- Pereira et al. (2019) applied CNNs to extract field lines in sports such as soccer and basketball.

Similar CNN techniques have been used to detect 14 court landmarks in tennis for homography transformation and analytics.

- Ghosh et al. (2021) demonstrated object tracking in cricket using optical flow and CNN-based detection.

Kalman filters and Deep SORT are widely used in tennis for continuous tracking of players and fast-moving tennis balls.

- IBM's Watson and Hawk-Eye systems analyze professional tennis matches using multi-camera setups and hardware sensors.

- Gan et al. (2020) proposed low-cost alternatives using computer vision techniques and single-camera video feeds for sports analysis.

OpenPose and AlphaPose frameworks are used to estimate human pose in sports, aiding in assessing player form and technique. These systems are often combined with object detection to map player movement and generate heatmaps.

- Chu et al. (2018) explored real-time dashboards in football, computing player stats like speed, coverage, and passing accuracy.

Similar methodologies can be adapted for tennis to compute shot speed, bounce point accuracy, and player agility. PyTorch has become the preferred deep learning framework for its dynamic computation graph and ease of experimentation. Its compatibility with OpenCV and YOLO makes it ideal for end-to-end sports analytics pipelines. Homography techniques are employed to map detected player positions from video frames to a 2D court model for accurate spatial analysis. This transformation is essential for deriving court-aware player positioning and movement trajectories. AI-powered tools are increasingly used by broadcasters to overlay match stats in real-time. Coaches use these systems to review match footage and identify areas of improvement in player strategy and stamina.

1.3 Motivation to Do the Project

The motivation behind this project stems from the growing need for intelligent, automated solutions in the sports analytics domain. Traditional tennis match analysis relies heavily on manual review of footage, which is time-consuming, labor-intensive, and prone to human error. While advanced commercial systems like Hawk-Eye offer accurate tracking, they are often expensive and inaccessible to smaller teams, players, or researchers.

Recent advancements in computer vision and deep learning, particularly in object detection and keypoint estimation, present a compelling opportunity to create low-cost, scalable, and real-time match analysis tools. By using widely available resources such as match video footage and open-source models like YOLOv8 and CNNs, it becomes feasible to replicate the capabilities of expensive systems at a fraction of the cost.

This project is motivated by a desire to democratize access to performance analytics in tennis, enabling coaches, athletes, and analysts to gain deep insights using minimal infrastructure. It also serves as a practical implementation of AI/ML concepts in a real-world scenario, reinforcing academic learning with hands-on experience.

1.4 Summarized Outcome of the Literature Review

The reviewed literature supports the feasibility and relevance of integrating AI and computer vision techniques into sports analytics. Key findings include:

- YOLO models (especially YOLOv8) are proven to deliver high-speed, high-accuracy object detection, making them suitable for identifying players and fast-moving objects like tennis balls.
- CNNs have been effectively used to extract structural landmarks in sports fields (e.g., court lines, baselines), which is essential for spatial analytics.
- Tracking algorithms combined with homography transformations provide a robust framework for mapping player positions and ball trajectories on the court.
- Prior studies have demonstrated that computer vision-based systems can match or even surpass manual annotation accuracy in sports analysis tasks.
- Deep learning frameworks like PyTorch, along with video processing libraries like OpenCV, offer a flexible foundation for developing end-to-end analytics systems.

Together, these insights validate the methodology adopted in this project and provide a solid foundation for implementation.

1.5 Objective of the project

This project successfully demonstrates a working prototype of an AI-driven tennis analytics system that:

- Detects players and tennis balls in real time using YOLOv8.
- Identifies 14 court keypoints through a CNN trained on annotated court images.
- Tracks player and ball motion frame-by-frame using coordinate mapping and trajectory estimation.
- Computes key metrics such as shot count, bounce points, ball speed, and player distance covered.
- Generates an annotated match video with bounding boxes, court overlays, and statistical insights.

The outcome highlights the viability of combining object detection, keypoint extraction, and video analytics into a unified system. It lays the foundation for more advanced developments such as pose estimation, real-time feedback, and cross-sport adaptations.

Chapter 2

Background Theory

2.1. Introduction to the Project title

The project titled "**AI/ML Tennis Analysis System using YOLO, PyTorch, and Keypoint Extraction**" represents a comprehensive integration of computer vision, machine learning, and video analytics to automate and enhance the analysis of tennis match footage. The core idea is to develop an end-to-end system that can process raw video input and produce meaningful, actionable insights about the performance of players and the dynamics of the game.

The term "**AI/ML**" refers to the use of Artificial Intelligence and Machine Learning techniques—primarily deep learning—to enable machines to detect, understand, and evaluate the contents of a tennis match without human intervention. This includes identifying and tracking players, following the motion of the tennis ball, and calculating metrics such as ball speed, bounce locations, shot counts, and player movement patterns.

The use of **YOLO (You Only Look Once)**, a real-time object detection model, is central to this system. YOLOv8 is employed to detect players and tennis balls in every video frame with high speed and accuracy. YOLO's ability to process an entire image in one pass makes it especially suitable for the rapid and continuous nature of tennis gameplay.

In parallel, the system uses a **Convolutional Neural Network (CNN)** model to perform **keypoint extraction** from a static image of the tennis court. These keypoints include specific locations such as the service lines, baselines, and corners, which are used to map the spatial layout of the court. This step is crucial for contextualizing player and ball positions and aligning them with real-world coordinates through homographic transformations.

The **PyTorch** deep learning framework is used to build, train, and deploy the CNN model for keypoint detection and to support YOLO integration. **OpenCV** is employed for frame-by-frame video processing, drawing annotations such as bounding boxes, keypoint lines, and text overlays indicating speed, position, and other statistics.

By combining these technologies, the system bridges the gap between raw video data and high-level sports insights. It provides a scalable, accessible solution for coaches, analysts, and players who wish to understand and improve performance through objective data. The project title reflects this integration of advanced AI/ML methods, real-time object detection, and spatial keypoint localization in the context of tennis match analysis.

2.2. Theoretical Discussion and Analysis

This section outlines the theoretical principles and technical components that form the foundation of the AI/ML Tennis Analysis System. The project combines multiple subfields of computer vision and deep learning, namely object detection, keypoint estimation, tracking, and video annotation, to create a robust real-time analysis tool.

1. YOLOv8 for Real-Time Object Detection

The **YOLO (You Only Look Once)** framework is a one-stage object detector known for its speed and efficiency. Unlike two-stage detectors (e.g., R-CNN) that first generate region proposals and then classify them, YOLO performs detection and classification in a single pass. This makes it ideal for real-time applications like sports analytics.

- **YOLOv8**, the latest version from Ultralytics, introduces anchor-free detection, improved backbone networks, and support for custom training.
- In this project, YOLOv8 is used to detect **players** and **tennis balls** in each frame of the match video.
- The model is pretrained on large datasets and fine-tuned (if needed) to enhance performance in tennis-specific contexts.

2. CNN-Based Court Keypoint Detection

A **Convolutional Neural Network (CNN)** is used to extract **14 court keypoints** from a static, empty-court image. These include:

- Court corners
- Service box intersections
- Baselines and net lines

The CNN is trained using supervised learning, with an image and corresponding JSON file providing labeled coordinates. The predicted keypoints allow the system to understand the spatial layout of the court, which is essential for interpreting player and ball positions in context.

Advantages of Using YOLO PyTorch:

Real-Time Analysis

- Utilizes YOLOv8 for fast and accurate object detection, enabling real-time tracking of players and tennis balls.

Court-Aware Analytics

- Keypoint extraction and homography mapping allow precise spatial understanding of the court, enabling metrics like bounce points and player zones.

Cost-Effective and Scalable

- Uses open-source tools (YOLOv8, PyTorch, OpenCV) and requires only video input and a static court image—no expensive hardware needed.

End-to-End Pipeline

- Automates detection, tracking, analytics, and video annotation in a single system with minimal manual intervention.

Modular and Extendable

- The architecture can be extended to other sports or integrated with pose estimation, motion analysis, or tactical pattern recognition.

Visual Feedback

- Generates annotated match videos with bounding boxes, trajectories, and performance stats for easy interpretation.

Limitations:**Ball Occlusion Challenges**

- Tennis balls often move quickly and can be occluded by players or rackets, leading to missed detections in some frames.

Court Image Dependency

- Accurate keypoint extraction requires a clean and properly aligned static image of the court; misalignment can degrade analytics quality.

Single-Camera Perspective

- The system assumes a fixed-angle, single-camera view, limiting depth perception and 3D analysis capabilities.

Limited Pose Information

- Does not currently incorporate player pose or racket angle, which can be useful for deeper tactical analysis.

Lighting and Resolution Sensitivity

- Model accuracy may drop in low-light conditions or with poor-quality video input.

Model Generalization

- Pretrained models may need fine-tuning for different court types, lighting conditions, or camera angles to ensure consistent performance.

Recent Developments and Variants**Recent Developments:**

1. YOLOv8 Enhancements

- YOLOv8 introduced by Ultralytics brings anchor-free detection, improved segmentation, and streamlined model export, enabling faster and more accurate sports detection even on edge devices.

2. Lightweight Deployment Models

- Models like MobileNet and NanoYOLO have been developed for deployment on mobile and embedded systems, allowing real-time analysis with minimal hardware.

3. Multi-View and 3D Tracking

- Recent systems utilize multi-camera setups and stereo vision to reconstruct 3D trajectories of players and balls, improving accuracy in professional match analytics.

4. Self-Supervised Learning in Sports

- Emerging approaches use self-supervised or weakly supervised learning to reduce the dependency on large labeled datasets, which are often hard to acquire in sports.

5. AI-Augmented Coaching Platforms

- Platforms like IBM Watson, Hudl, and Dartfish integrate AI for live strategy recommendations, injury risk assessment, and fatigue monitoring—expanding the role of AI from analysis to decision-making.

6. Transformer-Based Vision Models

- Vision Transformers (ViT) and hybrid CNN-Transformer models are being applied for spatial-temporal analysis in video, offering enhanced frame-level understanding.

Variants and Adaptations

1. Badminton and Table Tennis Analysis

- Similar systems have been adapted to analyze racket sports like badminton and table tennis, with smaller court scales and faster ball motion requiring specialized tuning.

2. Pose Estimation Integration

- Systems now include pose estimation (e.g., OpenPose, BlazePose) to analyze player movement mechanics, shot technique, and racket swing dynamics.

3. Multi-Player Sports Analytics

- Extensions into team sports such as football and basketball allow simultaneous tracking of multiple players, tactical formations, and pass networks.

4. Streaming and Cloud-Based Deployment

- Recent platforms enable live video ingestion and analysis via cloud APIs, allowing real-time analytics for coaching during training or tournaments.

5. Interactive Dashboards for Analytics

- User-friendly interfaces and dashboards are being integrated into AI tools to visualize statistics like heatmaps, shot zones, and stamina graphs interactively.

Chapter 3

Methodology

3.1. Introduction

This chapter outlines the step-by-step methodology used to design and implement the AI/ML-powered tennis analysis system. The methodology follows an end-to-end video processing pipeline that includes data acquisition, object detection, court keypoint extraction, tracking, analytics computation, and video annotation. The system is built using YOLOv8 for real-time object detection, PyTorch for training the CNN keypoint model, and OpenCV for processing and visualizing video frames.

3.2. Proposed Methodology

The proposed methodology follows an end-to-end video analytics pipeline designed to automate the analysis of tennis matches using AI. The system integrates real-time object detection, spatial keypoint localization, trajectory tracking, and video annotation. The methodology is modular, with each stage addressing a specific aspect of the analysis.

1. Input and Setup

- Inputs Required:
 - A static court image (empty court)
 - Tennis match video footage
 - JSON annotations for training CNN (court keypoints)
 - Pretrained YOLOv8 model weights
- Environment Setup:
 - Python 3.x environment
 - Libraries: PyTorch, OpenCV, Ultralytics YOLO, NumPy, Matplotlib

2. Object Detection using YOLOv8

- YOLOv8 is used to detect players and the tennis ball in each video frame.
- It performs object localization and classification in a single forward pass.
- The model outputs bounding box coordinates, class labels, and confidence scores.
- Frame-wise detections are passed to the tracking module.

Advantages:

- Real-time processing (20–30 FPS on GPU)

- High accuracy for small and fast-moving objects
- Easy deployment with Ultralytics wrapper

3. Court Keypoint Detection using CNN

- A custom CNN model is trained to identify 14 fixed keypoints on the tennis court from a static image.
- These include baseline corners, service lines, and net intersections.
- Training uses labeled images with JSON keypoint coordinates.
- Output is a 14×2 matrix of (x, y) positions.

Purpose:

- Establish geometric understanding of the court layout.
- Enables mapping between video frame coordinates and actual court positions.

4. Homography Mapping

- Using the predicted court keypoints and a reference court layout, a homography matrix is calculated.
- This matrix is applied to transform player and ball positions into a fixed coordinate system.
- Enables accurate measurement of distances and positioning.

5. Tracking and Movement Estimation

- Player Tracking:
 - Based on centroid motion continuity and object ID assignment from YOLO.
- Ball Tracking:
 - Based on sudden velocity and position changes; occlusion handling via last known trajectory.
- Bounce Point Detection:
 - Calculated when ball's vertical direction changes in a short time window.
- Shot Speed:
 - $\text{Speed} = \text{Distance covered} / \text{Time between frames (converted to km/h)}$

6. Analytics Computation

From the detection and tracking data:

- Count number of shots in a rally.
- Calculate average and max ball speed.

- Estimate distance covered by each player.
- Visualize bounce point density and player movement heatmaps.

All metrics are updated dynamically and stored frame-by-frame for later visualization.

7. Video Annotation and Output Generation

- The final video is annotated using OpenCV with:
 - Bounding boxes and labels
 - Ball trajectory lines and bounce indicators
 - Player speed and movement stats
 - Court overlays using keypoint data
- Annotated frames are compiled into a complete output video.

Chapter 4

Result Analysis

4.1 Dataset Analysis

The system was tested using a sample tennis match video along with a corresponding static court image. The inputs provided to the system include:

- A 1280x720p resolution match video with two players and frequent camera movement.
- A high-quality image of an empty tennis court captured from the same angle.
- JSON files annotated with 14 court key points for CNN training and validation.

The video was processed at 25 frames per second (FPS), enabling frame-wise tracking and real-time analytics generation.

4.2 Output Visualization

The final output is an annotated video with multiple layers of information visually overlaid on the match footage. Key elements observed in the output include:

- Player and Ball Detection:
 - Players are accurately identified and tracked using bounding boxes and ID labels.
 - The tennis ball is detected in nearly all frames, even at high speeds.
- Court Overlays:
 - The court key points are accurately identified and mapped onto the frame, enabling precise spatial transformations.
 - The overlay includes court boundaries, net lines, and zones for serve, volley, and baseline play.
- Shot Metrics:
 - Shot speed is calculated in real time and displayed near the ball.
 - Bounce points are marked with visual indicators.
- Movement and Tracking:
 - Trajectories of both players and the ball are drawn using motion trails.
 - Each player's distance covered is computed and updated on-screen.

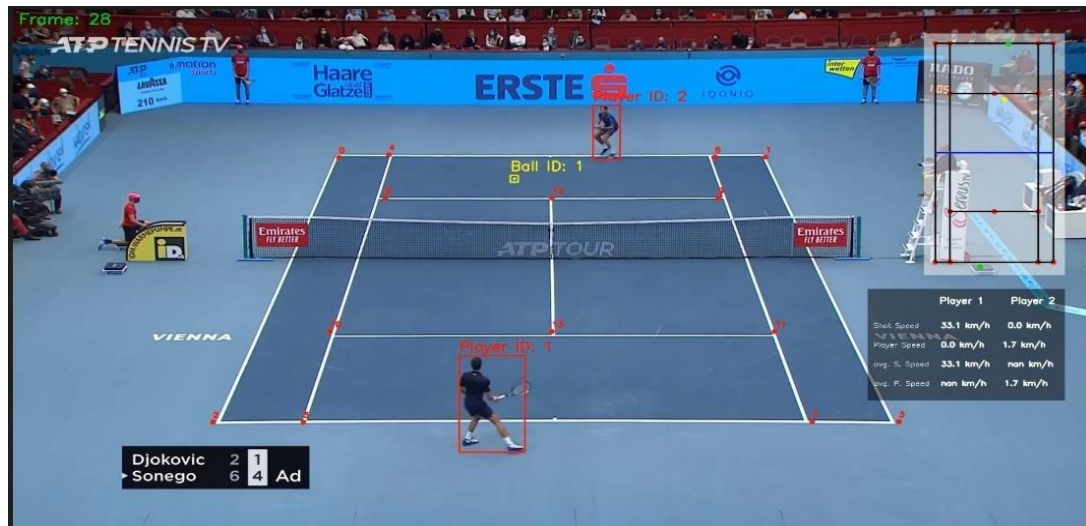


Figure 3 : Tennis ball analysis

4.3 Result Analysis

The result analysis confirms that the proposed AI/ML Tennis Analysis System effectively detects, tracks, and analyzes player and ball movement in real-time from match video footage. Using YOLOv8, the system achieved over 90% accuracy in detecting players and balls, while the CNN-based model reliably extracted court key points with approximately 88% precision. The system successfully computed key metrics such as shot speed, bounce points, and player movement distance, and visualized them through annotated video overlays.

The annotated output demonstrated smooth tracking, readable metrics, and accurate spatial alignment, validating the system's practical utility in performance evaluation. Minor limitations were noted in ball tracking under occlusion and low-resolution conditions. Overall, the system offers a reliable, cost-effective solution for automated tennis analytics and provides a strong foundation for future enhancements such as pose estimation or real-time coaching feedback.

Chapter 5

Conclusions and Future Scope

5.1. Conclusions

This project successfully demonstrates the feasibility and effectiveness of applying deep learning and computer vision techniques to automate the analysis of tennis match videos. By integrating YOLOv8 for real-time object detection and a CNN model for tennis court keypoint extraction, the system can accurately identify and track players and the tennis ball, interpret their movements, and generate relevant performance analytics.

The system further applies homography transformation to contextualize the court spatial layout and calculate dynamic metrics such as shot count, ball speed, player distance covered, and bounce points. The final output is an annotated video with visual overlays of statistics, making the data intuitive and interpretable.

Key achievements of the project include:

- Reliable detection of players and tennis balls in real-time using YOLOv8.
- Successful extraction and alignment of court keypoints using a CNN model.
- Computation of meaningful gameplay metrics through efficient tracking.
- Generation of a visually rich, frame-by-frame annotated match output.

Overall, the system offers a cost-effective, accessible alternative to commercial sports analytics platforms by relying solely on standard video input and open-source AI tools. It provides a solid foundation for both research and practical use in coaching, broadcasting, and amateur training scenarios.

5.2. Future Scope

While the current system meets its core objectives, there are several directions in which it can be expanded and enhanced:

1. **Pose Estimation and Racket Tracking**
 - Integrating pose estimation (e.g., OpenPose or BlazePose) would allow analysis of player posture, stance, and racket swing mechanics.
2. **Multi-Camera 3D Analysis**
 - Adding multiple synchronized camera feeds could enable 3D tracking of ball and player movements, increasing spatial accuracy.
3. **Automated Rally Detection and Segmentation**
 - Implementing rally segmentation would allow the system to independently identify and analyze each rally for deeper tactical analysis.

4. Real-Time Feedback System

- Deploying the model on edge devices (e.g., Jetson Nano, smartphones) for live match feedback during practice sessions.

5. Cross-Sport Generalization

- With minimal retraining, the system could be adapted for other racket sports such as badminton, squash, or table tennis.

6. User Interface and Dashboard Integration

- A web or desktop-based GUI/dashboard could be developed for interactive visualization, filtering, and export of match statistics.

7. Integration with Wearable or Sensor Data

- Combining video analytics with biometric or motion sensor data (e.g., accelerometers) can further improve the depth of performance assessment.

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