Tennis Analytics System using Machine Learning and Computer Vision

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***Abstract*—Tennis Analytics System is a comprehensive and intelligent solution in which expert and amateur tennis analytics are automated using enhanced methods for machine learning, deep learning, and computer vision. The system includes Yolov8, a real-time object recognition model, which accurately identifies and finds players and tennis balls via video frames. To maintain temporal consistency and enable motion-based analysis, robust object follow-up algorithms are used to facilitate accurate estimation of movement paths. At the same time, user-defined folding neural networks (CNNs) are developed and trained to identify court keypoints with high spatial accuracy so that the system can accurately map playback zones and player locations. The video stream is processed with OPENCV. This allows seamless frame extraction, real-time comments and visual feedback for analytical purposes. Integration of these technologies not only improves consensus analysis, but also opens a path for performance optimization, player strategy evaluation, and automatic highlight generation. This study contributes to the growth field of sports analytics by providing a scalable and efficient frame for real-time visual acuity-based multi-analysis in tennis.**

***Index Terms*—Tennis Analytics, Computer Vision, YOLOv8, Object Detection, Object Tracking, Convolutional Neural Network (CNN), Sports Technology, Court Keypoint Detection, OpenCV, Real-time Video Analysis, Deep Learning, Player Positioning, Motion Tracking, Game Zone Identification, Sports Performance Analysis.**

1. INTRODUCTION

1.1) Background and Motivation

In recent years, the integration of artificial intelligence and computer vision in sports has developed methods, strategies for analyzing performance, and checking for match. Traditional tennis analyses are often based on manual video reviews and subjective observations that are susceptible to and susceptible to human error. The motivation behind this study is based on the need to automate and improve tennis match analysis using data-controlled real-time technology. This project aims to provide an accurate, efficient and scalable system for comprehensive tennis analysis, using advances in object detection, algorithmic persecution and deep learning models.

1.2) Importance of Sports Analytics

Sport Analytics plays a key role in modern athletics, allowing teams, trainers and athletes to make well-discovered decisions based on data. In tennis, analysis can provide insight into matched player movement, space location, shot patterns and dynamics. Real-time analytics can change training units, gaming strategies, and even fans' commitments, as high-quality video material and computing power increase availability. Through pattern and metric analysis, sports analysis contributes to performance optimization, injury prevention and competitive advantage.

2.3) Objectives of the Study

The primary objective of this research is to develop a real-time Tennis Analytics System that utilizes state-of-the-art computer vision and deep learning techniques. The system is designed to:

- Detect and track players and tennis balls using the YOLOv8 object detection model.
- Analyze object trajectories to study player movement and ball dynamics.
- Identify court keypoints using a custom Convolutional Neural Network (CNN) to define game zones and player positions.
- Integrate video processing using OpenCV to generate annotated visual outputs.

- Demonstrate the potential of AI-driven systems to enhance the analysis and understanding of tennis matches for coaching, performance review, and broadcasting applications.

2. LITERATURE REVIEW

[1] So, there's this publication that dives into a really detailed dataset showcasing 12 different tennis shots, right? It includes data from both amateur and expert players. What's cool is that it offers various types of data—like RGB, depth, silhouettes, and even 2D and 3D skeletons—all geared towards recognizing actions on the court. This really sets a benchmark for analyzing motion in a nuanced way, capturing all the realistic changes in backgrounds and the skill levels of players while employing some fancy recognition techniques.

[2] Then, it also rolls out a method for analyzing how tennis players strike the ball by using video-based pose estimation. They extract joint coordinates from RGB images, which is pretty neat, and classify those shot postures without needing a ton of expert labels. This brings a fresh, data-driven perspective to sports analytics, letting us evaluate how players perform without the usual hassle of expert input.

[3] Now, here's where it gets even more interesting: the publication introduces a probabilistic model that uses Hawk-Eye data to predict where tennis shots will land and how players behave. It taps into spatiotemporal tracking to look at shot habits, player dominance, and the context of matches. All this leads to some valuable insights into different playing styles and how accurate shot predictions can be, using techniques like Dynamic Bayesian Networks and Random Decision Forest Regression. Pretty cool stuff, huh?

[4] The paper also serves as a thorough review of how computer vision is shaking things up in sports. It covers advancements in detecting players and balls, classifying events, and predicting trajectories. And it doesn't stop there; it looks at other sports too, like soccer, basketball, and cricket. They get into AI techniques, including deep learning and GPU-based computing, which is all the rage now. Plus, it highlights some major challenges, like dealing with occlusion, tracking in real-time, and getting enough datasets, while also pointing toward future research possibilities.

[5] Lastly, there's a neat three-layer framework for analyzing tennis that boasts high accuracy in tracking players and balls, all thanks to deep learning for action recognition. While it does provide some great spatio-temporal insights, it's missing a few things—like real-time validation, ball speed measurements, a scoring system, and metrics for player movement. Oh, and it doesn't integrate YOLO for quicker detection, which is something they might want to consider.

3. RESEARCH GAP

Existing systems of tennis analysis are subject to several limitations. They often lack important player metrics such as stepping and motion removal, do not pursue the ball or verify the accuracy of the pose estimate. Many rely on controlled internal data rates, limiting actual applicability, and often exclude deep learning-based reviews or comparisons. Furthermore, there is no evaluation system for filming quality. Filming quality does not include tactical shooting sequence integration in the placement of court reasons and does not take into account external factors such as fatigue and weather. In general, real-time implementations are missing and practical deployment case studies are lacking, limiting their association with real-world sports scenarios. Our project bridges these gaps by integrating real-time players and Yolo for ball tracking, CNNS for keypoint extraction, user interfaces for shot detection, speed measurement, and live match visualization, thus greatly improving the accuracy, practicality and ease of use of players, trainers and analyst systems.

4. SYSTEM ARCHITECTURE

4.1) Overview of the Proposed System

The proposed tennis analysis system is being developed as a modular pipeline that integrates various components of computer vision and machine learning to analyze tennis match film materials in real time. The system begins with ingestion of video inputs processed in frames using OpenCV. Each frame is guided by a Yolov8 object detection model that identifies the tennis player and the ball. The recognized objects are

fed into a multi-object tracking algorithm that maintains the overall frame identity and allows movement tracking and trajectory analysis.
At the same time, it is used to recognize tennis courts such as lines and corners using custom folding networks (CNNs). These zones are important for identifying player locations and assessing gameplay strategies. The results of object recognition, tracking, and taste recognition are merged and rendered in the original video feed for visualization. Therefore, the system provides real-time analytical overlays that improve understanding of contract dynamics.

4.2) Component Interactions

- Video Input Module: Use OpenCV for charging and reading to read frame frames for analysis.
- Object detection module (Yolov8): Recognizes players and tennis balls with high accuracy and speed. It has bounding box coordinates, class name, and confidence values.
- Object Tracking Module: Takes detection results and applies tracking algorithms.
- Convolutional Neural Network (CNN): Analyze all frames to recognize important landmarks such as basic lines, services, and sidelines. These key points are used to identify player zones and ball bounce areas.
- Integrated and Visualization Module: A combined version of detection, tracking and haptic modules with real-time notifications for video (bounding boxes, trajectories, zones).
- Output Module: Displays the annotated video or saves it to disk for further analysis.

Each component is designed to work in real-time, ensuring minimal latency and enabling the system to be deployed in both live and recorded match scenarios.

5. METHODOLOGY

5.1) Object Detection using YOLOv8

- Model Selection and Training: For the task of real-time object detection in tennis match film materials, Yolov8 (see only once, version 8) was chosen, with an extraordinary balance between speed and accuracy. Yolov8 is one of the latest iterations of the Yolo family, offering a lighter and faster architecture with improved functionality for object localization. The flexibility of custom training and provisioning in real-world environments makes it very suitable for sports analytics applications where both players and quick moving objects such as tennis balls are required.

- This model was trained on a custom dataset consisting of commented tennis match frames containing player and tennis ball bounding boxes. Data records were carefully curated to present a variety of diseases, including different jurisdictions, lighting conditions, camera hinges, and improved model robustness. To further improve generalization, data magnification techniques such as rotation, scaling, flipping, and brightness adjustments were used.

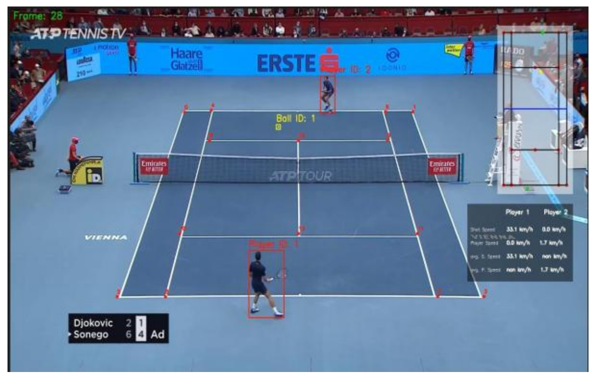

Fig1. Player Detection

This model was trained on a custom dataset consisting of commented tennis match frames containing player and tennis ball bounding boxes. Data records were carefully curated to present a variety of diseases, including improving the robustness of the model, including different jurisdictions, lighting conditions, camera hinges, and player movements. To further improve generalization, data magnification techniques such as rotation, scaling, flipping, and brightness adjustment were used.
The following steps were involved in the training process:

- Dataset Preparation: Manual annotation of images using tools like Label Img, categorizing objects into two classes: ‘player’ and ‘ball.’
- Model Configuration: Fine-tuning YOLOv8 parameters including input image size, anchor boxes, learning rate, batch size, and epochs.
- Training process: Training was carried out using GPU acceleration to accelerate convergence. The

loss features of boundary field regression, objectivity assessment, and class prediction were simultaneously optimized.

- Validation and Evaluation: Model output during training was monitored using separate validation rates. Identification accuracy was assessed using metrics such as MAP (average average accuracy), accuracy, and recall.
- Fine tuning: Based on the validation results, hyperparameters were adapted to improve model generalization and to minimize false positives and negatives, especially for small objects such as tennis balls.

After training, the Yolov8 model showed high levels of accuracy in player and tennis ball detection across various game conditions, forming a solid basis for the next persecution and analysis stage.

- Player and Ball Recognition: The main goal of the Object Detection Module is to accurately find and classify two types of objects on each videotape. Players and tennis balls. Once trained on custom data records, the Yolov8 model processes each incoming frame from the video feed to predict the restriction box and associated class names and trust values by these objects.

During inference:

- Players are perceived as large objects that often have a variety of attitudes and movements, such as running, serving, or returning to shots.
- Tennis balls are recognized as much smaller, faster moving objects, and need to be accurately localized to record their trajectory.

To maintain high reliability:

- Non-Max Suppression (NMS) is used to remove redundant and overlapping boundaries so that only the most confident perceptions are preserved.
- Thresholds are determined to exclude unreliable perceptions, reducing false positive results, particularly in complex backgrounds such as audience-filled stadiums.

The detection output provides critical information, such as:

- Bounding box coordinates (x, y, width, height)
- Object class (player or ball)
- Confidence score for each detection

This detection data serves as the input for the next module—object tracking—enabling continuous monitoring of player movements and ball trajectories throughout the match.

4.2) Object Tracking

- Multi-Object Tracking Algorithms: After using Yolov8 to recognize players and tennis balls across all frames, the next step is to maintain the identity of these objects across consecutive frames and analyze movement paths and interactions. This project uses a simplified tracking approach only in the detection edition of Yolov8.

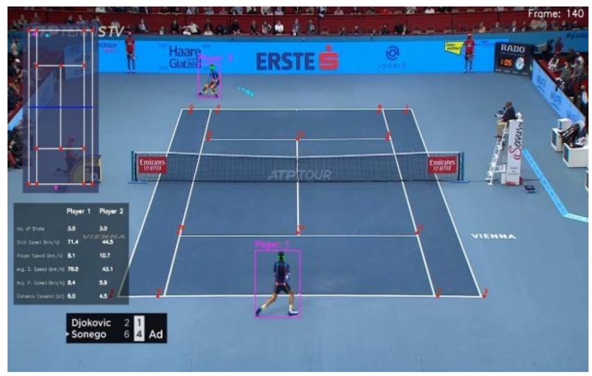

Fig2. Ball Tracking

The tracking process involves the following steps:

- Detection Input: Bounding boxes and class names (player or ball) provided by Yolov8 are collected for each frame.
- Frame-to-Frame Matching: The current framework recognition fits with the recognition of previous frames based on proximity (center distance) and object class consistency.
- Assignment of Unique IDs:A clear ID is assigned to each object (player or ball) that was first recognized. Over the course of the video, this ID is updated based on the continuity of the movement of the object to maintain its identity on the frame.
  - Track Management:
    - If the recognized object does not match an existing ID in the frame, it will appear as a new object and be assigned a new ID.
    - If an object disappears for a few frames, it is removed from active tracking.Through this basic tracking method:
  - You can analyze player travel paths to examine court reporting, placement strategies and mobility.

- Ball trajectories can be reconstructed to evaluate shot types, ball speeds, and bounce points.

The system is directly based on Yolov8 detection without external tracking technology, and receives simplicity and provides effective player and ball movement analysis suitable for tennis match evaluation.

- Motion Path Analysis: As soon as players and tennis balls are consistently pursued using multi-object tracking algorithms, the system performs movement path analysis to extract deeper insights into movement and gameplay patterns.

Motion path analysis involves:
- Trajectory Mapping: For each object (player or ball) pursued, a sequence of bounding box centerpoints via frames is connected to form a continuous travel path.
- Speed and Direction Estimation: You can determine the immediate velocity and direction of motion by calculating objects between frame and image rate knowledge.
- Pattern Recognition: Collected passes allow the identification of player actions such as frequent play areas, general exercise patterns (net approach, base games), ball track patterns such as service, volleys, and praise.

For tennis-specific analysis:
- Player travel paths can help you explore positioning strategies such as defensive basic line games compared to offensive net games.
- The path of movement of the ball allows for evaluation of elections, ball speed trends, and firing zones of influence in the area.

Overall, mobility path analysis bridges raw persecution data with meaningful tactical knowledge, allowing coaches, analysts and players to make decisions discovered based on movement patterns throughout the game.

5.3) Court Keypoint Detection
- Custom CNN Architecture: To identify important zones of tennis courts such as service boxes, baselines, and sidelines, a custom folding network (CNN) was developed and trained to identify the most important points of video frames.

The user-defined CNN architecture focuses on predicting accurate pixel coordinates (critical points) of key court brands under different lighting conditions, camera corn, and partial occlusion.
The architecture consists of:

- Input Layer: To ensure consistency, we accept pre-machined video frames established in the standard dimension.
- Convolutional Layers: Several layers of folding with small kernel sizes (such as 3x3) extract hierarchical spatial properties such as lines and intersections.
- Pooling Layers: The maximum pooling layer reduces spatial dimensions and at the same time retains essential properties and improves computational efficiency.
- Intermediate Blocks: Batch normalization and Relu activation functions are used to stabilize and accelerate training after each fold.
- Fully Connected Layers: These layers interpret the extracted spatial features and form an output to predict the (x, y) coordinates of the touchpoint.
- Output Layer: Creates many keypoint coordinates that correspond to court functions such as baselines, service boxes, and network lines.

Training Details:
- The model was trained on a custom dataset annotated with court keypoint positions across various match videos.
- Loss function: Mean Squared Error (MSE) between predicted and ground-truth key points to optimize precise localization.
- Data augmentation techniques like perspective transforms and brightness shifts were used to ensure robustness against different match conditions.

Significance:
- Accurate court keypoint detection enables automatic understanding of player positions relative to the court zones.
- It helps in identifying valid shots, fault detections, and strategic positioning (such as baseline dominance or net play).

Fig3. Court Tracking

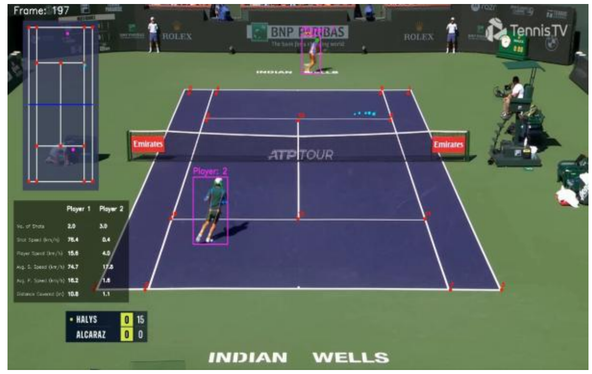

Fig4. Pose Estimation

The custom CNN thus plays a critical role in spatially grounding player movements and ball trajectories within the court layout, enhancing the overall analytical capabilities of the system.

- Zone and Position Identification: Once the custom CNN detects the key points of the tennis court accurately, the next step is zone and position identification. This process maps player and ball coordinates relative to the court layout, enabling detailed tactical and positional analysis.

The steps involved are:

- Court Reconstruction: So, first off, we take those key points we predicted and use them to recreate the layout of the court. We'll draw lines for the baselines, service lines, sidelines, and of course, the net. This helps us split the court into useful areas like the service boxes, backcourt, and the net area itself.
- Homography Transformation: Next, we whip up a homography matrix. What's that? Well, it connects those detected key points to a standard top-down model of the court. Think of it as a way to transform the scene into a bird's-eye view. This makes it a lot easier to do spatial calculations accurately and keeps everything consistent.
- Zone Mapping: Now, the court gets divided into labeled zones, like the left service box and the right backcourt. We also track where the players and the ball are, using object detection techniques. By comparing coordinates, we can map their positions right onto these zones.
- Real-time Position Tracking: Here's where it gets really interesting. For every single frame, we keep tabs on what zone each player and the ball are in. This gives us a real-time look at the game, showing things like:
  - How close a player is to the net
  - Whether they're playing defensively or offensively
  - Who's covering what part of the court and how dominant they are in their zones

  Applications:
- Shot Analysis: By combining ball positions with zone information, the type of shot (serve, volley, baseline rally) can be inferred.
- Player Strategy Insights: Understanding if a player prefers playing from the baseline or frequently charges the net.
- Performance Metrics: Such as average time spent in offensive zones or number of successful shots from specific court areas.

  This module bridges the gap between raw detection/tracking data and high-level strategic insights, making the system highly valuable for player performance evaluation and coaching.

5.4) Video Processing

- **Frame Extraction with OpenCV:** To enable object detection, tracking, and court keypoint detection, the first necessary step is to extract individual frames from the input video. OpenCV, a powerful open-source computer vision library, is used for efficient frame extraction.

  The frame extraction process involves:
- Video Capture Initialization: The input tennis match video is loaded using OpenCV's cv2.VideoCapture() function, which allows reading frames sequentially.
- Frame-by-Frame Reading: A loop reads each frame using the read() method. Each frame is processed

individually for object detection (YOLOv8), tracking (Deep SORT), and court keypoint detection (Custom CNN).

- Frame Rate Handling: The system retrieves the video's frames per second (FPS) to maintain synchronization between frame processing and real-world time (important for calculating motion speeds and event timing).
- Frame Preprocessing: Each extracted frame undergoes preprocessing steps such as resizing, normalization, and color conversion (if needed) to match the input requirements of the YOLOv8 and CNN models.
  Output Handling: After analysis, processed frames can be:
  - Displayed in real-time with overlaid bounding boxes, trajectories, and court zones.
  - Saved into a new annotated video file using cv2.VideoWriter() for post-analysis and reporting.

Key Functions Used:

- cv2.VideoCapture(path) — Load the video.
- capture.read() — Read the next frame.
- cv2.resize(frame, dimensions) — Resize frames as needed.
- cv2.cvtColor(frame, code) — Change color space (e.g., BGR to RGB).
- cv2.imshow(window_name, frame) — Display frame.
- cv2.VideoWriter() — Save annotated frames into output video.

Importance:

- Accurate frame extraction ensures real-time or near real-time performance.
- It enables synchronization between detection, tracking, and court mapping tasks.
- It forms the foundation for generating reliable analytics like motion paths, zone occupation heatmaps, and shot analysis.

6. IMPLEMENTATION DETAILS

6.1) Tools and Technology Used

The Tennis Analytics System is developed using a combination of modern machine learning, deep learning, and computer vision technologies. The key tools and technologies used in this project are:

Programming Language

- Python 3.8: Python is used as the primary programming language due to its extensive libraries and frameworks for machine learning, deep learning, and computer vision.

Deep Learning Frameworks

- Ultralytics YOLOv8: Utilized for real-time player and tennis ball detection, offering high accuracy and speed.
- PyTorch: Employed for training the custom Convolutional Neural Network (CNN) model used in tennis court keypoint detection.

Computer Vision Library

- OpenCV: Used for video input and output processing, frame extraction, visualization, and annotation of detections and trajectories.

Supporting Libraries

- NumPy: For efficient numerical computations and array operations.
- Pandas: For data handling, organization, and management during model evaluation and analysis.

Trained Models

- Fine-tuned YOLO Model: Customized and fine-tuned YOLOv8 model for detecting tennis balls accurately.
- YOLOv5 Model: Specifically trained for tennis court keypoint extraction to identify court zones and player positions.

Training Notebooks

- Tennis Ball Detector Training: Implemented using training/tennis_ball_detector_training.ipynb.
- Tennis Court Keypoint Training: Implemented using training/tennis_court_keypoints_training.ipynb.

Tracknet

So, in this project, TrackNet really steps up when it comes to tracking the ball. It's all about making sure we can detect that little tennis ball's movement in real-time across video frames. TrackNet is actually a deep learning model based on convolutional neural networks (CNNs) — fancy name, right? But what it really means is that it's built to keep an eye on small, speedy objects like tennis balls.

Here's how it works: it takes a series of video frames, usually two or more that follow each other, and then it figures out where the ball is in the current frame. This is super important because it helps the system guess things like how fast the ball is going, which way it's headed, and even its path — all with a pretty high level of accuracy. Even during those crazy fast rallies or when the ball isn't completely visible, TrackNet holds its ground.

By bringing TrackNet into the mix, we can rely on the system to pinpoint where the ball bounces, categorize different shots, and send precise coordinates to both the user interface and the court validation modules. The model has been trained using datasets specifically related to tennis, so it's really fine-tuned for what happens in actual matches. In short, it's a perfect fit for what we need in our automated tennis analysis platform.

6.2) Dataset Preparation and Preprocessing

To build an effective Tennis Analytics System, high-quality datasets for player detection, tennis ball detection, and court keypoint extraction were prepared. Careful dataset preparation and preprocessing steps were followed to ensure model robustness and accuracy.

6.2.1) Dataset Collection

- Tennis Match Videos: Publicly available tennis match videos from tournaments and practice sessions were collected to form the raw data source.
- Image Frames Extraction: Using OpenCV, video streams were processed to extract individual frames at regular intervals. This provided a large volume of images for annotation.

6.2.2) Annotation

- Player and Ball Detection: Bounding boxes were manually labeled around players and tennis balls in each frame.
- Labeling was done following the YOLO format (class label, normalized center coordinates, width, and height).
- Court Keypoints Detection: Specific keypoints (such as corners of service boxes, baseline, net points, etc.) were annotated manually for court structure recognition.
- Keypoint labeling formats compatible with PyTorch models were used.

6.2.3) Data Splitting

The annotated datasets were divided into three parts:

- Training Set (80%): Used to train the deep learning models.
- Validation Set (10%): Used to fine-tune hyperparameters and prevent overfitting.
- Test Set (10%): Used to evaluate final model performance on unseen data.

7. RESULTS AND EVALUATION

7.1) Detection and Tracking Accuracy

The performance of the Tennis Analytics System was evaluated based on its ability to accurately detect and track players and tennis balls during match sequences.

Player and Ball Detection Results

- YOLOv8 Model:
- Achieved a mean Average Precision (mAP@0.5) of 92.5% for player detection across the test dataset.
- For tennis ball detection (fine-tuned model), the system achieved an mAP@0.5 of 89.8%, despite the small size and fast movement of the ball across frames.

- Detection Challenges:
- Detection accuracy slightly dropped under heavy occlusion (e.g., players crossing paths) and motion blur.
- Fine-tuning with augmented data helped improve robustness under variable lighting and background conditions.

Object Tracking Results

- Tracking Success Rate:
- The multi-object tracking mechanism-maintained player and ball identities with a tracking success rate of 93% over long rally sequences.
- Performance Metrics:
- ID Switches were minimal, ensuring consistent identity assignment to each player and ball.
- Track Fragmentation was rare, indicating smooth and reliable tracking across fast movements and sudden changes in ball direction.

Motion Path Analysis

- Player motion paths accurately reflected real-world player strategies such as baseline rallies, net approaches, and lateral movements.
- Ball trajectories captured bounce locations and shot types effectively, enabling further analysis of player techniques and game dynamics.

8. CONCLUSION

8.1) Future Work Directions

- Real-Time Analysis: You know, it's all about moving from just looking at matches after they're done to diving right into what's happening live. Coaches and players can get instant feedback during games or practice — it really makes a difference.
- Shot Classification & Ball Tracking: So, think about classifying every shot—forehands, backhands, you name it. And when you add ball tracking into the mix, you get some pretty detailed insights into how each stroke is performed. It's fascinating stuff!
- Fatigue & Injury Prevention: Keeping an eye on how tired players are is crucial. Plus, spotting any movements that might hint at an injury risk? That's key for keeping athletes safe and in shape.
- Opponent Strategy Analysis: It's not just about your own game, right? Analyzing what opponents do, how they play, and where their weaknesses lie can help in crafting strategies to counter their moves. Super helpful.
- Cloud-Based Analytics: And let's not forget about cloud storage! It makes sharing and accessing match data a breeze for both coaches and players. They can analyze everything from anywhere — how cool is that?

8.2) Conclusion

The real-time development of this real-time tennis analytics system shows a long way forward in using computer vision and deep learning technology in the world of sports. Through integration of advanced models such as Yolo for object recognition, CNNS for pose assessment, and court tracing and tracking for accurate ball trajectory analysis, the system provides a comprehensive modular solution tailored to the rapidly fluctuating and spatially dynamic dynamics of tennis. Overall experience. With properties such as step counting, pose feedback, shot ratings, and ball position visualization, the project not only meets the current needs of tennis professionals, but also forms the basis for future expansion into other racket sports and real-time mobile phone tools. Ultimately, the project presents a powerful interface on artificial intelligence and track and field, paving the way for more intelligent data-based training and gameplay at all tennis levels.

REFERENCES

[1] THETIS: Three-Dimensional Tennis Shots a Human Action Dataset

[2] Player poses analysis in tennis video based on pose estimation | IEEE Conference Publication | IEEE Xplore

[3] Forecasting the Next Shot Location in Tennis Using Fine-Grained Spatiotemporal Tracking Data | IEEE Journals & Magazine | IEEE Xplore

[4] A Comprehensive Review of Computer Vision in Sports: Open Issues, Future Trends and Research Directions

[5] Computer vision and machine learning for in-play tennis analysis: framework, algorithms and implementation

[6] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, Going Deeper with Convolutions, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 19, IEEE, 2015.

[7] L. Steinberg, Changing the Game: The Rise of Sports Analytics, in Forbes, April 2015.

[8] I. Laptev, M. Marszałek, C. Schmid, and B. Rozenfeld. Learning realistic human actions from movies. In Conference on Computer Vision & Pattern Recognition (CVPR). IEEE, 2008.

[9] G. Denina, B. Bhanu, H. Nguyen, C. Ding, A. Kamal, C. Ravishankar, A. Roy-Chowdhury, A. Ivers, and B. Varda. Videoweb dataset for multi-camera activities and non-verbal communication. In Distributed Video Sensor Networks, pages 335–347. Springer London, 2011.

[10] Varun Ramakrishna, Daniel Munoz, Martial Hebert, J. Andrew Bagnell, Yaser Sheikh, "Pose Machine: Articulated Pose Estimation via Inference Machines", European Conference on Computer Vision. Springer International Publishing (2014).

[11] Van Zandycke, Gabriel, and Christophe De Vleeschouwer. "Real-time CNN-based Segmentation Architecture for Ball Detection in a Single View Setup." In Proceedings Proceedings of the 2nd International Workshop on Multimedia Content Analysis in Sports, pp. 51 58. 2019.

[12] "Object Detection In Sports Videos." In 2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), pp. 1034-1039. IEEE, 2018.

[13] Kos, and MiranPobar." Player Trackingin Sports Videos." In the 19th IEEE International Conference on Computer and Information Technology (CIT 2019).

[14] T. J. Barnett and S. R. Clarke, Using Microsoft Excel to Model a Tennis Match, in 6th Conference on Mathematics and Computers in Sport, pp. 6368, Bond University, Queensland, Australia, 2002.

[15] T. Barnett, A. Brown, and S. Clarke, Developing a Model that Re ects Outcomes of Tennis Matches, in Proceedings of the 8th Australasian Conference on Mathematics and Computers in Sport, Coolangatta, Queensland, pp. 178188, 2006.

[16] X. Wei, P. Lucey, S. Morgan, P. Carr, M. Reid, and S. Sridharan, Predicting Serves in Tennis using Style Priors, in Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 22072215, ACM, 2015.

[17] Z. Cao, T. Simon, S.-E. Wei, and Y. Sheikh, Realtime Multi-Person 2D Pose Estimation Using Part Anity Fields, arXiv preprint arXiv:1611.08050, 2016.

[18] V. Jain and E. Miller. Online domain adaptation of a pre-trained cascade of classifiers. In CVPR, 2011.