Automated Tennis Player and Ball Tracking with Court Keypoints Detection (Hawk Eye System)

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Abstract

This study presents a complete pipeline for automated tennis match analysis. Our framework integrates multiple deep learning models to detect and track players and the tennis ball in real time, while also identifying court keypoints for spatial reference. Using YOLOv8 for player detection, a custom-trained YOLOv5 model for ball tracking, and a ResNet50-based architecture for court keypoint detection, our system provides detailed analytics including **player movement patterns, ball speed, shot accuracy, and player reaction times**. The experimental results demonstrate robust performance in varying court conditions and match scenarios. The model outputs an annotated video along with detailed performance metrics, enabling coaches, broadcasters, and players to gain actionable insights into the dynamics of the game.

1 Introduction and Problem Statement

Tennis is a sport characterized by rapid movements, split-second decisions, and complex strategies. The ability to analyze these elements quantitatively has become increasingly important for players, coaches, and broadcasters. Traditional manual analysis methods are time-consuming, subjective, and limited in their precision. This creates a significant demand for automated systems that can provide objective, comprehensive, and immediate analysis of tennis matches.

In professional tennis, systems like Hawk-Eye [1] have revolutionized officiating and broadcast experiences by providing accurate ball tracking. However, these systems typically require multiple high-speed cameras placed at precise locations around the court. There is a clear need for more accessible solutions that can work with standard video equipment while still providing valuable analytical insights.

Tennis coaches and players increasingly rely on quantitative metrics to identify strengths, weaknesses, and areas for improvement. Broadcasters seek enhanced visualizations to enrich viewer experience. Tournament organizers require efficient tools for match statistics and automated line calling. All these stakeholders would benefit from an integrated system that can analyze matches comprehensively from standard video input.

Our study addresses these needs by developing an end-to-end framework for tennis match analysis that integrates player tracking, ball detection, court mapping, and performance metrics calculation. The main objectives of this work is:

- To detect the player and the ball using YOLOv8 and custom YOLOv5 model.
- To detect the court keypoints/ dimensions using ResNet50 architecture
- To compute the player speed and shot speed using distance coverages
- To predict the player reaction time to the opponent's shot

2 Literature Review

2.1 Player Detection and Tracking

Recent works has taken advantage of deep learning techniques to detect more players. Voeikov et al. [3] introduced TTNet, a two-stage deep neural network for table tennis analytics that performs ball tracking and event spotting. Their approach demonstrated improved accuracy in player and ball position estimation compared to traditional methods.

The emergence of the YOLO (You Only Look Once) family of object detectors has significantly advanced real-time player detection capabilities. Redmon and Farhadi's YOLOv3 [4] and subsequent iterations have become popular choices for sports applications due to their balance of speed and accuracy. Our work builds upon these advances by implementing YOLOv8, the latest in this family, for player detection.

2.2 Ball Tracking

Tennis ball tracking presents unique challenges due to the ball's small size, high speed, and frequent occlusions.

Deep learning has transformed ball tracking capabilities. Huang et al. [7] applied a two-stage detection framework that first identifies potential ball regions and then refines the detections, achieving improved accuracy on standard benchmarks. Reno et al. [8] demonstrated the effectiveness of convolutional neural networks for ball detection in various sports including tennis. Our approach extends this work by implementing a custom-trained YOLOv5 model specifically optimized for tennis ball detection.

2.3 Court Detection and Calibration

Court detection provides crucial spatial context for player and ball tracking. Farin et al. [9] proposed a method using the Hough transform to detect court lines, followed by a homography estimation to map the court. Yan et al. [10] introduced a more robust approach using particle filters to track court lines across frames.

Recent work has shifted toward deep learning-based approaches. Homayounfar et al. [11] introduced a deep structured model for sports field localization that learns the higher-order structure of the scene. Our work builds on these advances by implementing a ResNet50-based model for keypoint detection, allowing accurate court mapping across various court types and camera angles.

2.4 Integrated Tennis Analysis Systems

Several works have attempted to create integrated systems for tennis analysis. Diaz et al. [12] presented a computer vision system that combines court detection, player tracking, and shot classification. Commercial systems like PlaySight [13] offer comprehensive match analysis but require permanent installation of multiple cameras.

More recently, Carboch et al. [14] analyzed the effectiveness of various tennis analysis systems for tactical decision-making. Mora and Knottenbelt [15] proposed an automated system for extracting match statistics from broadcast tennis videos. Our work differs from previous approaches by providing a more comprehensive analysis that includes not only tracking data but also derived metrics like shot speed, player reaction time, and movement patterns, all integrated into a single system.

3 Data Sources and Analysis[1]

The development and evaluation of our tennis match analysis system relied on several key datasets, each serving specific components of the overall framework. This section details these datasets and provides insights from our exploratory data analysis.

3.1 Tennis Ball Detection Datasets

For the critical task of ball detection, we experimented with multiple datasets to identify the optimal training data for our model.

3.1.1 Initial Dataset Exploration

Our initial approach utilized a large-scale tennis ball detection dataset comprising 8,763 training images, 584 validation images, and 390 test images. Despite the substantial size of this dataset, our exploratory analysis revealed significant limitations:

- **Viewing Angle Variability:** The dataset contained images captured from widely varying camera angles, making it difficult for the model to learn consistent ball features.
- **Ball Visibility Issues:** In many frames, the ball was partially or completely occluded, appearing as a blur, or represented as an extremely small portion of the overall image.
- **Annotation Inconsistency:** The quality of ball annotations varied significantly across the dataset, with some frames having imprecise bounding boxes.

This initial exploration highlighted a critical insight: for specialized object detection tasks like tennis ball tracking, dataset quality and consistency are more important than sheer quantity of images. Models trained on this data set exhibited poor generalization in most models.

3.1.2 Refined Tennis Ball Dataset [17]

Based on our findings, we transitioned to a more focused dataset containing 428 training images, 100 validation images, and 50 test images. Despite being significantly smaller, this dataset demonstrated several advantages:

- **Consistent Perspective:** Images were captured from standardized broadcast angles, closely matching typical tennis match footage.
- **Enhanced Ball Visibility:** The ball was clearly visible in most frames, with fewer instances of extreme motion blur.
- **Precise Annotations:** Bounding box annotations were more consistent and accurate.

Tennis balls appear more frequently are near the centre of the court, which is typical during rallies as Fig .2. Clusters on the right side may indicate balls reaching the baseline, possibly after serves or aggressive shots. Sparse detections outside the court (green box) may be from errors, out-of-bounds shots, or incomplete annotations.

This histogram in Fig 1. shows the distribution of tennis ball sizes (measured in pixels²) across the dataset. The majority of detected tennis balls have an area between 50 to 200 pixels², indicating smaller object sizes, which is typical for distant or fast-moving balls. The right tail of the graph shows

[1] https://drive.google.com/drive/folders/1PO71eTCGV-C8wAwdPiOOwMtIzBiHcm1V?usp=sharing

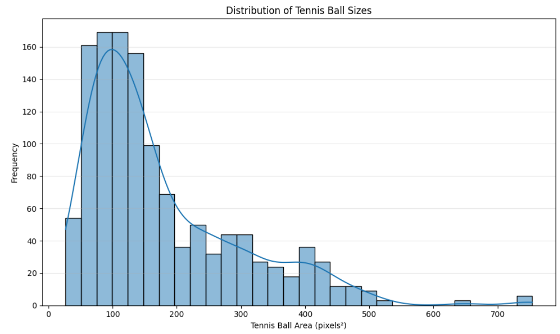


Figure 1: Tennis ball size distribution

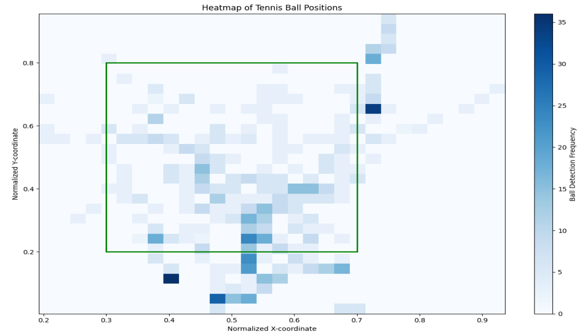


Figure 2: Tennis ball position

a few larger ball sizes, possibly from close-up shots or inaccurate detections. The smooth density curve helps visualize the skewed distribution, suggesting a need for size normalization or additional size-aware model adjustments. While most images (99.5%) contain a single tennis ball, a smaller percentage (0.5%) contains no ball or zero balls. Images with balls in motion are overrepresented compared to stationary balls, potentially biasing models toward detecting moving balls.

Augmentation

To further enhance the performance of the model and the generalization capabilities, we expanded our training data by creating a custom dataset. Starting with the 578 high-quality images from the refined dataset, we increased the collection to approximately 3,000 images through. We applied controlled augmentations including rotation, scaling, and brightness adjustments to simulate varying match conditions.

This custom dataset was divided with a 70%-20%-10% split for training, validation, and testing respectively. Models trained on this dataset achieved 89% mAP on our validation set and demonstrated superior generalization to unseen match footage.

3.2 Tennis Court Detection Dataset [18]

For court keypoint detection, we utilized a comprehensive dataset containing 8,841 images of tennis courts from various tournaments, surfaces, and lighting conditions. Each image was annotated with 14 keypoints corresponding to critical court landmarks including baseline corners, service line intersections, center marks, and net posts.

Our exploratory analysis of this dataset revealed:

- **Court Surface Diversity:** The dataset contained approximately 45% hard courts, 35% clay courts, and 20% grass courts, providing good representation of major playing surfaces.
- **Camera Angle Distribution:** About 70% of images were from standard broadcast angles, while 30% represented more challenging perspectives (overhead, courtside, player perspective).
- **Lighting Conditions:** The dataset included both indoor (35%) and outdoor (65%) courts, with varying lighting conditions including natural daylight, artificial lighting, and shadows.

Visualization of the keypoint annotations revealed some interesting patterns:

- **Keypoint Visibility:** On average, 12 out of 14 keypoints were visible in each image, with the most commonly occluded points being the far-side net posts and baseline corners.

- **Annotation Precision:** The standard deviation of keypoint annotations across multiple annotators was approximately 3-5 pixels, indicating good consistency in the ground truth.

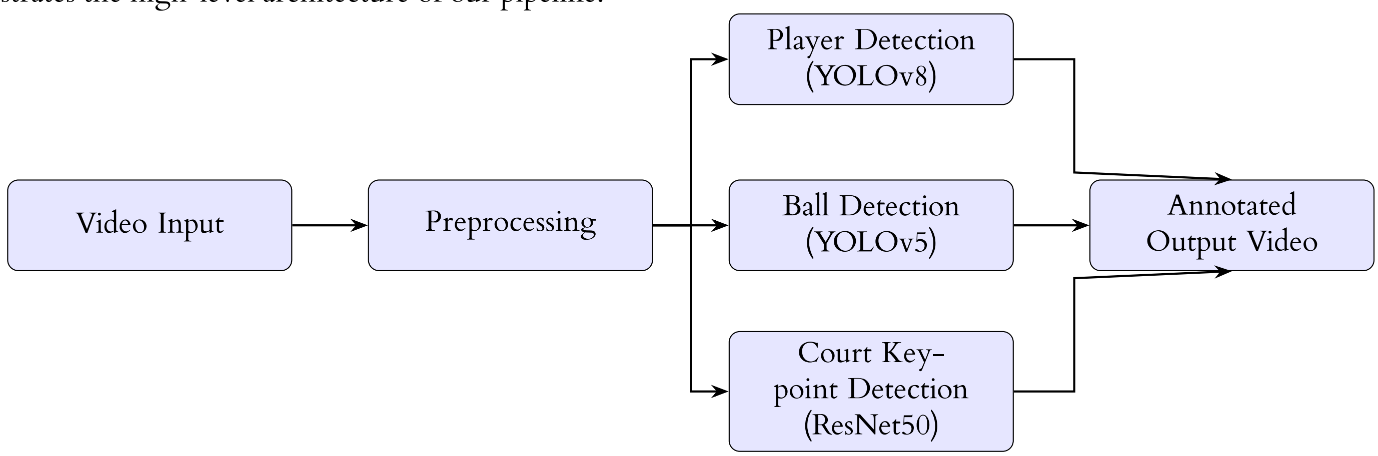
This dataset was split 75%-25% for training and validation, respectively, providing sufficient examples for our court keypoint detection model while reserving a substantial portion for validation.

4 Methodology

Our tennis match analysis system consists of four primary components that work together to provide comprehensive analytics: player tracking, ball detection, court keypoint detection, and performance metrics calculation. This section details the technical approach for each component.

4.1 System Architecture[2]

The overall architecture of our system is designed to process tennis match videos frame by frame, extract relevant information about players, ball, and court, and generate insightful analytics. The block diagram illustrates the high-level architecture of our pipeline.



The pipeline begins with video preprocessing to ensure consistent input quality, followed by parallel processing of player detection, ball detection, and court keypoint detection. The outputs from these components are then integrated to calculate performance metrics and generate visualizations.

4.2 Player Tracking

4.2.1 Detection Model

For player detection, we implemented YOLOv8, the latest iteration in the YOLO family of object detectors. YOLOv8 offers several advantages for our application:

We used the pre-trained YOLOv8x model, which uses a CSPDarknet53 backbone with additional cross-stage partial connections for enhanced feature extraction. The model was initialized with weights pre-trained on the COCO dataset, which already includes a 'person' class well-suited for player detection.

[2] https://drive.google.com/drive/folders/1vl7qyzC68B93YgKR4Dbq5rapqak-ARy8?usp=drive_link

4.2.2 Player Identification and Filtering

Tennis videos often capture audience members, referees, and ball boys/girls in addition to the players. To focus our analysis on the active players, we implemented a filtering algorithm based on court position:

Algorithm 1 Player Identification and Filtering

Input: Set of detected persons P, court keypoints K
Output: Identified tennis players P_{players}
Initialize empty set P_{players}
Create court boundary polygon B from keypoints K
for each person detection $p \in P$ **do**
    $foot\_position \leftarrow$ bottom center of p's bounding box
    if $foot\_position$ is within or near B **then**
        Add p to candidate set $P_{\text{candidates}}$
    end if
end for
Sort $P_{\text{candidates}}$ by proximity to court center
Select top two candidates as P_{players}
Assign player identities (Player 1 and Player 2) based on court position
return P_{players}

This approach effectively filters out non-player detections and correctly identifies the two active players in the match, assigning them consistent identities throughout the video sequence.

4.3 Ball Detection

4.3.1 Custom YOLOv5 Model

We chose YOLOv5s due to its balanced trade-off between speed and accuracy, making it suitable for detecting small, fast-moving objects like tennis balls.

The model was trained on our custom augmented dataset described in Section 3, using the following training configuration:

- **Input Resolution:** 640×640 pixels
- **Batch Size:** 16
- **Epochs:** 100
- **Optimizer:** SGD with momentum (0.937) and weight decay (0.0005)
- **Learning Rate Schedule:** Cosine annealing from 0.01 to 0.001
- **Data Augmentation:** Mosaic augmentation, random affine transformations, color jittering

4.3.2 Ball Trajectory Interpolation

Even with a highly accurate detection model, the ball may occasionally be missed in some frames due to occlusions, motion blur, or challenging lighting conditions. To address this issue, we implemented a trajectory interpolation algorithm that estimates ball positions in frames where detection confidence is low or missing entirely:

This interpolation approach ensures a continuous ball trajectory throughout the match, enabling accurate calculation of metrics like ball speed and shot trajectories.

Algorithm 2 Ball Trajectory Interpolation

Input: Sequence of ball detections B with confidence scores
Output: Complete ball trajectory B'
Initialize $B' \leftarrow B$
for each frame i with missing or low confidence (< 0.4) detection **do**
    Find nearest preceding frame p with high confidence detection
    Find nearest subsequent frame s with high confidence detection
    if both p and s exist **then**
        $\text{position}_i \leftarrow$ Linear interpolation between position_p and position_s
        $B'_i \leftarrow \text{position}_i$
    end if
end for
Apply Kalman filter smoothing to B'
return B'

4.4 Court Keypoint Detection

4.4.1 ResNet50-Based Keypoint Model

For court keypoint detection, we implemented a ResNet50-based architecture that predicts the 14 key court landmarks. The model takes a single video frame as input and outputs the (x,y) coordinates for each keypoint.

We compared several backbone architectures including ResNet50, EfficientNet-B0, and EfficientNet-B7. After extensive experimentation, we selected ResNet50 due to its optimal balance of accuracy and computational efficiency. The model was trained with the following configuration:

- **Input Resolution:** 448×448 pixels
- **Loss Function:** Mean Squared Error (MSE) for keypoint regression
- **Optimizer:** Adam with learning rate 0.001
- **Epochs:** 50
- **Batch Size:** 32
- **Regularization:** Dropout (0.2) and L2 weight decay (0.0001)

The model achieved an average keypoint error of 3.8 pixels on our validation set, demonstrating high precision in court mapping.

4.4.2 Mini-Court Visualization

Using the detected keypoints, we implemented a mini-court visualization that provides a standardized top-down view of the match. This visualization maps player and ball positions from the camera perspective to a standardized court representation, enabling clearer visualization of player movements and shot placements.

The mapping is accomplished through a homography transformation:

$$\mathbf{p}' = H\mathbf{p} \tag{1}$$

where $\mathbf{p}$ represents a point in the original image, $\mathbf{p}'$ is the corresponding point in the mini-court view, and H is the homography matrix computed from the detected court keypoints.

4.5 Performance Metrics Calculation

Our system calculates a comprehensive set of performance metrics to provide detailed insights into player and match dynamics:

4.5.1 Ball Shot Detection

To identify individual shots, we analyze the ball trajectory for characteristic patterns:

Algorithm 3 Ball Shot Detection

Input: Ball trajectory B'
Output: Set of shot frames S
Initialize empty set S
for each frame i in sequence **do**
    Calculate velocity vector v_i from positions at frames $i-2$, $i-1$, i
    Calculate velocity vector v_{i+1} from positions at frames i, $i+1$, $i+2$
    Calculate angle θ between v_i and v_{i+1}
    if $\theta > \text{threshold}_\theta$ AND velocity magnitude changes significantly **then**
        Add frame i to shot set S
    end if
end for
Filter S to remove detections too close in time
return S

4.5.2 Shot and Player Speed Calculation

For each detected shot, we calculate the ball speed by measuring the distance covered by the ball between consecutive shot frames and dividing by the time elapsed:

$$\text{Ball Speed} = \frac{\text{Distance (meters)}}{\text{Time (seconds)}} \times 3.6 \tag{2}$$

Where the constant 3.6 converts from meters per second to kilometers per hour. The distance in meters is calculated by converting pixel distances to real-world distances using the known width of court lines:

$$\text{Distance (meters)} = \text{Distance (pixels)} \times \frac{\text{Known line width (meters)}}{\text{Line width (pixels)}} \tag{3}$$

Similar calculations are performed to determine player movement speeds between shots.

4.5.3 Player Reaction Time

We define player reaction time as the time taken for a player to respond to an opponent's shot:

$$\text{Reaction Time} = \frac{\text{First significant movement frame} - \text{Opponent shot frame}}{\text{Frame rate}} \tag{4}$$

Where "significant movement" is defined as player displacement exceeding a minimum threshold.

5 Experiments and Results[3]

We conducted extensive experiments to evaluate the performance of our tennis match analysis system, both at the component level and as an integrated framework.

5.1 *Component-Level Evaluation*

The YOLOv8 model demonstrated robust player detection capabilities across various match conditions. Qualitative analysis showed that the model maintained consistent player identification throughout matches, with occasional confusion only during close player interactions (e.g., handshakes at the net).

The model demonstrated particular strength in detecting the ball during normal rallies, with slightly reduced performance during high-speed serves and smashes due to increased motion blur.

Based on this analysis, we selected ResNet50 as our production model due to its excellent balance of accuracy and inference speed. .

5.2 *Qualitative Results*[4]

Our system generates several visualizations that provide insights into match dynamics :

- **Ball Trajectory Heatmap:** Fig 3 Visualizes the spatial distribution of ball positions throughout the match, highlighting areas of frequent play.
- **Player Movement Paths:** Fig 5 Shows the movement patterns of each player, revealing tactical tendencies and court coverage.
- **Shot Speed Distribution:** Fig Displays the distribution of shot speeds for each player, indicating playing style and strength patterns.
- **Mini-Court Animation:** Provides a standardized top-down view of the match, making spatial patterns more apparent.
  Fig 4 shows the shot speed of different players over the match time and Fig 6 shows the time taken to the player to respond to the opponent's shot. The player took less time during the match and more time in the start and end of the match.

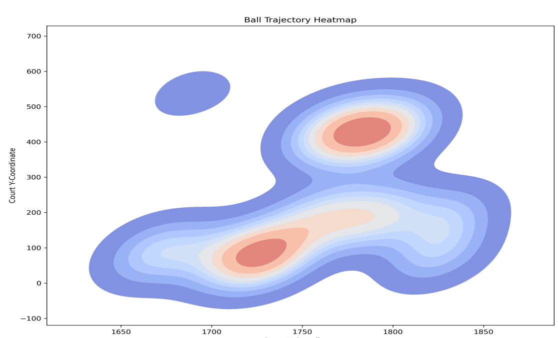


Figure 3: Trajectory of the ball

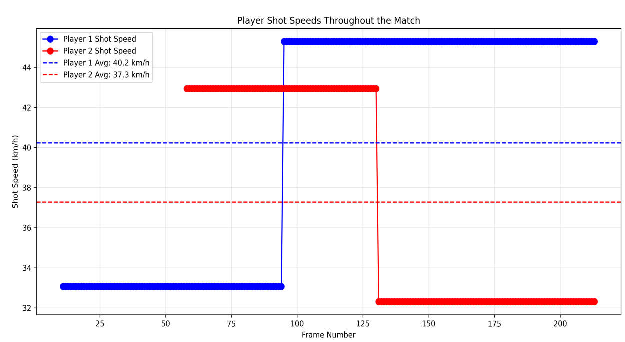


Figure 4: Speed of the shot over frames

[3] https://drive.google.com/drive/folders/1e_eV7VfVg7Tq25qCkMlSMtV112f5F7GI?usp=drive_link

[4] https://drive.google.com/drive/folders/172U7i-Ac2DuQL_2CPgCX5vZyg9OZOisY?usp=drive_link

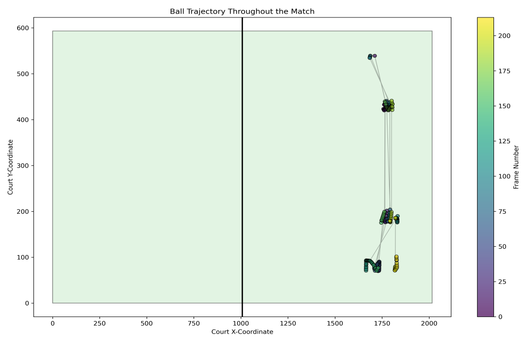


Figure 5: Trajectory of the Player

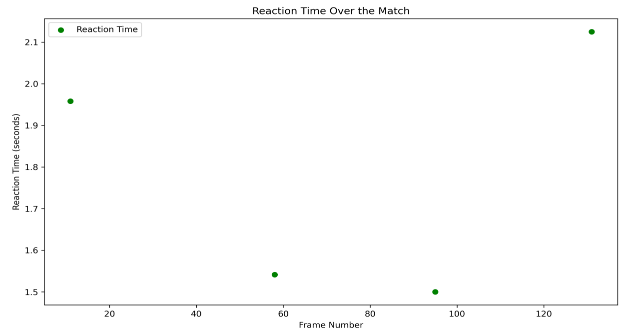


Figure 6: Time Taken to react to the opponent's shot

These visualizations, combined with the quantitative metrics, provide a comprehensive understanding of match dynamics that can be valuable for players, coaches, and broadcasters.

6 Limitations and Future Work

While our system demonstrates strong performance across various conditions, several limitations and areas for future improvement have been identified:

6.1 *Current Limitations*

- **Camera Position:** The system performs best with standard broadcast camera angles. Performance degrades with unusual camera positions or extreme angles.
- **Occlusion Handling:** Despite our interpolation algorithms, prolonged ball occlusions (e.g., when the ball is hidden behind a player) can still lead to tracking errors.
- **Type of shot:** The current system tracks ball movement and calculates speed but does not classify shot types (forehand, backhand, serve, volley, etc.).

6.2 *Future Work*

Based on these limitations, we have identified several promising directions for future work:

- **Shot Classification:** Implementing a machine learning model to classify different shot types would enhance the system's analytical capabilities, providing insights into playing styles and tactical patterns.
- **Multi-Camera Integration:** Extending the system to process footage from multiple synchronized cameras would improve the accuracy of 3D ball tracking and enable more precise speed and trajectory calculations.
- **Player Pose Estimation:** Incorporating full-body pose estimation would enable biomechanical analysis of player movements and strokes, offering deeper insights into technique and efficiency.

7 Challenges Faced

- Initial dataset has good number of images, but performance and accuracy is not up to the mark when trained and tested with different architectures

- The model was unable to detect the balls when overlapped with the player in the frame
- Response time is same for both the players which is not the case, initial time for player 2 is taken as 2nd frame which is not truly
- Model may not work well for the videos where the entire court is not visible, with different camera angles and video with top vies

8 Conclusion

This study presented a complete tennis match analysis system that combines deep learning techniques to track players and the ball, detect keypoints on the court, and calculate performance metrics. Our approach leverages YOLOv8 for player detection, a custom YOLOv5 model for ball tracking, and a ResNet50 architecture for court keypoint detection, combining these components into a cohesive framework that generates valuable insights into match dynamics.

Through extensive experimentation, we demonstrated that our system achieves robust performance across various match conditions, with high accuracy in player and ball detection, and precise calculation of performance metrics.. Although current limitations exist, particularly in shot classification and single-camera constraints, these present clear directions for future work.

9 References

[1] P. Hawk, "Hawk-Eye: The story of tennis' most important invention," Tennis Magazine, vol. 45, no. 6, pp. 36–42, 2018.

[2] J. Ren, J. Orwell, G. A. Jones, and M. Xu, "Tracking the soccer ball using multiple fixed cameras," Computer Vision and Image Understanding, vol. 113, no. 5, pp. 633–642, 2009.

[3] R. Voeikov, N. Falaleev, and R. Baikulov, "TTNet: Real-time temporal and spatial video analysis of table tennis," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, 2020, pp. 884–885.

[4] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," arXiv preprint arXiv:1804.02767, 2018.

[5] X. Yu, C. H. Sim, J. R. Wang, and L. F. Cheong, "A trajectory-based ball detection and tracking algorithm in broadcast tennis video," in 2004 International Conference on Image Processing, 2004, vol. 2, pp. 1049–1052.

[6] G. S. Pingali, Y. Jean, and I. Carlbom, "Real time tracking for enhanced tennis broadcasts," in Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 1998, pp. 260–265.

[7] Q. Huang, S. Cox, X. Zhou, and W. Lu, "Tennis ball tracking using a two-layered data association approach," IEEE Transactions on Multimedia, vol. 21, no. 8, pp. 2114–2127, 2019.

[8] V. Reno, N. Mosca, R. Marani, M. Nitti, T. D'Orazio, and E. Stella, "Convolutional neural networks based ball detection in tennis games," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2018, pp. 1758–1764.

[9] D. Farin, S. Krabbe, P. H. N. de With, and W. Effelsberg, "Robust camera calibration for sport videos using court models," in Storage and Retrieval Methods and Applications for Multimedia, 2004, vol. 5307, pp. 80–91.

[10] F. Yan, W. Christmas, and J. Kittler, "Tennis ball tracking using a ball detection and Kalman filter tracking with enhanced court detection," in Proceedings of the British Machine Vision Conference, 2005.

[11] N. Homayounfar, S. Fidler, and R. Urtasun, "Sports field localization via deep structured models," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 5212–5220.

[12] G. Diaz, F. Foley, and G. Laamarti, "A computer vision system for tennis analytics," in 12th Conference on Computer and Robot Vision, 2015, pp. 166–173.

[13] PlaySight Interactive Ltd., "PlaySight Smart Court Technology," White Paper, 2019.

[14] J. Carboch, T. Vejvodova, and V. Suss, "Analysis of match characteristics and rally pace in male and female tennis players," Physical Activity Review, vol. 6, pp. 57–63, 2018.

[15] S. V. Mora and W. J. Knottenbelt, "Automated extraction of player statistics from tennis match footage," in Digital Sport for Performance Enhancement and Competitive Evolution, 2017, pp. 41–53.

[16] T. Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, "Microsoft COCO: Common objects in context," in European Conference on Computer Vision, 2014, pp. 740–755.

[17] "https://universe.roboflow.com/viren-dhanwani/tennis-ball-detection".

[18] ,"https://drive.google.com/file/d/1lhAaeQCmk2y440PmagA0KmIVBIysVMwu/view".

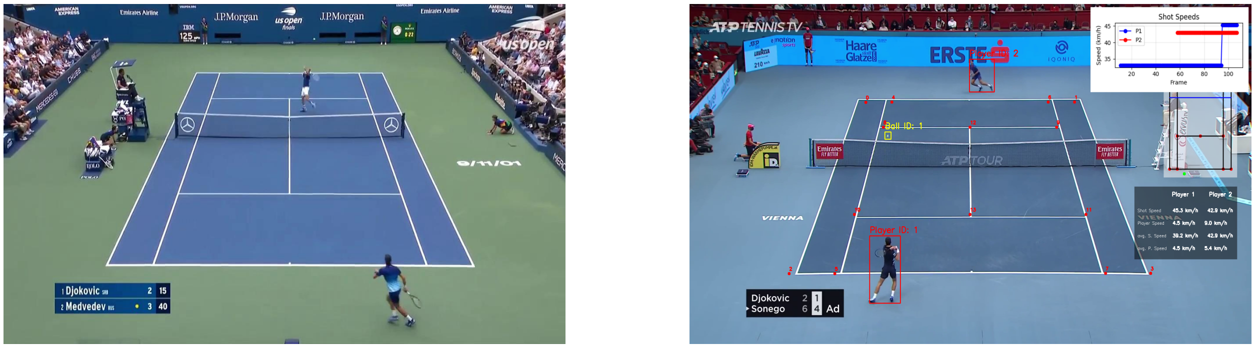
10 Appendix[5]

The input frame and output frames with annotations is given below .

The entire repository, figures, results are available in the below google drive.[6]
Github Repository Link: `https://github.com/fawaz-exe/hawk-eye-system.git`

[5] `https://drive.google.com/drive/folders/1EGGfy8eFoCVgMSdUOXjMF3M31yyuKj8A?usp=drive_link`

[6] `https://drive.google.com/drive/folders/1_llwdLPxpYRW-Io1YMCBO1sXRCmRgfaQ?usp=drive_link`



(a) Input Frame (b) Output Frame

Figure 7: Comparison between input and processed output frame

Match Summary Statistics

Metric	Player 1	Player 2
Number of Shots	2.0	2.0
Shot Percentage (%)	50.0%	50.0%
Average Shot Speed (km/h)	39.2	37.6
Maximum Shot Speed (km/h)	45.3	42.9
Average Movement Speed (km/h)	5.6	5.4

Figure 8: Summary

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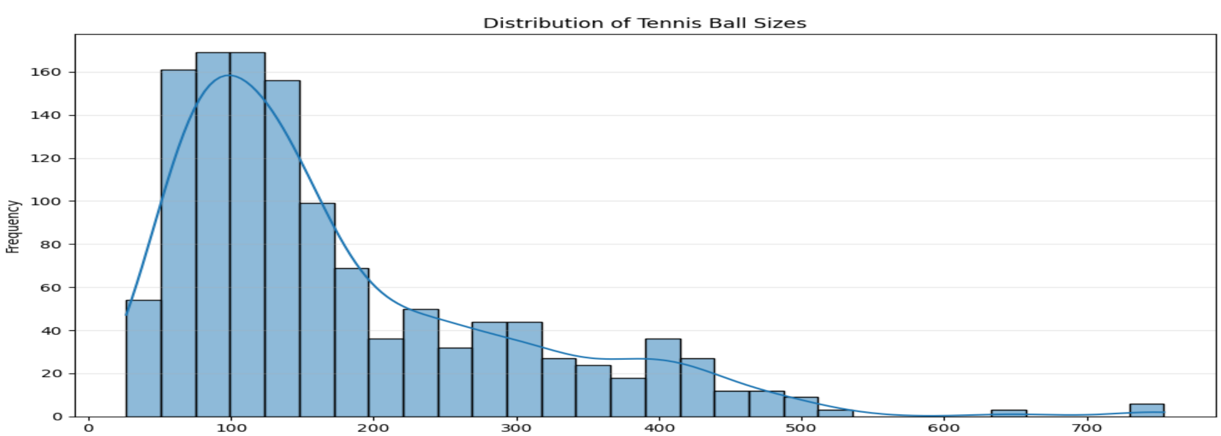

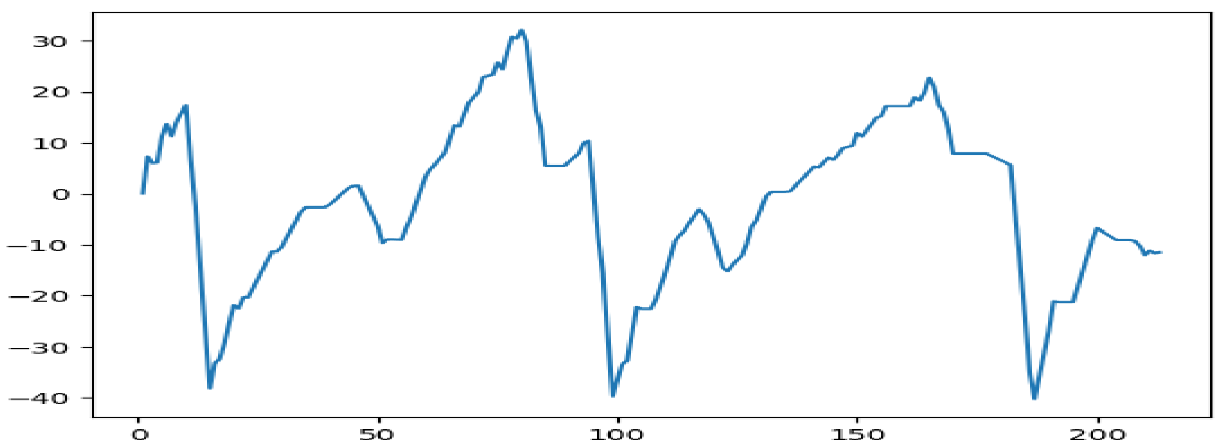
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