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Enhanced Computer Vision Techniques for injury prevention and Stance improvement, a novel method in 3D generative Perspective identifying frame of stability and frame of force for a tennis player

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ABSTRACT

This study presents a comprehensive framework for enhancing tennis performance by optimizing biomechanical postures during specific shots, utilizing advanced video analysis and stabilization techniques using 2D and 3D. Recurrent Neural Networks (RNNs) are employed in conjunction with pose estimation algorithms to accurately extract skeletal key points representing the number of key joints. Joint angles θj are computed using the vector dot product formula Dong et al [1]:

$\theta_j = \cos^{-1} \left(\overleftarrow{U} \cdot \overleftarrow{V} \big/ \left|\overleftarrow{U}\right| \cdot \left|\overleftarrow{V}\right| \right)$ where u⃗ and v⃗ are vectors formed by adjacent key points.

The research systematically addresses challenges inherent to video-based analysis, including motion artifacts, variable lighting conditions, low-resolution imaging, suboptimal signal-to-noise ratios (SNR), and limited frame rates. High-SNR imaging devices, optimized camera calibration, and daylight capture protocols are employed to mitigate these issues. Computational analysis is performed on cloud platforms, leveraging scalable processing power while maintaining strict data confidentiality.

Key contributions include the integration of pose-detection key points into spatial frame coordinate systems for advanced kinematic analysis of player movements. The skeletal structure is modelled using part affinity fields (PAFs), represented as:

$$L = \sum_{c} \sum_{p \in \mathcal{C}} w(p) \cdot \log\big(1 + \exp(-s_c(p))\big),$$

where w(p) is the weighting function, and Sc(p) represents the score map for a candidate connection. TensorFlow Lite facilitates real-time skeletal visualization, providing immediate feedback on biomechanical alignment. Zhe Cao et al [2].

In this study, we are able to create both 2D and 3D video analysis and compare them to suggest best use based on scenarios. The proposed methodology overcomes the limitations of traditional video analysis by integrating state-of-the-art computational algorithms, including Convolutional Neural Networks (CNNs), with tailored hardware solutions. This robust approach highlights the critical importance of accurate joint angle computation and motion pattern analysis in refining tennis biomechanics and advancing performance optimization.

Keywords: *Tennis player pose analysis, Joint accuracy, Frame of force, Frame of stability, 3D image generation, evaluating player performance.*

1. INTRODUCTION

In the realm of elite sports performance, tennis stands out for its rigorous demands on precision, agility, and biomechanical accuracy. The advancement of player training methodologies increasingly hinges on the integration of computational technologies, particularly those enabling the simulation and optimization of athlete posture and motion dynamics. This research presents a novel framework for the analysis and enhancement of tennis player stances through both 2D and 3D video analytics using mobile device cameras based on work done by Kurose et al [3]. The approach democratizes access to advanced motion analysis by leveraging ubiquitous, low-cost imaging devices in place of traditional laboratory-based motion capture systems.

The study employs state-of-the-art computer vision techniques, including pose estimation and Recurrent Neural Networks (RNNs), to extract and model skeletal keypoints from dynamic player movements. These keypoints serve as the basis for calculating joint angles and evaluating the biomechanical effectiveness of various stances. Comparative evaluations between 2D and 3D analysis modalities are conducted to determine context-specific applicability and accuracy.

Furthermore, unsupervised learning algorithms—such as k-means clustering—are utilized to classify and interpret stance variations, enabling the identification of movement patterns correlated with performance optimization and injury prevention. To mitigate the inherent limitations of mobile video input—such as fluctuating illumination, motion blur, and lower resolution—the methodology incorporates high signal-to-noise ratio (SNR) imaging and advanced video stabilization techniques.

This fusion of mobile imaging technology, machine learning, and biomechanical analysis not only enhances the accessibility of high-fidelity training tools but also extends the analytical capabilities available to coaches and athletes. By moving beyond traditional coaching paradigms, this study sets a precedent for the integration of mobile-based, AI-driven biomechanics in sports performance enhancement.

2. PERSPECTIVE VARIATION AND EFFECTS ON VISION ANALYTICS

In sports analytics, the perspective from which data is captured plays a crucial role in determining the accuracy and reliability of the analysis. This is particularly evident in the context of tennis, where the choice of camera angle and positioning can significantly impact the quality of motion capture and subsequent data interpretation. This is observed by Shin et al. [8].

When capturing motion from a single, fixed perspective—specifically, a court-level view from behind the player—several unique challenges and advantages arise. This setup primarily affects the way joint movements are recorded, the visibility of specific body parts, and the overall quality of the extracted data.

Impact on Joint and Pose Estimation

- Visibility of Joints and Occlusion, like the observations by Sun et al [9]:
  - Back View Characteristics: The back view captures the posterior aspects of the player, including the back, shoulders, arms, and legs. While this perspective is ideal for analysing the player's movement along the court's depth axis, it may not clearly capture the front-facing joints, such as the chest, knees, and elbows, especially if the player's body or racket obscures them.
  - Occlusion Challenges: Joints like the elbows and wrists can be occluded by the body or racket, leading to partial or missing data points. This can pose difficulties for pose estimation algorithms, which rely on clear visibility of all key points to provide accurate joint coordinates.
- Accuracy of Angle Calculation, like the observations by Sun et al [9]:
  - Calculating angles such as shoulder and elbow flexion from a back view can be challenging. The depth information is limited, and even small deviations in the player's orientation relative to the camera can significantly impact angle measurements.
  - Despite these challenges, the back view provides an excellent opportunity to measure the rotation of the torso and the alignment of the spine, which are critical for evaluating the biomechanical efficiency of various tennis strokes. Gholami et al [12].

3D Reconstruction Technique:

We employed Mediapipe, a sophisticated computer vision model, to capture the joint coordinates of the human body in 3D space. Mediapipe provides coordinates along three axes: X, Y, and Z, which allows for precise inference of joint locations. Although the Z-axis calculation is still in its experimental phase and is optimized for cameras equipped with LiDAR technology, it has demonstrated satisfactory results with standard cameras as well as observed by Shotton et al [14].

To validate the model's output and develop a robust calculation approach, we utilized Blender—an open-source 3D software. Blender enabled us to visualize the joint coordinates from three different perspectives, providing a comprehensive view of the data. This visualization was crucial for assessing the accuracy of the captured data and refining our technique.

By leveraging Blender's powerful visualization capabilities, we were able to identify any discrepancies in the joint coordinates and make necessary adjustments to our calculation methods. This iterative process of visualization and refinement ensured that our 3D reconstruction technique was both accurate and reliable. Additionally, the use of Blender allowed us to experiment with different visualization angles and perspectives, further enhancing our understanding of the joint movements and improving the overall precision of our model.

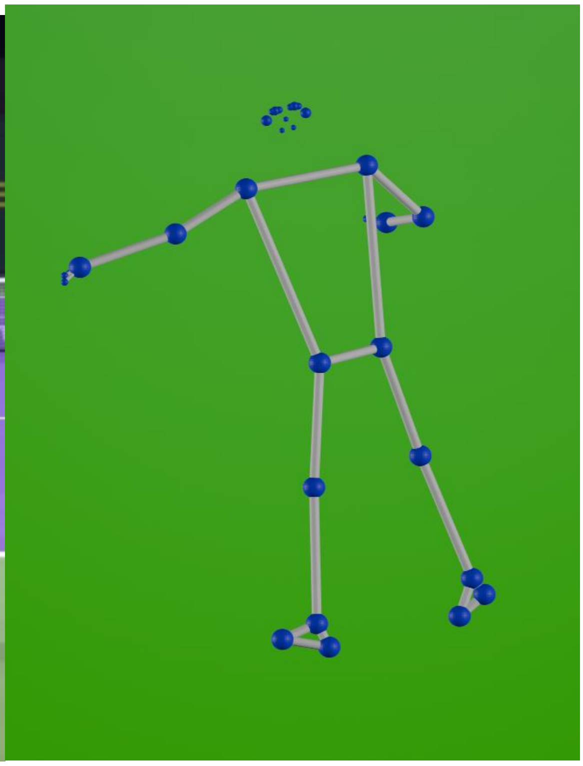
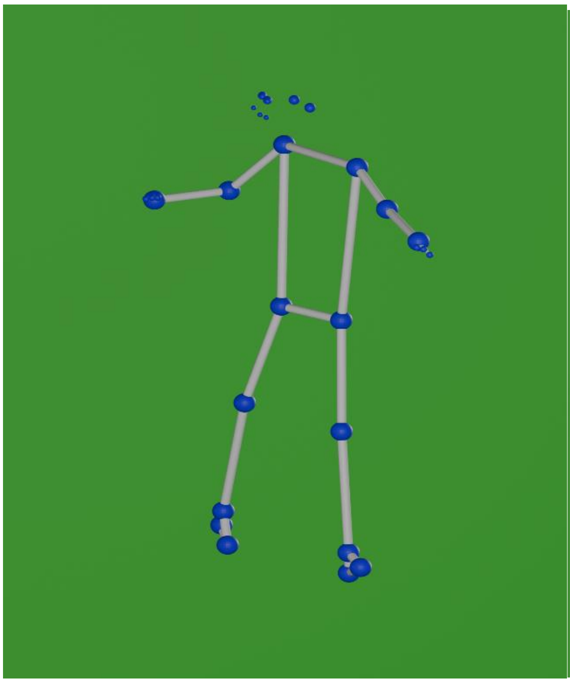


Fig 3.3: Snapshot of a shot played **Fig 3.4: 3D reconstruction of the shot in Front-View perspective**



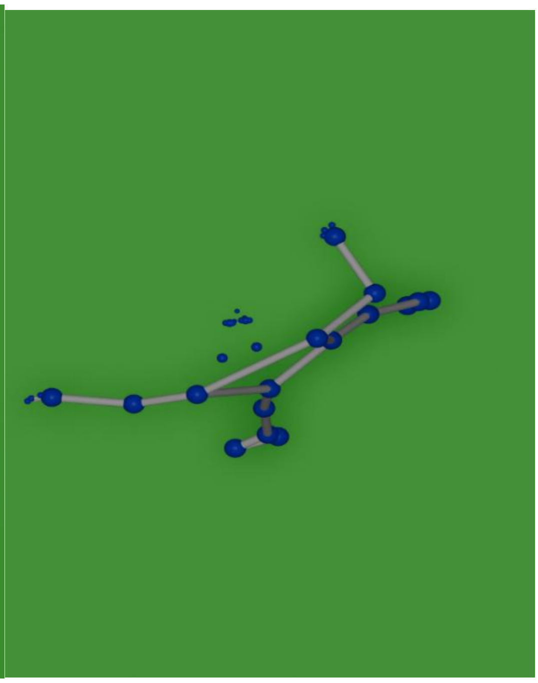


Fig 3.5: Side view perspective of the shot **Fig 3.6: Top-view perspective of the shot played.**

3. FRAME OF FORCE AND FRAME OF STABILITY

In the context of tennis biomechanics, we observed that the effectiveness of a player's shot relies heavily on two primary sets of joints: the **Frame of Force** and the **Frame of Stability**. These sets serve distinct roles in the execution of a shot, particularly for a right-handed player, and their coordination is crucial for achieving optimal performance.

1. Frame of Force: Generating Power and Control

For a right-handed player, the **Frame of Force** consists of the following joints:

- **Right Wrist, Elbow, and Shoulder:** These joints are directly responsible for controlling the racket and delivering the shot. The shoulder provides the main source of power through its rotation, the elbow controls the angle and speed, and the wrist adjusts the final shot direction and spin.
- **Left Hip and Right Hip:** The hips are pivotal in transferring force from the lower body to the upper body. The left hip acts as a counterbalance, while the right hip, in conjunction with the shoulder, facilitates torso rotation, which is crucial for generating force.
- **Right Knee and Right Ankle:** These joints contribute to the lower body's stability and power. By pushing against the ground, they create a force vector that travels through the body to the racket. This "ground reaction force" is essential for powerful strokes and enables quick changes in direction after the shot.

Biomechanical Functions as noted in the study by Manu et al [4]:

- **Force Generation:** The Frame of Force joints work in unison to generate kinetic energy. The sequence begins with the legs, as the player pushes off the ground. This energy travels up through the hips and torso, culminating in the arm and racket. Effective coordination between these joints maximizes shot power and precision.
- **Body Rotation and Flexion:** The hip joints play a crucial role in spine flexion and body rotation. The left hip provides a stabilizing effect, while the right hip rotates the torso, allowing the player to generate torque, which is transferred to the racket arm for powerful shots.

2. Frame of Stability: Maintaining Balance and Readiness

The **Frame of Stability** involves joints that counterbalance the force exerted during the shot, ensuring the player maintains a stable posture. For a right-handed player, the stability frame typically includes:

- **Left Wrist, Elbow, and Shoulder:** While the right arm generates force, the left arm provides balance. This "non-dominant" arm helps in maintaining the player's center of gravity and assists in stabilizing the body during and after the shot.
- **Left Knee and Left Ankle:** These joints support the body's weight as the right leg exerts force. They prevent overextension and help absorb the impact, reducing the risk of injury and enabling a quick recovery to a neutral position.

Biomechanical Functions as noted in the study by Manu et al [4]:

- **Maintaining Balance:** The Frame of Stability joints counter the rotational forces generated by the Frame of Force, preventing the player from losing balance. This balance is essential not only for the current shot but also for transitioning efficiently to the next movement.
- **Recovery and Readiness:** After executing a shot, the stability frame helps the player return to a balanced stance, preparing them for the next shot. This quick recovery is vital for maintaining a competitive edge, especially during fast-paced rallies.

3. Individual Variations in Frames:

It is important to note that the specific positioning and role of these frames can vary between players and shot types:

- **Player-Specific Differences:** Each player has unique biomechanics, influenced by factors such as body type, strength, flexibility, and playing style. For example, some players may rely more on their lower body for force generation, while others might use their upper body more intensively. Mehta et al. [15].
- **Shot-Specific Adjustments:** Different shots require different frames. For instance, a serve may involve a more pronounced use of the shoulder and elbow in the Force Frame, while a backhand may shift the emphasis to the opposite hip and shoulder. Similarly, stability frames can shift based on shot complexity and player positioning. Mehta et al. [15].

4. Dynamic Interplay Between Frames

- **Force Transfer and Balance Coordination:** Effective shot execution requires precise coordination between the

Frame of Force and the Frame of Stability. As force is generated and transferred through the body, the stability frame adjusts to maintain balance, ensuring that the player does not overextend or lose control as quoted in the study by Manu et al [5].

- **Feedback Mechanism:** Players constantly adjust their frames based on real-time feedback. If the stability frame detects imbalance, it can modify the force frame's movement to compensate, such as adjusting hip rotation or knee flexion as quoted in the study by Manu et al [5].

5. Implications for Training and Performance Enhancement

- **Targeted Training:** Understanding these frames allows coaches to design exercises that strengthen specific joints and improve coordination. For example, plyometric exercises can enhance lower body force generation, while core stabilization drills can improve the stability frame's effectiveness.
- **Injury Prevention:** Proper coordination between the two frames reduces the risk of overuse injuries. By ensuring that the force frame's exertion is adequately supported by the stability frame, players can avoid undue strain on joints such as the shoulder or knee.

4. CRITICAL ANGLES FOR THE FRAMES

Critical angles are the specific angular measurements between joints that significantly impact a player's ability to generate force and maintain balance during shot execution. These angles play a key role in defining both the Frame of Force and the Frame of Stability. By understanding and optimizing these angles, players can maximize shot efficiency while minimizing the risk of injury.

Critical Angles in Frame of Force

For a right-handed player, the Frame of Force joints—right wrist, elbow, shoulder, hips, knee, and ankle—must work in harmony to generate power and control. The following are the critical angles associated with these joints:

- Right Elbow Angle
- Right Shoulder Angle
- Left Upper Hip Angle
- Right Lower Hip Angle
- Right Knee

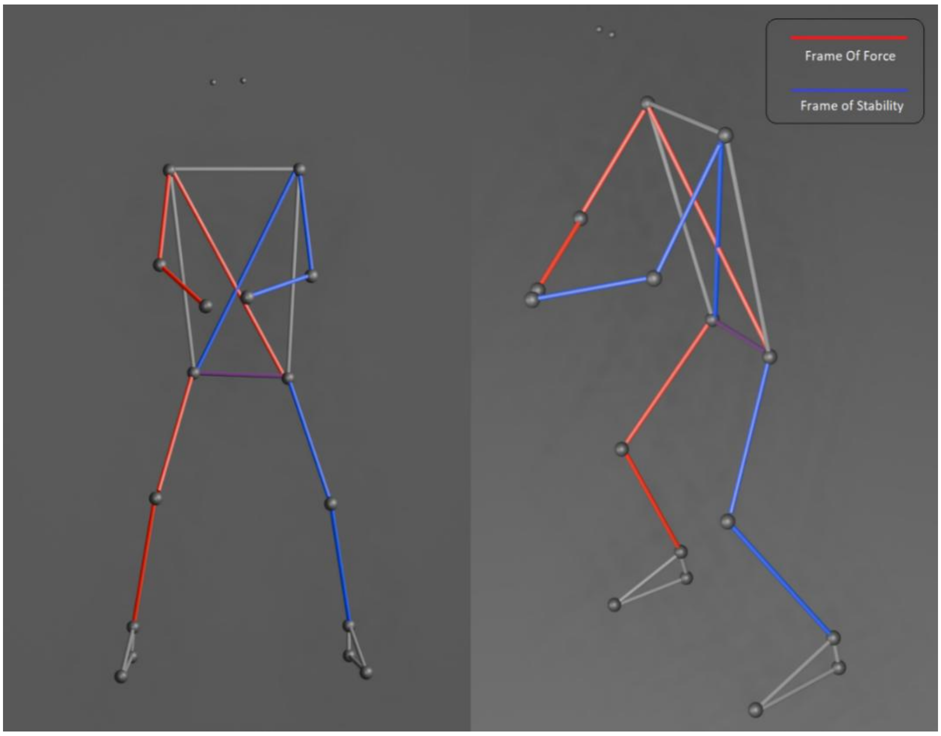


Fig 4.3: Visualization of the observed Frame of Force and Frame of Stability for a right handed player

Frame Of Force Angles
F-1: Right Elbow Angle
F-2: Right Shoulder Angle
F-3: Left Upper Hip Angle
F-4: Right Lower Hip Angle
F-5: Right Knee Angle

Frame Of Stability Angles
F-1: Left Elbow Angle
F-2: Left Shoulder Angle
F-3: Right Upper Hip Angle
F-4: Left Lower Hip Angle
F-5: Left Knee Angle

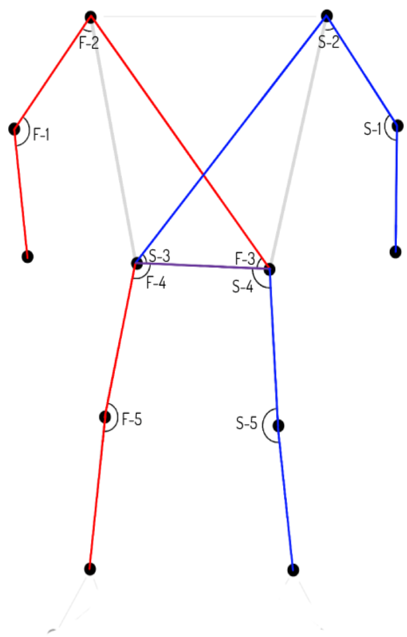


Fig 4.2: Visualization of the critical angles for the frames for a right-handed player.

Critical Angles in the Frame of Stability

The Frame of Stability involves joints that counterbalance the force exerted by the Frame of Force, helping the player maintain equilibrium. For a right-handed player, the key joints are on the left side of the body, with the following critical angles:

- Left Elbow Angle
- Left Shoulder Angle

- Right Upper Hip Angle
- Left Lower Hip Angle
- Left Knee

Variability and Adaptability of Critical Angles. Each player's biomechanics and playing style can introduce variability in critical angles.

Player-Specific Adjustments: Professional players may have slightly different optimal ranges for certain joints, depending on their flexibility, strength, and technique. For example, a player with greater shoulder flexibility may have a wider shoulder angle range than average.

Shot-Specific Adjustments: Different shots (forehand, backhand, serve) may require adjustments in critical angles. For instance, the elbow angle on a backhand may be more acute compared to a forehand.

5. CLUSTERING (DIFFERENT ALGORITHMS) AND CENTROID DISTANCES

In our analysis of tennis shots, we utilized joint angles extracted using the Mediapipe library to differentiate between various player types (left-handed, right-handed) and the shots they play (forehand, backhand, and serve). These angles were processed and structured to allow us to employ several clustering algorithms to group similar shots together as seen by studies quoted by Manu et al [6]. After extracting the joint landmarks using the Mediapipe library, the joint angles were calculated from three consistent dimensions: front view, side view, and top view. These angles provided the necessary data points for analysis. The following steps were performed to clean and structure the data:

Combine Data for Players and Shots: Left-handed and right-handed players were combined separately. The shots (forehand, backhand, and serve) were also separated and analyzed individually. Gholami et al. [10].

Check for Null Values: Each combined DataFrame was checked for any missing or null values, and appropriate imputation techniques were applied to clean the data.

Select Joint Angles with Minimum Standard Deviation: To reduce noise in the data, we identified and selected joint angles with the lowest standard deviation. This ensured that only the most consistent joint movements were considered for clustering. Wang et al [13].

Standardization: The selected joint angle data was standardized to have zero mean and unit variance. This ensured that all angles contributed equally to the analysis, regardless of their scale or range.

Dimensionality Reduction with PCA: Principal Component Analysis (PCA) was used to reduce the dimensionality of the data. By transforming the data into principal components, we retained the most significant variance while simplifying the dataset. This reduction allowed for easier clustering and visualization. Baoa et al. [11]

To group the players' shots into distinct clusters, we applied several clustering algorithms, each offering a unique approach to partitioning the data:

- K-Means Clustering
- Gaussian Mixture Model (GMM)
- Spectral Clustering

<u>Centroid Distance and Analysis</u>

After clustering the data, one of the key steps in analyzing the players' performance was calculating the distance of a new player's shot from the cluster centroids. This distance represents how close the new player's shot is to the ideal shot (as defined by the centroid of each cluster).

Centroid Calculation: For each cluster, the centroid represents the "average" position of the shots in that cluster. This is the mean position of the joint angles for all shots in the cluster.

Distance Metric: The Euclidean distance was calculated between the new player's shot and each cluster centroid. This distance quantifies how far the shot is from the centroid, with smaller distances indicating a shot closer to the cluster's ideal.

Shot Analysis: By calculating the distance to the nearest centroid, we could determine the quality of the shot. Shots closer to the centroid were considered more technically sound, while shots farther away indicated deviations from the optimal form.

Finally, the clustered data was visualized using 2D scatter plots. Each cluster was represented by a unique color, and the centroids were marked distinctly. By visualizing the data in this way, we were able to:

- **Compare Cluster Boundaries:** The scatter plots allowed us to visually assess how well-separated the clusters were. Tight, well-defined clusters indicated homogeneity in playing technique, while more dispersed clusters suggested greater variability.

- **Analyze Player Positioning:** The relative position of a player's shot within or outside a cluster provided insights into their technique. Shots within the core of the cluster were more consistent with the group, while shots near the periphery indicated variation.

6. RESULTS

Based on our analysis of the joints and their role in the shot, we calculated key angles for each frame. Below is a sample table representing the critical joint angles for both frames during specific shot types:

Perspective and Joints →	TopView	FrontView			SideView
Forehand Player shots	RightElbow	RightShoulder	LeftUpHip	RightDownHip	RightKnee
TestPlayer_001.png	137.265	42.087	63.891	110.64	172.23
TestPlayer_002.png	176.492	24.005	65.872	92.322	179.134
TestPlayer_003.png	147.898	49.256	61.296	116.68	174.85
TestPlayer_004.png	171.397	55.148	59.074	127.223	171.568
TestPlayer_005.png	133.675	64.559	58.93	110.499	167.704
TestPlayer_006.png	170.121	71.84	61.223	114.177	174.424
TestPlayer_007.png	171.518	41.912	61.837	115.615	179.846
TestPlayer_008.png	165.519	83.376	65.399	105.615	172.877
TestPlayer_009.png	179.656	45.533	56.906	122.476	162.91
TestPlayer_010.png	158.805	64.942	70.87	91.817	164.368

Table 6.1: Sample data of right handed players' forehand frame of force's selected critical angles

To simplify and analyze the angle data, we applied Principal Component Analysis (PCA). This technique reduces the dimensionality of the data while retaining the most significant variance, which helps in revealing patterns between players and their shot techniques.

Player shots	FOF-PCA1	FOF-PCA2	FOS-PCA1	FOS-PCA2
TestPlayer_001.png	-0.22	0.904	-1.468	-0.275
TestPlayer_003.png	0.228	0.535	1.045	0.948
TestPlayer_004.png	1.133	-0.401	1.887	-0.020
TestPlayer_005.png	-0.824	-0.281	1.370	0.215
TestPlayer_006.png	0.131	0.053	1.345	0.816
TestPlayer_007.png	1.23	1.072	0.298	-1.113
TestPlayer_008.png	-0.887	0.312	1.541	1.015
TestPlayer_009.png	1.619	-0.923	-0.453	0.240
TestPlayer_011.png	0.774	0.244	1.080	0.062

TestPlayer_013.png	-0.522	0.109	-0.005	-1.818

Table 6.3: Sample data of PCA performed on table with outliers removed.

After applying PCA to the angle data from the Frame of Force (FOF) and Frame of Stability (FOS), we reduced the dimensionality to two principal components. These components capture the maximum variance in the data, making it easier to visualize the underlying patterns. The primary objective of plotting the PCA values is to identify clusters or groups of data based on joint angles. We perform 3 clustering algorithms to reveal natural groupings, indicating differences in shot tecniques among players.

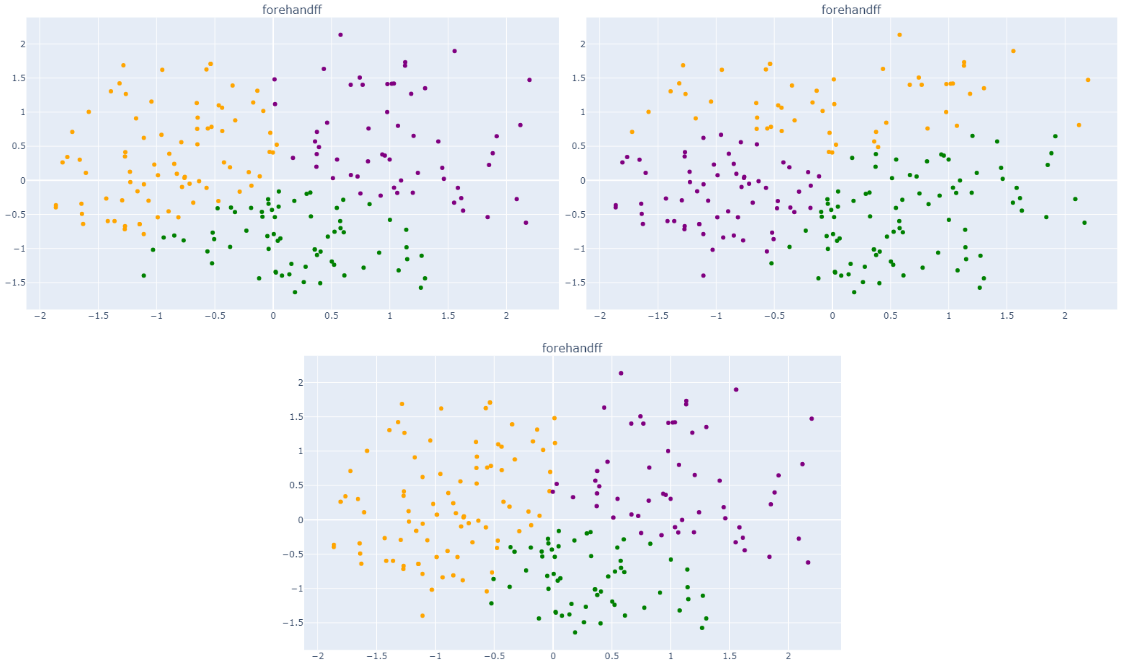


Fig 6.1 Kmeans, GMM and Spectral Clustering for FOF right handed players

Once the data is clustered using KMeans, the centroids of each cluster are calculated. These centroids represent the "mean" or "central point" of each cluster in the PCA-transformed space. Calculating and analyzing these centroids is critical for understanding the ideal shot techniques and evaluating player performance. The purpose of centroid calculation is that it acts as a benchmark for analysis. Centroids act as reference points that represent the ideal or most common shot characteristics within each cluster. The distance of a player's shot from the nearest centroid provides insights into how closely they align with the ideal shot technique for that cluster. Centroids help confirm the distinctiveness of clusters, ensuring meaningful segmentation of data.

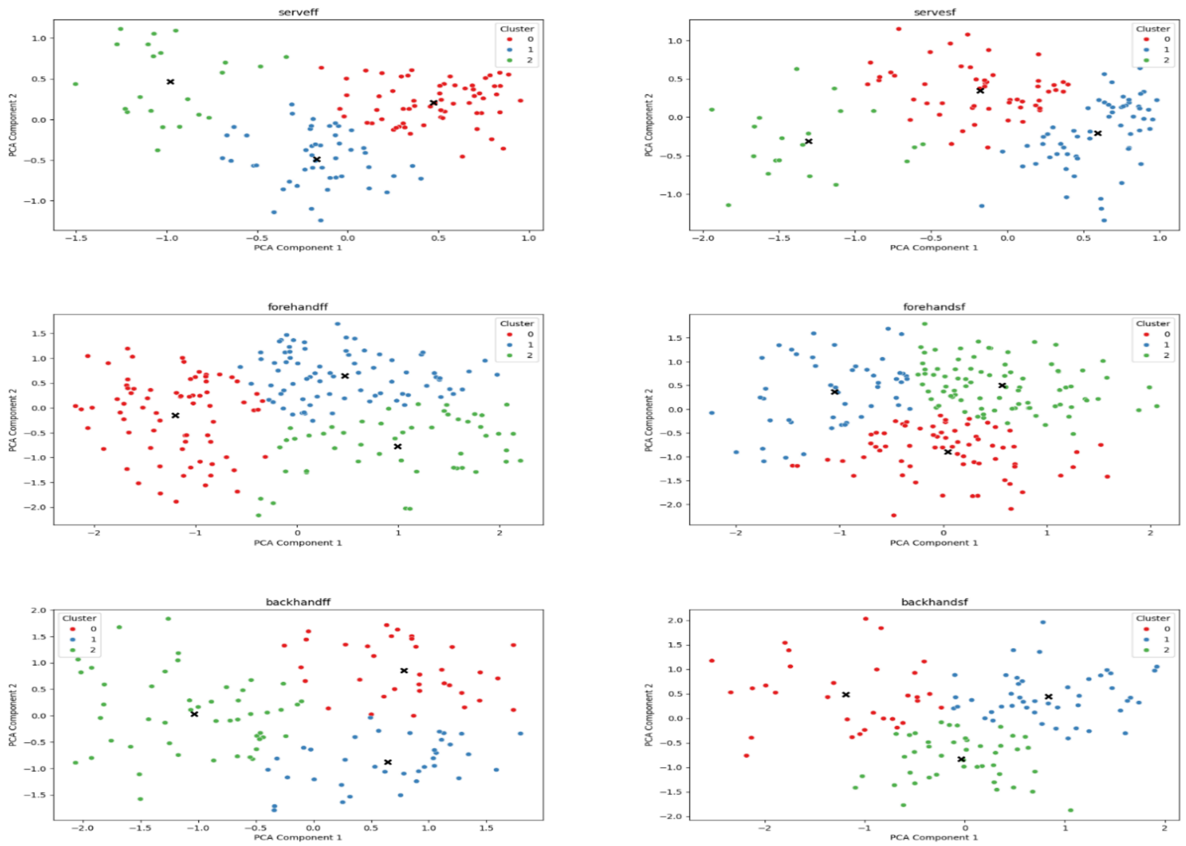


Fig 6.2 FOF and FOS Plots for right handed players for the three type of shots played with clusters and their centroids.

Evaluating a New Player's Alignment with Established Clusters - To evaluate how well a new player's technique aligns with the established clusters of ideal techniques, we follow a structured approach that leverages machine learning methods. This process enables us to quantify the similarity between the new player's performance and the ideal characteristics of the technique, highlighting areas for potential improvement. The steps are outlined below:

1. **Data Extraction and Consistency Across Datasets**:
   - In the first step, the joints and key features relevant to the player's shot technique extracted from the training dataset is used to extract from the test dataset (representing the new player's performance).
   - The same set of features such as angles will be extracted from both the training and test datasets to ensure consistency. This guarantees that we're comparing similar data points from both the old and new players.
2. **Dimensionality Reduction with PCA**:
   - The PCA model trained on the training dataset, capturing the primary components that define the variations in shot techniques is applied to the new player's test data, ensuring that both datasets are mapped onto the same reduced feature space.
   - The resulting PCA-transformed data provides a simplified representation of the player's shot technique, focusing on the most significant characteristics.
3. **Classifying the New Player Using K-Nearest Neighbors (KNN)**:
   - To determine which established cluster the new player belongs to, we apply a **K-Nearest Neighbors (KNN) classifier** as conclude din the study by Manu et al [7].
   - KNN compares the new player's shot technique (in the reduced PCA space) with the centroids of the existing clusters formed from the training data. By calculating the distance between the new player's shot and the nearest cluster centers, KNN assigns the new data point to the most similar cluster.
   - KNN is ideal for this task since it's a non-parametric method that makes decisions based on the proximity to other data points, making it well-suited for identifying how similar the new player's technique is to the

established patterns.

4. **Cluster-Center Distance Calculation**:
   - Once the new player’s shot is classified into a cluster, the next step is to calculate how closely it aligns with the ideal shot in that cluster.
   - This is done by measuring the **distance from the new player’s shot to the centroid** (the center) of the assigned cluster. The centroid represents the "ideal" shot for that cluster, which is a composite of all the data points within that group.
   - The distance between the new player's shot and the centroid serves as an indicator of how much the new player's shot deviates from the ideal technique. A smaller distance indicates a shot that is very similar to the ideal, while a larger distance suggests significant deviation.
5. **Actionable Feedback for Improvement**:
   - The calculated distance provides valuable insights into areas where the new player's technique diverges from the established ideal.
   - If the new player's shot is far from the centroid, this could point to specific technical aspects that need improvement. For example, certain joint angles, movements, or timing might differ from the optimal pattern.
   - Based on these deviations, targeted feedback can be generated, helping the new player focus on refining their shot technique to align more closely with the ideal model represented by the clusters.

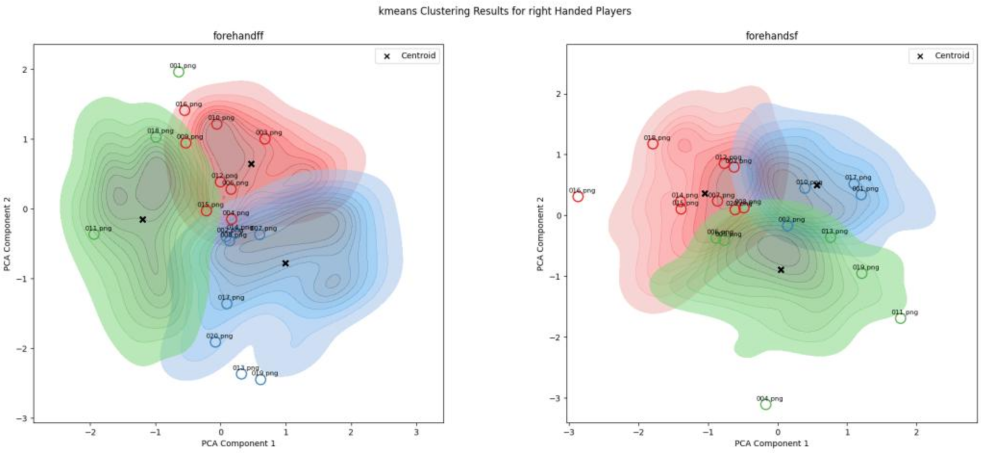


Fig 6.3 KDE Contours to visualize the new data points for right hand forehnad shots

This process of evaluating a new player's alignment with established clusters provides a systematic way to assess their shot technique. By utilizing PCA for dimensionality reduction, KNN for classification, and distance calculations for deviation analysis, we can effectively compare the new player’s performance against the ideal clusters and offer actionable feedback for improvement. This approach not only facilitates the identification of technique gaps but also aids in guiding the player toward more optimal performance.

Scoring / Evaluating the performance of the shot played

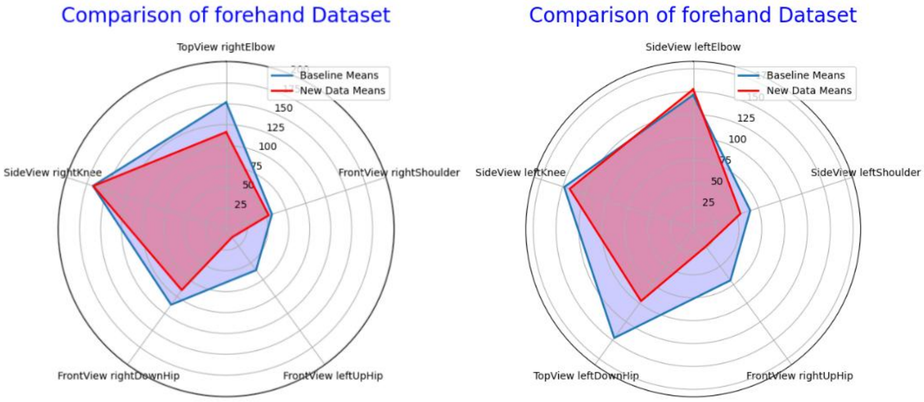


Fig 6.4 Spider / Radar graph of means of training set against the test set

The spider graph provides a critical visual representation of the player's joint flexion during the shot, highlighting the difference between the test player's performance and the optimal or ideal body mechanics. The graph uses a red shade to represent the test player's data and a blue shade to show the average flexion of professional players, providing an immediate comparison. From this visualization, it becomes evident that the test player's body frame, particularly in terms of joint flexion, is not aligned with the optimal range during the shot. One notable observation is the test player's right elbow, which shows insufficient flexion compared to the ideal positioning seen in professional players. This lack of optimal flexion in the right elbow is a key factor that likely contributed to less effective shot execution. If the test player had flexed the right elbow more, it would have improved their overall shot mechanics, bringing their body posture closer to the professional standard. This discrepancy is further validated by the KDE (Kernel Density Estimate) plot, where some of the test points are found to be significantly distant from the centroid. These outliers represent instances where improper joint flexion, like in the right elbow, negatively impacted the shot's performance, leading to deviations from the optimal trajectory.

7. CONCLUSION

Mastering the correct stance for each tennis shot is fundamental to enhancing performance and minimizing the risk of injury. The open stance for forehands facilitates greater power generation, improved topspin, and better reach, making it ideal for modern aggressive play. For backhands, selecting the appropriate stance based on grip—closed for one-handed and neutral for two-handed—ensures balance and precision during execution. The serve stance, particularly the platform stance, provides a solid base for efficient weight transfer and rotational power, crucial for accuracy and consistency. So based on the results of the study, we can conclude the following:

Forehand Shot:

Correction: For a forehand shot, use an open stance. Stand sideways to the net with your non-dominant shoulder pointing toward the net. Your feet should be shoulder-width apart. Shift your weight to your back foot as you prepare, then transfer your weight forward as you swing.

Importance: An open stance allows you to generate power, topspin, and reach for balls effectively.

Backhand Shot:

Correction: The stance for a backhand depends on whether you're using a one-handed or two-handed grip. For a one-handed backhand, use a closed or semi-open stance, with your non-dominant shoulder pointing toward the net. For a two-handed backhand, a neutral stance with both shoulders facing the net is common.

Importance: The appropriate stance for your backhand grip allows you to maintain balance and control during the shot.

Serve:

Correction: The serve stance can vary, but the platform stance, where your feet are parallel to the baseline, is a good starting point. Keep your feet shoulder-width apart, with your non-dominant foot slightly in front. As you initiate the serve, transfer your weight from your back foot to your front foot and rotate your hips and shoulders for power.

Importance: The correct serve stance ensures power and control over the direction and placement of your serve.

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