Ace Advantage: Serve Optimization for Tennis Players

DSI-SG-42
Ngan Han Kiong

Who Am I?

Sports Performance Data Science Consultant

Who Are You?

Tennis coaches and fellow sports performance consultants

AGENDA

01

INTRODUCTION

02

PREDICTING TENNIS SERVES OUTCOMES

03

POSE ESTIMATION & ANALYSIS

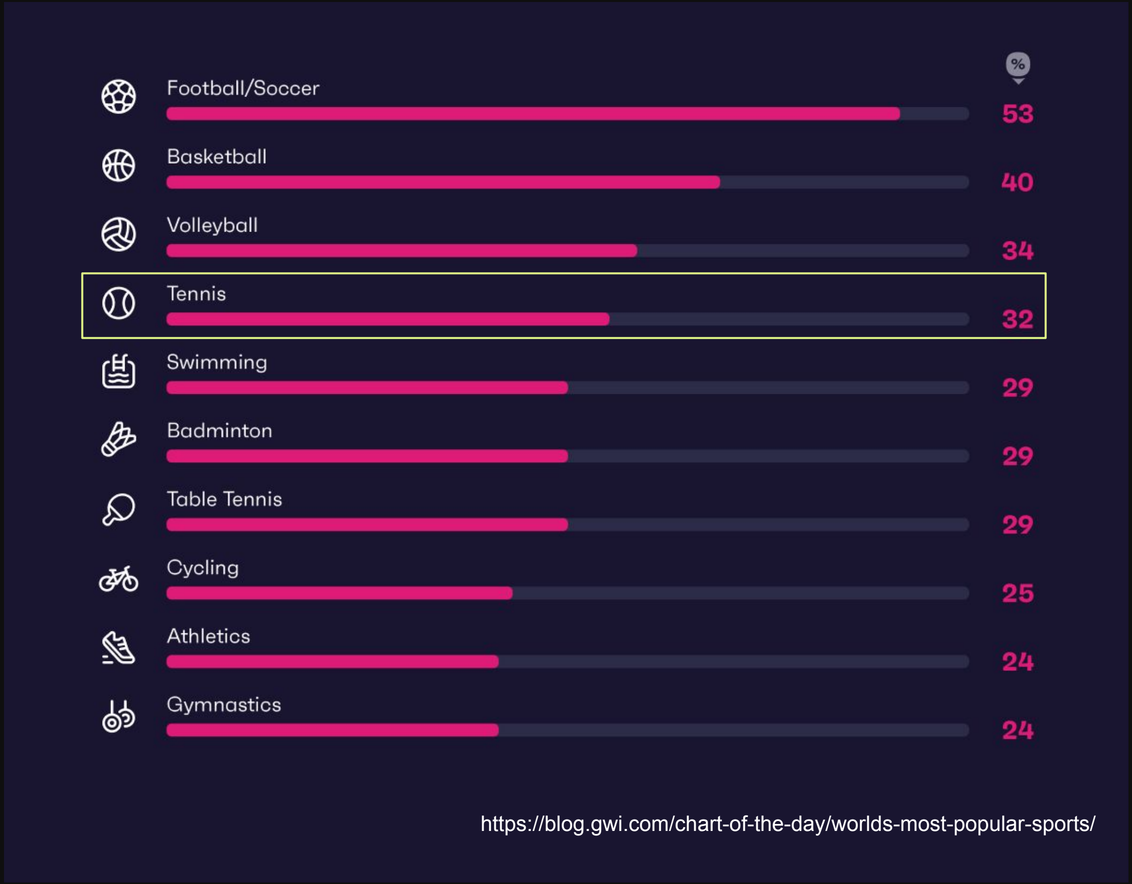
04

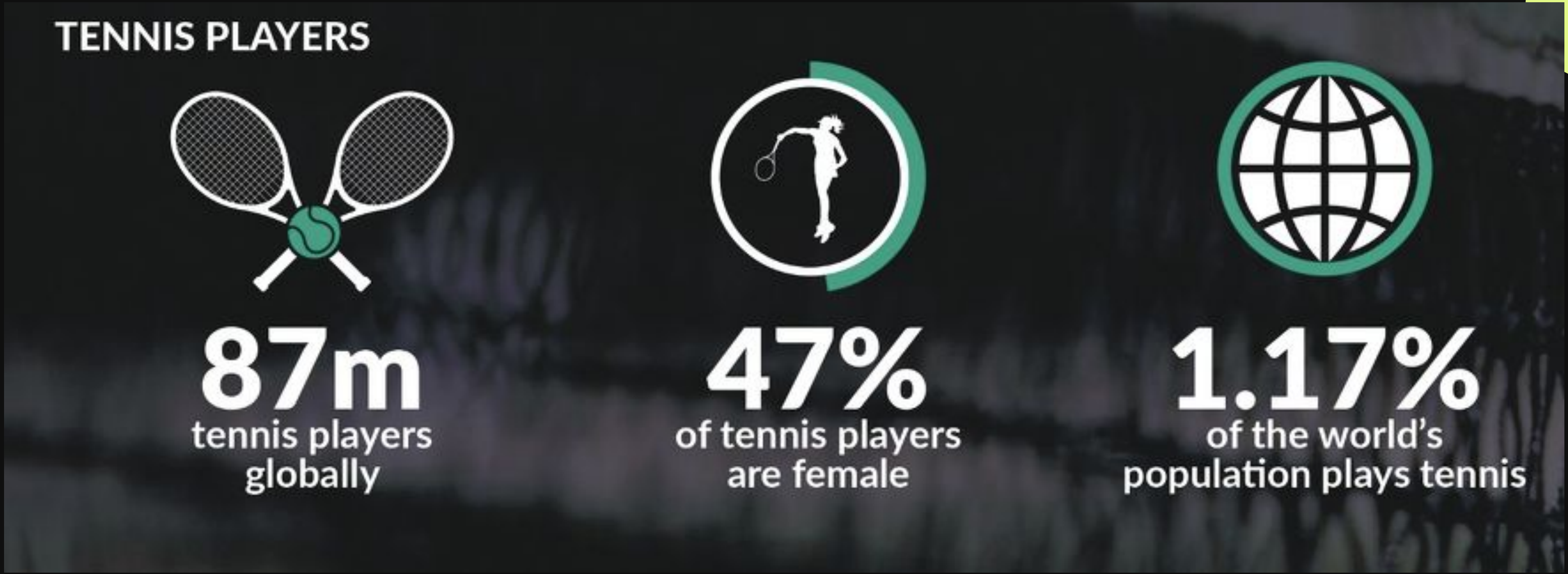
CONCLUSION & RECOMMENDATIONS

01

INTRODUCTION

Tennis is the 4th most watched sports in the world in 2023

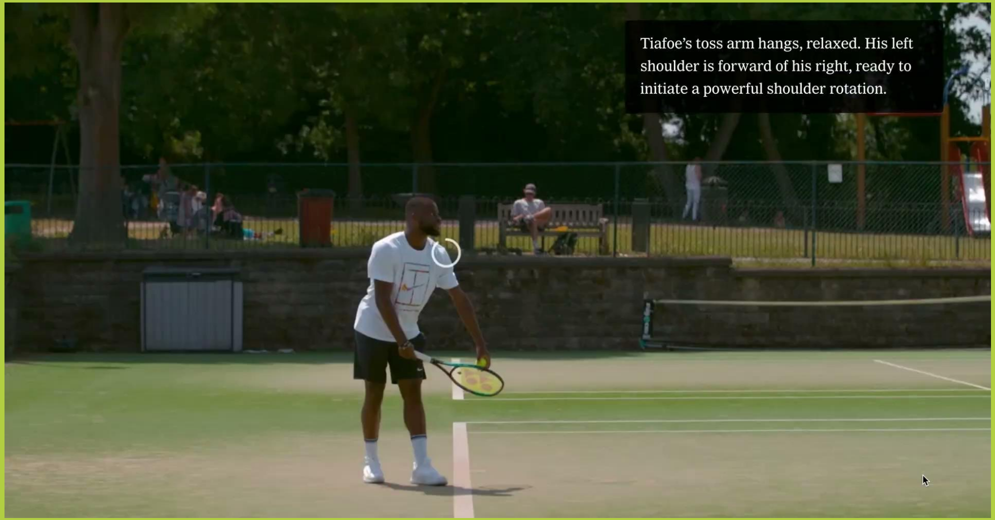




Itf-global-tennis-report-2019

Breaking Down the Serve...

Placing The Toss



Holding the Ball

Breaking Down the Serve…

Into the Air

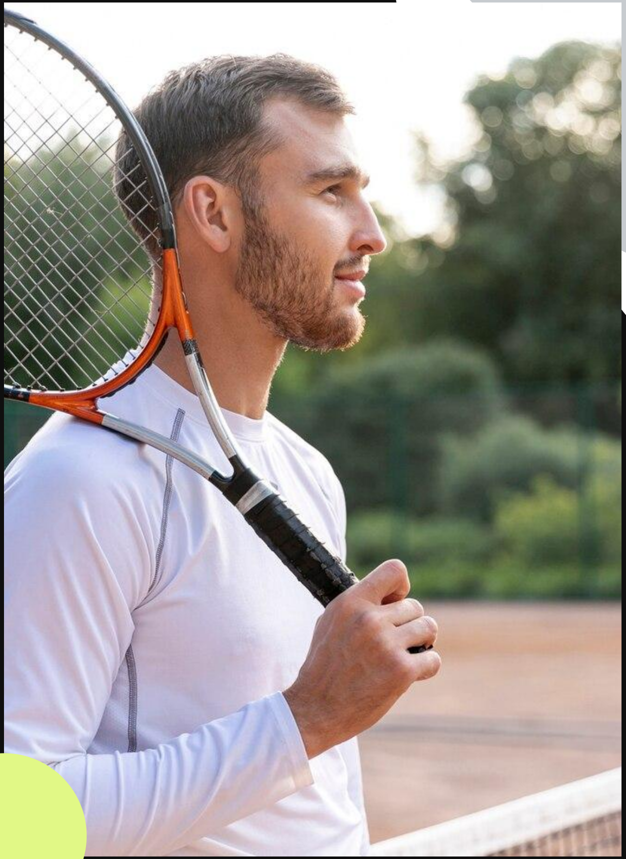
Foot Placement

Breaking Down the Serve…

Point of Contact

Problem Statement

How might we develop a **data-driven approach** to **analyze serve performance data** and **develop personalized strategies for optimizing serve** accuracy, power, and placement, thereby empowering tennis players to enhance their on-court performance and gain a competitive edge in matches?



Alex, a seasoned tennis coach, brings over 15 years of experience to the court.

Passionate about player development, he **seeks innovative, data-driven solutions to optimize serves** and gain a competitive edge in tournaments.

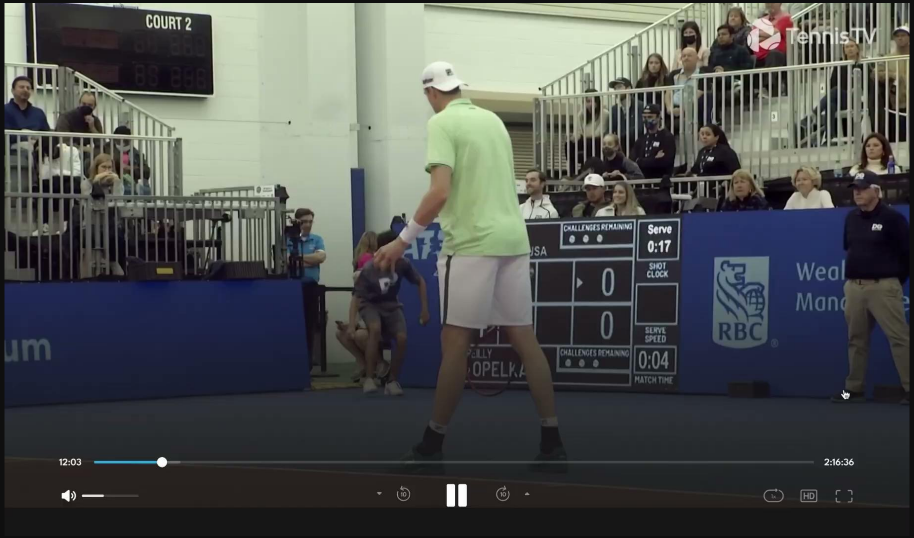
Alex's goal is to help players of all levels reach their full potential while **staying ahead of industry trends and technology advancements**.

With a focus on enhancing serve accuracy, power, and placement, Alex navigates challenges and pressures to maintain his reputation as a top-tier coach, driven by a commitment to excellence and success on the court.

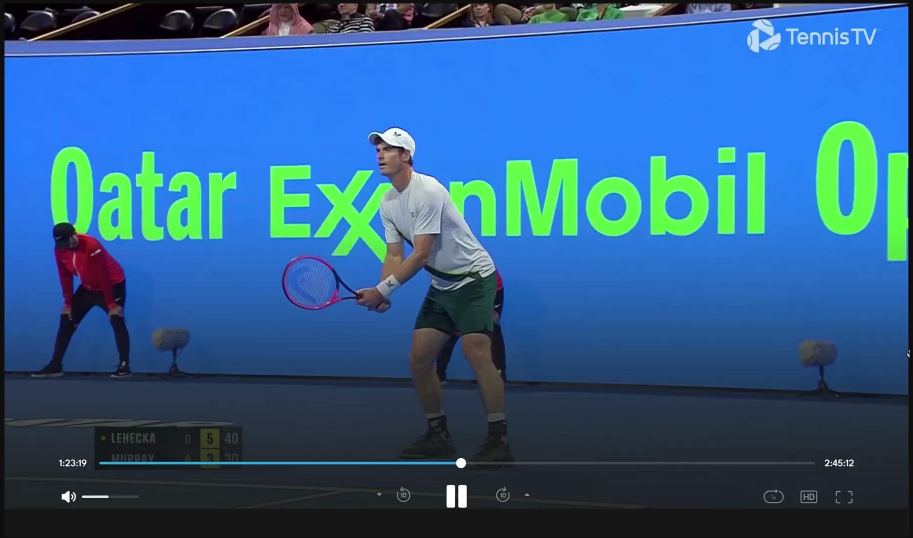
02

PREDICTING TENNIS SERVE OUTCOMES

TENNIS SERVES OUTCOMES - GOOD SERVES



Outcome 1: Ace



Outcome 2: Unreturned

TENNIS SERVES OUTCOMES - BAD SERVES

Outcome 3: Fault

Outcome 4: Returned

PREDICT TENNIS SERVE OUTCOMES

DATA COLLECTION

Match Charting Project

RANDOM SELECTION

32 match samples

DATA COLLECTION

YouTube, TennisTV
20 match samples

LABEL SERVES

Label serves as aces. faults, returned & unreturned

CONVERT VIDEO AS IMAGE FRAMES

7 frames per video

PREPROCESSING

Turning video frame data into x and y data matrices

TRAIN-TEST SPLIT, NORMALIZATION

Split data into training and testing set and normalize

MODELLING

3D-CNN and Convolutional LSTM

FRAME EXTRACTION

- 7 frames per video were extracted using OpenCV
- All frames of video that were less than 7 frames removed (problems in reading by OpenCV library)

MODEL ARCHITECTURE

MODEL 1 - 3D-CNN

convolutional layer: 64 filters with a kernel size of (3, 3, 3) and applies the ReLU activation function

conv3d_4 (Conv3D)
Output shape: **(None, 7, 224, 224, 64)**

max_pooling3d_4 (MaxPooling3D)
Output shape: **(None, 3, 112, 112, 64)**

max pooling layer with a pool size of (2, 2, 2), downsample the feature maps by a factor of 2 along each spatial dimension

convolutional layer: 32 filters with a kernel size of (3, 3, 3) and applies the ReLU activation function

conv3d_5 (Conv3D)
Output shape: **(None, 3, 112, 112, 32)**

max_pooling3d_5 (MaxPooling3D)
Output shape: **(None, 1, 56, 56, 32)**

max pooling layer with a pool size of (2, 2, 2), downsample the feature maps by a factor of 2 along each spatial dimension

flatten layer: flattens feature maps into a one-dimensional vector

flatten_2 (Flatten)
Output shape: **(None, 100352)**

fully connected Dense layer with 96 units and ReLU activation function

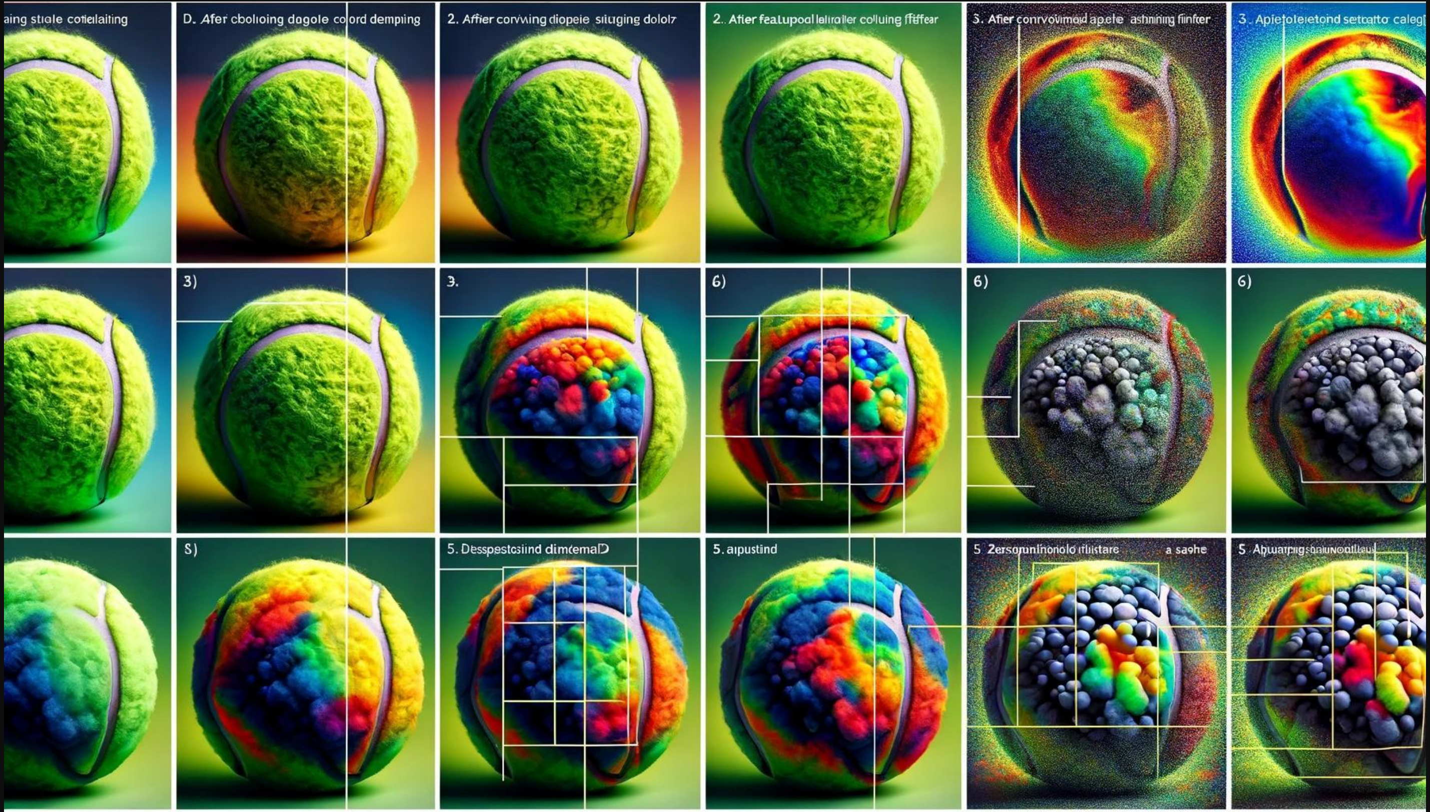
dense_4 (Dense)
Output shape: **(None, 96)**

dense_5 (Dense)
Output shape: **(None, 4)**

Dense layer with 4 units added with softmax activation function

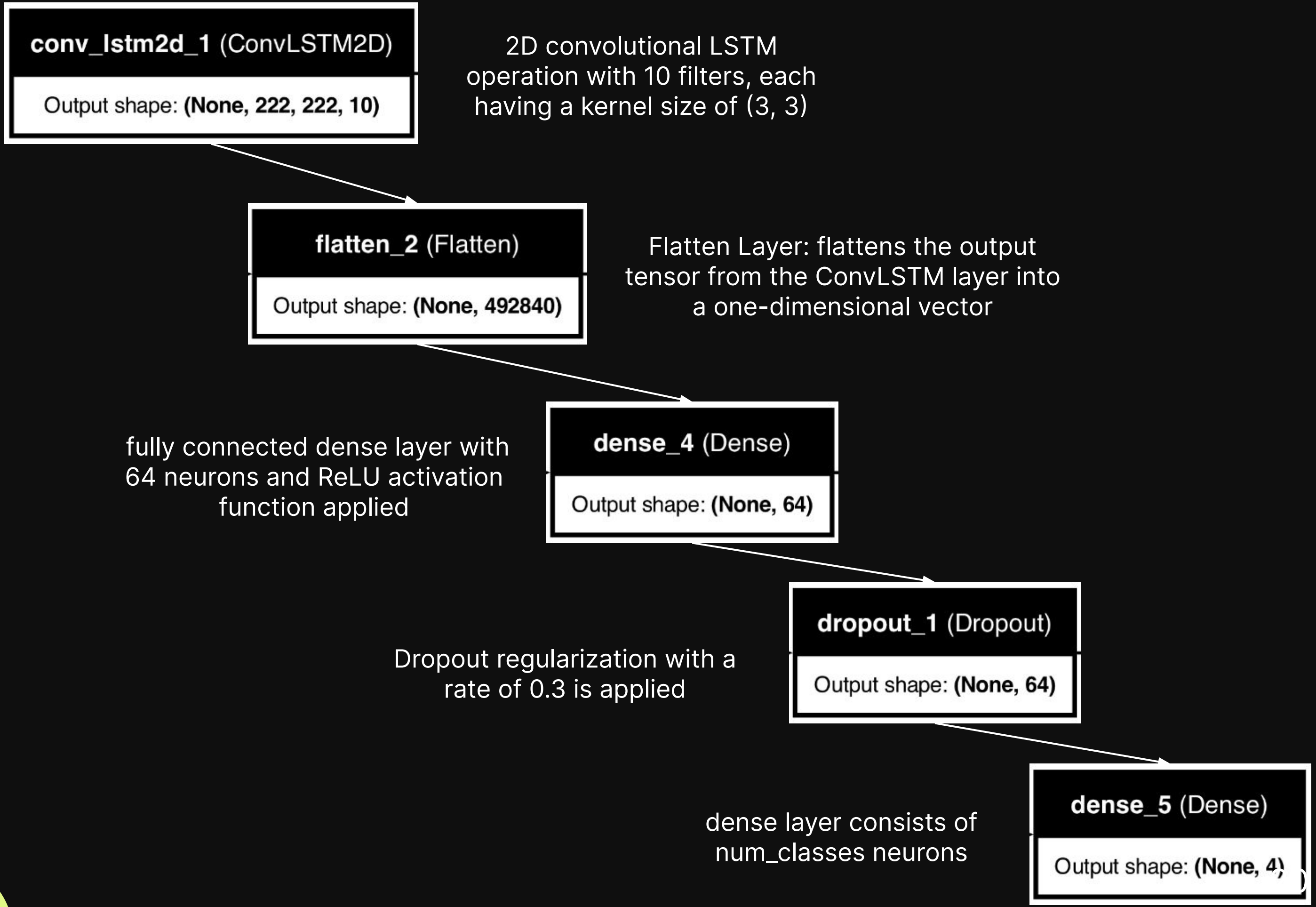
MODEL ARCHITECTURE

MODEL 1 - 3D-CNN



MODEL ARCHITECTURE

MODEL 2 - CONVOLUTIONAL LSTM



MODEL ARCHITECTURE

MODEL 2 - CONVOLUTIONAL LSTM

MODEL COMPARISON

MODEL 1 - 3D-CNN

MODEL 2 - CONVOLUTIONAL LSTM

Feature	Model 1	Model 2
Overview	like a series of filters viewing different parts of a video simultaneously	watches video frame by frame, focusing on changes over time
Method of Analysis	identifies patterns using 3D filters, then shrinks to focus on important parts	compares each frame to the previous, looking for changes
Focus	patterns in shape, color, and movement.	changes and movements over time
Conclusion	makes a guess based on observed features.	uses cumulative information to make a guess.

MODEL EVALUATION & COMPARISON

MODEL 1 - 3D-CNN

MODEL 2 - CONVOLUTIONAL LSTM

An accuracy of 25% means that the model correctly classifies 1 out of 4 tennis serves into their correct categories

On average, the model's predictions are around 1.39 units away from the actual values.

Model	Mean train accuracy	Test accuracy	Mean train loss	Test loss
3D-CNN	0.2554	0.2536	1.38632	1.3866
Convolutional LSTM	0.2679	0.2536	1.38624	1.3868

Model 2 demonstrates a slight edge in training performance, both models perform comparably on unseen test data.

03

POSE ESTIMATION AND ANALYSIS

OBJECTIVES

TIMELY FEEDBACK

Enable players to adjust their strategies and improve their serve accuracy, power, and placement.

PERSONALISED STRATEGIES

Based on the analysis of pose estimation, catering to individual player strengths and weaknesses.

POSE ESTIMATION AND ANALYSIS

DEFINE FUNCTIONS

Analyse Tennis Serve

DRAW KEYPOINTS

17 keypoint joints

DRAW EDGES

LOAD MODEL

MoveNet model

MAKE DETECTIONS

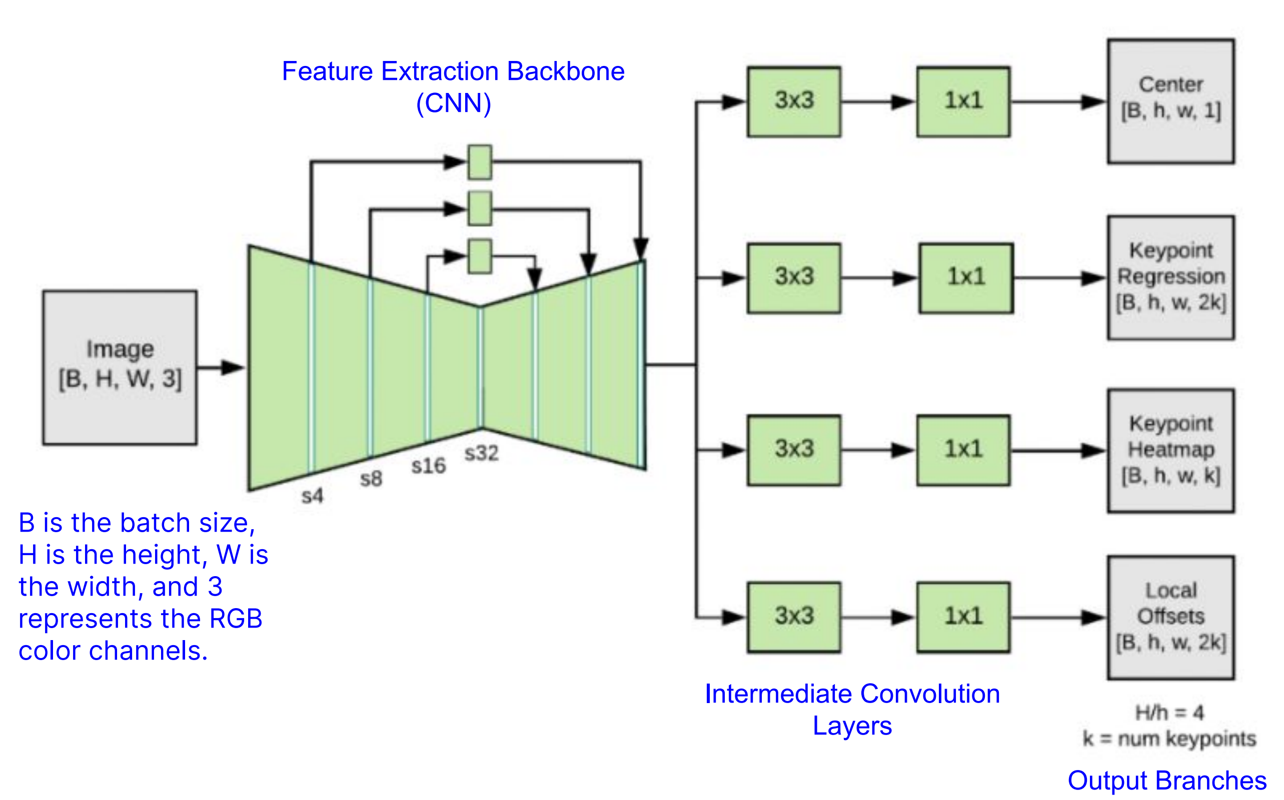
PLOT DATA & ANALYSIS

Left & right wrist positions, angles of right elbow, right shoulder, right knee over time

COMPARISON

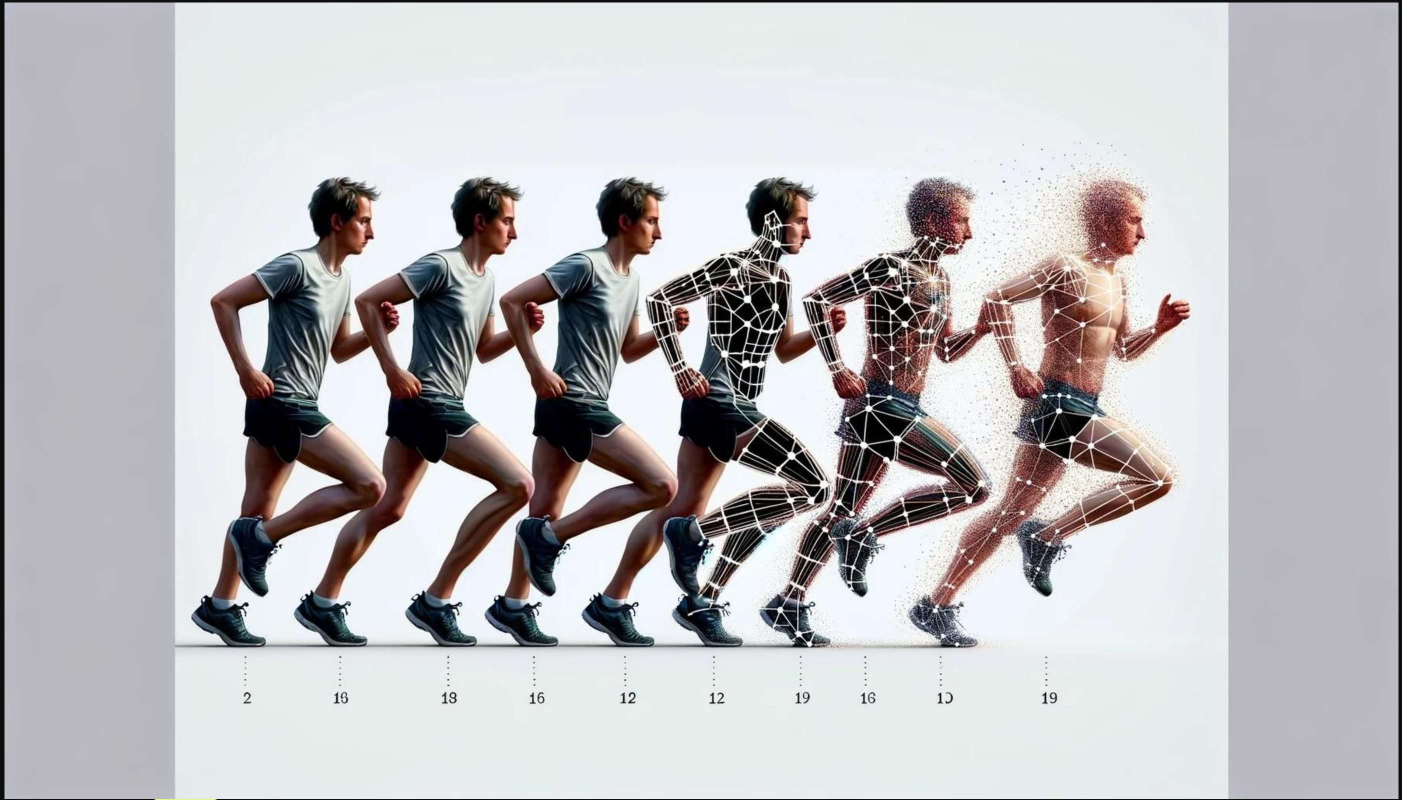
Professional & Amateur Player

MoveNet Model Architecture

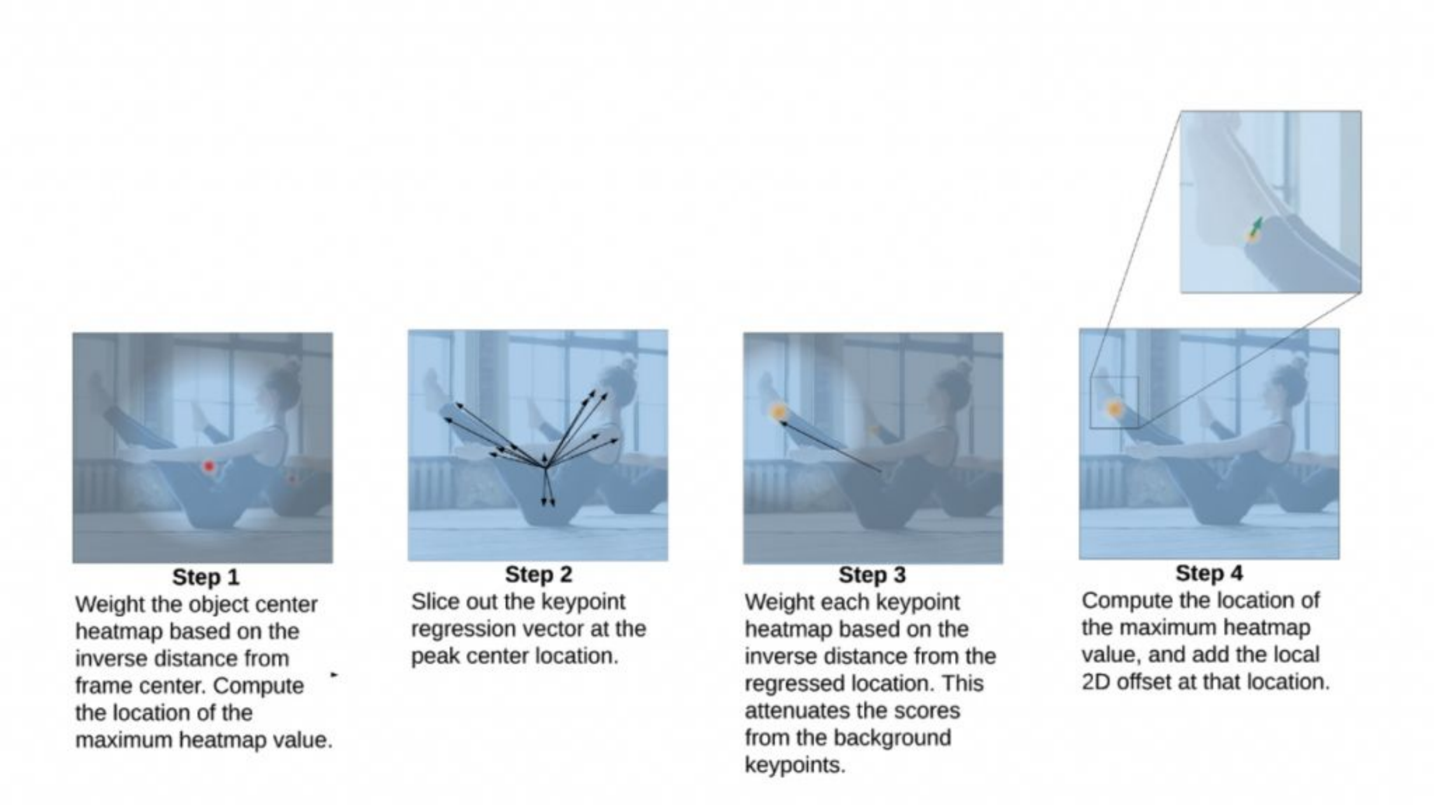


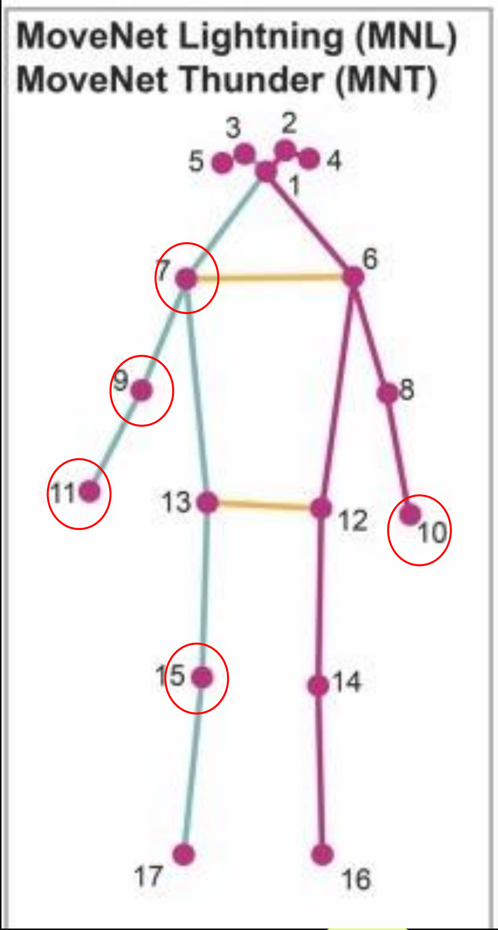
B is the batch size, H is the height, W is the width, and 3 represents the RGB color channels.

Progression of an image through the layers of the MoveNet architecture, becoming increasingly detailed.



MoveNet Model Operations



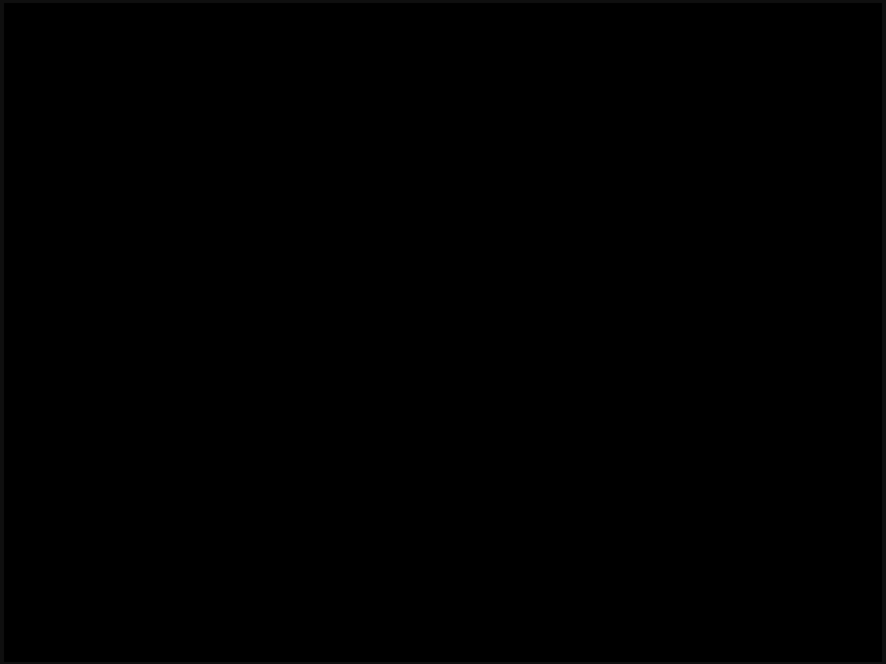


17 Keypoint Joints

The order of the 17 keypoint joints is:

1	nose	7	right shoulder	13	right hip
2	left eye	8	left elbow	14	left knee
3	right eye	9	right elbow	15	right knee
4	left ear	10	left wrist	16	left ankle
5	right ear	11	right wrist	17	right ankle
6	left shoulder	12	left hip		

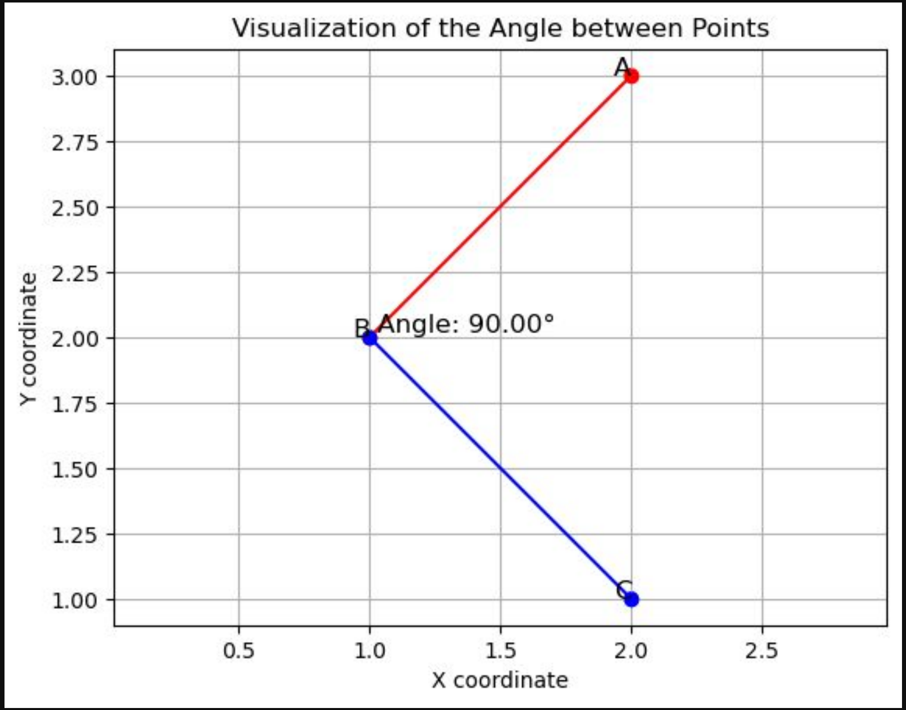
POSE DETECTION



Professional tennis player

Amateur tennis player

THE LAW OF COSINES



The Law of Cosines is a trigonometric law that relates the length of the sides of a triangle to the cosine of one of its angles.

It states that the square of one side is equal to the sum of the squares of the other two sides, adjusted by twice the product of those sides and the cosine of the included angle.

$$C^2 = a^2 + b^2 - 2ab\cos(\theta)$$

right elbow angle

right shoulder angle

right knee angle

COMPARATIVE BIOMECHANICAL ANALYSIS OF TENNIS SERVE

PROFESSIONAL VERSUS AMATEUR

DESCRIPTIVE ANALYSIS

Histograms and boxplots showing distributions of:

- right wrist (x and y coordinates)
- right elbow angles
- right shoulder angles
- right knee angles

TIME SERIES ANALYSIS

Line plots of:

- left and right wrist (y-coordinates) over time
- left and right wrist (x and y-coordinates) over time
- right elbow angles, right shoulder angles, right knee angles over time

CORRELATION ANALYSIS

Scatterplots and correlation heatmaps of:

- left and right wrist (x and y-coordinates) with right elbow angles
- right wrist with right elbow angles

STATISTICAL ANALYSIS

T-test for:

- right elbow angles
- right shoulder angles
- right knee angles

BIOMECHANICAL ANALYSIS OF TENNIS SERVE
STATISTICAL ANALYSIS

Null Hypothesis (H_0):

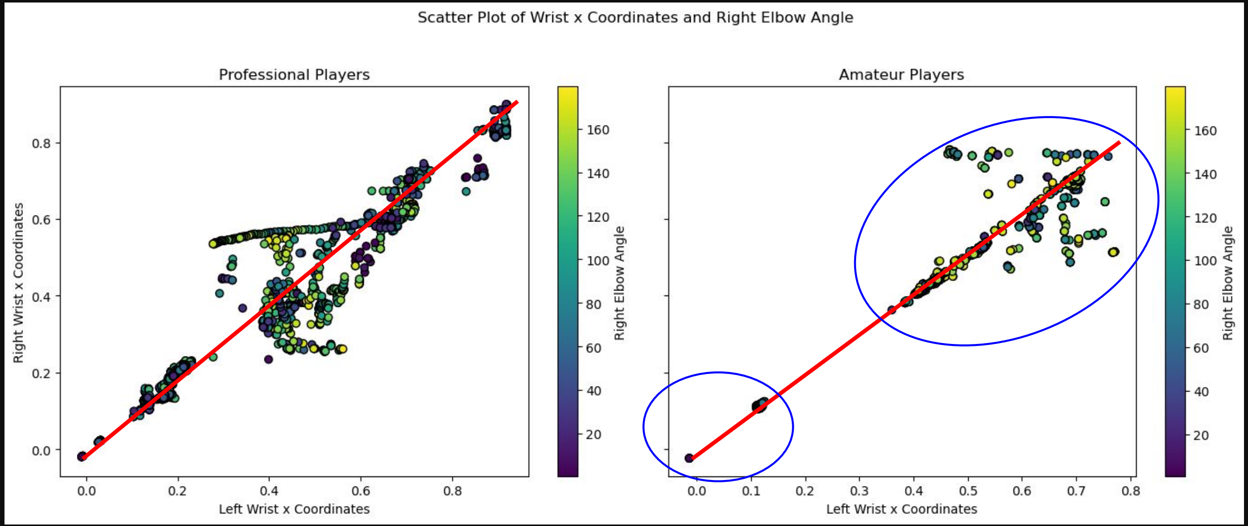
H_0: $\mu_1 = \mu_2$ - The null hypothesis states that there is no difference in the mean right (elbow/shoulder/knee) angles between professional (μ_1) and amateur (μ_2) tennis players.

Alternative Hypothesis (H_1):

H_1: $\mu_1 \neq \mu_2$ - The alternative hypothesis states that there is a difference in the mean right (elbow/shoulder/knee) angles between professional and amateur tennis players.

angle	t-statistic	p-value
right elbow	-21.26	< 0.0001
right shoulder	17.11	< 0.0001
right knee	-21.26	< 0.0001

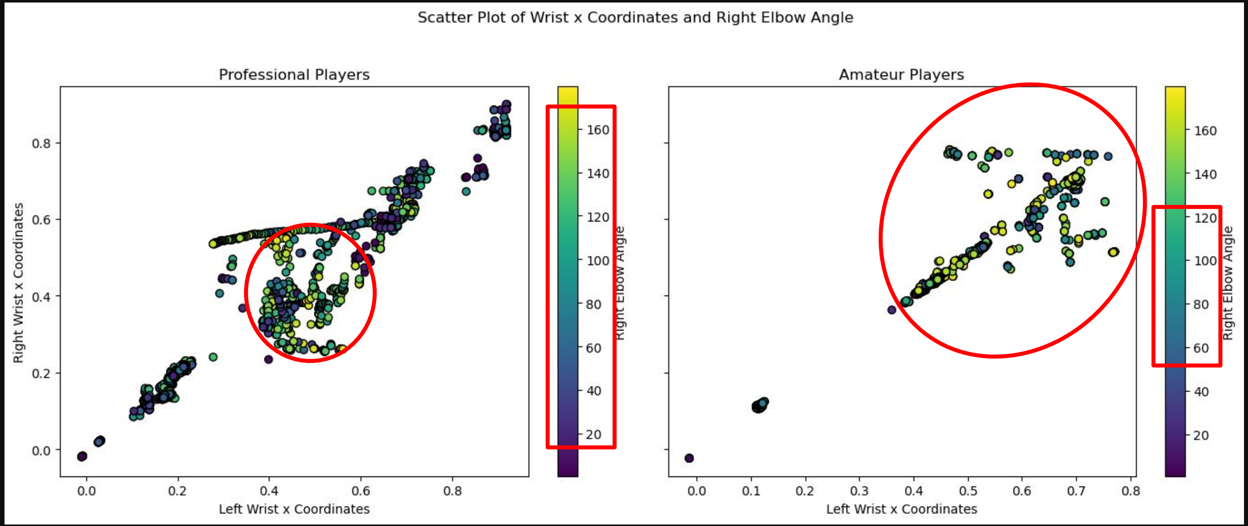
- Given that the p-values are all much lower than significance level of 0.05, reject the null hypothesis.
- Positive t-statistic for right shoulder angle: larger mean angle in professional



CORRELATION ANALYSIS

- Scatterplots display the relationship between the left wrist x-coordinates (x-axis) and the right wrist x-coordinates (y-axis)
- Color of each point representing the corresponding right elbow angle

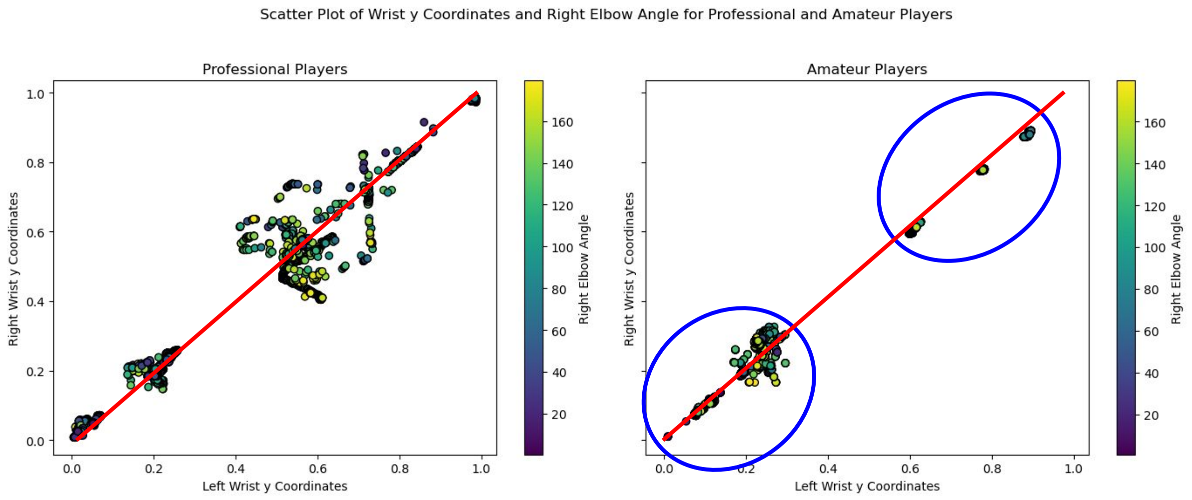
Comparison	Professional	Amateur
Correlation (left and right wrist x-coordinates)	positive correlation, forming a distinct diagonal line of higher gradient	positive correlation but is less defined with a lower gradient
Clustering	points are more densely clustered, suggesting a more consistent technique	points are more spread out, suggesting greater variability in technique



CORRELATION ANALYSIS

- Scatterplots display the relationship between the left wrist x-coordinates (x-axis) and the right wrist x-coordinates (y-axis)
- Color of each point representing the corresponding right elbow angle

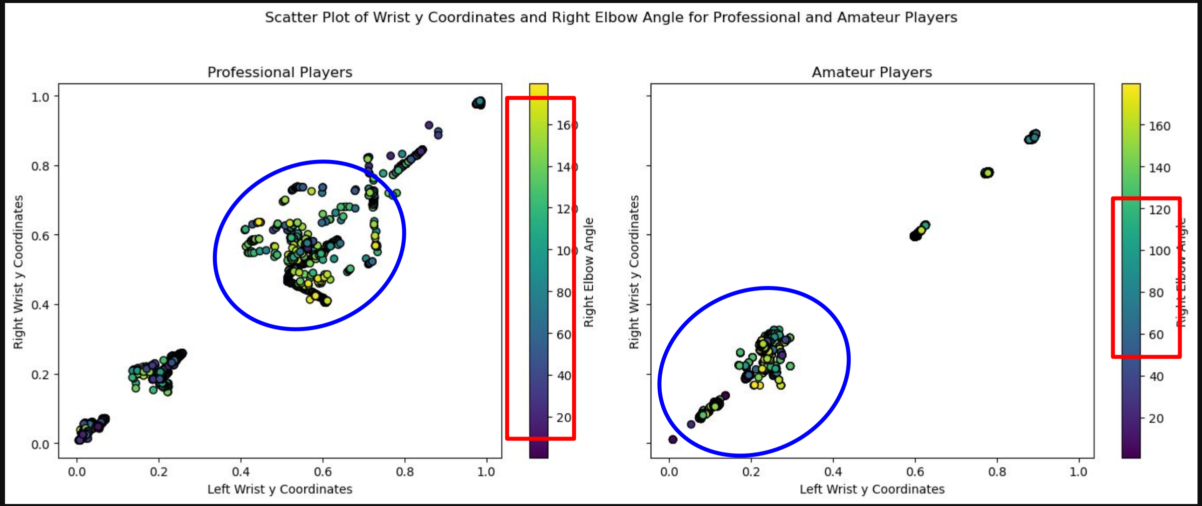
Comparison	Professional	Amateur
Range of right elbow angles	broader with angles ranging from around 20 to 160 degrees	narrower, mostly between 60 and 120 degrees
Correlation (wrist positions and right elbow angles)	higher right elbow angles (warmer colours) correspond to wrist x-coordinates of a narrower range	higher right elbow angles (warmer colours) correspond to wrist x-coordinates of a wider range



CORRELATION ANALYSIS

- Scatterplots display the relationship between the left wrist x-coordinates (x-axis) and the right wrist x-coordinates (y-axis)
- Color of each point representing the corresponding right elbow angle

Comparison	Professional	Amateur
Correlation (left and right wrist y-coordinates)	positive correlation, forming a distinct diagonal line with similar gradient to amateur	positive correlation, forming a distinct diagonal line with similar gradient to professional
Clustering	points are more densely clustered, suggesting a more consistent technique	points are more spread out, suggesting greater variability in technique



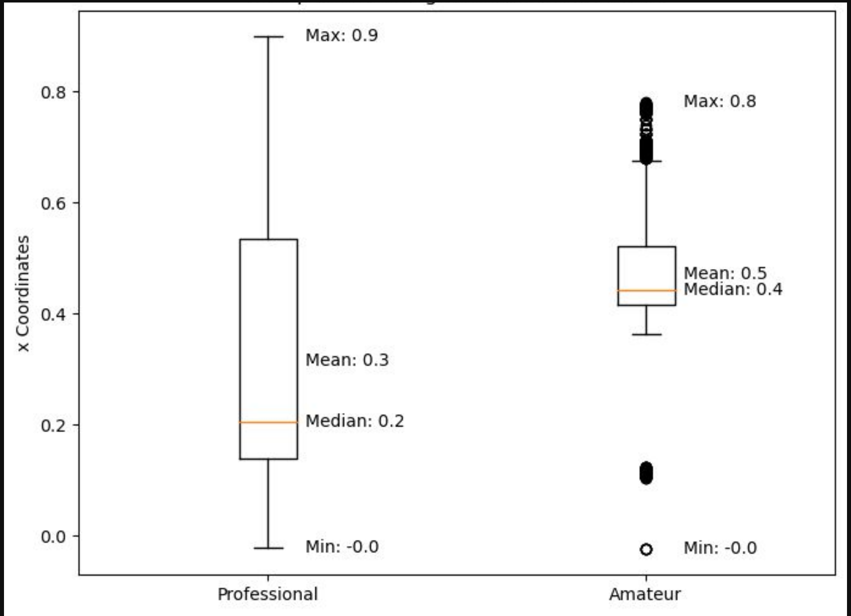
CORRELATION ANALYSIS

- Scatterplots display the relationship between the left wrist x-coordinates (x-axis) and the right wrist x-coordinates (y-axis)
- Color of each point representing the corresponding right elbow angle

Comparison	Professional	Amateur
Range of right elbow angles	broader with angles ranging from around 20 to 160 degrees	narrower, mostly between 60 and 120 degrees
Correlation (wrist positions and right elbow angles)	higher right elbow angles (warmer colours) correspond to higher wrist y-coordinates	higher right elbow angles (warmer colours) correspond to lower wrist y-coordinates

DESCRIPTIVE ANALYSIS

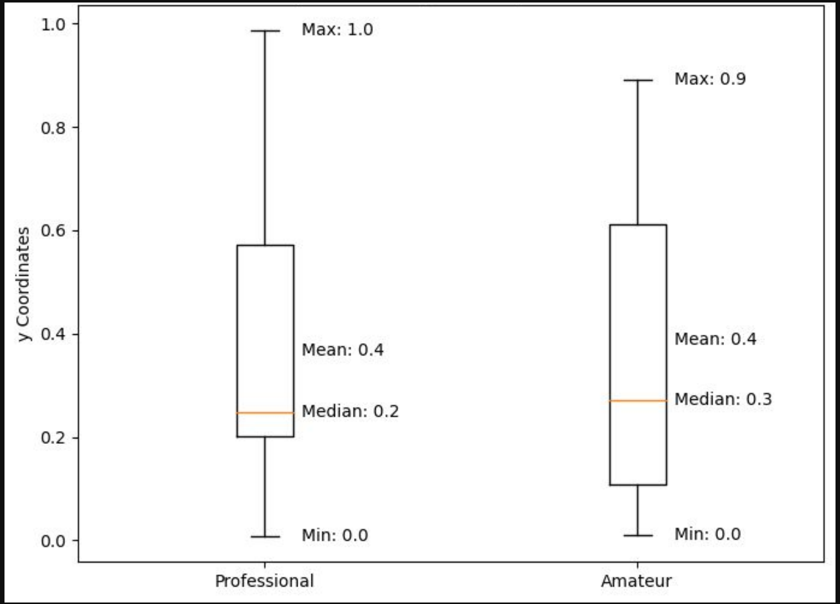
Comparison of Right Wrist x-Coordinates



Group	Distribution	Insights
Professional	• right-skewed, concentrated around center. • high variability in lower x-coordinates.	most data points are lower, indicating controlled movement
Amateur	• right-skewed, wrist positions further to the right • outliers suggest extreme positions	wider spread may affect shot effectiveness.

DESCRIPTIVE ANALYSIS

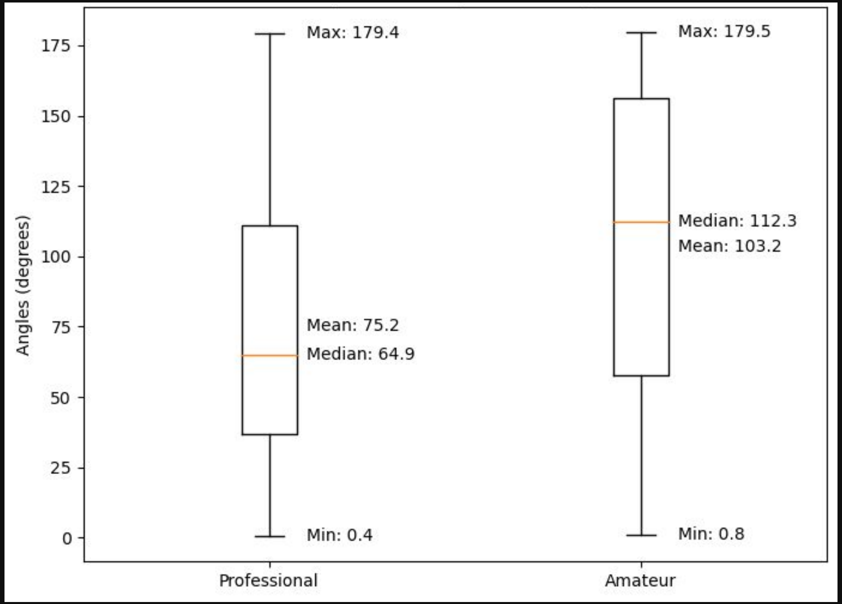
Comparison of Right Wrist y-Coordinates



Group	Distribution	Insights
Professional	right-skewed, positions mostly lower but capable of high reach.	indicates a technique involving lower wrist positions.
Amateur	symmetric across the vertical range, less reach to the top compared to professionals.	less variability in height during play.

DESCRIPTIVE ANALYSIS

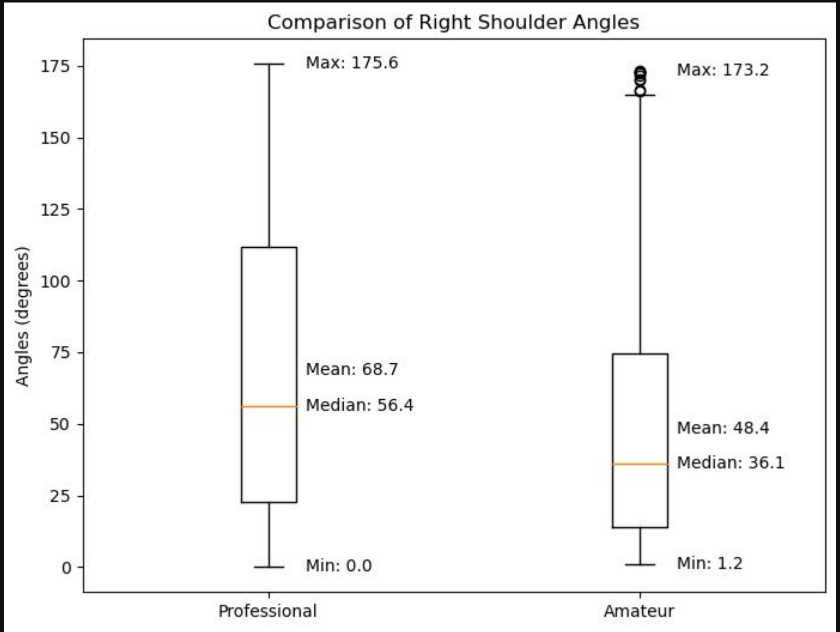
Comparison of Right Elbow Angle



Group	Distribution	Insights
Professional	narrower interquartile range (40 to 110 degrees), consistent technique with acute angles.	optimized for power, reflects consistent technique.
Amateur	broader interquartile range (60 to 160 degrees), higher variability and less optimal biomechanics.	indicates potential inefficiency in serve mechanics.

DESCRIPTIVE ANALYSIS

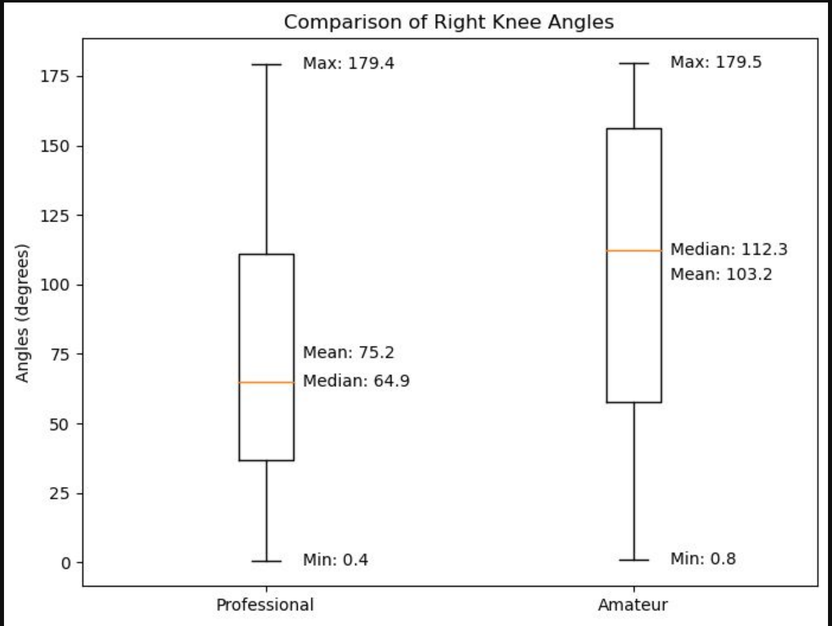
Comparison of Right Shoulder Angle



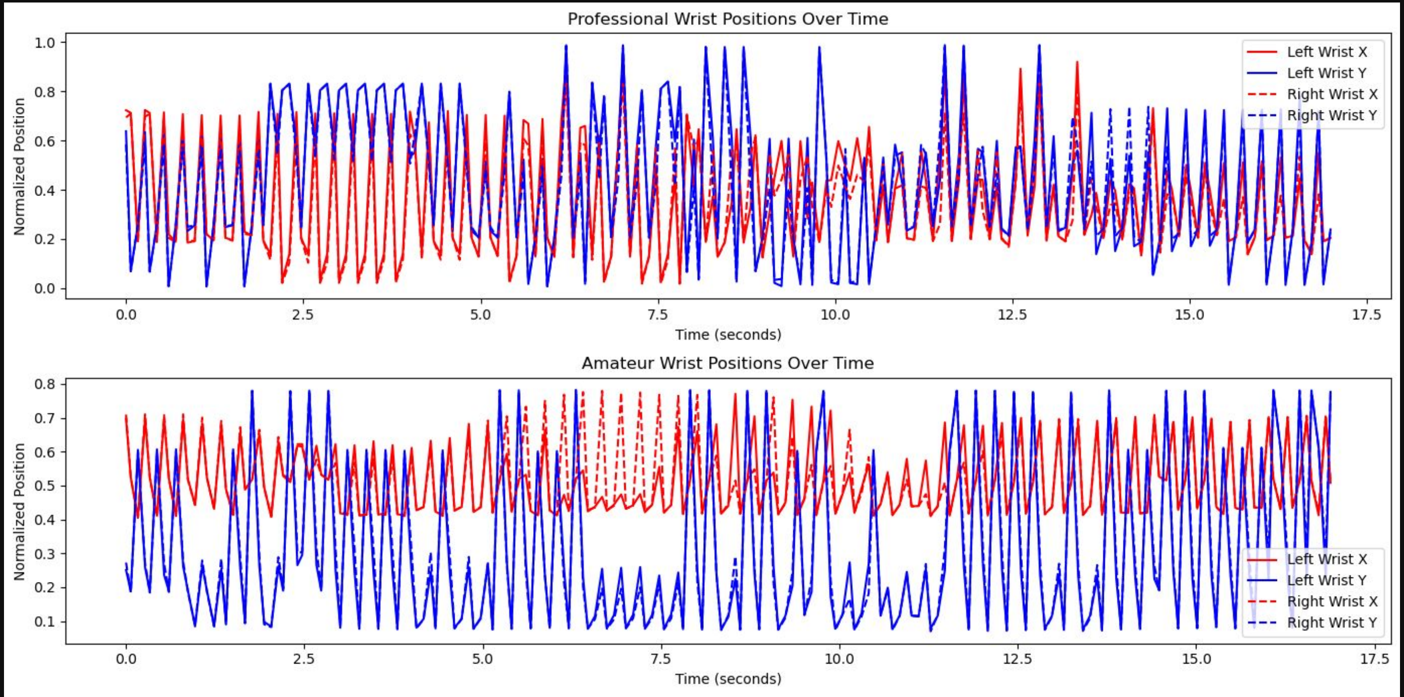
Group	Distribution	Insights
Professional	distribution shows dynamic technique with high variability and some extreme values.	ability to vary technique dynamically.
Amateur	less extreme angles, tighter concentration around the median despite a wide range.	suggests less aggressive techniques.

DESCRIPTIVE ANALYSIS

Comparison of Right Knee Angle



Group	Distribution	Insights
Professional	predominantly moderate flexion, indicating stable and powerful stance.	conducive to effective play.
Amateur	higher knee flexion, suggesting less efficient movement and a potential area for technique improvement.	higher flexion may indicate inefficiencies.



TIME SERIES ANALYSIS

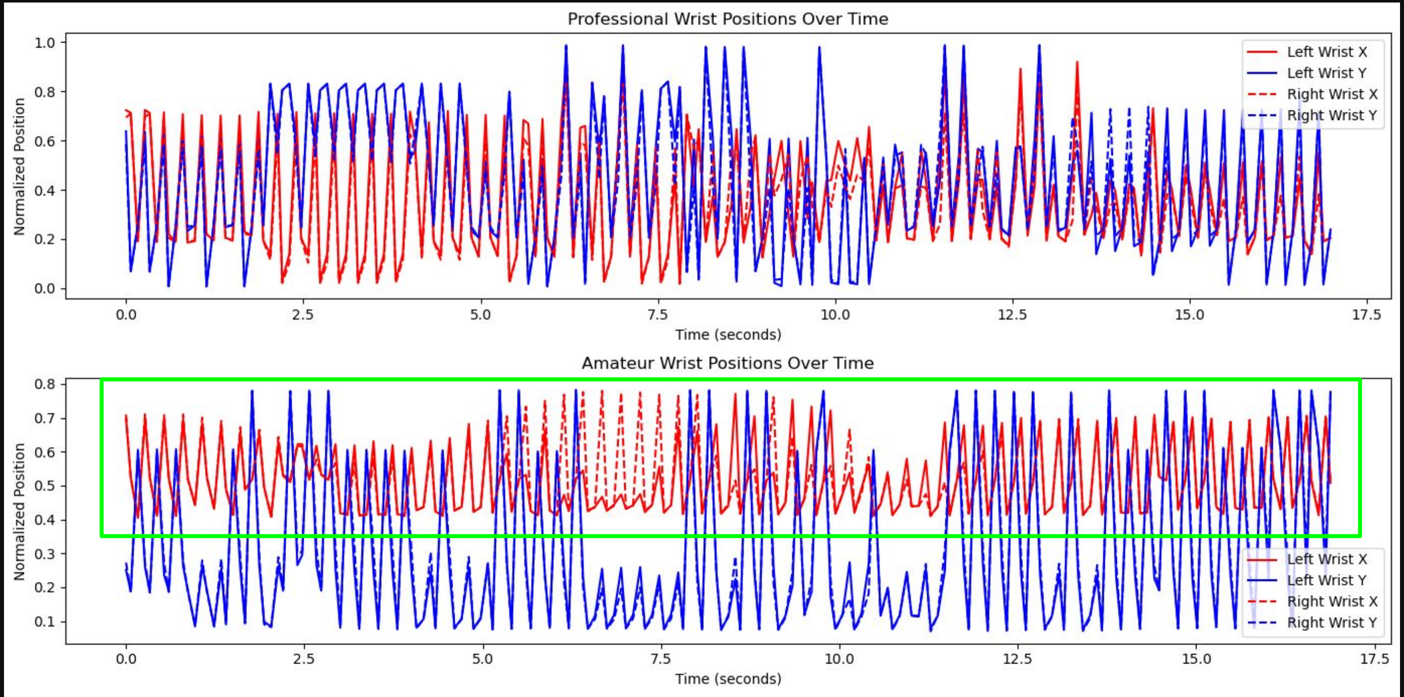
FIRST GLANCE

red: x-coordinates

blue: y-coordinates

Professional: The wrist positions exhibit clear periodic oscillations, indicating the repetitive and controlled motions involved in professional tennis strokes and swings.

Amateur: The wrist movements lack a clear periodic structure and appear more erratic and irregular.

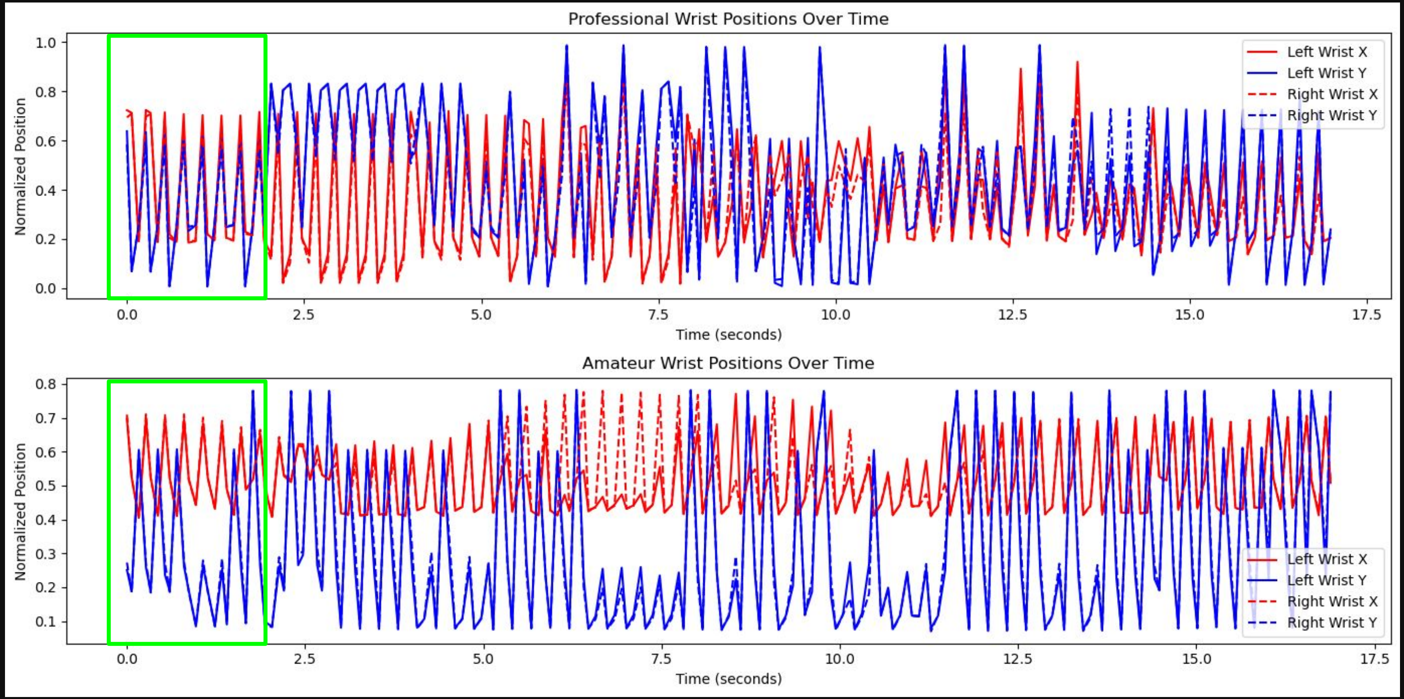


TIME SERIES ANALYSIS

red: x-coordinates

blue: y-coordinates

- The wrist x-coordinates for amateurs have a higher value which suggest that amateurs have a tendency to extend their wrist reflecting less optimal biomechanics.
- The amplitudes of the oscillations are smaller from 0.3 to 0.7 which indicates lesser wrist articulation and range of motion.



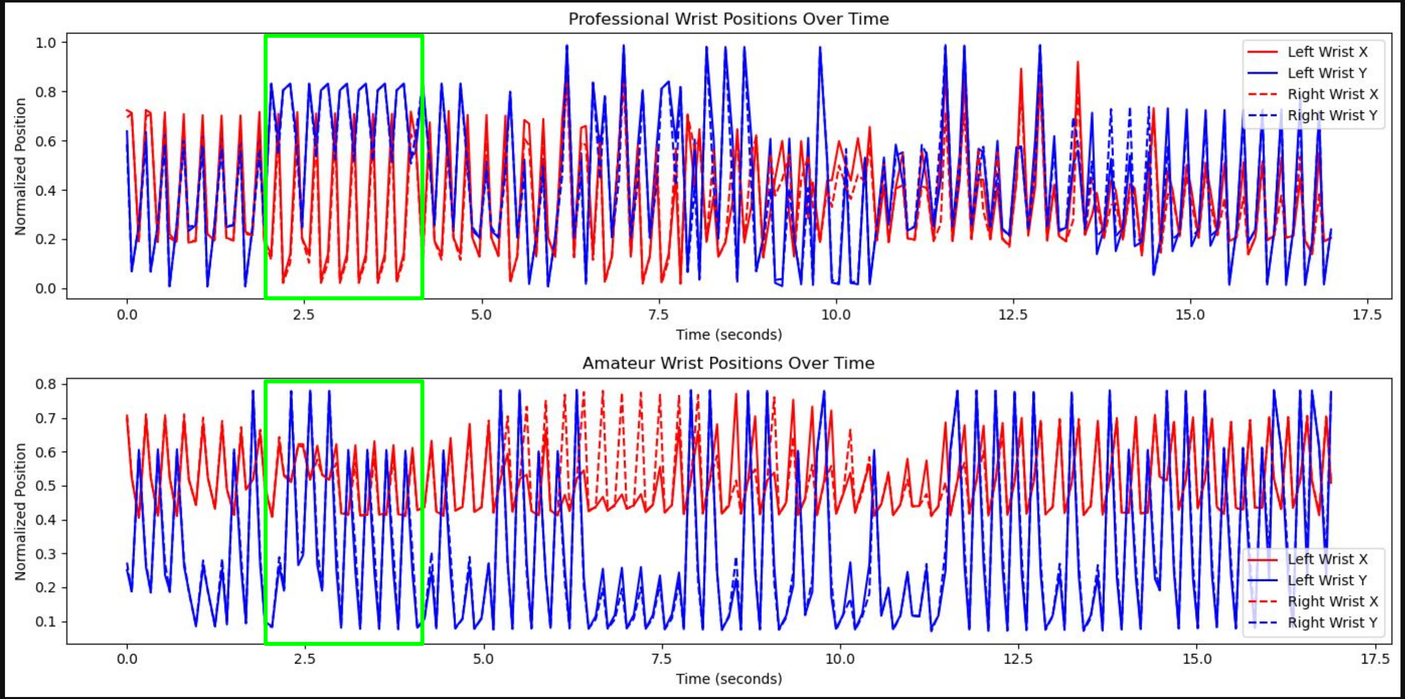
TIME SERIES ANALYSIS

red: x-coordinates

blue: y-coordinates

- Amateurs: In the first few seconds (around 0-2 seconds) of the plotted time, the left wrist x-coordinate and y-coordinate appear to move in opposite directions. The x-coordinate starts higher, then decreases, while the y-coordinate begins lower and increases.
    - reflect the amateur players initially setting up their wrist positions during the serve motion's trophy pose or early backward hand pronation before they start the forward swing.

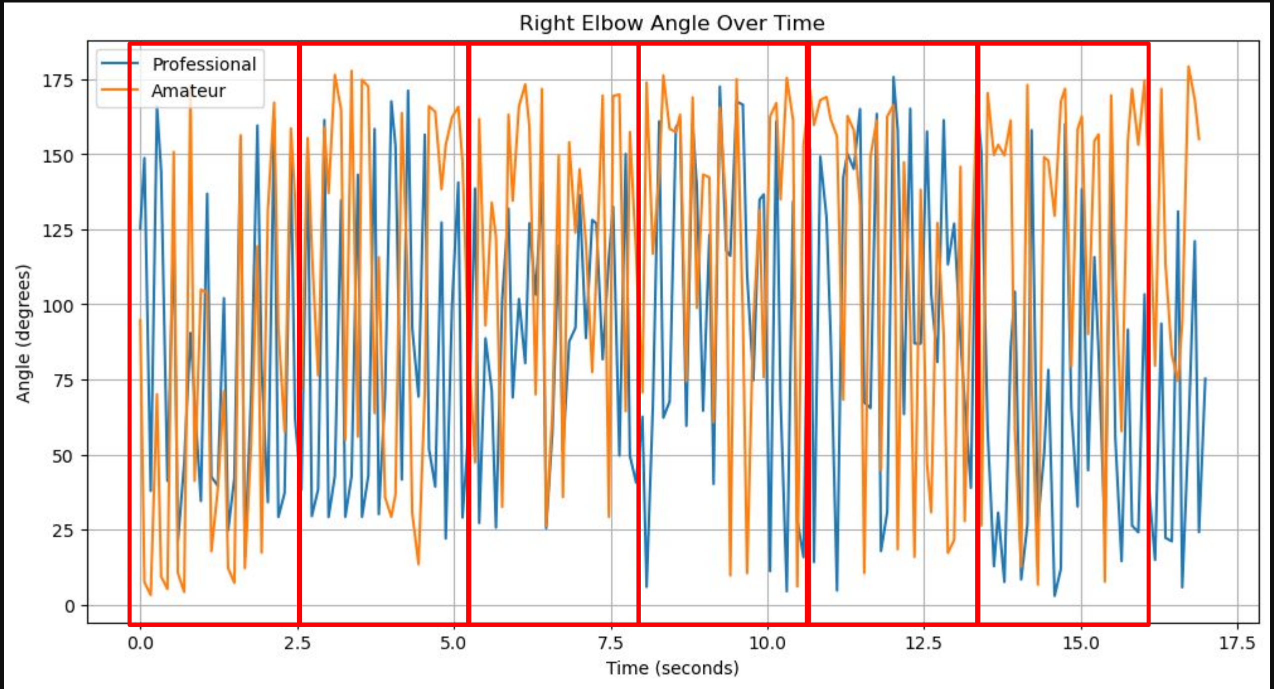
TIME SERIES ANALYSIS



red: x-coordinates

blue: y-coordinates

- Professionals: From 0.25 to 4 seconds of the plotted time, the left wrist x-coordinate and y-coordinate appear to move in opposite directions.
  - may correspond to the professionals setting up and preparing for their next shot after completing the previous stroke.

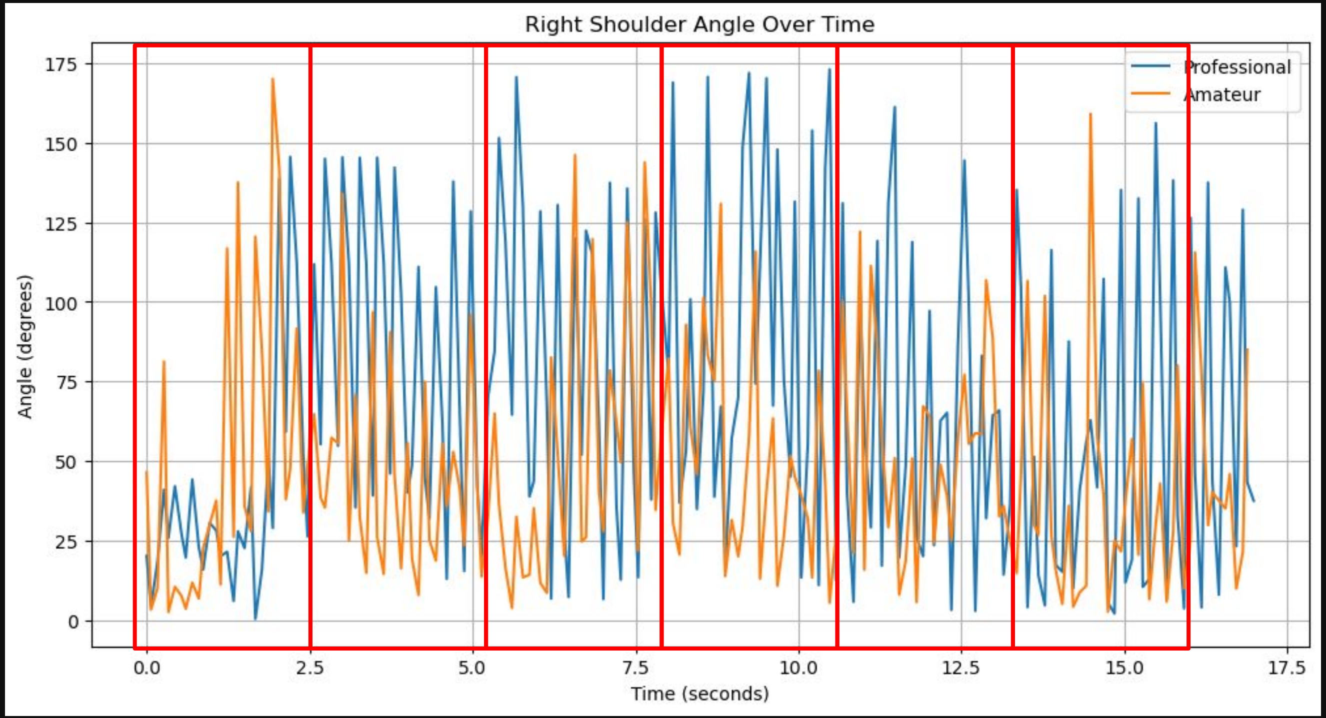


TIME SERIES ANALYSIS

RIGHT ELBOW ANGLE STABILITY

Professional: The right elbow maintains a relatively **stable range**, primarily staying within a **narrower angle window**. This stability is crucial for delivering powerful and accurate serves, as it indicates a controlled release of energy.

Amateur: The elbow angle of the amateur spans a **broader range**, showing **significant fluctuations** that could contribute to less effective and less predictable serves.

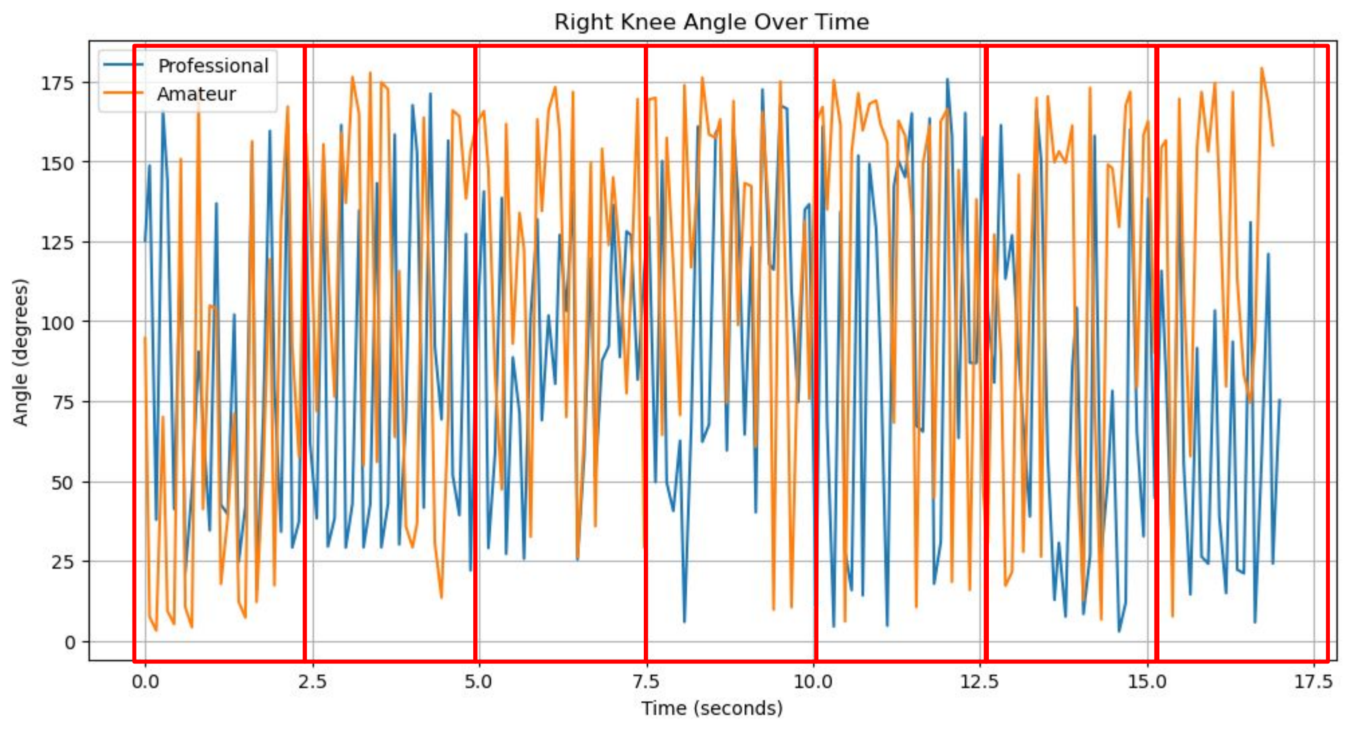


TIME SERIES ANALYSIS

RIGHT SHOULDER ANGLE STABILITY

Professional: The right shoulder angle maintains a **smooth oscillatory pattern** which means that it follows a **consistent change in angles**.

Amateur: The shoulder angle of the amateur spans a **broader range**, with some angles dropping quite low and others peaking suddenly, indicates lack of control and less predictable, less powerful serves.



TIME SERIES ANALYSIS

RIGHT KNEE ANGLE STABILITY

Professional: The right knee maintains a relatively **stable range**, primarily staying within a **narrower angle window**.

Amateur: The knee angle of the amateur spans a **broader range**, showing **significant fluctuations**.

Optimizing tennis serves for the amateur

1. Focus on Key Biomechanical Differences

- Angle Adjustments: Based on the statistical findings, Alex could focus on adjusting the amateur player's elbow, shoulder, and knee angles to match those observed in professional players.

  This might involve:

- Lowering the right elbow and knee angles during the serve to create more acute bends, as seen in professionals, which could aid in achieving more power and control.
- Adjusting the shoulder angle for better alignment and force transmission throughout the serve.

2. Use of Technology

- Implement Pose Estimation Tools: Regularly use pose estimation tools in training sessions to gather data on the player's serve mechanics, allowing for ongoing adjustments and monitoring improvements over time.

04

CONCLUSIONS AND RECOMMENDATIONS

PREDICTING TENNIS SERVES OUTCOMES

CONCLUSIONS

Model Performance:

- The models tested did not demonstrate significant learning or improvement over the training period.
- Both models showed a consistent performance with an accuracy of around 25.36%, which suggests that the models might be struggling with the complexity of the task or issues related to data quality.

Loss Metrics:

- Both models exhibited nearly constant loss values across all training epochs, suggesting that neither model effectively reduced its error rate, possibly indicating that the models reached a local minimum.

RECOMMENDATIONS

Hyperparameter Tuning:

- Adjusting hyperparameters such as the learning rate, increasing the number of epochs to enhance the model's ability to learn from the data.

Data Quality and Preprocessing:

- Reassess the data preprocessing steps to ensure that the input data is optimally prepared for the models could also help.
- Segment or augment the data to provide more varied learning examples.

POSE ESTIMATION AND ANALYSIS
CONCLUSIONS

These are the key insights:

Shoulder Angle Optimization:

- Professionals often utilize lower shoulder angles, typically between 23.4 to 32.1 degrees, optimizing power and control.
- Amateurs display a broader range of shoulder angles, with a peak around 64.1 to 73.8 degrees, indicating a less consistent and possibly less effective technique.

Elbow and Knee Angle Differences:

- There is a significant difference in elbow and knee angles between professional and amateur players, with professionals using angles that likely enhance stability and efficiency, while amateurs show greater variability and less biomechanical advantage.

Statistical Significance:

- A t-statistic of -21.27 with a p-value near zero confirms a significant difference in right knee angles between the two groups, suggesting different biomechanical strategies or conditioning.

POSE ESTIMATION AND ANALYSIS
RECOMMENDATIONS

Predictive Modeling:

- Develop machine learning models to predict outcomes of serves (e.g., successful, fault) based on pose data. Techniques such as logistic regression, decision trees, or more complex models like Random Forests and SVM can be used to understand what features most significantly predict serve success.

Segmentation of Player Styles:

- Use advanced clustering techniques to segment players or serves into distinct styles or types based on biomechanical data. This can help in customizing coaching strategies to player-specific needs.

Biomechanical Simulation and Modeling:

- Simulate Serve Motions: Use the data to create biomechanical models that simulate different serve techniques. These models can help in visualizing the serves and understanding the mechanical loads on different body parts.

Thank you!

Do you have any questions

adiemus80@gmail.com

CREDITS: Diese Präsentationsvorlage wurde von **Slidesgo** erstellt, inklusive Icons von **Flaticon** und Infografiken & Bildern von **Freepik**

Please keep this slide for attribution