Cricket Fast Bowling Optimization Using Machine Learning Pose Estimation Modeling

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Cricket Pose Estimation GitHub Repository

Contents

Abstract

Fast bowling in cricket is a biomechanical process that involves multiple phases: Run-up, Jump, Ball Delivery, and Follow-through. The goal of my project was to analyze the jump and ball delivery phases using computer vision, ML-based pose estimation, and physics-based analysis to identify key differences between professional and novice bowlers, providing both visual feedback (annotated videos) and data-driven insights (statistical clustering).

After evaluating multiple models, I developed a program using the Python-based Mediapipe Pose Estimator library, which utilizes 33 pose points. Among 34 biomechanical parameters, the study identified 17 key parameters that affect bowling performance, with a focus on arm, leg, wrist, and foot positioning, as well as wrist speed. The original dataset was created from 30 professional and 5 novice bowlers' (46 balls) MP4 videos.

The software reliably captured and annotated the video of novice bowlers, overlaying body angles on video frames and maximum wrist speed for subjective analysis. Statistical clustering with Dynamic Time Warping revealed that novice bowlers formed distinct biomechanical clusters separate from professionals, highlighting inefficiencies in their technique.

Using Dynamic Time Warping, the data were successfully aligned despite the different time frames of the videos. The novices in this study achieved skill parity with professionals, ranging from 35% to 64%. The rate of change in the right leg, foot, and wrist did not significantly impact the bowling action. Novice bowlers exhibited lower wrist speed and greater variability in joint angles, which affected ball velocity and led to inconsistent mechanics.

This study employed a data-driven approach to enhance fast bowling techniques, demonstrating the potential of AI and biomechanics to improve sports performance. Future work on this study will expand to incorporate a multi-person model, allowing for the analysis of a broader range of videos and enabling 3D pose estimation to enhance the accuracy of the angles. The addition of a supervised AI learning model and ball detection will enable real-life AI coaching and analysis, making it easier for fast bowlers to receive clear, actionable feedback and quantitative data. Making this into an app will allow for easy accessibility on even a phone, so that bowlers can receive real-time AI coaching.

1. Introduction

For over 400 years, cricket has been a game of strategy and precision, with fast bowling playing a critical role in shaping the sport's modern form. Speed and body mechanics are crucial for elite bowlers, yet many novices struggle with proper alignment, which limits their performance.

To address this issue, I developed a project that compares novice fast-bowl action with that of professionals using computer vision and pose estimation, identifying areas where novice bowlers lag behind professionals.

(a) Jasprit Bumrah vs. Akash Deep

(b) Virat Kohli's back-foot block

Figure 1: Pose estimation comparison between bowlers and batsmen in the 2025 Border-Gavaskar Trophy

Pose estimation has already seen widespread use across various domains, including sports performance analysis, injury prevention, and virtual coaching. In cricket, it has primarily been applied to ball tracking (e.g., FullTrack AI) and batsman stroke analysis, especially at the elite level. This technology has even made its way into international broadcasts.

During the 2024–2025 Border-Gavaskar Trophy in Australia, pose estimation software was integrated into live coverage to provide technical insights, as seen in Figure 1. During these broadcasts, analysts often discussed how players were bowling and batting, using pose estimation to highlight key differences in technique. For instance, they demonstrated how Jasprit Bumrah's unique bowling action allows him to release the ball later than Akash Deep, making the delivery harder to pick up—thus explaining why Bumrah is more challenging to play.

In batting analysis, pose estimation has been used to assess players such as KL Rahul, Rohit Sharma, and Virat Kohli. Analysts found that Rahul's foot and head positions consistently aligned with the ball. In contrast, Rohit and Virat occasionally displayed imbalance, leading to mishits off the edge rather than the middle of the bat.

Despite extensive research, there has been a lack of comparison between professional and novice fast bowlers using pose estimation. This represents a significant gap, as novice bowlers often lack access to specialized equipment or affordable tools to assess and improve their technique. Therefore, developing a method that enables aspiring fast bowlers to compare their biomechanics with those of professionals objectively would be highly valuable, especially for those without access to high-end facilities. Due to the limited availability of pre-trained machine learning models and side-on-angle bowling footage, I selected MediaPipe, along with a Python-based clustering approach using Dynamic Time Warping (DTW), for this project. The objective of the software is to provide an open-source, accessible tool using Python libraries that others in the cricket and data science community can further develop. The program consists of three core components:

1. **Video Analysis & Dataset Creation**: Automatically processes fast bowling videos to extract and annotate pose data, generating labeled visual outputs for further analysis and model training.
2. **Clustering & Biomechanical Visualization**: Segments bowlers into distinct groups based on biomechanical similarities (e.g., joint angles, motion patterns), and presents these clusters visually for interpretability.
3. **Bowler-Specific Performance Metrics**: Computes individualized metrics such as arm extension angle, angular velocity, and estimated ball speed to provide targeted insights and feedback for technique optimization.

This approach introduces a data-driven, objective method for analyzing fast bowling, offering an alternative to traditional tools such as radar guns. As demonstrated in the India vs. Australia Border-Gavaskar Trophy, pose estimation has already proven valuable in professional contexts. By extending this technique to help analyze and improve amateur bowling, the software aims to support fast bowlers in identifying and addressing deficiencies in their action using only video input and free tools.

2. Literature Review

Introduction

This project encompasses several areas of interest, including cricket biomechanics, pose estimation software, and existing studies focused on improving and analyzing bowling speed. Hence, the literary analysis required was extensive.

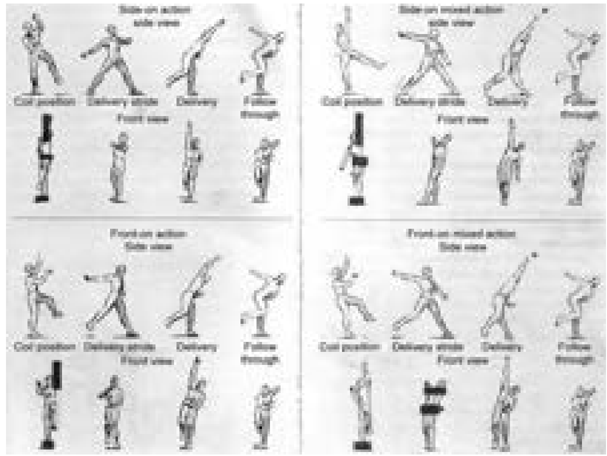
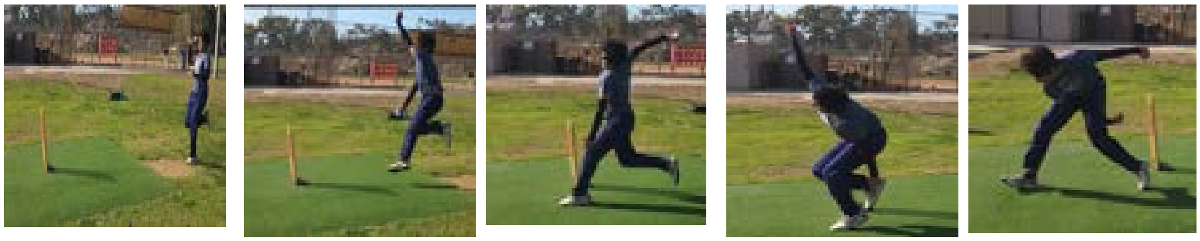


Figure 2: Stages of fast bowling for different types of bowling actions

Many questions needed to be answered to start this project. What factors affect bowling speed? What pre-existing methods exist to improve fast bowling? What is pose estimation, and how is it used? Do other sports use technology in this way to help their players improve? The purpose of this review was to answer these questions and gain an understanding of the current state of the field.

Fast Bowling Action

Bowling actions can vary between individuals, as seen in Figure 2. However, any fast bowler can split their action into several stages. First is the run-up, where the bowler runs to the crease from a distance away, usually 15-25 steps, although it can be more or less based on the bowler. The goal during this stage is to gain momentum 3. Once the bowler is close to the crease, they transition into the delivery stride or jump, where they conserve the momentum from the run-up as energy while “loading up” by holding the ball closer to their chest. After their back foot lands, they transition into the delivery phase, where they straighten their front foot and land while rotating their arms to “bowl” the ball. The momentum from the rest of the body is transferred into the ball, allowing it to be bowled at a fast speed. The final phase is the “follow-through,” as overall momentum pushes your body forward even after you deliver the ball.



Run up Jump Delivery phase Release point Follow through

Figure 3: Real-Time Bowling Action Phases Captured

Key Parameters for Fast Bowling Action

It is no secret that body angles and positions are directly correlated to increased speed in fast bowling. The article “Relationships Between Fast Bowling Technique and Ball Release Speed in Cricket(Worthington, King, Ranson)” [17] mentions 11 main factors that they looked at involving fast bowling speed and the correlation each factor had with explaining variations in speed.

Figures 4 and 5 highlight the key factors to consider when evaluating bowling speed and the significant contributors to it, expressed as a percentage. They reference that parameters like knee and shoulder angles at the release point were critical towards bowling speed, meaning that how straight your arms and legs are during the release helped contribute to a faster speed. Additionally, shoulder rotation played a significant role in increasing bowling speed. Another study [18] “Validating an inertial measurement unit for cricket fast bowling: a first step in assessing the feasibility of diagnosing back injury risk in cricket fast bowlers during a telesport and exercise medicine consultation” refers to using measurement to capture bowling kinematic motion to identify actions that could cause harm to the bowler themself.

Table 2 Regression equations for release speed using stepwise linear regression

Number of Parameters	Technique Parameter(s)	Coefficient	*P*-Value	Percentage Explained
1	Shoulder angle at BR	0.060	.012	30.3
2	Shoulder angle at BR	0.061	.002	56.9
	Run-Up speed	1.485	.005	
3	Shoulder angle at BR	0.038	.074	
	Run-Up speed	1.623	.002	65.5
	Knee angle at BR	0.033	.063	
4	Shoulder angle at BR	0.035	.084	
	Run-Up speed	1.555	.002	70.1
	Knee angle at BR	0.029	.087	
	Shoulder angle at FFC	0.017	.150	

Abbreviations: front foot contact (FFC); ball release (BR).

Figure 4: Bowling parameters from "Relationships Between Fast Bowling Technique and Ball Release Speed in Cricket" and their correlation to bowling speed

These IMUs (Inertial Measurement Units) are sensors that detect the motion created when someone is bowling, although they require extensive laboratory equipment.

The study consisted of 8 players who combined bowled a total of 192 balls while wearing these IMU sensors. By doing this, they can determine how much certain variables contribute to the overall bowling speed and, hence, determine where someone is lacking. While we look at how specific body kinematics come into the picture, there is a question of whether men and women fast-bowlers rely on the same biomechanics to produce their speed. In the study [19] "Anthropometric and biomechanical factors in elite male and female fast bowlers," the researchers not only examined biomechanical factors but also compared the biomechanical characteristics of male and female fast bowlers.

In their results, they found that height-related variables, such as shoulder span and arm span, were all reduced in women, which tended to make them bowl at lower speeds than males. They also found that women tended to have reduced hip flexion and slower run-ups compared to males, instead having increased trunk and pelvis rotation during their bowling action. This difference in the way females bowl compared to males suggests that the biomechanics they use to generate pace differ from those used by males. Hence, identifying bowling parameters for women differs from those for men. Due to this situation and our limited resources, our study consisted of male professional and novice bowlers.

Cricket Biomechanics and Technology

There are several other papers focused on the usage of pose estimation. [14] “Cricket Biomechanics Analysis of Skilled and Professional Fast Bowling Techniques,” [16] “Objective Analysis of Cricket Fast Bowling Intensity,” and [14] “Enhancing Cricket Performance Analysis with Human Pose Estimation and Machine Learning.” The first two papers deal with injury to fast bowlers and use sensors attached to the body, like IMUs, to check what their body angles are and correlate them to how much they are getting injured.

Table 1 Range, mean and standard deviation of the 11 technique parameters

Technique Variable	Range	Mean ± SD
Run-Up speed ($m \cdot s^{-1}$)	4.77–6.76	5.79 ± 0.58
Knee angle at FFC (°)	148.3–172.7	164.1 ± 6.1
Knee angle at BR (°)	120.3–186.2	167.3 ± 18.8
Knee flexion from FFF till BR (°)	0.0–44.8	17.5 ± 11.2
Knee extension from FFF till BR (°)	0.3–26.3	11.9 ± 7.4
Shoulder girdle forward-rotation (°)	80.6–143.4	115.5 ± 18.2
Upper trunk flexion from FFC till BR (°)	11.2–50.6	31.0 ± 8.3
Shoulder angle at FFC (°)	288.0–365.0	331.2 ± 22.1
Shoulder angle at BR (°)	186.9–257.6	219.4 ± 15.3
Min. pelvis-shoulder separation (°)	–63.3 to –27.5	–39.6 ± 9.6
Time of min. pelvis-shoulder separation (s)	–0.020 to 0.057	0.031 ± 0.019

Abbreviations: front foot contact (FFC); front foot flat (FFF); ball release (BR).

Figure 5: Bowling parameters from “Relationships Between Fast Bowling Technique and Ball Release Speed in Cricket” and the range, mean, and deviation across all participants

The last paper examines the stroke play of cricket batsmen, as observed in the Border-Gavaskar Trophy match, where they analyze body positions when playing specific shots.

Another set of literature involved the uses of pose estimation and which models were most beneficial. An article from viso.ai, titled “Human Pose Estimation- Ultimate Overview in 2025,” discusses the various types of pose estimation models and their benefits. Pose estimation is a computer vision task that tracks different key points in a person, such as the left shoulder or the right ankle. They discuss three main types of pose models: Kinematic, Planar, and Volumetric, as illustrated in Figure 6. The kinematic model is a skeleton-based model that includes both a set of joint positions and limb orientation to represent the human body. This model primarily focuses on how joints move in relation to one another and makes sure that joints only move in ways that the human body can physically move. The planar model uses rectangles to better mimic the appearance of the human body. It can't capture depth, but is better able to show gestures and other motions. The volumetric model can be shaped to represent the human body entirely, but it is also a lot more complex to install. It is usually used for motion capture for animations or video games. Due to the project's specific needs, I chose to examine a kinematic model. There is also discussion about the most popular pose estimation models, such as MediaPipe and OpenPose. The article expands on pose estimation by discussing deep learning techniques that enable objects to be detected within their surroundings. It also discusses some of the flaws, such as difficulty detecting smaller joints and how different clothing and surroundings can interfere with pose estimation.

Fast bowling involves multiple stages, and biomechanical factors, such as joint angles, contribute to performance. Prior research used IMUs, MoCap, and sensors to measure body movement.

Pose Estimation in Sports

One paper closest to my research is [12] "Analysis of professional and professional tennis serves using computer pose detection" for tennis serves, where they used skilled professionals (control) with novices, using 72 frames of serve action and Welch's t-test technique. To account for timing differences, they aligned the data at the point where the racket made contact with the ball, allowing them to analyze overall trends and determine whether the timing of a serve affected its quality.

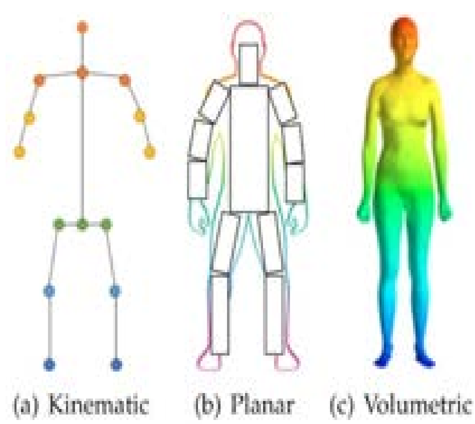


Figure 6: Main types of pose estimation

Additional Technological Advances for Cricket Players

The idea of using accessible technology to improve fast-bowling cricket actions is one that has been around for a while. The article [20] “Accessibility of Motion Capture as a Tool for Sports Performance Enhancement for Beginner and Intermediate Cricket Players” discusses how motion capture or “MoCap” can be used to help beginner bowlers. It has been used in both the batting and bowling aspects of cricket. During bowling, high-tech cameras can capture a variety of essential variables to help players improve their performance. Cricket bowlers are limited to flexing their arms less than 15 degrees during their delivery, something that can make certain variations, especially for spin bowlers, more challenging to bowl legally and safely. However, MoCap can analyze the bowler’s joint moments and determine areas for improvement. Although some concerns exist since cricket is played outdoors, innovations have already been developed to address these issues. Researchers have developed a wearable arm sensor that does not interfere with bowling actions, allowing for the measurement of arm flexion angles. Although still in development, it could have potentially helped spinners. They also discuss another group that used a cricket ball with magnetometers to measure the speed and rate of turn, while also having the bowlers wear IMU sensors. This allowed them to demonstrate a relationship between several kinematic variables in the arm, such as the wrist and the rate of turn. A few other examples explained and discussed the use of IMUs in measuring specific fast bowling angles, such as knee and trunk bending, and how rear leg movement affects fast bowling.

3. Procedure

Flow Diagram

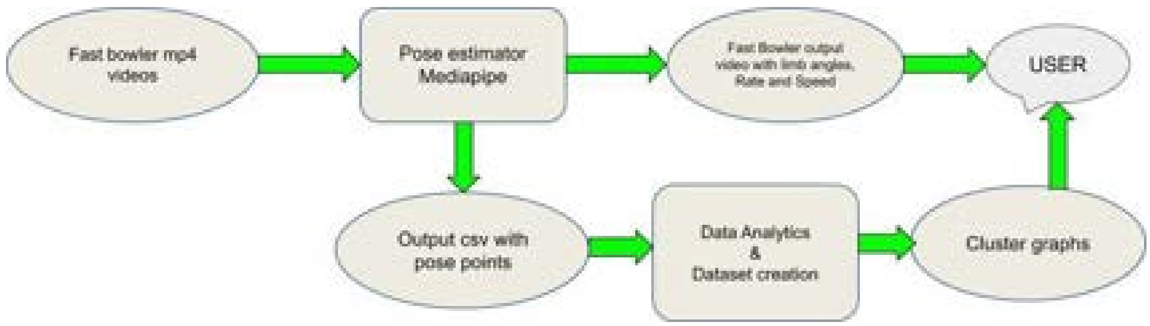


Figure 7: Outputs produced by the pose estimation model

Pose estimation model

Identified the best Pose estimation machine learning model after evaluating Openpose, YOLO, OpenCV/TensorFlow, to narrow down on Mediapipe, which is capable of 33 pose points. I wrote the Mediapipe workflow in Python using Jupyter Notebooks, which takes any mp4 video file to process frame-by-frame, identifying 16 pose points like shoulder, elbow, hip, wrist, fingers, etc, critical for bowling action. The points are provided in (x,y) coordinates for each frame. I calculated eight limb angles, Right and Left: Leg, Arm, Foot, and Wrist angles using numpy. The ball release frame is manually inputted and marked with time T=0 to time-align all videos. Negative time indicates cricket runup and jump, and positive time indicates ball delivery and follow-up. The model is optimized to run on a PC without a GPU. A GPU would allow for better video processing, but since this is meant to be a quick and easy way for bowlers to process their videos, a model that works without a GPU is sufficient. The MP4 video can be captured via smartphone or a computer camera side-on to the bowler. The program provides live output MP4 video of Skeletal lines on the bowler and also annotates angles and wrist speed on the top left of the video.

Data Analytics

I created two datasets, one for professionals and one for novices. The best 30 professional Cricket bowlers are identified in the Fast and Fast-Medium categories, and their speeds are listed, as seen in Table 1. The videos are sourced from the internet, and pose estimation is run to create a CSV file of angles, frame number, wrist speed, and frame time for each processed frame, as seen on the left diagram of Figure 8. Similarly, Novice bowlers are captured and analyzed using a smartphone, and an individual CSV file is created 10b.

Table 1: Bowling speeds, types, and records of international bowlers.

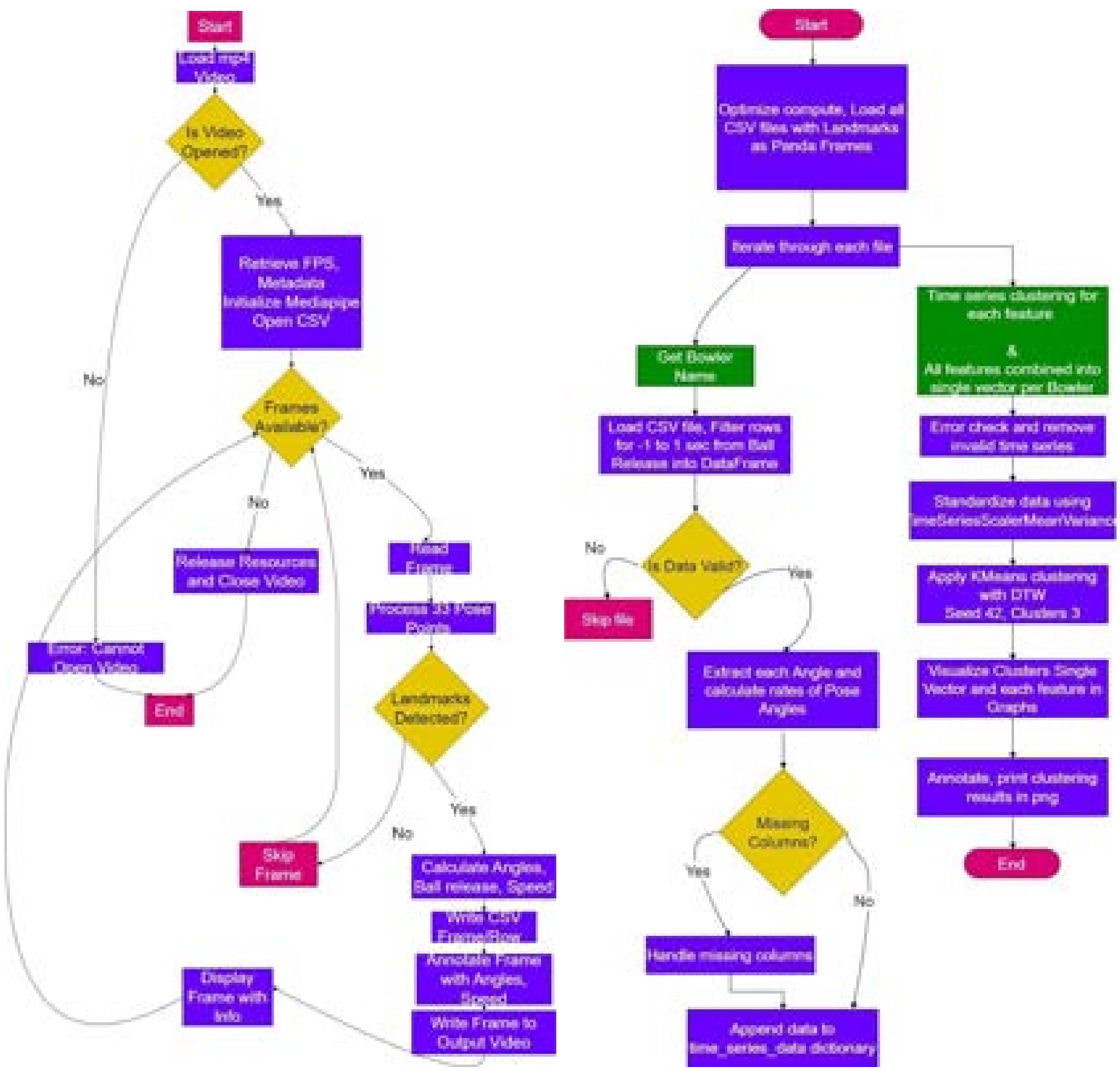
Bowler Name	Avg Bowling Speed	Max Bowling Speed	Type	International Wickets	Total Matches Played
Bumrah	142 km/hr	153.26 km/hr	Fast	443	204
Hardik Pandya	138.7 km/hr	146 km/hr	Fast medium	195	212
Jimmy Anderson	133 km/hr	145 km/hr	Fast medium	991	401
Jofra Archer	144 km/hr	154.65 km/hr	Fast	132	76
Dale Steyn	143.5 km/hr	156.2 km/hr	Fast	699	265
Anrich Nortje	147 km/hr	156.22 km/hr	Fast	159	83
Mohammad Shami	142.7 km/hr	153.3 km/hr	Fast	458	193
Umesh Yadav	143.8 km/hr	152.5 km/hr	Fast	288	141
Naseem Shah	144.1 km/hr	150 km/hr	Fast	132	74
Bhuvneshwar Kumar	133 km/hr	145 km/hr	Fast medium	294	229
Josh Hazlewood	137 km/hr	150 km/hr	Fast medium	484	215
Chris Woakes	133 km/hr	140 km/hr	Fast medium	385	212
Mark Wood	138 km/hr	154.4 km/hr	Fast	253	144
Trent Boult	138.7 km/hr	146 km/hr	Fast medium	611	253
Sean Abbott	138 km/hr	146 km/hr	Fast medium	59	48
Shoaib Akhtar	150.5 km/hr	161.3 km/hr	Fast	444	224
Pat Cummins	142.8 km/hr	153.5 km/hr	Fast	503	214
Scott Boland	135 km/hr	140 km/hr	Fast medium	75	30
Ishant Sharma	135 km/hr	145 km/hr	Fast medium	434	199
Mohammad Siraj	140 km/hr	145 km/hr	Fast medium	185	96
Arshdeep Singh	130 km/hr	135 km/hr	Fast medium	113	72

Dataset Creation

I used three different methodologies for the analysis of CSV files

- Time series where all the parameters for a bowler are combined into a single vector. Then different clusters are created.
- A time series is created for each feature and clustered
- Each feature is plotted without a time series, with the X-axis representing the frame time.

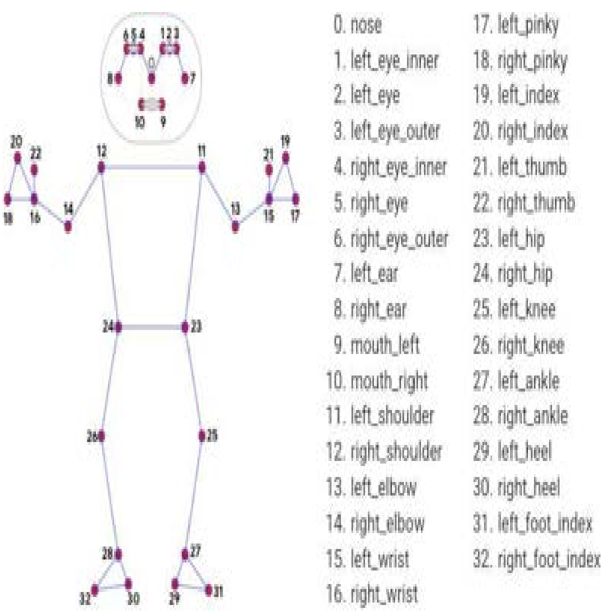
I used Python libraries (numpy, opencv, SKlearn, tslearn, pandas) to create a time series. Then applied Z score normalization in order to give all the data a mean of 0 and a standard deviation of 1, making it easier to analyse and getting rid of potential outliers that could occur from unique bowling actions or a bad ball. Then, the Time Series K-Means algorithm with DTW (Dynamic Time Warping) as metric for three clusters with a seed of 42. Using K-Means with Dynamic Time Warping allows for the data to be compared even though video lengths vary between the subjects and allows us to set a parameter from -1 to 1 seconds with the release point being t = 0, as shown by the right diagram of Figure 8. By creating 3 clusters, we got the optimal results and were able to compare the data using K-Means algorithm. I also computed the Pearson correlation coefficient between time steps for each feature and the average for a cluster in order to tell us how similar the data within a cluster was to each other.



Video process flow Output file processing and clustering graphs

Figure 8: How the video processing works

Figure 9: Output annotated video with bowler landmarks



1	frame_counter	frame_time	left_arm_angle	right_arm_angle	left_leg_angle	right_leg_angle	left_foot_angle	right_foot_angle	left_wrist_angle	right_wrist_angle	Speed
26	68	-0.2	173.65	187.84	195.63	184	127.6	179.15	168.52	191.61	4
27	69	-0.17	171.9	174.86	181.73	189.85	100.74	162.85	179.97	188.9	3.3
28	70	-0.13	170.15	188.24	178.83	208.86	98.12	147.17	168.86	195.47	2.7
29	71	-0.1	175.02	186.72	183.83	249.45	142.61	106.08	165.58	190.24	2.7
30	72	-0.07	172.47	189.59	195.69	207.09	144.49	135.8	178.75	191.35	3
31	73	-0.03	184.2	194.22	206.85	277.29	139.37	99.19	140.33	188.87	4.2
32	74	0	177.51	190.6	216.52	257.67	131.39	109.54	173.04	166.54	6
33	75	0.03	164.08	171	232.78	241.67	136.79	132.38	171.28	215.32	10.4
34	76	0.07	147.64	180.43	224.6	224.9	129.88	138.16	173.47	193.51	8.6
35	77	0.1	156.12	181.36	230.47	217.07	115.49	124.31	180.56	185.78	4.6
36	78	0.13	164.49	194.73	222.9	202.52	132.74	101.88	80.94	178.53	4.7
37	79	0.17	179.38	164.69	220.74	194.93	132.05	109.75	163.18	174.92	1.5
38	80	0.2	132.71	132.68	217.06	194.62	138.86	134.13	65.35	192.25	2.1
39	81	0.23	172.39	140.17	212.81	191.98	147.62	138.83	169.63	170.09	0.4
40	82	0.27	170.21	157	212.48	202.3	149.93	129.38	107.24	114.23	1.4
41	83	0.3	167.93	168.05	210.11	203.57	146.53	131.92	188.47	183.11	1.3
42	84	0.33	172.2	171.96	204.21	195.65	142.63	138.51	182.95	194.72	1.7
43	85	0.37	175.99	182.89	197.35	189.7	143.66	140.28	188.89	185.35	1.1
44	86	0.4	172.36	172.45	195.86	181.69	141.24	151.18	186.13	176.14	3.5

(a) Landmarks (b) output csv file

Figure 10: Output Landmarks and CSV File

4. Results

Pose Estimation Outputs

The outputs created by the program are :

- Output video annotated with Bowler Landmarks and pose points 9
- Cluster output with all features of a bowler combined 11

- Cluster output per feature, ex rightArmAngle or Rate of change 12
- Frame Time graphs for each bowler feature for deeper analysis 13

Summary

17 Cricket Fast bowling parameters were considered for clustering due to their high impact on a fast bowler’s action. These included the main points used in fast bowling to help provide the most beneficial data. 8 of these parameters are the angles of the arm, leg, wrist, and ankle, relative to the body, on both sides. These parameters were chosen because arm and leg straightness directly correlates with improved bowling speed, due to the ability to propel the ball with greater force. This was indicated by [17] “Relationships Between Fast Bowling Technique and Ball Release Speed in Cricket(Worthington, King, Ranson)” and the other fast bowling studies looked at. Wrist and Ankle position also correlates with producing a greater force behind the ball. The next 8 parameters were the rate of change of the arms, legs, wrist, and ankle on both the left and right sides. The rate of rotation of these points can also indicate higher bowling speeds, as a faster arm or leg rotation can increase the initial velocity of the ball when released. The final parameter is linear wrist speed on the right wrist. This parameter was chosen due to the majority of bowlers being right-handed. At the release point, the wrist moves forward to propel the ball; therefore, tracking not only the angular change but also the linear change can help identify where novice bowlers may lack compared to professional ones.

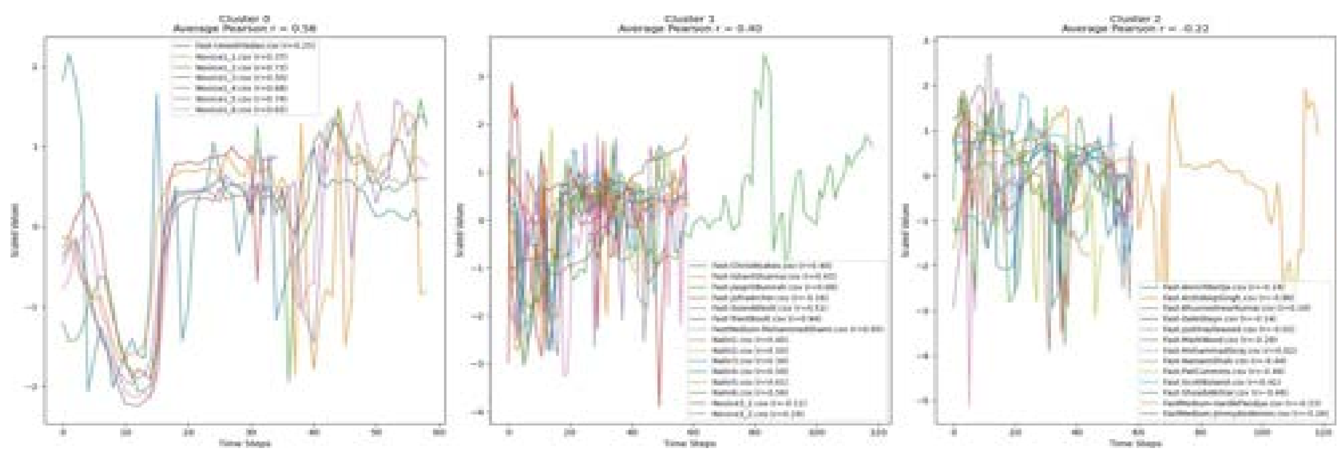
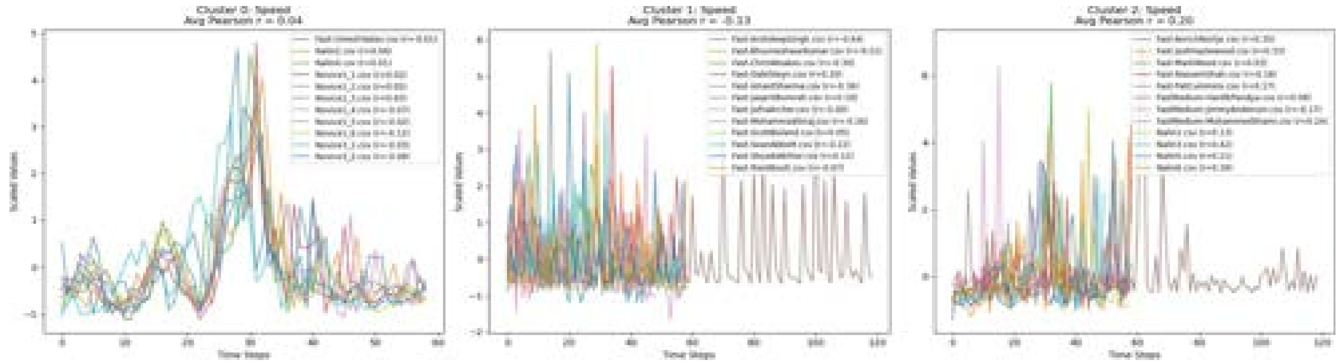
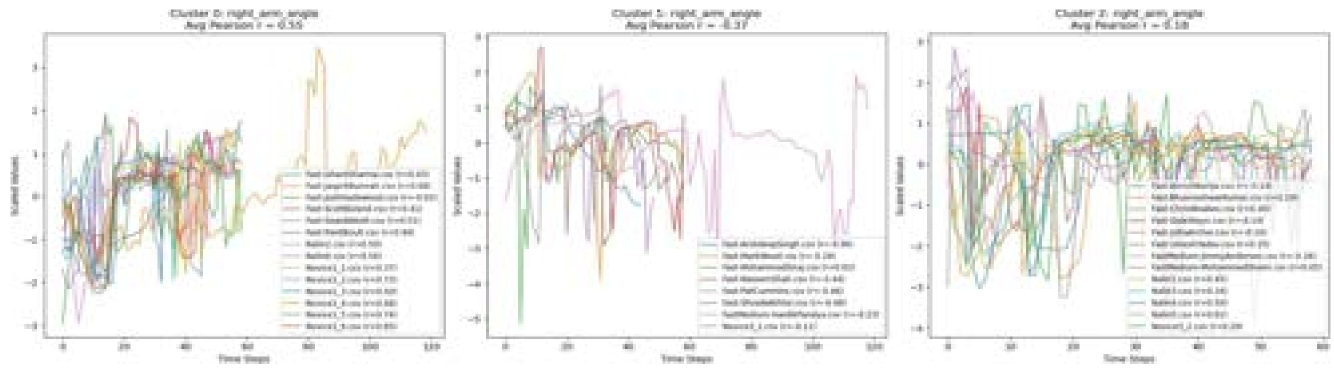


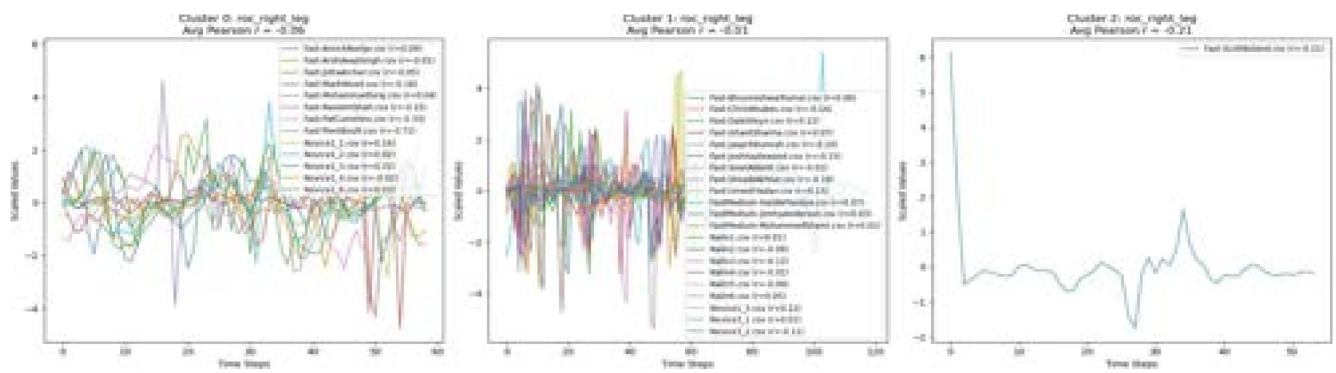
Figure 11: KMeans clustering with Pearson correlation: Vectorized representation of each bowler.



(a)Feature Clustering - Part 1



(b)Feature Clustering - Part 2



(c)Feature Clustering - Part 3

Figure 12: K-Means clustering of individual features for professional and novice bowlers using Pearson correlation.

After dataset noise reduction, 22 professional and 14 novice balls are selected - 78%

Figure 11 (each bowler feature vectorized to one) - Cluster 2 has no novices, and 8 balls from novices are in cluster 1 with 7 professional bowlers. Nalin's (Novice) action aligns more with professional bowlers compared to Novice 1. No novice achieved any ball delivery with 13 professional bowlers

Figure 12 (cluster/each bowler feature individually - 17 parameters). Right Arm, Left Leg, Right wrist angle, rate of change, and wrist speed are critical for Fast bowling action. Novice 1 RightArmAngle, LeftfootAngle are aligned with professionals, but parameters that need improvement are the rate of change of right arm, wrist speed, and wrist angle.

5. Analysis

Pose estimation model: The Mediapipe pose estimation worked well in all cases where the bowler has no overlap with another person. I analyzed multiple models like OpenPose, OpenCV/TensorFlow, etc. There are three enhancements needed in Model

1. Capability to identify the bowler from the umpire, fielder, non-striker batsman, thus requiring a multi-person model like YOLO.

2. Able to identify reliably 3D (x,y,z) pose points to calculate Euclidean distance at any camera pose.

3. Modify the Model object file with pre-trained data with supervised learning and add the capability to identify cricket ball for ball release point alignment. Professional videos: Although the Internet (Youtube, Cricket match clips etc.) has videos, they are at random angles and frame speeds (SloMo, HD, SD). For data reliability, preferably a camera angle side-on angle to bowler recording is recommended. LeftArm and RightArm Fast bowlers need to be adjusted in the program.

Data Analytics: I did the following enhancements as I progressed with analyzing data for Professional Vs Novice

1. Time and Frame alignment with “Ball Release Frame” as time = 0, Negative - runup and jump, Positive - delivery and follow through, to standardize all the data.

2. Filter data +1 sec to -1 sec from ball release due to large variation in Arm, Jump, Leg, wrist angles, and doesn’t contribute to bowler action. Also helps standardize comparisons between videos of various lengths, so that only a necessary and equal-length portion is examined.

3. Limit OpenMP threads to 3 to analyze on PC w/o GPU

4. Moved from a scatter plot of professional vs. novice with Time Vs Feature to Time Series (variable change over time)

5. Applied normalization and standardization for dataset clustering in order to make comparison easier.

6. Did Time Series per feature per bowler and Time Series all features per bowler to allow bowlers to see how similar their bowling action overall is to professionals, as well as the similarity for each parameter.

7. Used K-Means Clustering (ideal clusters came to be 3, seed 42) with DTW (Dynamic Time Warping) 8. Added Pearson correlation coefficient per time series and average for cluster to identify noisy data (¡ 0.3, data has noise).

Observed, only Novice bowler comparison graphs have a high Pearson correlation coefficient of 0.6-0.8 as they are controlled data with a side-on camera angle.

Bowler	Skill Achieved	%age
Nalin	**11/17**	**64%**
Novice1	**6/17**	**35%**
Novice3	**10/17**	**58%**
Novice4	**7/17**	**41%**
Novice5	**6/17**	**35%**

Table 2: Skill achievement by bowlers

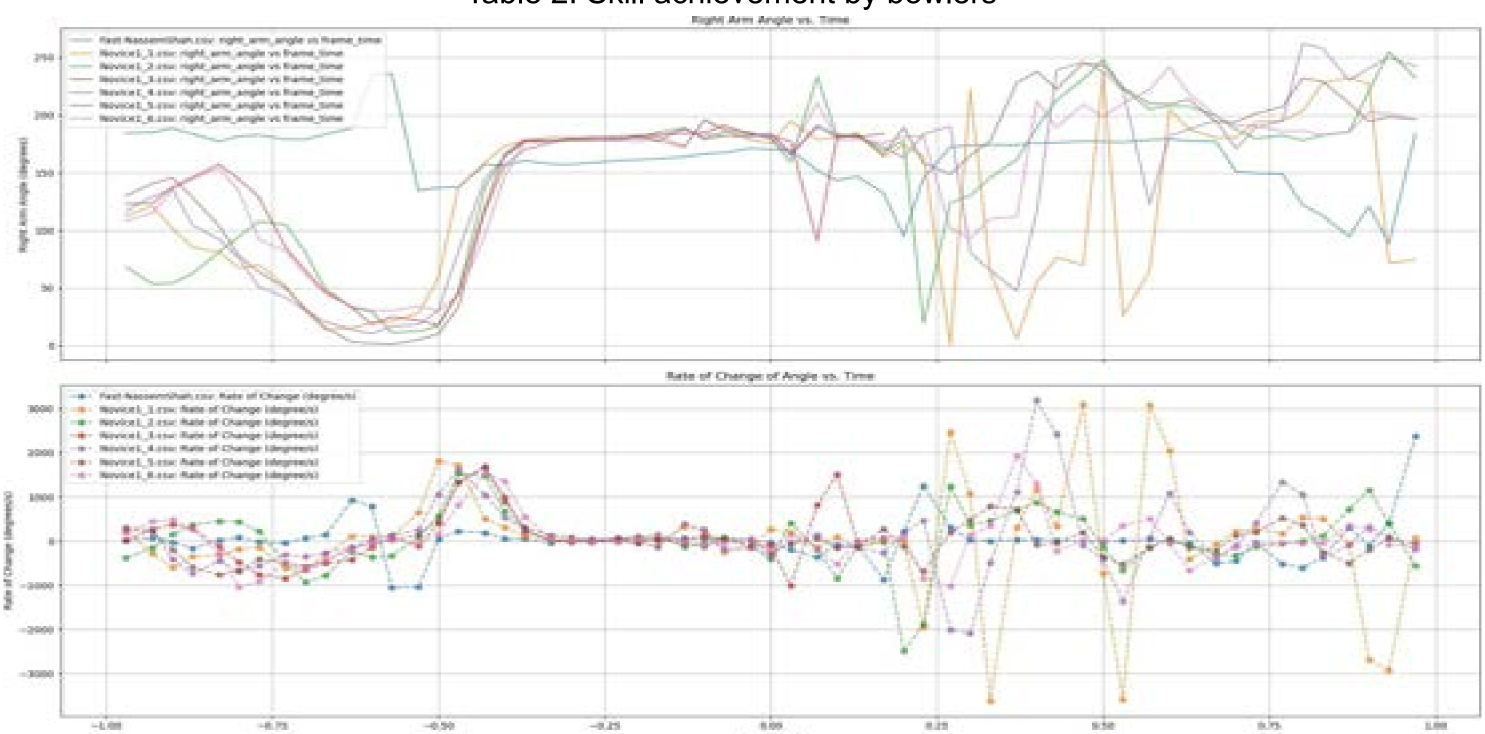


Figure 13: Bowler individual features

6. Conclusion

How did the Program work out? Earlier, the hypothesis was that combining pose estimation and data analytics techniques would identify where novice bowlers' biomechanics differ from those of professionals, indicating where they can improve their speed. Through pose estimation and clustering, we were able to compare novice bowlers with professional bowlers. The results showed, as seen in Table 2, 17 main parameters that were compared and one overall vectorized graph with all the angles combined. Out of the 17 main parameters, novice bowlers tended to align with professionals for around 6-11 of the parameters. Novice bowlers were also clear outliers for a few parameters, such as rotation of the right arm or wrist speed, when compared to professionals, indicating a significant skill gap. Since those parameters are confirmed to contribute to overall bowling speed, this shows where novice bowlers can improve their skills. Hence, the use of pose estimation and data analytics has identified where novice bowlers differ from professionals and shows clearly where to improve their speed. This has made a clear leap from previous technology, where pose estimation methods were used to analyze bowling data, but no comparison to a reliable database could be made, nor was the program readily available to the public. Instead, now comparisons are easily drawn, allowing novices to find their weak areas and improve them, to be on par with the professional bowlers.

Future Application: This methodology of using Pose estimation has applications in sports like Cricket, Tennis, and Baseball, where the player's action and posture are key to achieving speed. It is especially useful for training 7 to 16-year-olds, as most of their initial development happens in sports, body posturing, and technique. To run this program as a smartphone app, backend AI/ML infrastructure would need to be used for fast processing and comparison with professional players.

7. Future Work

Pose Estimation Model/Video Improvements: During this project, several problems arose due to various factors. The pose estimation software sometimes struggled to identify bowler limbs and angles when there were players in the background. If the video wasn't of good quality or if the camera angle caused some overlap between the bowler and the other people on the field, specific vital points wouldn't be detected. I would like to continue with the project using a multi-player detection model like YOLO or Openpose with pipelining.

Dataset improvements: Another issue involved the lack of a comprehensive dataset of cricket fast bowlers' action metrics, such as limb angles and foot leg positioning, with a side-on angle. Since I had to compile a database myself using public videos, the camera angles were often varied, and there wouldn't be many videos that contained the entire pose of the bowler, which made it difficult to create a comprehensive database. Plus, when I actually tested the videos, some of them had quality issues, which meant I couldn't use them. Although I got five novice bowlers, including myself, getting a large set would help, as cricket bowling actions can vary a bit, and more samples would have led to better clustering. I would try to get more novice bowlers, especially of my age, by contacting cricket clubs in California. If this project were to be continued, it could take many directions. In the short term, using the provided data, I could conduct another experiment with myself and the other novices to determine how much we can actually improve. Over a set amount of time, if we practice bowling with better biomechanics, how much will our speed improve? This could help gain a better idea of how much improvement can be made using biomechanics.

Data Analytics Improvements: The use of Time series and clustering for Bowling action analysis is relatively new, particularly in terms of bowler features. A long-term goal would be to have a small AI model trained on curated professional and novice bowling data to analyze and provide specific instructions on where to improve, allowing bowlers to focus solely on working hard and not on self-analysis. The long-term product for this would be an app where anyone could take a video of their bowling and instantly receive feedback on where to improve their action. This would be an efficient and cost-effective way to help bowlers improve, as it is easy to do outdoors and does not require extensive or expensive equipment.

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