Explaining Cricket Shot Techniques with Explainable AI

How can Explainable AI methods simplify the understanding of pose-based classification results for cricket shots?

1. INTRODUCTION

In this paper I explore the usability XAI techniques in cricket shot analysis.

BACKGROUND

With the rapidly evolving AI technologies, more and more are becoming incorporated into sports, be it in the form of AI-assisted VAR, game predictions, or technique checking. AI is quickly becoming a must-have tool for athletes looking to improve in their respective sports, and one of those sports is cricket. There is no research combining XAI with pose estimation based cricket shot classification.

OBJECTIVES

- Identification of XAI techniques that effectively explain pose-based classification results.
- Visualizations and explanations that highlight keypoint (e.g. shoulder) contributions and interdependencies in cricket poses.

2. METHODOLOGY

- Research and select potential suitable XAI models.
- Construct classification models and implement XAI on top
- Evaluate and conclude which XAI model is best suited

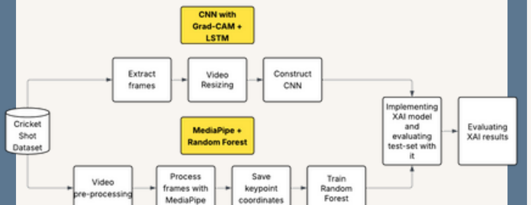

Figure 1: Implementation Pipeline

Model	Explanation	Compatibility
SHAP	Local + Global	Model-agnostic
Grouped SHAP	Local + Global	Model-agnostic
LIME	Local	Model-agnostic
Permutation	Global	Model-agnostic
Feature	Global	Model-specific (RF)
ALE Plots	Global	Model-agnostic
Grad-CAM	Local	Model-specific

Table 1: Evaluated XAI models

3. RESULTS

DATASET & POSE-ESTIMATION

722 videos of 5 different cricket shot techniques processed per frame, 17 body keypoints x,y,z extracted (head and arms)


Figure 2: Video frame to keypoint extraction

XAI MODEL EFFECTIVENESS

XAI Model	Interpretability	Usefulness	Interdependencies	Visual Clarity
Feature Importance	Plain-text overall importances; human-readable	Global analysis; shot-type-level focus points	Not captured; requires manual testing	Plain-text or bar chart
Permutation Importance	Same as Feature Importance	Same as Feature Importance; good for comparison	Same; manual changes needed	Plain-text or bar chart
SHAP	Local + global attributions; numerical feature weights	Explains both specific shots & global trends	Some co-occurrence inference; not direct	Force, waterfall, summary plots
Grouped SHAP (Joint)	Grouped coordinates per joint; easier to interpret	Highlights joints; good for joint-level feedback	Patterns across joints; not direct	Bar plots per joint
Grouped SHAP (Limb)	Grouped by limbs; intuitive for coaches	Highlights limbs; useful for high-level insights	Inter-limb only; not detailed	Simple bar plots
LIME	Local explanations; human-readable but less intuitive	Explains single shots; low impact values	None built-in; possible over multiple samples	Plain-text only
ALE Plots	Effect of single features; easy with guidance	Reveals feature effect types; struggles with high-dim data	Second-order effects only; time-consuming	1D/2D plots; noisy with outliers
Grad-CAM	Visual heatmaps; highly intuitive	Shows spatial attention; validates model focus	Visual co-activation (e.g., bat+head); not keypoint-specific	Frame heatmaps

Table 2: XAI Model Evaluation table

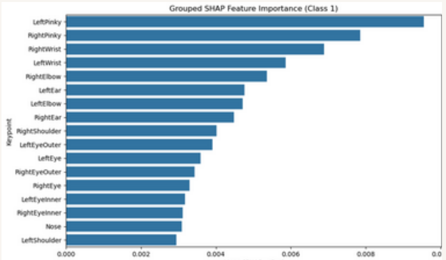

Figure 3: GroupedSHAP (Joint)

Grad-CAM COMPLICATIONS

Lack of CNN trained on Pose-Estimation datasets caused focus on wrong image elements, but with high accuracy of 92%

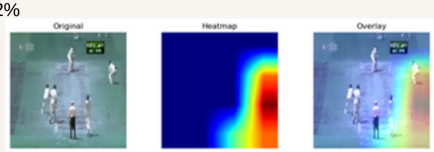

Figure 4: Grad-CAM results with focus on terrain

KEYPOINT CONTRIBUTIONS

- Most influential keypoints easily distinguishable by observing Feature & Permutation Importance and SHAP summary plot and GroupedSHAP (Joint)
- RightPinky_y and LeftPinky_y (keypoints connected directly to bat) consistently among most important

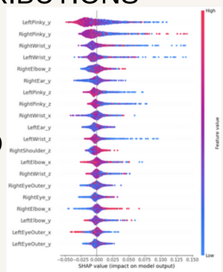
Figure 5: SHAP summary plot

KEYPOINT INTERDEPENDENCIES

- Interdependencies observed through local SHAP and LIME explanations, and global Grouped SHAP (Limb) explanations
- Interdependencies between naturally connected body parts observed (e.g. wrist and pinky, elbow and wrist). Most visible in wrist and pinky SHAP values in Waterfall Plots
- GroupedSHAP (Limb) presents prediction reliance more on Right Arm than Left Arm except in Reverse Sweep shot technique.

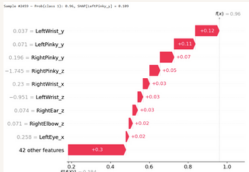
Figure 6: SHAP waterfall plot


Figure 7: SHAP waterfall plot

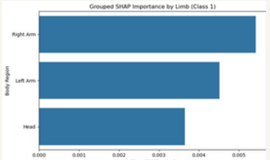

Figure 8: GroupedSHAP (Limb)

LeftPinky_y: 0.0155
RightPinky_y: 0.0151
RightWrist_y: 0.0103
LeftWrist_y: 0.0062
RightElbow_y: 0.0041
RightElbow_x: 0.0040
LeftPinky_x: 0.0040
RightElbow_z: 0.0039
LeftElbow_y: 0.0038
RightPinky_x: 0.0037

Figure 9: Permutation importance

4. CONCLUSION

XAI MODEL RECOMMENDATION

SHAP proved to be the best performing model for cricket shot analysis due to its global and local explanations allowing for observation of feature interdependencies, flexibility in explanation visualizations and it being model-agnostic.

FUTURE RECOMMENDATIONS

- Refine dataset used - more shot techniques, data processing based on dominant hand and skill level, greater volume and higher quality of videos.
- Test alternative classification models and pose-estimation models (e.g. OpenPose, XGBoost, etc...)
- Test alternative XAI models (e.g. alternative saliency maps (SmoothGrad), Anchors, learned features).
- Systematic benchmarking of explanation quality, using objective metrics such as fidelity, sparsity, and stability of the explanations.
- Expert evaluation of explanations to assess their alignment with textbook definitions of cricket shot techniques.

CONNECTED WORK

For a detailed overview of how SHAP explanations of cricket shots can be used in real-world applications, refer to "Generating expertise specific explanations in cricket pose estimation" by Ansh Kumar

ACKNOWLEDGEMENTS

- Waqas Ahmad et al. "Optimized deep learning-based cricket activity focused network and medium scale benchmark". In: Alexandria Engineering Journal 73 (2023), pp. 771– 779.
- Siddiqui et al. "Enhancing cricket performance analysis with human pose estimation and machine learning". Sensors, 23(15), 2023. ISSN 1424- 8220. doi: 10.3390/s23156839. URL https://www.mdpi.com/1424-8220/23/15/6839.
- Christoph Molnar. Interpretable Machine Learning. 3 edition, 2025. ISBN 978-3-911578-03-5. URL https://christophm.github.io/interpretable-ml-book.

CONTACT INFO

Student name: Bruno Martinović
B.Martinovic-1@student.tudelft.nl
Supervisor: Danning Zhan
Responsible Professor: Ujwal Gadiraju