

1. Introduction

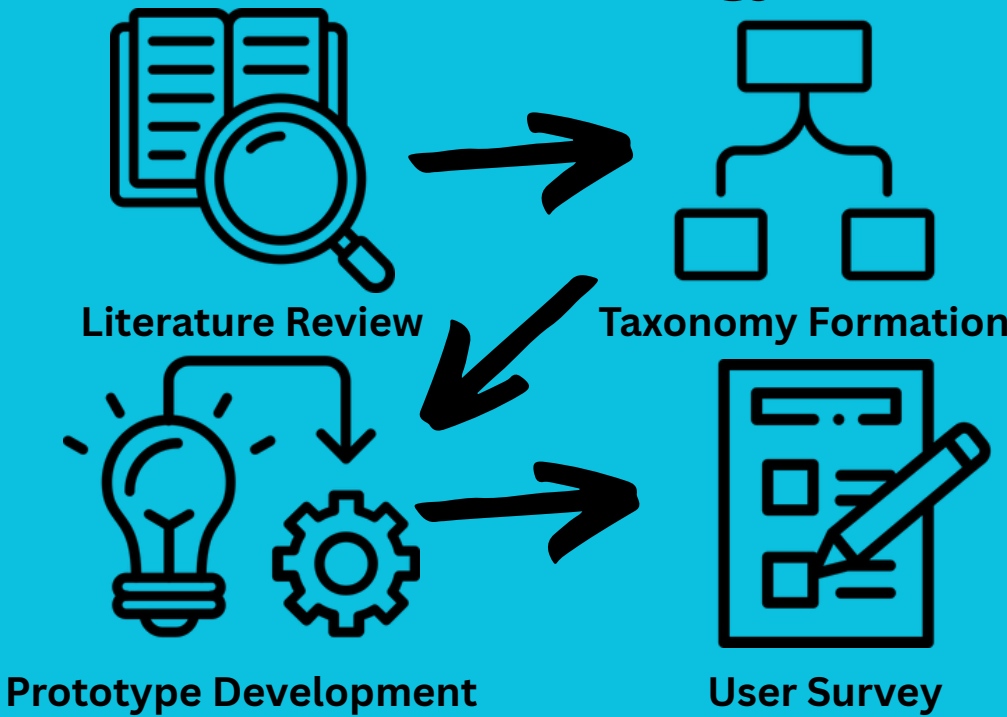
Background

- Use of AI-based pose estimation tools is increasing in sports like cricket
- Many explanation methods follow a one-size-fits-all approach
- This lack of personalization can reduce the usefulness of AI-generated feedback

Research Gap

- In cricket, explanation effectiveness depends on the user’s expertise, yet current systems don’t take them into account
- No current method tailors pose estimation explanations to different player expertise levels in cricket.

3. Methodology



4. Explanation Taxonomy

User Level	Explanation Details
Beginner	Format: Annotated Visuals, color-coded overlays Content: One key issue, no jargon Model Exposure: Hidden
Intermediate	Format: Comparative poses, annotated angles Content: Multiple focus points, light metrics Model Exposure: Moderate
Expert	Format: Dashboards, raw pose data Content: Full analysis, causal insights Model Exposure: High

2a. Research Question

What are the best ways to generate explanations across different levels of cricket expertise?

2b. Sub-Questions

How do the explanation needs differ between beginners, intermediate players, and advanced cricket experts?

What types of explanations are most effective for each level of expertise?

How can explanations be structured to provide actionable feedback tailored to different skill levels?

5. Prototypes

Figure 1: Beginner - 1 Focus Point

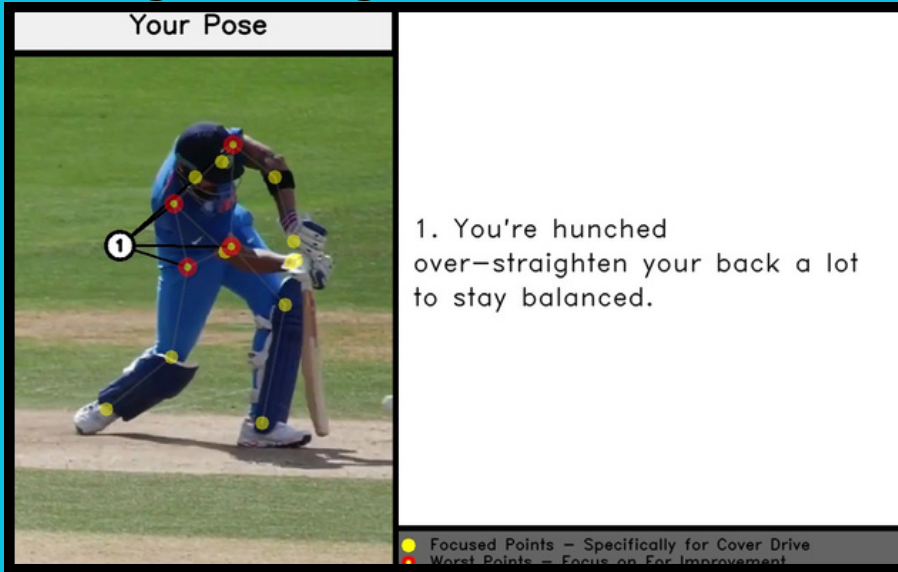


Figure 2 : Intermediate - 5 Focus Point

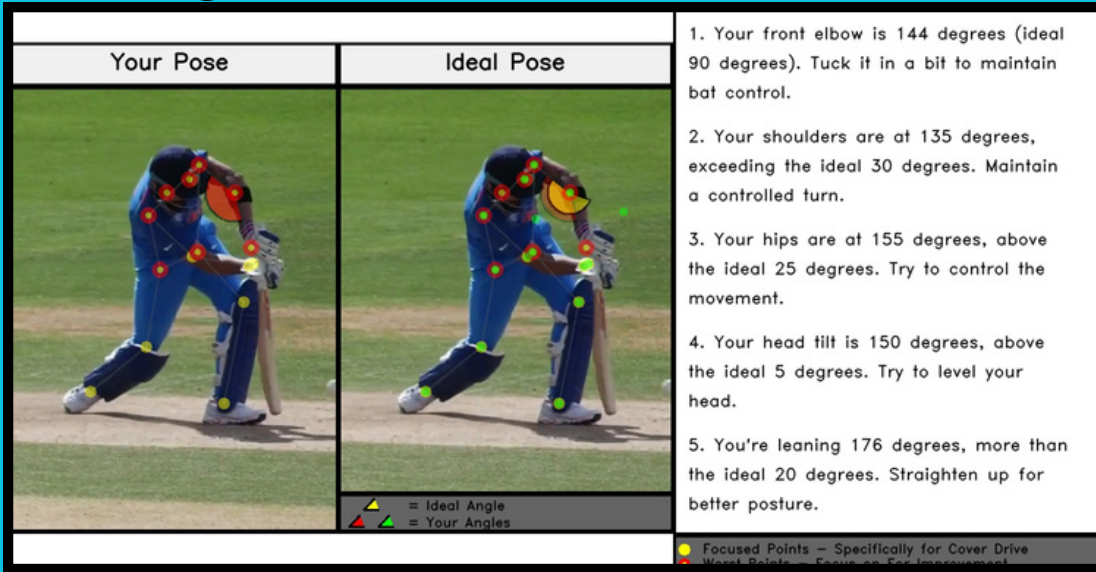
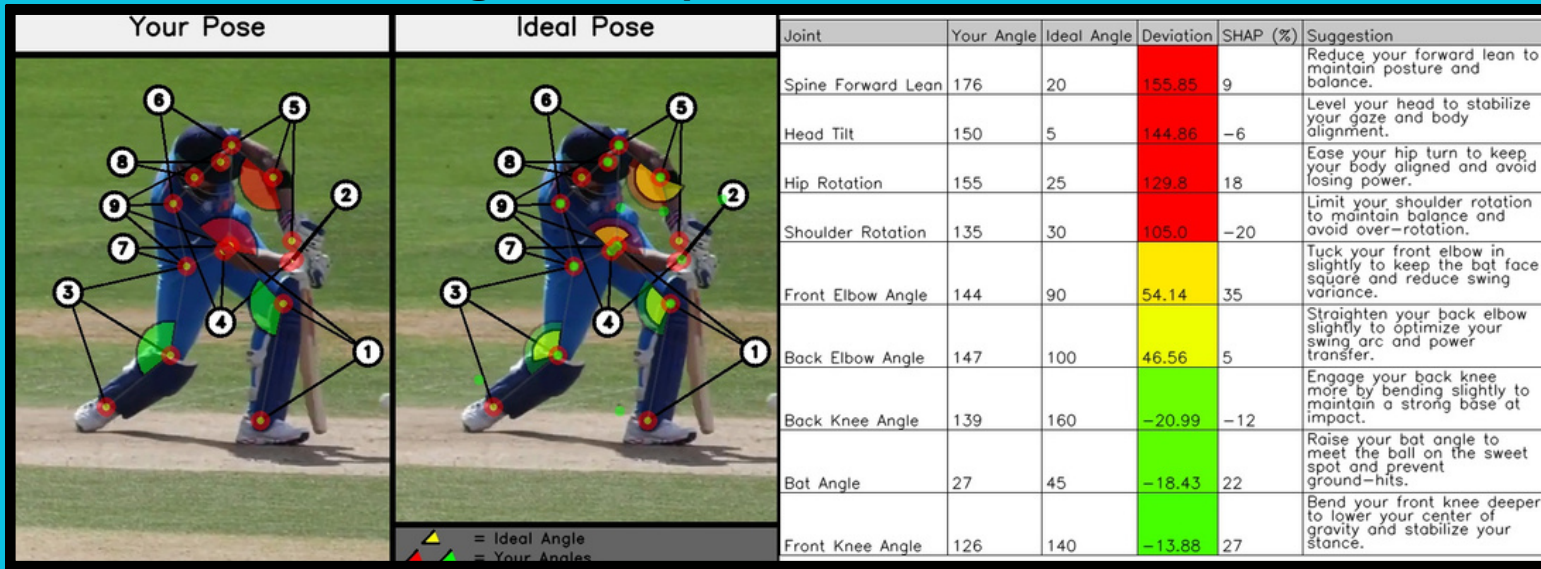


Figure 3 : Expert - 10 Focus Point



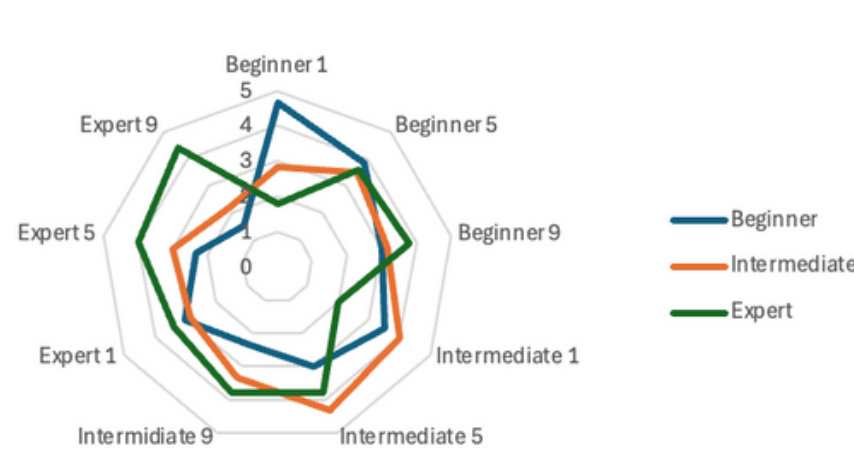
6. Small-Scale Survey Setup

- 17 participats - 6 Beginner - 6 Intermediate - 5 Expert
- 9 Prototypes (3 of each expertise level)
- 7 Likert Scale Questions (Inspired by Explanation Satisfaction Scale)
 - ESS is a Validated questionnaire specifically for user satisfaction with AI explanations [1]

7. Results + Evaluation I

- Beginner users** favoured strongly visual explanations, rating them higher in usefulness and ease of understanding
- Intermediate users** benefited from hybrid explanations (textual + visual). They found explanations with joint angles more useful, without becoming overwhelmed.
- Expert users** Clearly preferred explanations involving detailed technical content such as SHAP-based feedback. They rated these prototypes as highly useful, easy to understand, and appropriately matched to their expertise.

Usefulness



8. Evaluation II

- Two statistical tests were done to confirm that preference differences were signifigant enough
- Kruskal-Wallis Test**
 - Non-parametric test, used to check whether there are statistically significant differences in how these groups rated the explanation prototypes
 - The test revealed statistically significant group differences across nearly all evaluation dimensions (highlighted in green).

Kruskal-Wallis Test p-values	Usefulness	Ease of Use	Trust	Appropriate Skill Level	Visual Elements	Help	Too many Elements	Too many points
Beginner 5	0.686	0.017	0.065	0.109	0.206	0.025	0.076	
Expert 9	0.003	0.005	0.016	0.004	0.026	0.004	0.005	
Intermediate 5	0.047	0.057	0.046	0.024	0.077	0.004	0.009	
Intermediate 9	0.066	0.039	0.114	0.013	0.133	0.041	0.003	
Expert 1	0.633	0.014	0.171	0.64	0.307	0.011	0.002	
Beginner 9	0.284	0.006	0.767	0.375	0.793	0.025	0.024	
Beginner 1	0.004	0.139	0.017	0.003	0.141	0.4	0.4	
Expert 5	0.018	0.01	0.02	0.021	0.04	0.016	0.014	
Intermediate 1	0.005	0.019	0.005	0.005	0.258	0.225	0.011	

Table 1 : Kruskal-Wallis Test p-values

- Dunn’s Test**
 - Used after Kruskal-Wallis finds significant differences, to identify which group pairings differ
 - Beginner vs Intermediate** - Differences were less pronounced. Suggests some shared preferences, particularly toward visual or hybrid feedback that maintains simplicity.
 - Intermediate vs Expert** - Moderate differences were found, especially for technical clarity and trustworthiness.
 - Expert vs Beginner** - The most significant differences.

9. Conclusion

- Explanation needs vary by expertise, and beginners, intermediates, and experts, each benefit from tailored explanations.
- The explanation taxonomy proved to be effective
- User study confirms significant difference in preference
- These findings validate the need for expertise-sensitive explanations in sports AI feedback systems.
- Furthermore they support that existing literature can be used in the domain of cricket.

10. Future Improvements

- Expand participant pool
 - Greater statistical power and generalizability of results
- Automatically determine expertise level of users, as they are currently self reported
- Implement real-time feedback, giving the user feedback on their current form
- Include a wider range of cricket techniques
- Investigate effectiveness of other XAI methods

Project Supervisors :

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[1] Robert R. Hoffman, Shane T. Mueller, Gary Klein, and Jordan Litman. Measures for explainable ai: Explanation goodness, user satisfaction, mental models, curiosity, trust, and human-ai performance. Frontiers in Computer Science, Volume 5 - 2023, 2023. ISSN 2624-9898. doi: 10.3389/fcomp.2023.1096257. URL <https://www.frontiersin.org/journals/computer-science/articles/10.3389/fcomp.2023.1096257>.