

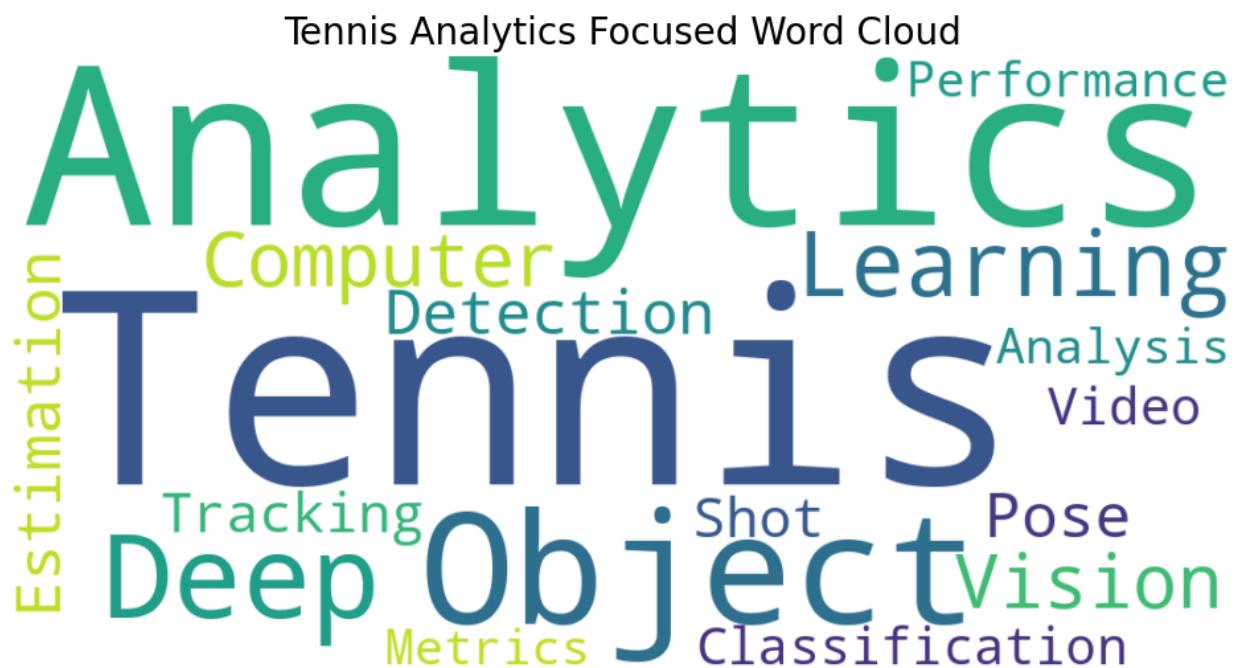


## A Deep Learning-Based Framework for Real-Time Tennis Match Analysis Using Object Detection, Key point Extraction, and Object Tracking to Evaluate Player Performance and Shot Patterns from Video Data

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**Keywords**

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## Introduction

Tennis, a well-known racket sport of global appeal ([Why Tennis Remains the Most Popular Racket Sport | 40LOVE, n.d.](#)) requires a combination of high technical accuracy, physical dexterity and strategic intelligence. Matches are typically decided by a blend of player positioning, shot selection, and real-time tactical decisions, making performance evaluation a crucial component of athlete development. Performance analysis in tennis is largely based on manual notation systems and commercial tracking systems such as Hawk-Eye, which are only affordable for major professional tournaments given their high cost and infrastructure dominance. Consequently, amateur players, grassroots programs, and independent coaches remain largely excluded from data-driven training tools.

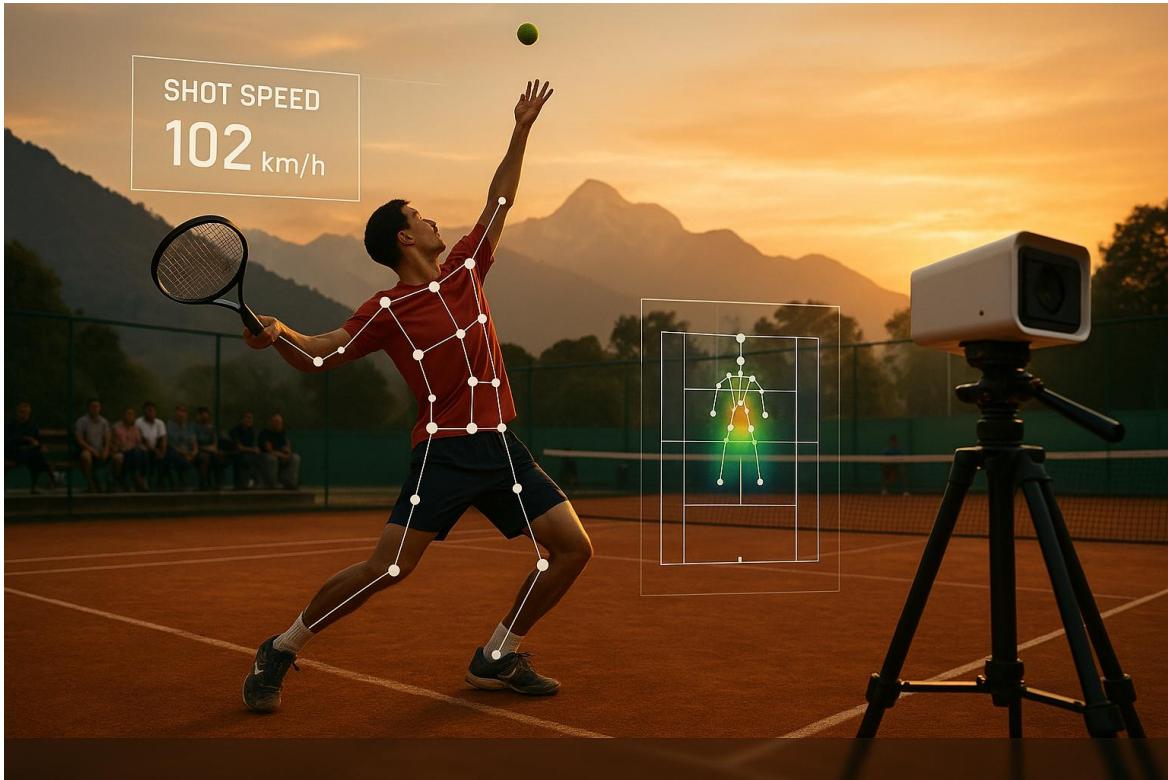


Figure 1 : Introduction to Tennis

The absence of accessible, real-time analytical solutions has created a significant disparity in the availability of performance metrics for non-professional players. Without affordable and scalable systems, objective assessments of shot quality, player movement, and tactical patterns are rarely achievable at community and academy levels. For this reason, decision-making is often still based on subjective visual assessment, which may restrict targeted skill acquisition and evidence-based coaching. Moreover, **psychological factors** such as player motivation, performance anxiety, and confidence levels are significantly influenced by the availability of objective, data-driven feedback. A lot of recreational or semi-amateur level players are averse to competitive or open play, because they lack personalized feedback on their own gameplay. The proposed system tries to address this by providing automatic video analysis tools that give players the opportunity to monitor their own

mistakes, progress, and performance metrics, and thus improve their motivation and reduce their anxiousness towards the subjective evaluations they receive from their coaches.

To address this problem, a modular video analysis framework based on deep learning techniques has been proposed. Through the combination of object detection, pose estimation, and multi-object tracking models, it seeks to enable the automatic derivation of performance measures like player position analysis, shot prediction, or rally trend analysis from regular high-definition video. The proposed framework will provide cost-effective, near real-time feedback using open-sourced features available to the public, opening performance analytics to everyone, which should allow for inclusive athlete development ecosystems.

### Aim

To design and evaluate a tennis video-based learning system that capable of providing near real-time performance indicators for tennis matches using standard high-definition recordings, while considering both technical and psychological impacts on amateur players.

### Objectives

- Learn and understand tennis as a sport and the role of performance analytics.
- Understand deep learning and computer vision and how these techniques are used in sports and other industries.
- Analyze how professional systems like Hawk-Eye are used in elite tennis to identify the best global practices.
- Conduct a literature review to identify the gap in performance analysis tools for the amateur tennis community in Nepal.
- Develop a prototype video analysis framework that integrates all modules and provides insights on a visual dashboard.
- Evaluate the performance of frameworks, gather feedback from users, and document all the findings in the research report.

### Objectives

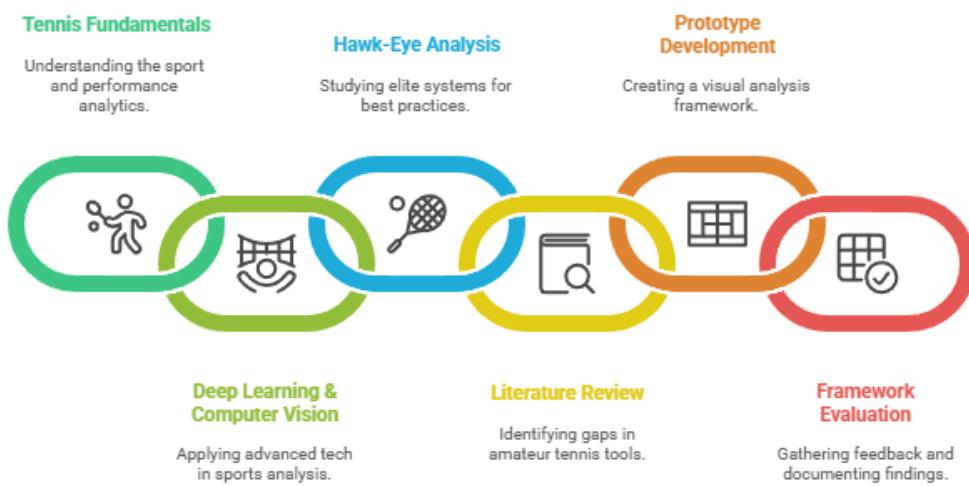


Figure 2 : Objectives

## Justification

The system is proposed based on both technical and psychological as well as socio-economic point of view especially in the context of developing sports infrastructure of Nepal. From a technological point of view, there is a clear lack of real-time AI-powered video analysis tools in Nepal grassroot and amateur tennis. Viewers at a professional tournament might get the benefit of [Hawk-Eye](#) technology or something like it but the ecosystem outside of everyman's local tennis sphere doesn't have cheap data-driven feedback tools, which means everyone is stuck with what their coach says, what they can feel and a hacky homemade system that maybe flashes a number for a second after you hit a shot. This technological divide is further magnified by players at the amateur level who can't afford (or stand) 24/7 personalized in-person coaching.



Figure 3: Evolution of Grassroots Tennis Through AI-Based Video Performance Analytics

The introduction of AI-driven analysis to amateur tennis has psycho-logical implications that should not be overlooked. When they have real insights driven by data, athletes can concentrate on improvement that can be genuinely measured instead of casting doubt upon themselves with the wrong information. Clubs, such as [Brentford FC](#) and [FC Midtjylland](#), on the other hand ([Arastey, 2019](#)), were able to outperform teams with higher budgets by applying data-orientated methods this, and other examples in the industry, prove the psychological and strategic value of objective feedback in the development of athletes. To do the same for amateur tennis in Nepal is refreshing and needed. This project may further be perceived as an educational resource rather than a replacement for actual coaching. AI-based systems create opportunities for players to take ownership of analyzing their own

match footage, and cultivate a culture of self-reflection, data literacy and mental discipline for athletes.

The implementation of these frameworks also acts to redress the inherent inequity in coaching resource allocation that exists at the [grassroots level](#). "Nothing can replace physical learning, but with live analytics each player can receive bespoke performance data, even in coach scarce environments. These sorts of systems democratize the process of performance appraisal, which fosters fairness among trainees.

From an ethical standpoint, concerns surrounding privacy and data usage have been acknowledged. Ethical design principles take precedence in this framework, making responsible sourcing of video data and keeping algorithms in-tune with culture (including the norms as to attire and the conduct of a player in society) primary. The potential risks of promoting uniform tactical approaches or reinforcing narrow performance benchmarks will be mitigated through continuous dataset diversification and localized user testing, preserving individuality and cultural authenticity. In addition, **psychological theories** such as

[Herbert Simon](#), bounded rationality, argues that amateur players have limited abilities for deciding among complex events and technical structures of the match. These real-time analytics tools facilitate that decision-making by focusing attention on key performance indicators, reducing cognitive load, and allowing for timely adjustments. The paradox of choice, another well-documented behavioral economics concept, suggests that athletes can become overwhelmed when presented with excessive, unfiltered performance data. Through generating personalized context-aware metrics, our system achieves an improvement in information presentation to achieve optimal decision-making performance without suffering from cognitive overload. Taken together, the proposed video analysis framework is a technically feasible, psychologically beneficial, and ethically responsible alternative to overcome the analytical resource discrepancy among the amateur tennis segment within Nepal.

## Research Question

1. How can open-source computer vision modules be integrated to provide accurate, real-time statistics from single-camera tennis video, and what are the key technical obstacles limiting the system's accuracy?
2. How does automated data feedback affect motivation, confidence, and tactical understanding of amateur tennis players, and what are the key usability challenges in designing an effective analytical dashboard for them?
3. What are the key ethical considerations of introducing an AI coaching tool to grassroots sports? Specifically, how can system design mitigate the risks of data misuse, algorithmic bias, and overreliance on technology?

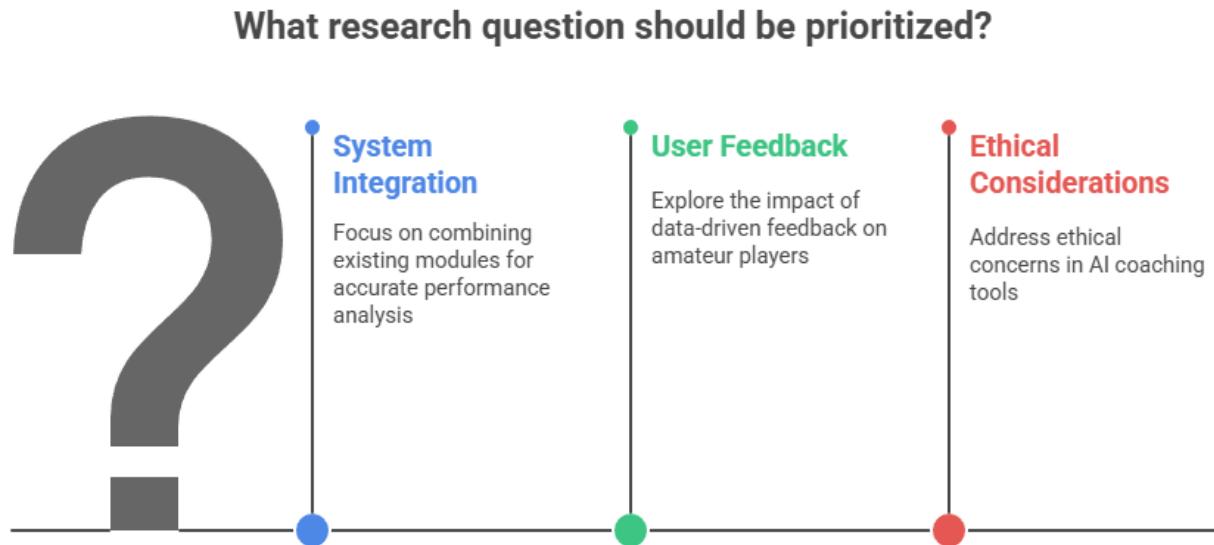


Figure 4: Research Questions?

## Literature Review

### Desk-Based Research Methodology

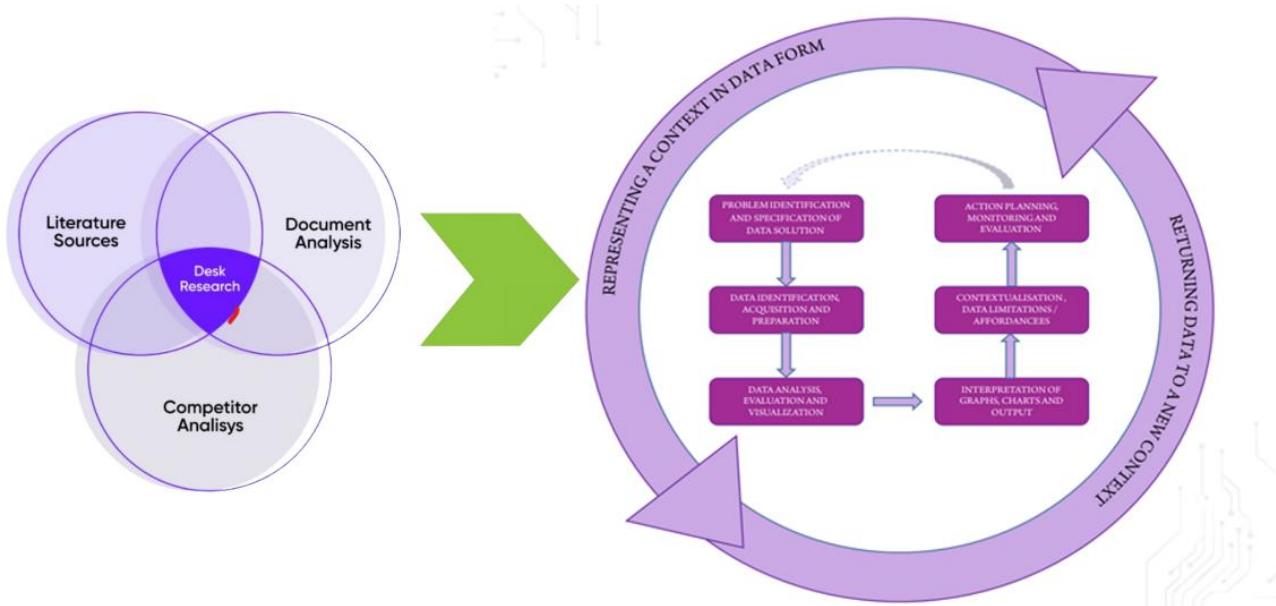


Figure 5: Desk Based Research

The desk-based research methodology for this project is systematically guided by the Institute of Analytics ([IoA, 2025](#)) Competency Framework to ensure a structured approach. It begins with linking the project's objectives to the Data Competency Framework and progresses through key phases including problem identification, a comprehensive literature review from secondary sources, data analysis, and strategic evaluation. At each stage, course materials contribute to the development of

analytical thinking and technical proficiency, with particular emphasis on data ethics and governance. Frequent meetings with the thesis advisor help maintain alignment with these guiding principles. To manage the research process efficiently and flexibly, an **Agile methodology** has been adopted. This approach emphasizes iterative progress, regular feedback, and the ability to adapt to new findings or changes in direction throughout the research cycle. By breaking the work into manageable phases or "sprints," Agile supports continuous evaluation and refinement of goals, enabling the methodology to remain responsive to emerging developments in artificial intelligence (AI) and sports analytics.

Existing literature provides substantial insights into AI-based video analysis systems, particularly in object detection, tracking, and sequential pattern recognition. Early systems relied on traditional statistical methods, which were later enhanced through the use of Convolutional Neural Networks ([CNNs](#)). Pioneering models like the R-CNN and [You Only Look Once \(YOLO\)](#) series significantly advanced detection speed and accuracy in complex environments. Among these, YOLO has proven especially effective for real-time detection of fast-moving objects such as tennis balls and players. Advancements in pose estimation, notably through [High-Resolution Networks \(HRNet\)](#), have enabled accurate tracking of athletes by identifying joint positions. Multi-object trackers like [Deep SORT and ByteTrack](#) further support identity preservation across video frames, even during occlusion or rapid movement.

Additional desk-based research highlights AI's broader applicability in sectors such as retail and transportation, where video analysis is increasingly feasible on standard consumer hardware. This makes technology more accessible for use in grassroots and youth sports. However, several ethical issues have been raised, including concerns around data privacy, algorithmic bias, and the lack of regulatory oversight in sports settings. With organizations like the [International Tennis Federation \(ITF\)](#) and [International Olympic Committee \(IOC\)](#) yet to establish formal guidelines, developers are left to define and uphold their own ethical standards.

Furthermore, limited efforts have been made to improve data literacy among young athletes, despite its potential to enhance long-term performance. This study seeks to address these gaps by proposing an accessible, AI-based video analysis solution tailored for tennis, grounded in ethical design and practical implementation.

## Case Study

Empirical examples demonstrate the real-world impact of artificial intelligence (AI) in professional tennis. Data-driven insights have been effectively utilized for tactical planning, injury management, and training optimization.

### **Naomi Osaka's coaching team ([Naomi Osaka's](#))**

Predictive modeling has been employed by Naomi Osaka's coaching team to analyze opponents' strategic behavior. By feeding historical and real-time opponent data into machine learning algorithms, the team can forecast high-probability patterns that are often missed by human observation alone. The models identify tendencies like an opponent's shot selection on break points or serve placement after long rallies. The output is a predictive playbook used to simulate matches, scenarios and develop specific counterstrategies, effectively turning data analysis into a direct competitive advantage.

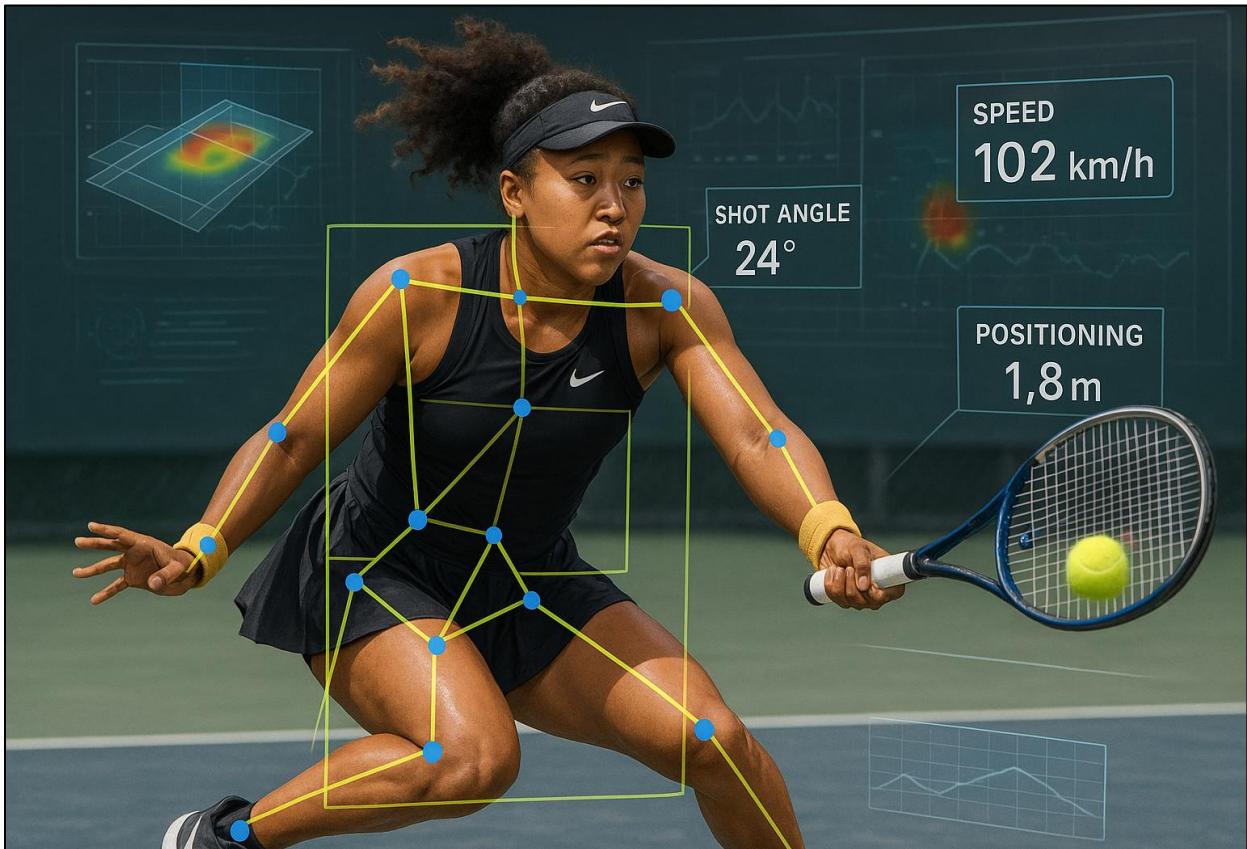


Figure 6: Naomi Osaka analytics

### **Andy Murray's post-injury rehabilitation program ([Andy Murray](#))**

Following injury, Andy Murray's rehabilitation was guided by an AI-driven biomechanics system that used motion capture and wearable sensors. The AI analyzed his movements in real time, comparing his kinematic data against a pre-injury baseline or an ideal model to provide immediate feedback on unsafe motions like excessive joint load or asymmetry. This data-driven feedback loop transformed his recovery from a subjective process based on "feel" into an objective, measurable science, accelerating recovery while minimizing the risk of reinjury.



Figure 7: Andy Murray analytics image

The technology central to this program typically involves a combination of high-speed motion capture cameras and wearable sensors placed on critical joints like the hip, knees, and ankles. As Murray performed specific movements, the AI system would analyze the kinematic data in real time, comparing it against its own pre-injury baseline or an ideal biomechanical model. If the system detected excessive load, asymmetrical movement, or compensatory motions indicative of guarding the injury, it would provide immediate auditory or visual feedback to Murray and his physiotherapy team. This data-driven feedback loop transforms rehabilitation from a subjective process based on "feel" to an objective, measurable science, ensuring that every repetition during recovery is both safe and maximally effective for rebuilding strength and stable movement patterns.

#### **IBM's AI Analytics at Grand Slams ([Henschen, 2025](#))**

A prominent case is IBM's Watson AI platform at major tournaments like Wimbledon (Henschen, 2025). The system processes millions of historical data points to generate predictive "Keys to the Match," such as flagging that a player wins 70% of matches when their first-serve success rate is above 65%. During matches, it provides real-time momentum analysis to broadcasters and fans by tracking shifts in key performance indicators. The platform uses Natural Language Generation (NLG) to translate complex data into human-readable insights, enhancing the fan experience while offering a layer of tactical analysis.

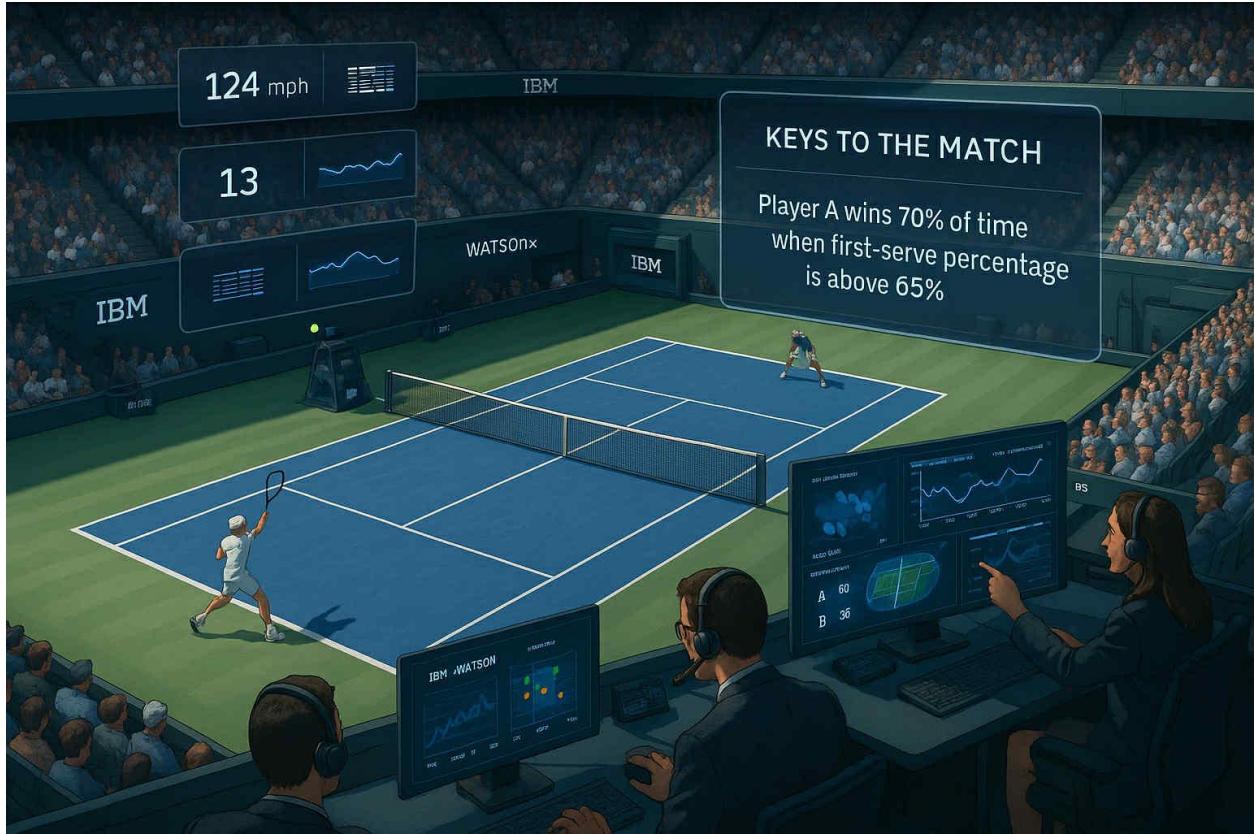


Figure 8: IBM's AI Analytics

#### SAP Tennis Analytics for Coaches ([Dot, 2025](#))

Another significant example is the SAP Tennis Analytics platform, widely adopted by the Women's Tennis Association ([WTA](#)) ([Dot, 2025](#)). Designed specifically for coaches, this tablet-based application delivers real-time statistical insights during matches. Metrics such as serve direction, shot placement, rally length, and types of unforced errors are continuously tracked. The visual dashboard supports coaches in identifying performance patterns in both their players and opponents, enabling timely, data-informed feedback during matches. This case is particularly relevant for its demonstration of user-friendly dashboards, aligning closely with the intended goals of this study, translating complex data into actionable coaching insights.

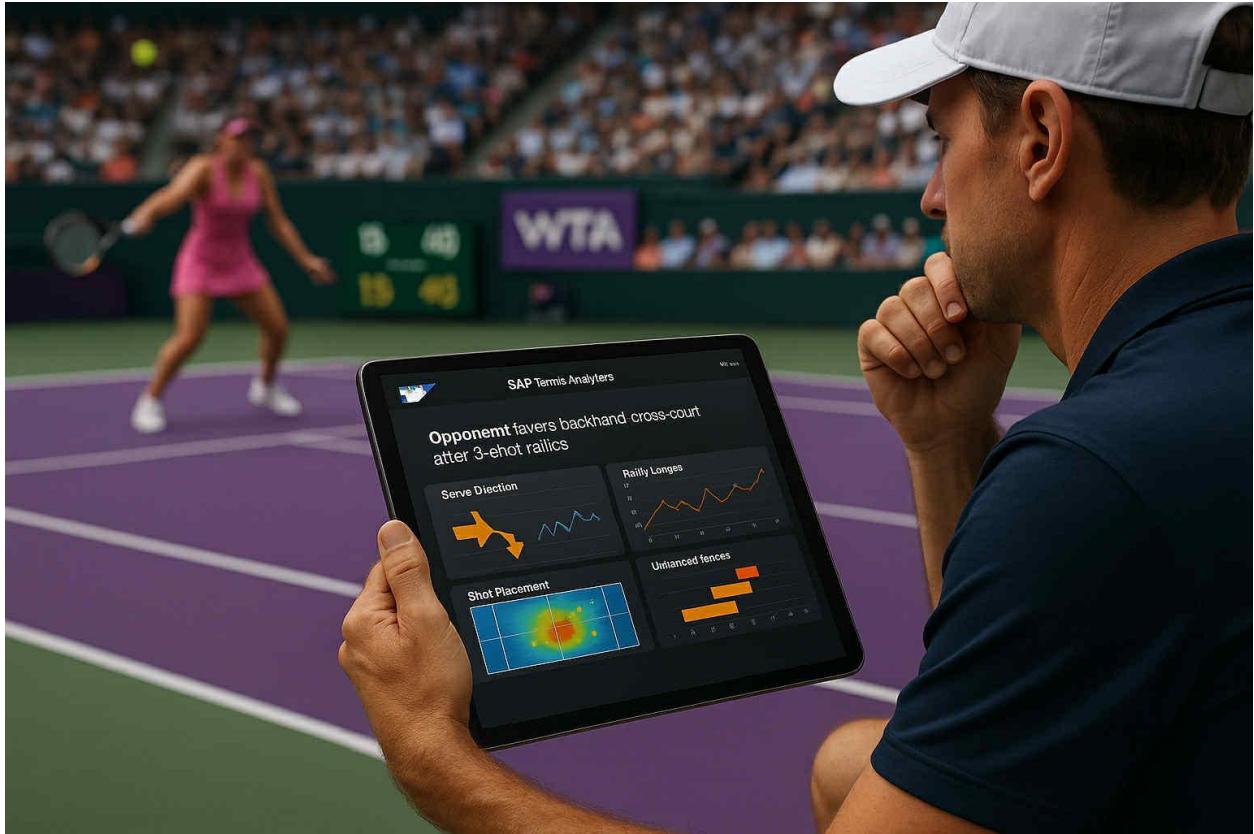


Figure 9: SAP Tennis Analytics for Coaches

These applied case studies collectively illustrate the practical implications of AI tools in elite tennis. Evidence suggests that AI-driven solutions contribute to performance optimization, injury prevention, and strategic decision-making at the highest levels of the sport.

Furthermore, concurrent research in sports psychology emphasizes the importance of feedback systems in reducing performance anxiety and enhancing athlete motivation. Recent literature indicates that access to data-based performance feedback independent of subjective coach observation empowers players and fosters a sense of control, particularly in competitive or open sessions. Applications of AI in other sports contexts have shown improvements in athlete confidence and psychological readiness. These findings reinforce the psychological value of integrating AI-based video analysis systems into amateur and grassroots tennis environments.

## Integration

The picture illustrates the integration of our system in detail.

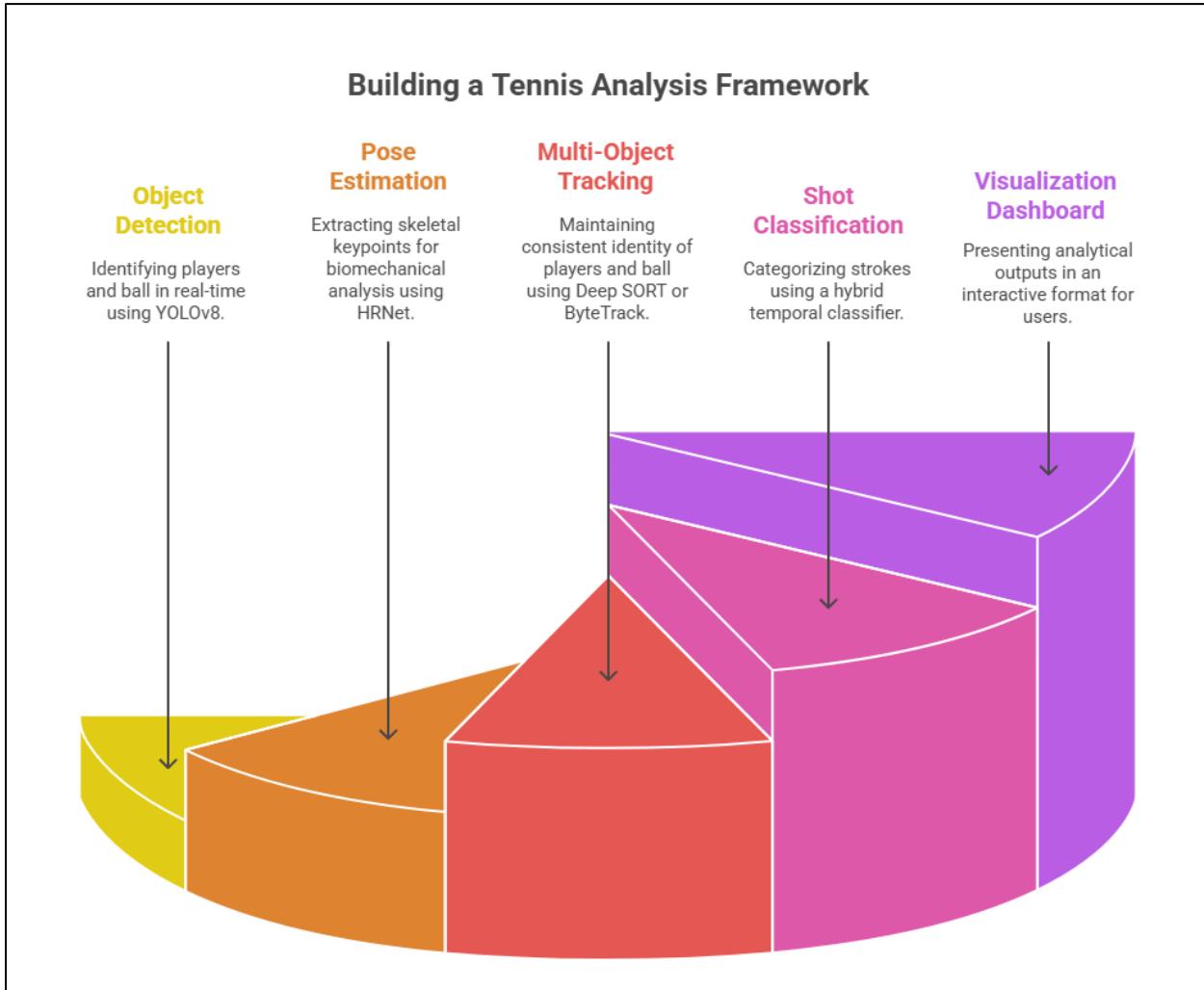


Figure 10: How will things Integrate?

## Project Plan

Here is the Gantt chart for the project plan:

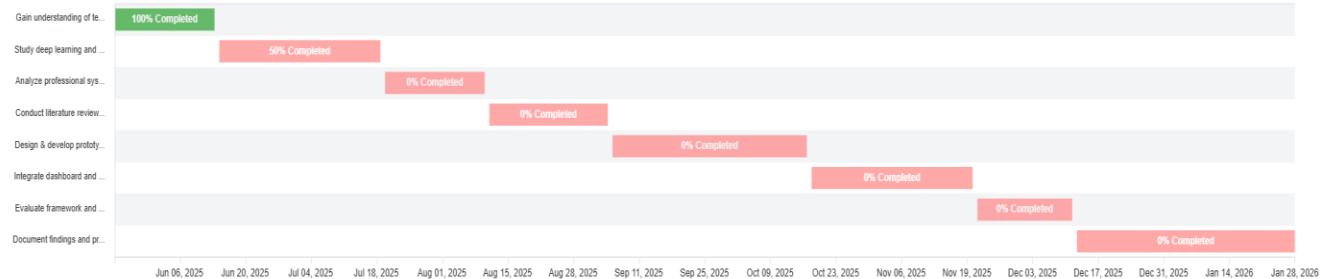


Figure 11: Gantt Chart

## Methodology

The picture below illustrates the Methodology for this system:

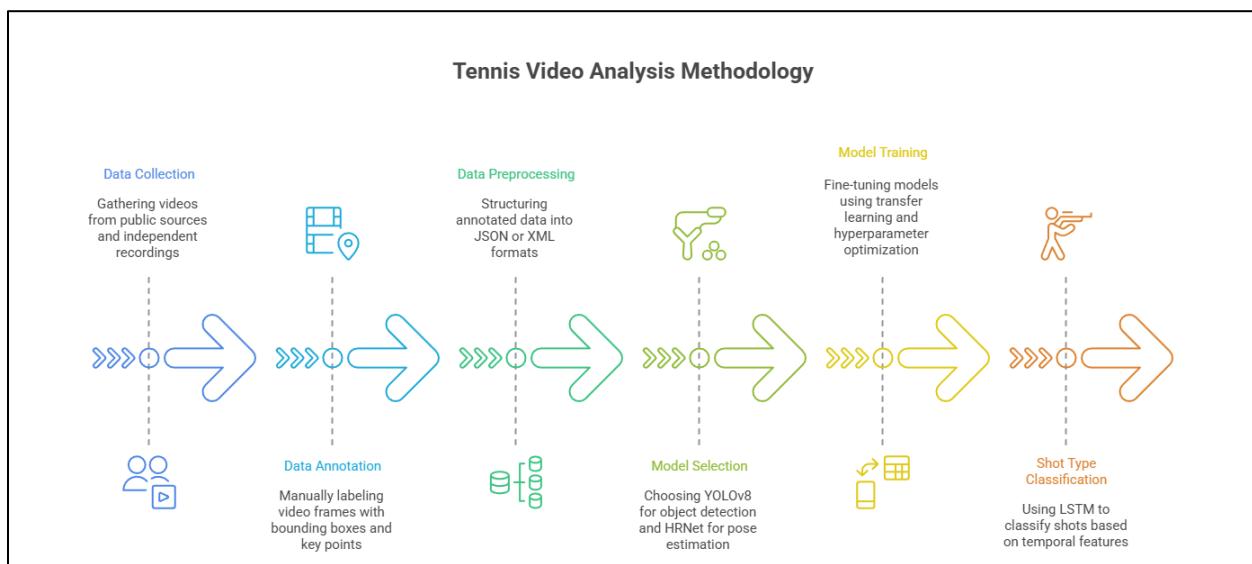


Figure 12: Methodology

## Evaluation Metrics

Framework performance will be quantitatively assessed through several established evaluation metrics.

| Metric   | Description                                  |
|--|--|
| A/C ↑ Mean Average Precision (mAP)             | Precision and recall of object detection     |
| 30% ↘ Percentage of Correct Key points (PCK)   | Accuracy of skeletal key point predictions   |
| 50% ↗ Multiple Object Tracking Accuracy (MOTA) | Consistency/correctness of identity tracking |
| 1 F1 Score                                     | Stroke classification accuracy               |
| FTP ↑↓ Frames Per Second (FPS)                 | Real-time system processing speed            |

Figure 13: Evaluation metrics and their description

## Risk Plan



Figure 14: Risk Plan

## Conclusion

This project aims to narrow the ANZ Centre Analytical gap that exists between professional and social level players by developing a low-cost, open-source video analysis platform. Using state-of-the-art deep learning models developed for detection, pose estimation and tracking, the system turns standard video footage into an automated data capturing tool on key performance indicators. But instead of just a technological tool, it is meant to be an empowering framework for players at the grassroots level in Nepal to find motivation and get confidence from an objective, data-based feedback. While acknowledging the technical and ethical challenges inherent in AI development, this research ultimately aims to foster a more inclusive, equitable, and data-literate sporting environment for athletes at all levels.

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## Appendix

### SWOT Analysis

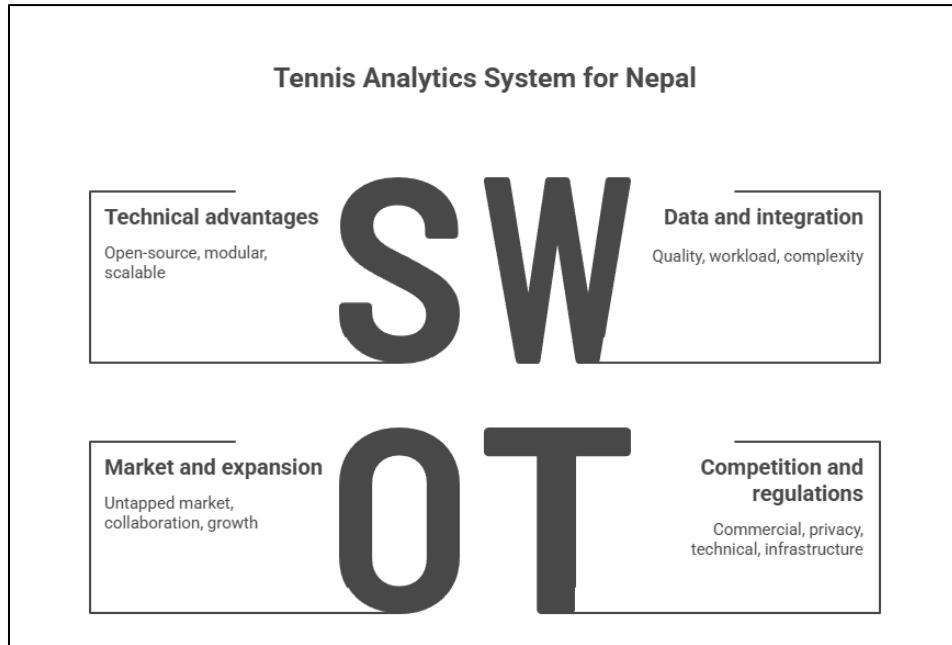


Figure 15: SWOT analysis

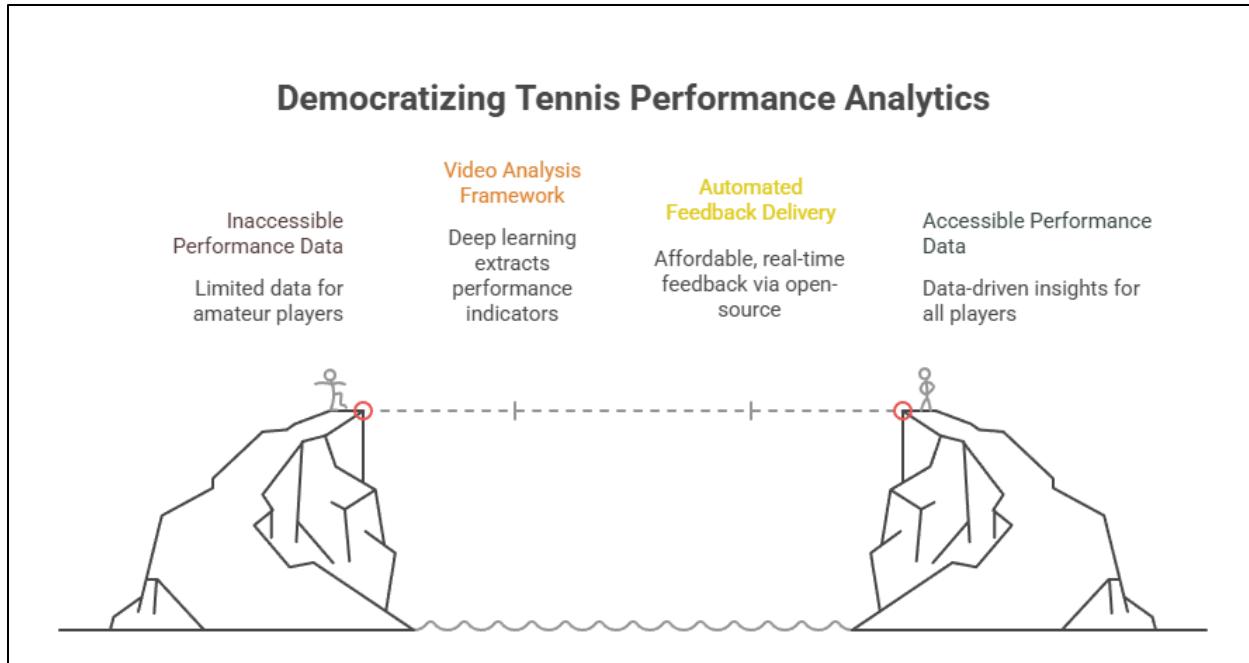


Figure 16 : Analytics in Tennis

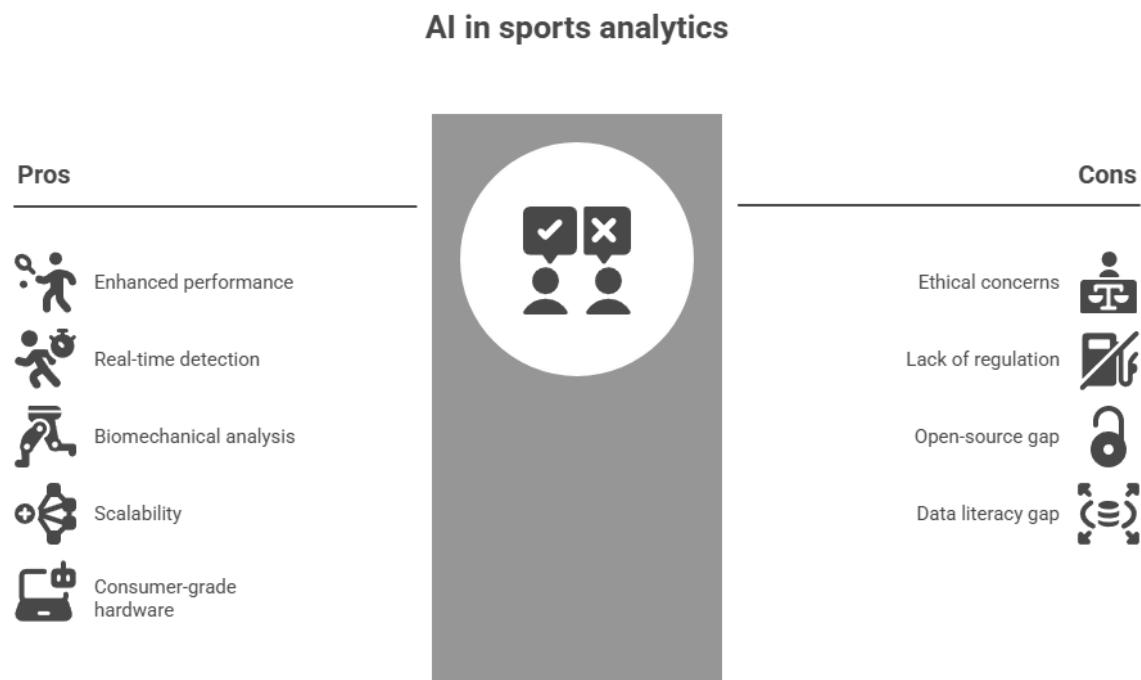


Figure 17: Pros and Cons

**AI-driven video analysis bridges the gap in Nepal's amateur tennis, enhancing player development.**

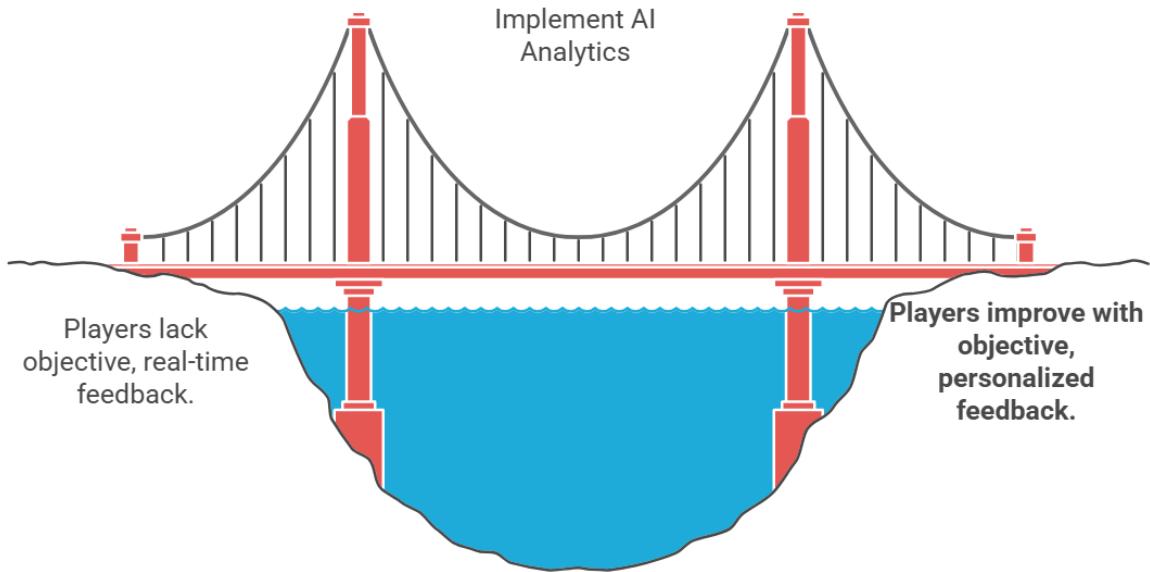


Figure 18: Methodology

### Risk Mitigation Strategy for AI-Based Tennis Analytics



Figure 19: Risk mitigation

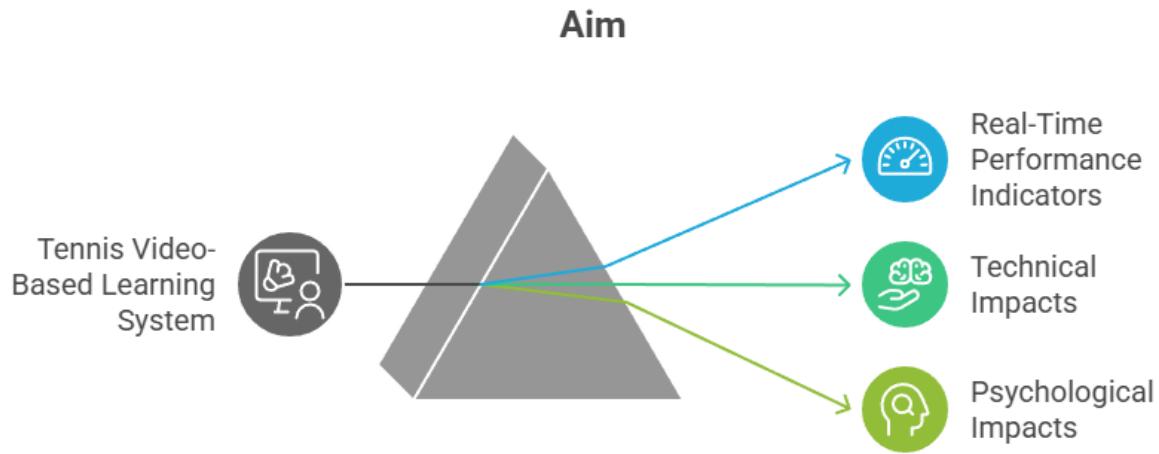


Figure 20: Aim of the Project

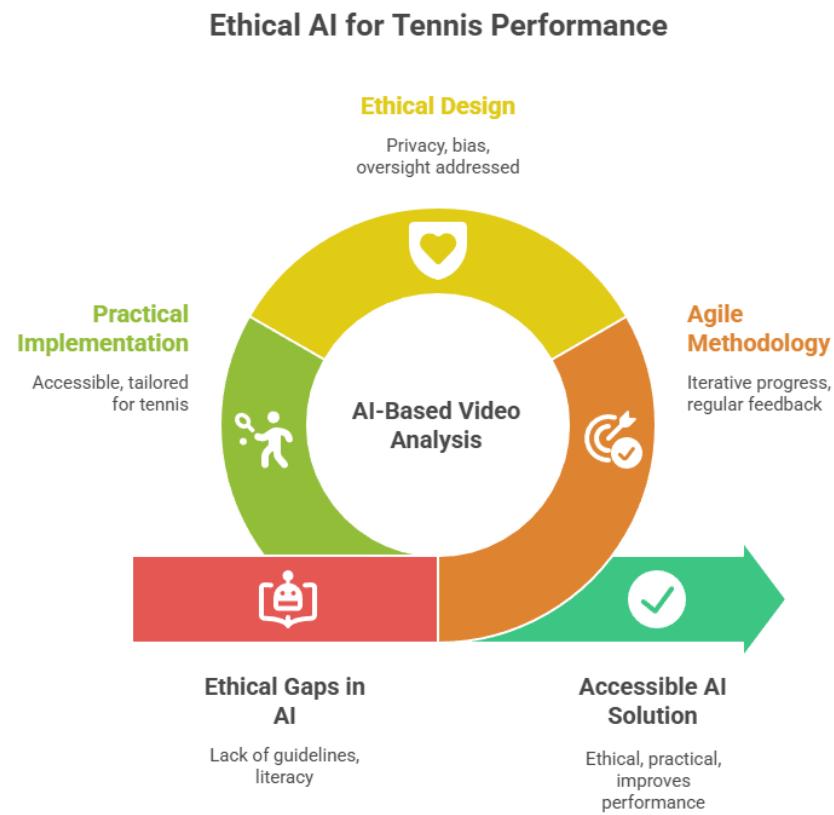


Figure 21: Ethical AI for Tennis

## Balancing Technical, Psychological, and Ethical Considerations in AI-Driven Tennis Analytics

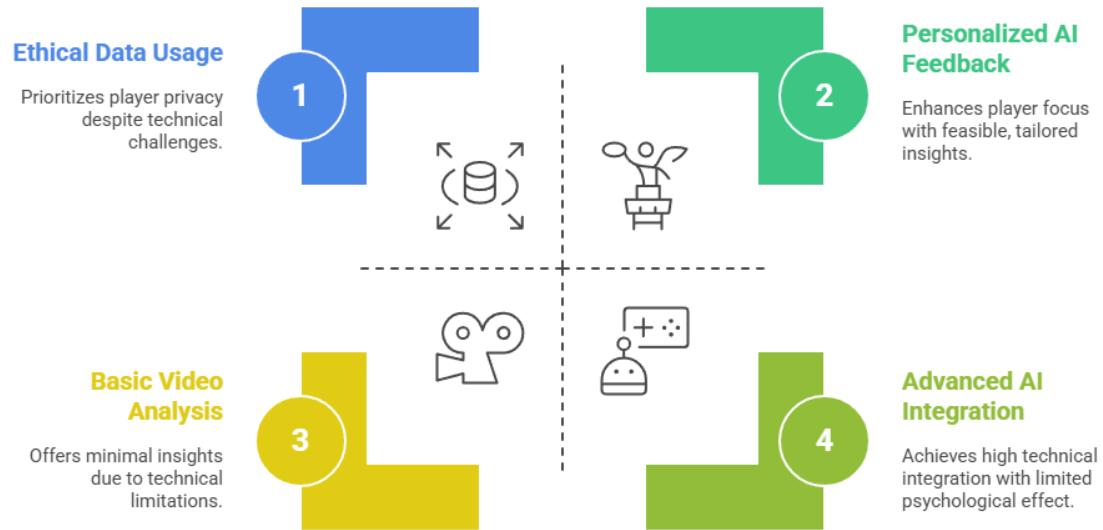


Figure 22: Balancing Technical, Psychological, and Ethical Considerations in AI-Driven Tennis

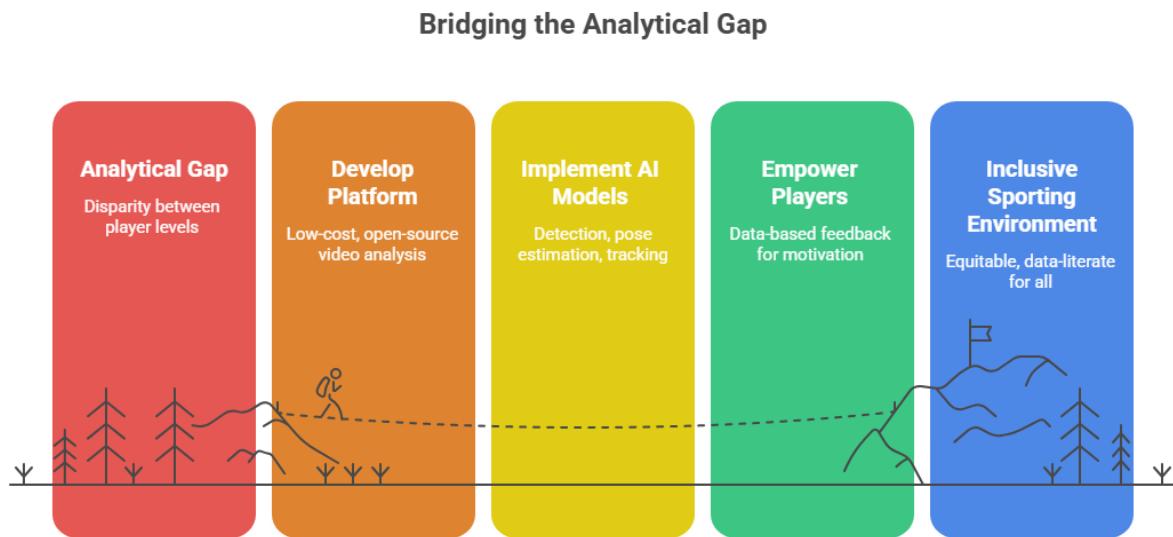


Figure 23: Bridging Analytical Gap