Archery Analytic Workflow in a Web-Based Application

Basil Andy Lease
Curtin Malaysia Research Institute

King Hann Lim
Curtin University Malaysia

Jonathan Then Sien Phang
Curtin Malaysia Research Institute

Dar Hung Chiam
Curtin Malaysia Research Institute

Abstract: The integration of sports science and camera sensing technology has recently emerged to be an advanced analytical tool in sportsperson performance enhancement. The use of computing power and a web-based application can provide quick information analysis and data reporting between coaches and athletes. The design of an archery analytic workflow is demonstrated in this paper using the Python Flask framework, video analytic algorithms, a structured video inventory framework, MongoDB database setup and integration of the Keypoint R-CNN machine learning backend. A user-friendly data visualisation interface on the front end is integrated in the software to deliver athletes' analytical capabilities such as thorough frame-by-frame video analysis, posture consistency estimation and joint kinematic analysis. This web application framework is not limited to archery sports, and can be extended to numerous sports, such as shooting, weightlifting and cycling. The significance of integrating camera sensing technology with the sports science field can offer quantitative and qualitative observations to improve training programs and performance evaluation.

Keywords: Sports analytics, web application, biomechanics, Python Flask framework, archery

Introduction

Sports science through camera sensing technology in data analytics is an emerging area which assists in optimising biomechanics and movement abilities (Eitzen *et al.*, 2021; Richter *et al.*, 2021; Seshadri *et al.*, 2019; Taborri *et al.*, 2020). The collected imaging data is crucial for developing effective training schedules to improve athletes' performance. With the boom of

Copyright © 2024
http://doi.org/10.18080/jtde.v12n2.946

big data, conventional analytical methods may prove inefficient for revealing the data's results. By incorporating video processing methods in the area of sports analytics, it can provide rapid empirical insights into the strategic decision-making process in sports (Du & Yuan, 2021; Lease *et al.*, 2022; Morgulev *et al.*, 2018; Yuan *et al.*, 2021). In archery, the posture of archers during the aiming phase is correlated to higher score achievement. Obtaining the posture of archers requires a camera system to detect the micro-movements of posture during the aiming phase (Lau *et al.*, 2020; Vendrame *et al.*, 2022). The streaming of video information in a web-based application can provide a better understanding of biomechanics and posture analytics through highlighting the movement and biomechanical information. In this paper, a specialised web-based sports analysis application is designed primarily for archery but can be adapted to other sports. The development and design of the application are presented using the Python Flask framework, video processing methods and integration with a Keypoint R-CNN machine learning backend. The software enables analytics and insights into athlete performance through comprehensive frame-by-frame video analysis, posture consistency estimation and joint kinematic analysis.

Web Framework

The technical framework used in the web-based program is designed to enhance sports analytics, specifically in archery. The web application's framework is composed of four essential components, that is, web backend, session management with URL tracking, machine learning backend and the front-end user interface.

Backend web architecture

The web backend employs the Python Flask framework, well known for its effective routing, URL generation and capability to render dynamic content using Jinja2 templates (Pallets Projects, 2023). This setup is further improved by importing additional packages that enable connection to databases, validation of forms, authentication, distribution of workload, caching, and optimisation of queries. These features are essential for developing resilient applications, which collectively enhance the adaptability, safety and ease of use of the online infrastructure crucial for analysing sports and monitoring performance in archery web analytics.

Database structure

MongoDB, a NoSQL database, was popular for its scalability and adaptability (MongoDB, 2024). The schema-free architecture of this database is highly efficient in managing a wide range of data types, often found when collecting data from archery, including video recordings, athlete profiles and performance measures. Moreover, MongoDB's hierarchical document structure facilitates efficient data retrieval and rapid querying, crucial for conducting real-time analysis.

Video processing

The backend features a straightforward video processing pipeline that includes normalisation, frame extraction and compression. The initial phase involves normalising the incoming video sources to ensure uniform image brightness before progressing to the machine learning pipeline.

Video manifest structure

In sports analysis, especially in precision-focused sports like archery, having an efficient method to store and retrieve video data for precise motion analysis is vital. The web-based application fulfills this need by utilising a video manifest structure in JSON (JavaScript Object Notation) format. This methodical technique guarantees a well-organised and easily retrievable collection of video data.

The essential elements of this video manifest structure are outlined in a JSON format that provides important information for handling video frames. The structure of the video manifest file is explained as follows. The total number of frames in the video are denoted by 'num_frames', which is an integer value. The 'base_frame_path' is a string which indicates the directory path to the video frames, enabling the video player to access all the frames. Another integer, 'num_digits_frame' is the zero-padded number of frames to ensure order and consistency of file naming conventions. For example, value of 5 would have a file naming sequence of '00001.jpg', '00002.jpg', etc. The 'frame_ext' is a string representing the file format used to store the frame, typically '.jpg'. Lastly, the 'fps' element denotes the frame rate of the video playback in frames per second. This structure allows the video player to process the manifest efficiently and display the correct video. The JSON manifest, along with a JavaScript-based video player that also functions as a frame scrubber, allows the user to view the video frame by frame. This method operates by importing JPEG frames in a sequential manner.

URL tracking and archery session management

This web framework incorporates a URL tracking mechanism designed to enhance session management and user interaction tracking. This functionality is important for handling multiple archery sessions, where each session typically consists of 10 shots, and ensuring a user-friendly experience when accessing various video analyses.

URL structure and encoding

To track the current user's page, our web application uses a base64-encoded URL structure. This format effectively conceals and transmits essential parameters, enabling the backend to distinguish between different user sessions and video selections accurately. The structure of the URL follows a specific format:

https://<website>/<analyser_type>/<sport>?u=<user>&s=<session>&v=<video>

In this format, 'website' refers to the base URL of the web service. The 'analyser_type' is the current selected sports analyser, which varies depending on the required analysis of the user such as frame, segment, consistency, movement or hand release analyser. The 'sport' parameter is the current selected sport (for example, archery). The 'u' parameter represents the user's encoded email address, serving as a unique user identifier for the backend. The 's' parameter is an encoded string detailing the specific archery session, which includes information such as date, time, user identifier and session ID. The session ID represents one complete set of archery attempts, usually consisting of 10 shots. Lastly, the 'v' parameter is an encoded identifier for the video being analysed, specifically for one of the shots or sequences within a particular archery session. This structured URL format allows for secure and efficient transmission of user session information to the web backend.

HTTP GET requests and archery session tracking

Upon sending a HTTP GET method request from the user device, the web application decodes the base64-encoded URL to retrieve the user's details, the specific archery session and the selected video shot. This approach ensures that each user's interaction can be distinctly tracked and managed, even when multiple sessions or videos are accessed simultaneously across different browser tabs. Embedding these parameters within each URL allows for a robust session management system that maintains user context and video selection. It ensures that the analytics and data presented to the user are relevant to the specific shot or session being reviewed. This would prevent errors when the user submits an analytic request for a particular video and session which returns the desired output, rather than showing incorrect results from a previously opened video.

Machine learning backend

The core analytical functionality of the web application is provided by the machine learning backend, which uses the Keypoint R-CNN (He *et al.*, 2017, Chiam *et al.*, 2023) to extract human joint keypoints by identifying specific points on the human body and estimating the pose. This model was trained on the Common Objects in Context (COCO) dataset (Lin *et al.*,

Copyright © 2024
http://doi.org/10.18080/jtde.v12n2.946

2014), which consists of 330,000 photos annotated across 80 object categories, providing a rich foundation for accurate object detection and classification.

In the context of web application, the Keypoint R-CNN model is utilised to analyse individual video frames captured during sessions, with the primary purpose of identifying and defining the specific locations of human joints. The model architecture used in this application is illustrated in Figure 1. Keypoint R-CNN is a variant of Mask R-CNN (He *et al.*, 2017) where each mask is modified to find boundary boxes of a skeletal joint in the presented images with confidence scores. The head of the architecture consists of a combination of a residual network (ResNet) and a feature pyramid network (FPN) to extract feature maps from the input image. Subsequently, the regional proposal network (RPN) generates mask features that are passed on to the region of interest (ROI) align layers, a convolutional network (ConvNet) and a fully connected network (FCN) to infer skeletal keypoints estimations contained by masks, boundary boxes and confidence scores.

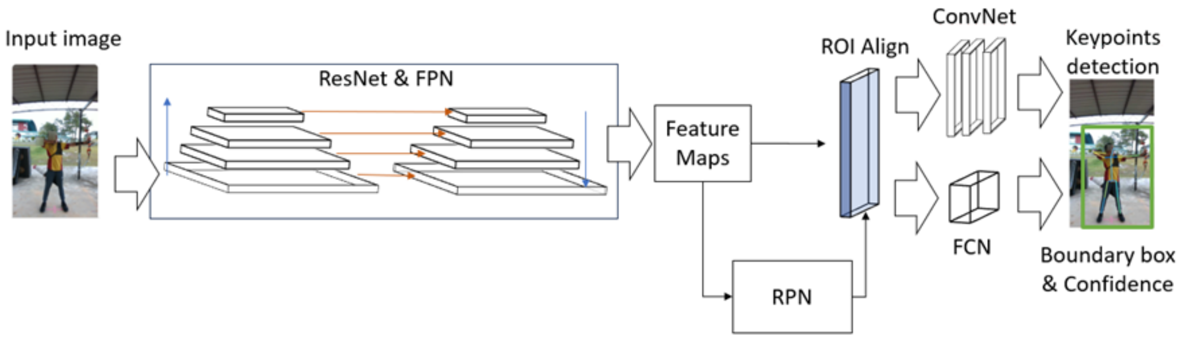

Figure 1. The model architecture of Keypoint R-CNN for extracting keypoints, boundary boxes and confidence scores.

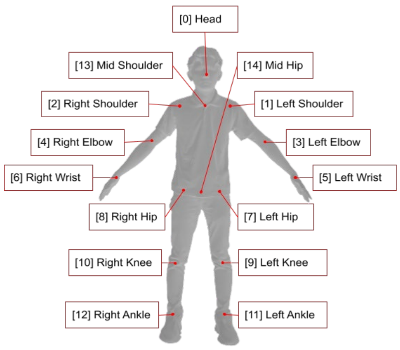

Figure 2. The extracted keypoints labels excluding eyes, ears and nose.

Keypoint R-CNN enables a thorough analysis of an archer's posture and technique. The model precisely analyses each frame to accurately identify and locate 2D keypoints corresponding to essential joints in the archer's body. Out of the total number of 17 skeleton keypoints found, 15 of them are selected for detailed analysis. The selected keypoints include essential joint locations, such as the shoulders, elbows, wrists, hips, knees and ankles, which are critical for conducting a full biomechanical examination in archery as illustrated in Figure 2. Notably, this analysis excludes specific details related to the eyes, ears, and nose in order to concentrate on the fundamental factors that impact archery posture and performance.

UI elements and analytical features

The web application's front end user interface is designed using Bootstrap 5 (Bootstrap, 2023), a framework that offers a user-friendly and responsive structure, improving user engagement. Designed specifically for archery sports analysis, this web application is equipped with a comprehensive suite of tools to support detailed evaluation and analysis. It includes a wide range of tools to assist in extensive examination and analysis. The interface is intentionally designed to be easily understood and is divided into two main categories of analysis tools: biomechanics and kinematics. Each category consists of analysers that are developed to concentrate on unique elements of archery technique and performance, ensuring a comprehensive and focused study.

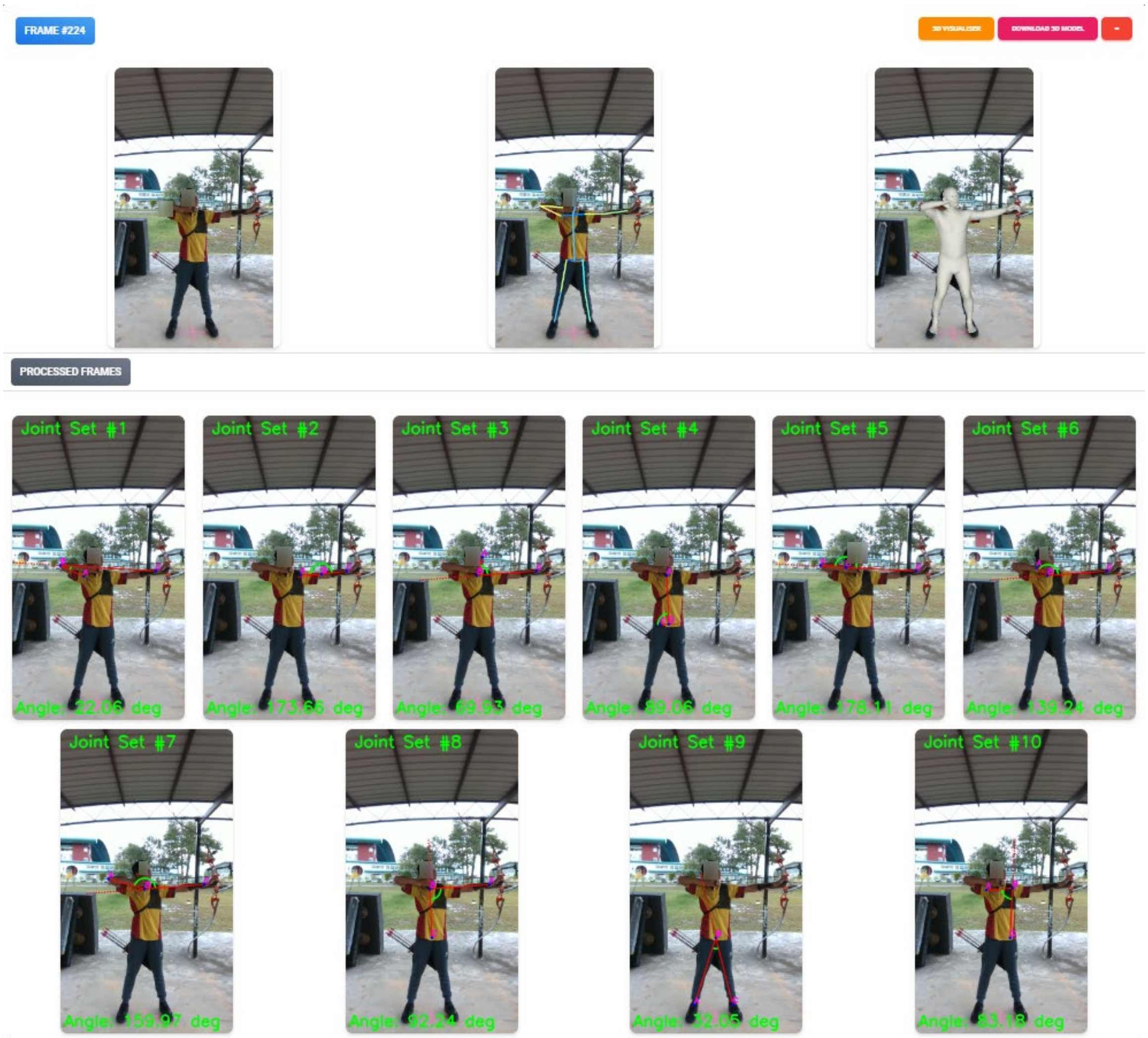

Figure 3. The result card output from the frame analysis tool.

1. Biomechanics: The biomechanics category examines the mechanical principles of the athlete’s movements, focusing on how their body functions during archery.
    a. Frame analyser: The frame analyser feature allows for the inspection of single frames from a video, where users can specify analyses on joint profiles to infer angles between specific joints. The outcome is shown on a display card, showing a primary 2D model, a 3D-rendered image, and the original frame with skeletal overlays as illustrated in Figure 3. Moreover, each processed image displays angular data and annotations overlaid for clarity.
    b. Segment analyser: The segment analyser enhances the frame analyser by evaluating a sequence of frames, where the user determines the start and end points of the frames to be analysed. It utilises the same joint profile approach as the frame analyser. The analysis outputs are shown on a result card, featuring a video sequence with skeletal overlays and a corresponding graph displaying joint angles over time as shown in Figure 4. Users can interact with the result card, choosing specific joints to examine, which updates the displayed video and graphs to reflect their selection.

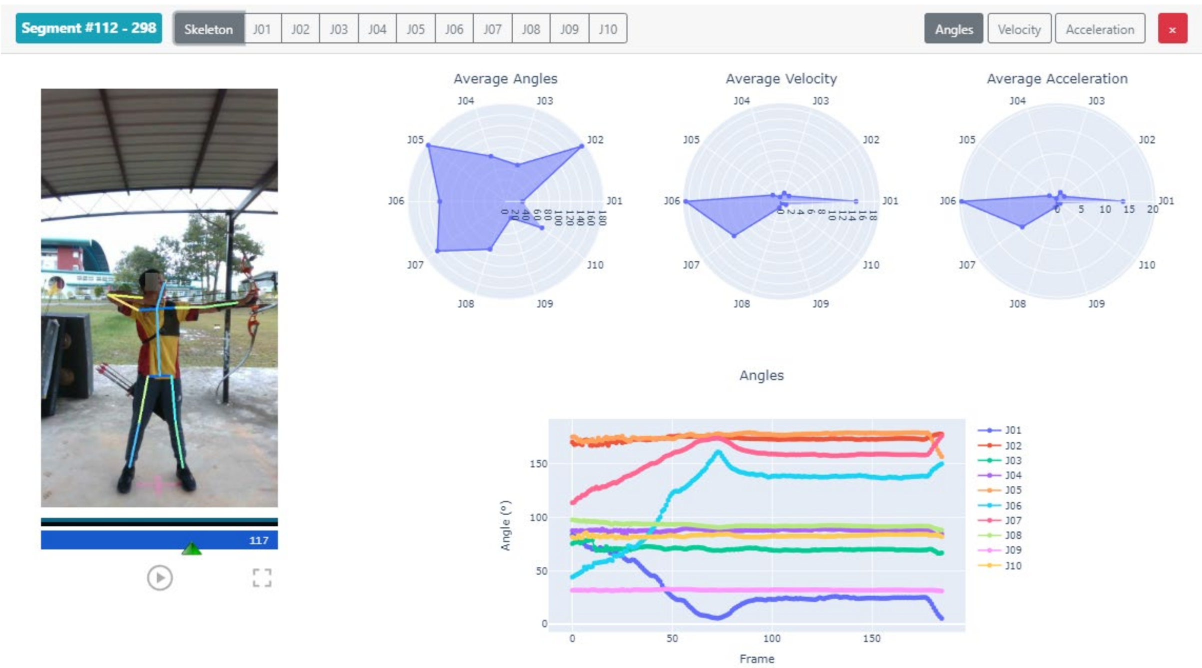

Figure 4. The result card output from the segment analysis tool.

    c. Consistency analyser: The consistency analyser provides an in-depth evaluation of the archery shooting-related consistency and metrics. The results are displayed on a card showing key metrics: joint variation, target scores, anchoring consistency and draw force line (DFL) consistency, average aiming time, and the inertial measurement unit (IMU) score as illustrated in Figure 5 (a)-(e). Each metric delivers valuable insights and is presented in a clear and informative manner. The summary card from the consistency analyser, as shown in Figure 6, reflects these insights.

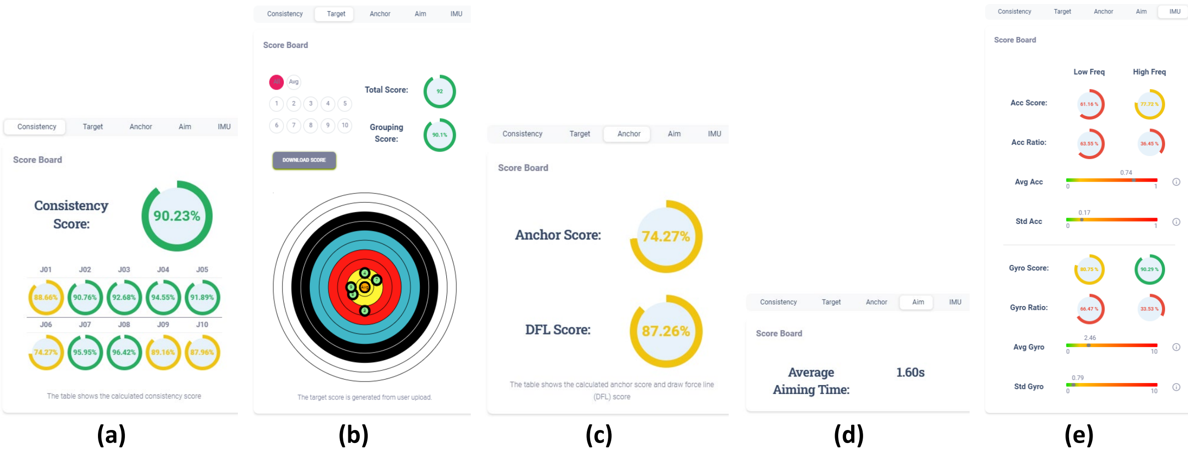

Figure 5. The result card output from the consistency analysis tool.

Figure 6. The result card output from the consistency analysis tool.

2. Kinematics: The Kinematics category focuses on analysing the detailed movements of the athlete, examining aspects such as velocity, acceleration and trajectory.
    a. Movement analyser: The movement analyser aims to identify and assess subtle body movements. The analyser assigns a score, as shown in Figure 7, reflecting the movement deviation during archery's aiming phase. A video player

Copyright © 2024
http://doi.org/10.18080/jtde.v12n2.946

highlights movement changes as red pixels, accompanied by motion visualisations and a graph that charts the movement index throughout the video sequence.

b. Hand release analyser: The hand release analyser focuses on the crucial moments executed by the archer by examining wrist movements during the release phase. The analyser utilises visual trackers and vectors, as shown in Figure 8, to represent wrist movement and velocity graphically, with indicators overlaid on the video player. By reviewing the release sequence frame by frame, athletes gain a deeper understanding of their form, providing insights into the nuances of their shooting technique.

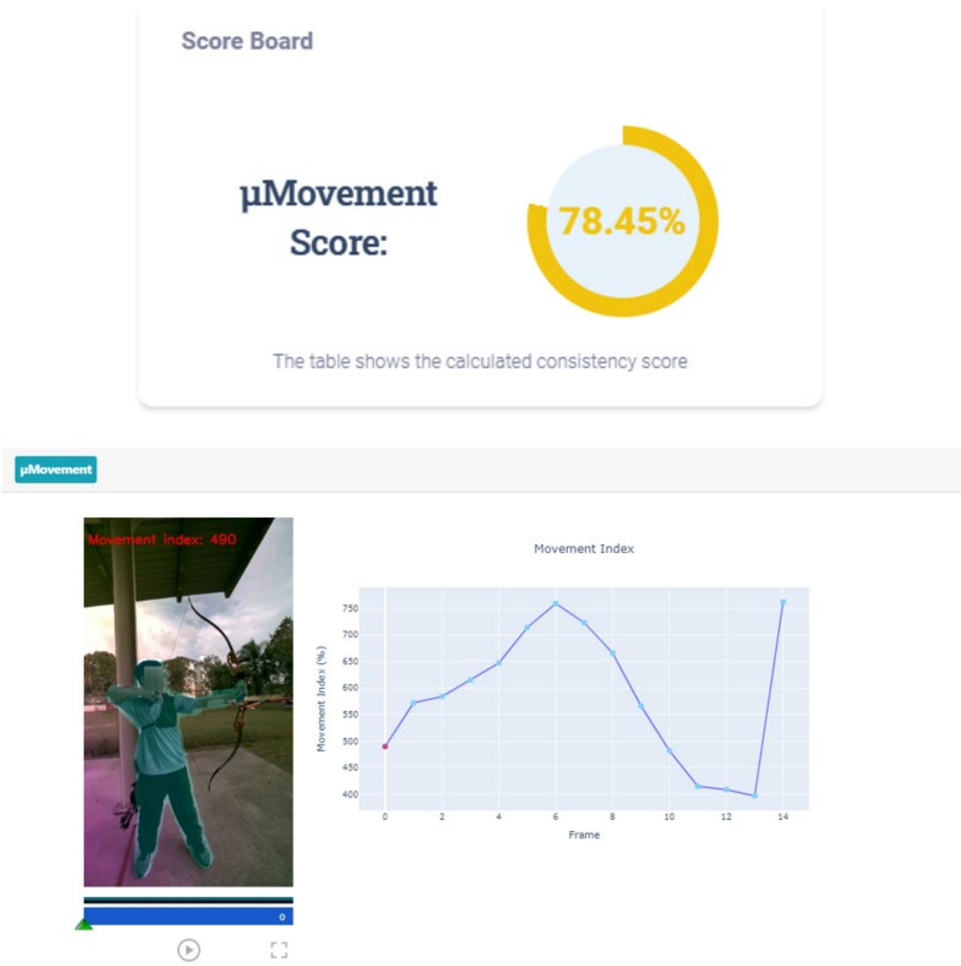

Figure 7. The result card output from the movement analysis tool.

Figure 8. The result card output from the hand release analysis tool.

The generated figures, data visualisations and interactive charts from the provided analysis tools enhance the user experience by offering objective and numerical analytical insights. These tools can be used by coaches and athletes for guidance and to inform training objectives.

Evaluating Features of the Web Framework Versus Existing Software

In the field of sports analytics, particularly for archery, various applications provide distinctive features for training and performance evaluation. However, the web framework presented in this paper distinguishes itself within this competitive domain. A comparison with existing applications, as outlined in the Table 1, highlights its unique attributes and advantages.

Table 1. Evaluating features of the web framework versus existing software

Application	Key features specific to archery
Archery Vision (Soong, n.d.)	Provides slow motion analysis to examine upper body posture, aiding in technique refinement.
Dartfish Express (Dartfish, n.d.)	Offers slow motion replay, manual annotation for detailed feedback, voiceover commentary for instruction, and screen recording capabilities for review and training purposes.
Kinovea (Charmant, n.d.)	Features include slow motion playback, side-by-side comparison, manual annotation for technique analysis, and motion measurement tools for precise feedback.
Onform (Onform, n.d.)	A mobile application which integrates advanced video analysis tools for athlete training, offering multi-camera capture, skeleton, joint tracking, and various recording modes including manual, Bluetooth-triggered and voice-activated. The software also features slow motion, side-by-side comparisons, and voiceover recordings for detailed movement analysis and technique improvement.
RyngDyng (Jochen & Patrick, n.d.)	Specialises in automatic arrow tracking, offering comprehensive measurements for each shot and integrated scorekeeping for effective performance tracking.

Application	Key features specific to archery
The web framework from this paper	Combines slow motion analysis with automatic posture extraction and overlay, detailed body posture and movement analysis, score tracking, grouping analysis for trends, and specific bow and wrist movement analysis during the arrow release phase for comprehensive archery training and assessment.

The comparative evaluation of features presented in Table 1 illustrates the unique capabilities of each archery analysis application. Archery Vision (Soong, n.d.) emphasises upper body posture, leveraging slow motion and automated replay functionalities, yet it falls short in providing a holistic set of analytical tools. Dartfish Express (Dartfish, n.d.) stands out with its manual annotation, slow motion features, coach narration and screen recording, catering to personalised feedback, though its effectiveness is constrained by the reliance on manual inputs. Kinovea (Charmant, n.d.) extends its utility with features for manual annotation, slow motion and motion comparison, but like Dartfish Express, it requires considerable user engagement for in-depth analysis, which could be a barrier for less experienced users. Onform (Onform, n.d.) is a mobile application which integrates advanced video analysis with features like multi-camera capture, skeleton tracking and a variety of recording modes, providing comprehensive tools for detailed movement analysis and technique improvement; however, since it is a mobile based application, it is not compatible with older versions of Android and iOS mobile operating systems. RyngDyng (Jochen & Patrick, n.d.) differentiates from other applications with automated arrow tracking and scoring, addressing a specific niche within archery analytics; however, it does not accommodate biomechanical analysis, limiting its utility for comprehensive technique evaluation. Each application, therefore, caters to different aspects of archery analysis, with distinct strengths and weaknesses, underscoring the importance of choosing the right tool based on the specific needs and skill levels of the user.

The web framework presented in this paper distinguishes itself by offering an extensive array of analysis tools that cater to a comprehensive analysis of archery performance. Unlike the other applications reviewed, whereby each focuses on specific areas of archery training, this framework integrates slow motion analysis with advanced features such as automated posture extraction and overlay. This application goes beyond basic video review to include detailed biomechanical and kinematic analysis, which is critical for understanding the intricate movements involved in archery. In addition, the framework's capabilities extend to wrist and bow movement analysis, score monitoring and arrow grouping dynamics, providing a holistic view of an athlete's technique and performance. This feature-rich approach facilitates a deeper and more nuanced understanding of training outcomes, making it a versatile resource for athletes and coaches aiming to enhance performance in archery.

Copyright © 2024
http://doi.org/10.18080/jtde.v12n2.946

Conclusion

The design of archery analytic workflow using camera technology and web-based application is presented in this paper to assist in studying an athlete's performance. The workflow comprises of Python Flask for server-side processes, MongoDB for streamlined data handling, and Keypoint R-CNN for pose estimation. The front end developed with Bootstrap offers both instructors and athletes with a user-friendly experience. This web application incorporates a base64-encoded URL tracking system, designed to ensure secure and accurate tracking of user interactions, particularly focusing on the management of multiple archery sessions. The URL structure enables the backend to distinguish effectively between different users, their specific archery sessions, and the individual video shots, thereby ensuring that data and analytics are aligned with the users' current contexts and activities. Within the web application, a suite of detailed analysis tools can be divided into biomechanics and kinematics categories. These tools allow for an in-depth examination and evaluation of an archer's techniques. The application comprises various analytical components including frame, segment and consistency analysers under the biomechanics category, and movement and hand release analysers under kinematics. This holistic approach furnishes users with a comprehensive platform for performance review and technique enhancement by offering a detailed analysis of movements for an objective assessment of athletic abilities. Future enhancements of the web application incorporating machine learning models can be expanded to a broader range of sports.

Acknowledgements

A prior iteration of this paper was presented at the GECOST 2024 conference in Malaysia, in January 2024. We would like to express our gratitude to the Sarawak Digital Economy Corporation (SDEC) and the Curtin Malaysia Research Institute (CMRI) for their collaborative efforts and support. Additionally, we acknowledge the generous contribution of the Quadro P6000 GPU by NVIDIA Corporation, which has significantly facilitated our research.

References

Bootstrap. (2023). Bootstrap 5.3. Retrieved March 16, 2024, from https://getbootstrap.com

Charmant, J. (n.d.). Kinovea. Retrieved March 18, 2024, from https://www.kinovea.org

Chiam, D. H., Phang, J. T. S., Lim, K. H., & Lease, B. A. (2023). Study of archery shooting phases using joint angle profile. In *2023 International Conference on Digital Applications, Transformation & Economy* (ICDATE), 1–5. https://doi.org/10.1109/ICDATE58146.2023.10248617

Dartfish. (n.d.). MyDartfish Express mobile. Retrieved March 18, 2024, from https://www.dartfish.com/mobile

Du, M., & Yuan, X. (2021). A survey of competitive sports data visualization and visual analysis. *Journal of Visualization*, *24*(1), 47–67. https://doi.org/10.1007/s12650-020-00687-2

Eitzen, I., Renberg, J., & Færevik, H. (2021). The use of wearable sensor technology to detect shock impacts in sports and occupational settings: A scoping review. *Sensors*, *21*(15), 4962. https://doi.org/10.3390/s21154962

He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask R-CNN. *In Proceedings of the IEEE International Conference on Computer Vision*, 2961–2969. https://doi.org/10.48550/arXiv.1703.06870

Jochen & Patrick. (n.d.). RyngDyng technology. Retrieved March 18, 2024, from https://www.archery-electronics.com/en/public/ryngdyng/technology

Lau, J. S., Ghafar, R., Zulkifli, E. Z., Hashim, H. A., & Krasilshchikov, O. (2020). A systematic review of Malaysian archery biomechanics research. *Theory and Methods of Physical Education and Sports*, (*3*), 91–96. https://doi.org/10.32652/tmfvs.2020.3.91-96

Lease, B. A., Phang, J. T. S., Chiam, D. H., & Lim, K. H. (2022). Online bio-mechanical evaluation system for posture assessment and correction. In *2022 International Conference on Green Energy, Computing and Sustainable Technology (GECOST),* Malaysia, (243–247). https://doi.org/10.1109/GECOST55694.2022.10010674

Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., & Zitnick, C. L. (2014). Microsoft COCO: Common objects in context. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6–12, 2014, Proceedings, Part V* (Vol. 13, 740–755). https://doi.org/10.1007/978-3-319-10602-1_48

MongoDB. (2024). What is MongoDB? Retrieved March 10, 2024, from https://www.mongodb.com/docs/manual

Morgulev, E., Azar, O. H., & Lidor, R. (2018). Sports analytics and the big-data era. *International Journal of Data Science and Analytics*, *5*(4), 213–222. https://doi.org/10.1007/s41060-017-0093-7

Onform. (n.d.). The ultimate mobile video coaching platform in lessons at practice and remote. Retrieved May 30, 2024, from https://www.onform.com

Pallets Projects. (2023). Flask. Retrieved March 16, 2024, from https://palletsprojects.com/p/flask

Richter, C., O'Reilly, M., & Delahunt, E. (2021). Machine learning in sports science: Challenges and opportunities. *Sports Biomechanics*, *20*(6), 1–7. https://doi.org/10.1080/14763141.2021.1910334

Seshadri, D. R., Li, R. T., Voos, J. E., Rowbottom, J. R., Alfes, C. M., Zorman, C. A., & Drummond, C. K. (2019). Wearable sensors for monitoring the physiological and biochemical profile of the athlete. *NPJ Digital Medicine*, *2*(1), 72. https://doi.org/10.1038/s41746-019-0150-9

Copyright © 2024

Soong, D. (n.d.). Archery vision. Retrieved March 18, 2024, from https://www.archeryvision.com

Taborri, J., Keogh, J., Kos, A., Santuz, A., Umek, A., Urbanczyk, C., van der Kruk, E., & Rossi, S. (2020). Sport biomechanics applications using inertial, force, and EMG sensors: A literature overview. *Applied Bionics and Biomechanics*, Volume 2020, Article 2041549. https://doi.org/10.1155/2020/2041549

Vendrame, E., Belluscio, V., Truppa, L., Rum, L., Lazich, A., Bergamini, E., & Mannini, A. (2022). Performance assessment in archery: A systematic review. *Sports Biomechanics*, *21*(1), 1–23. https://doi.org/10.1080/14763141.2022.2049357

Yuan, C., Yang, Y., & Liu, Y. (2021). Sports decision-making model based on data mining and neural network. *Neural Computing & Applications*, *33*, 3911–3924. https://doi.org/10.1007/s00521-020-05445-x