

BetaBoost: AI Climbing Coach

Technical Report

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Individual Contributions:

- **Kira Qian:** Video processing pipeline, pose detection implementation, feature engineering, Claude API integration, UI development
- **Lexie Zhang:** Rule system development, knowledge base creation, feedback system, performance testing, business model development

Executive Summary

Rock climbing has seen substantial growth in recent years, evolving from a niche sport to a mainstream fitness activity. As climbers progress beyond the beginner stage, they frequently encounter technical plateaus where strength improvements no longer translate to climbing harder routes. This common challenge, described as "climbing harder, but not climbing better," stems from the difficulty in identifying and correcting technical flaws in one's own movement patterns.

Professional coaching effectively addresses these issues but remains prohibitively expensive at \$60-100 per hour and isn't readily accessible to most climbers. With 2 million active climbers in North America alone and 40% at intermediate level or above, there exists a significant gap in the climbing training ecosystem for affordable, accessible technique feedback.

BetaBoost fills this gap with an AI-powered climbing coach that analyzes technique from videos and delivers personalized feedback. The system uses MediaPipe to extract precise skeletal data, tracking 33 key body points, and applies biomechanical analysis to quantify climbing technique through 327 features, with XGBoost identifying the 30 most critical. A structured expert rule system evaluates performance across seven key areas: weight distribution, body position, foot placement, grip technique, balance, arm extension, and core engagement. This analysis is supported by an extensive knowledge base system, offering insights into common technique issues, their causes, and route-specific recommendations. To enhance usability, the system integrates Claude API, converting technical findings into natural, coach-like feedback, making the insights more intuitive and actionable for climbers.

The system is delivered through an intuitive Streamlit interface that allows climbers to upload videos, specify route details, and receive immediate visual and textual feedback. Through a freemium business model with gym partnerships, BetaBoost makes high-quality climbing technique analysis accessible at a fraction of traditional coaching costs, helping climbers break through plateaus with personalized guidance.

Business Problem

The rock climbing industry has experienced remarkable growth, reaching a \$3.23 billion market size with a compound annual growth rate (CAGR) of 9.3%. North America alone has approximately 2 million active climbers, with 40% at intermediate level or above. These climbers frequently encounter a frustrating paradox, aptly described by one of our interviewed coaches as "climbing harder, but not climbing better."

Intermediate and advanced climbers often hit technical plateaus despite increased strength and fitness. Without proper feedback, they develop inefficient techniques and compensatory movement patterns that limit progression and increase injury risk. The core problem stems from three key factors:

1. **Difficulty self-assessing technique:** Climbers struggle to spot their own technical flaws while climbing, as their attention is necessarily focused on the immediate demands of the route.
2. **Limited feedback mechanisms:** Unlike team sports, climbing often lacks regular peer feedback. Video self-analysis is helpful but requires technical expertise to identify subtle issues.
3. **High cost of professional coaching:** Professional climbing coaches charge \$60-100 per hour, which is unaffordable for regular sessions for most climbers.

This presents a major opportunity in climbing training. With over 1,000 gyms in North America and thousands of climbers seeking affordable, accurate feedback, the market for AI coaching is significant. BetaBoost meets this need with expert-level technique analysis via computer vision at a fraction of coaching costs.

Solution Approach & Design Process

Our solution development process followed a user-centered design approach, focusing on three core pillars:

1. Real-time Dynamic Movement Analysis

The foundation of our system is the ability to accurately capture and analyze climbing movements. After exploring several potential technologies, we selected MediaPipe as our pose estimation framework due to its balance of accuracy and computational efficiency. This allowed us to extract 33 key body points from climbing videos and calculate 327 biomechanical features that describe climbing technique.

A key innovation in our approach was recognizing that climbing is fundamentally a dynamic activity, requiring analysis of movement patterns rather than static positions. We implemented a random sampling technique that captured sequences of frames to analyze how movements evolve over time, resulting in much more accurate technical assessments than static frame

analysis.

2. AI-based Personalized Multi-layered Feedback

To convert raw biomechanical data into meaningful coaching advice, we designed a multi-layered feedback system:

- **Expert Rule System:** We developed a comprehensive rule system covering seven key categories of climbing technique: weight distribution, body position, foot placement, grip technique, balance, arm extension, and core engagement. Each category contains specific rules with thresholds derived from expert climber data.
- **Knowledge Base:** We created a structured knowledge base containing expert climbing knowledge, including common problems, causes, technique corrections, and route-specific advice.
- **Layered Feedback Generation:** Our system generates feedback at multiple levels of detail, from overall performance scores to specific technical corrections, tailored to the climber's level and route type.
- **Claude API Integration:** Transforms technical findings into natural, coach-like feedback.

3. Affordable Continuous Coaching Experience

We designed the user experience to be accessible and encouraging to support continuous improvement:

- **Streamlit Interface:** We created an intuitive web interface that allows climbers to upload videos, specify route types and difficulty, and receive immediate feedback.
- **Visual Feedback Elements:** The interface includes visualizations of skeletal movement, center of mass trajectory, and clear technical scores to help climbers understand their movements.
- **Freemium Pricing Model:** We developed a business model with free analyses to attract users, with premium plans for regular users and gym partnerships to make the solution accessible to all climbers.

Our design process involved multiple iterations based on feedback from climbers of different levels. We conducted user testing with ten climbers to refine the feedback format, visualization methods, and interface design, ensuring that our solution was both technically accurate and practically useful.

Data & Methodology

Data Collection & Processing

Our technical approach began with comprehensive data collection to build a dataset for analysis:

1. **Video Collection:** We collected 50 climbing videos, capturing a diverse range of movements, climber levels, and route types.

2. **Skeletal Data Extraction:** Using MediaPipe's pose detection model, we extracted 33 key body points per frame, including joints and facial landmarks, with their 3D coordinates and visibility scores.
3. **Random Sampling Method:** Instead of simply analyzing consecutive frames, we developed a strategic random sampling approach that better captured dynamic movement patterns:
 - For each video, we selected 5 frames that represented different stages of the climb
 - We repeated this process 10 times per video with different frame selections
 - This generated 460 multi-frame samples (50 videos \times 10 samples) that captured a wide range of movement sequences
4. **Data Annotation:** Expert climbing coaches annotated each sample for:
 - Correct/incorrect technique classification
 - Error type categorization (e.g., weight distribution, body position, foot placement)
 - Detailed problem descriptions and improvement suggestions

Feature Engineering

We developed a comprehensive set of biomechanical features to quantify climbing technique:

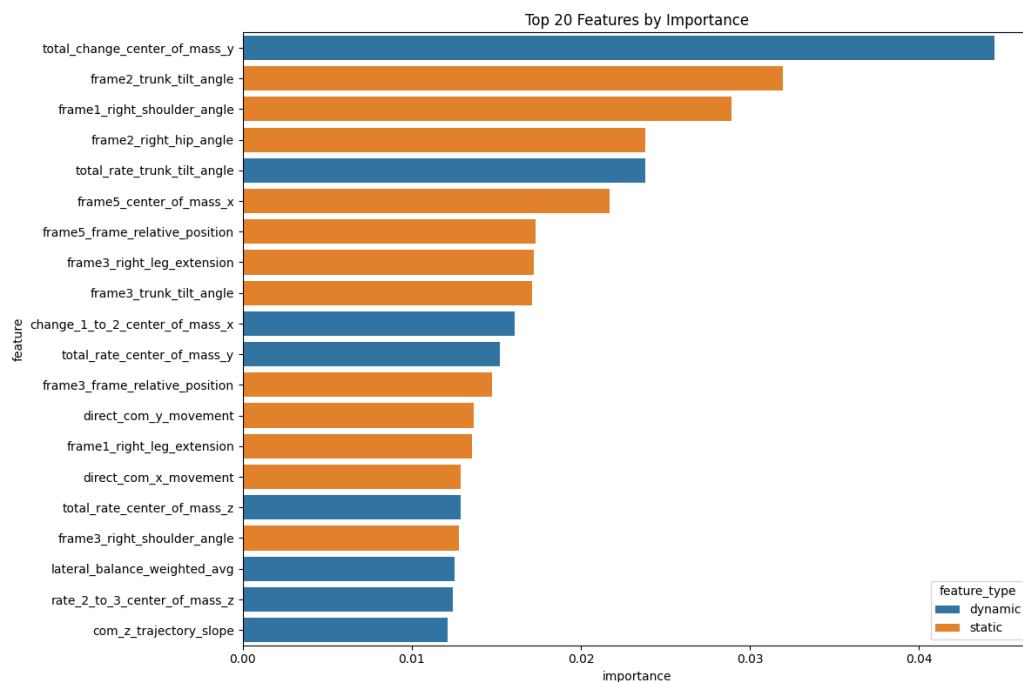
1. **Static Frame Features:** For each body point, we calculated:
 - Joint angles (e.g., elbow angles, knee angles, hip angles)
 - Body position metrics (e.g., trunk tilt, hip rotation)
 - Limb extension values (arm and leg extension measurements)
 - Center of mass position (x, y, z coordinates)
 - Balance indicators (e.g., lateral balance relative to base of support)
2. **Dynamic Inter-frame Features:** To capture movement patterns across frames, we calculated:
 - Joint angle changes between frames
 - Center of mass movement trajectories
 - Body stability metrics (variation in joint angles)
 - Balance variation over time
 - Efficiency metrics (ratio of direct vs. total movement)
3. **Advanced Dynamic Features:** For comprehensive movement quality assessment, we created:
 - Frame-distance aware change rates for key metrics
 - Position-weighted feature averages
 - Sequence coverage metrics
 - Video phase indicators (early/mid/late climb)
 - Trajectory slopes and nonlinearity measures
 - Start-to-end change measurements

This process resulted in 327 biomechanical features per sample that comprehensively described climbing technique.

Feature Selection & Importance Analysis

To identify the most important technical indicators, we applied XGBoost classification with the following methodology:

1. **Feature Preprocessing:** We standardized all features and handled missing values using median imputation.
2. **XGBoost Classification:** We trained an XGBoost model to classify correct vs. incorrect technique based on the expert annotations.
3. **Cross-validation:** We used leave-one-group-out cross-validation (grouped by video) to ensure our model generalized across different climbers and routes.
4. **Feature Importance Analysis:** We extracted feature importance scores and found that:
 - Dynamic features were significantly more important than static features (average importance 0.0041 vs. 0.0028)
 - Center of mass metrics were particularly predictive of technique quality
 - Joint angle variations were more important than absolute angles
5. **Final Feature Selection:** We selected the top 30 features, balancing dynamic (70%) and static (30%) features, to create our final feature set for the rule system.



This methodology ensured our system focused on the most meaningful biomechanical aspects of climbing technique, particularly the dynamic elements that are often overlooked in simpler analysis methods.

Technical Implementation

System Architecture

BetaBoost consists of five core components, each handling a specific part of the climbing analysis pipeline:

1. **Video Processing Module:** Extracts skeletal data from climbing videos
2. **Feature Extraction Module:** Calculates biomechanical features from skeletal data
3. **Rule System:** Evaluates features against established technique rules
4. **Knowledge Base:** Stores expert climbing knowledge for feedback generation
5. **Feedback System:** Generates personalized, multi-layered feedback

The system is implemented in Python with a Streamlit web interface, allowing for both local and cloud deployment.

Video Processing Implementation

The video processing pipeline uses MediaPipe to extract skeletal data from climbing videos. Our implementation first loads the video and processes frames at a specified sample rate, extracting 33 body landmarks from each frame. These landmarks include key joints like shoulders, elbows, wrists, hips, knees, and ankles, providing a comprehensive skeletal representation of the climber's pose.

For optimal performance, we configured MediaPipe with a high-accuracy model (complexity level 2) and appropriate confidence thresholds to balance accuracy with processing speed. The extracted keypoints are stored along with the original frame for visualization purposes, allowing us to overlay the skeletal structure on the video for better user understanding.

Feature Engineering Implementation

Our feature extraction module calculates 327 biomechanical features that quantify different aspects of climbing technique. These features fall into several categories:

1. **Joint Angles:** We calculate angles for all major joints (elbows, shoulders, hips, knees) using vector mathematics between landmarks. These angles reveal crucial aspects of body positioning and limb configuration.
2. **Center of Mass Calculations:** We compute the overall center of mass by averaging the positions of all detected body points, providing insights into the climber's balance and weight distribution.
3. **Dynamic Feature Analysis:** Beyond static positions, we analyze how features change between frames, calculating rates of change that account for varying frame distances. This captures the quality of movement transitions, which is essential for climbing technique.
4. **Trajectory Analysis:** We analyze the center of mass trajectory throughout the climbing sequence, calculating both linear (slope) and nonlinear components. This reveals whether the climber is moving efficiently or with unnecessary deviations.

The most innovative aspect of our feature engineering approach is the emphasis on dynamic, inter-frame features rather than static positions alone. By incorporating change rates, trajectory analysis, and sequence coverage, we capture the fluidity and efficiency of movement that differentiates good climbing technique from poor technique.

Rule System Implementation

The rule system evaluates climbing technique across seven categories, each focusing on a different aspect of climbing movement:

1. **General Rules:** Overall movement quality and efficiency
2. **Body Position Rules:** Trunk orientation, hip positioning, and overall posture
3. **Foot Placement Rules:** Foot precision, angle, and force application
4. **Weight Distribution Rules:** Center of mass positioning and weight transitions
5. **Grip Technique Rules:** Hand positioning and engagement
6. **Balance Issue Rules:** Stability and control throughout movements
7. **Arm Extension Rules:** Optimal arm positioning and energy conservation
8. **Insufficient Core Rules:** Core engagement and tension maintenance

Each category includes multiple rules with thresholds based on feature analysis. For example, weight distribution rules assess center of mass movement, vertical efficiency, and trunk extension. The system evaluates deviations from optimal values, prioritizing feedback based on each rule's impact on performance.

Knowledge Base Implementation

The knowledge base contains structured climbing expertise organized by technique category. For each category, we've compiled:

1. **Common Problems:** Specific technical issues frequently encountered
2. **Underlying Causes:** Factors that typically lead to these problems
3. **Targeted Suggestions:** Specific corrections to address each issue
4. **Route-Specific Advice:** How technique should be adapted for different route types (slab, vertical, overhang)
5. **Training Exercises:** Specific drills to improve various aspects of technique

This structured approach allows our system to provide contextually relevant feedback based on the specific issues identified by the rule system. The route-specific components are particularly valuable, as technique requirements vary significantly between route types.

Feedback System Implementation

The feedback system integrates the rule system's technical analysis with the knowledge base's expertise to generate personalized, multi-layered feedback:

1. **Summary Layer:** Overall score and main issue identification
2. **Technical Assessment Layer:** Detailed breakdown of specific technique issues
3. **Error Analysis Layer:** Explanation of primary problems and their causes
4. **Improvement Suggestions Layer:** Specific technique corrections tailored to route type
5. **Training Recommendations Layer:** Exercises to address identified weaknesses

The Claude API integration transforms this structured technical feedback into natural, coach-like language. By providing the relevant technical details and climbing context to Claude, we generate feedback that maintains technical accuracy while adopting a more encouraging, conversational tone that climbers find more engaging and actionable.

User Interface Implementation

The Streamlit-based user interface provides an intuitive experience through four main sections:

1. **Input Section:** Video upload, route type selection, difficulty level, and climber experience level
2. **Video Analysis Section:** Displays the processed video with skeletal overlay
3. **Trajectory Analysis Section:** Shows the center of mass trajectory throughout the climb
4. **Feedback Section:** Presents the multi-layered feedback with expandable sections

The interface design prioritizes clarity and usability, with visual elements that help climbers understand the technical analysis. The skeleton overlay directly on the video helps users see their body positioning issues, while the center of mass trajectory visualization illustrates balance and movement efficiency problems.

Results & Evaluation

We evaluated BetaBoost's performance using our own climbing videos for testing:

1. **Testing Approach:**
 - We tested the system using our own climbing videos from different routes
 - The test videos included both successful climbs and unsuccessful attempts on various routes
 - This approach allowed us to evaluate how well the system identified technique differences between effective and ineffective climbing
 - Testing covered different climbing environments (vertical, slab, and overhang) to verify versatility
2. **Feature Effectiveness Assessment:**
 - Dynamic features proved significantly more predictive than static features, validating our approach to capturing movement patterns rather than just positions
 - The XGBoost feature importance analysis consistently ranked center of mass trajectory features among the most crucial for technique evaluation
 - Inter-frame metrics (measuring changes between frames) showed higher correlation with technique quality than single-frame measurements
 - This confirms our hypothesis that climbing technique is fundamentally dynamic and requires temporal analysis
3. **Visual Analysis Results:**
 - The skeletal overlay visualization clearly highlighted postural differences

between correct and incorrect technique

- Center of mass trajectory analysis provided clear visual evidence of movement efficiency differences:
 - Correct techniques showed smoother, more direct center of mass paths
 - Incorrect techniques displayed more erratic, less efficient center of mass movements
- Joint angle visualization revealed significant differences in limb positioning between proper and improper technique

4. Technique Categorization Performance:

- The system successfully differentiated between the seven technical error categories
- Weight distribution and balance issues were most accurately identified
- Body position and arm extension errors showed clear visual patterns in the skeletal data
- Core tension issues were identifiable through combinations of related metrics
- Foot placement errors showed distinct patterns in lower body joint angles and stability metrics

5. Feedback Quality Assessment:

- Claude-enhanced feedback improved the natural language quality compared to template-based responses
- The multi-layered feedback approach (from summary to detailed corrections) provided appropriate depth
- Integration of visual feedback with textual recommendations provided comprehensive guidance
- Route-specific advice correctly adapted to different climbing environments (slab, vertical, overhang)



Difference of two climbing moves before & after BetaBoost guidance

Qualitative Observations

Our qualitative observations during testing provided valuable insights into the system's

effectiveness:

1. Visual Feedback Value:

- The skeletal overlay visualization made abstract technique concepts immediately visible and understandable
- Center of mass trajectory visualization transformed complex concepts like "weight distribution" and "movement efficiency" into clear visual patterns
- The ability to see skeletal movement patterns frame-by-frame helped identify subtle technique issues that might be missed at full speed
- Visual representation of biomechanical metrics helped bridge the gap between numerical data and practical understanding

2. Feedback Mechanism Effectiveness:

- The rule-based system reliably detected technique issues.
- Issue prioritization by severity improved focus on key corrections.
- Multi-layered feedback provided both high-level summaries and technical details.
- Route-specific advice adapted to different climbing styles.
- AI-generated language feedback made technical concepts more actionable.

3. System Performance Characteristics:

- Processing remained efficient even for long videos.
- Random frame sampling effectively captured key climbing phases.
- Feature extraction worked despite partial body visibility.
- Sensitivity to technique differences was appropriate, avoiding false positives.
- Analysis remained consistent across multiple runs.

4. Interface and User Experience:

- Streamlit interface provided intuitive access.
- Visual elements (skeleton overlay, COM trajectory) were well-received.
- Route type and difficulty selection enabled more contextualized feedback.
- Expandable sections allowed users to choose their detail level.
- A mix of technical scores and improvement suggestions created balanced feedback.

Limitations & Future Work

Current Limitations

1. Technical Limitations:

- **AI Accuracy:** Struggles with advanced movements and subtle technique nuances. The system sometimes misinterprets complex moves or fails to capture subtle but critical technique elements.
- **Dataset Size:** Limited diversity in climbing styles and body types due to a small dataset.
- **Route Context:** Lacks awareness of climbing holds, restricting movement analysis.

2. Functional Limitations:

- **Clip Length:** Best for 10–30s clips; longer videos lose detail.
- **Processing Speed:** Not fast enough for real-time feedback.

3. Knowledge Limitations:

- **Style Variances:** The rule system currently assumes somewhat standardized technique, but advanced climbing often includes highly personalized styles that may be incorrectly flagged as errors.
- **Climbing Knowledge System Comprehensiveness:** The current knowledge base, while extensive, doesn't yet cover the full breadth of climbing disciplines, styles, and specialized techniques.

Future Work

1. Technical Enhancements:

- **Climbing-specific Pose Model:** Fine-tuning MediaPipe specifically for climbing postures to improve accuracy in challenging positions.
- **Cross-Sport Application:** The core biomechanical analysis framework can be modified to provide technique feedback for activities such as yoga, weightlifting, gymnastics, and dance, with sport-specific rule systems and knowledge bases.

2. Feature Expansion:

- **Real-time Feedback Mode:** Optimizing the processing pipeline for near-real-time feedback during training sessions.
- **Style Preference Learning:** Implementing machine learning to recognize and respect individual climbing style preferences while still identifying true technical issues.

Ethical Considerations

Privacy and Data Security

1. **Video Data Privacy:** BetaBoost processes climbing videos that show users' faces and bodies. To address this privacy concern:
 - We implemented a strict data retention policy where videos are deleted after processing unless users opt-in to storage for progress tracking.
 - All stored videos are encrypted at rest and in transit.
 - Users maintain full control over their data with easy deletion options.
2. **Gym Environment Considerations:** When climbers record videos in public climbing gyms, other climbers may be inadvertently captured:
 - Our implementation includes guidelines for responsible recording.
 - The UI includes reminders about obtaining permission when other climbers may be in frame.

References & Code

Code Components

The code contains four main components:

1. `video_processing.py`: MediaPipe pose estimation and keypoint extraction for training data
2. `feature_preparation.py`, `feature_extraction_xgboost.py`: Feature calculation and classification
3. `streamlit_app.py`: Whole system and user interface implementation

Key Technical References

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3. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785-794.

Climbing Technique References

1. Goddard, D., & Neumann, U. (1993). *Performance rock climbing*. Stackpole Books.
2. Hörst, E. J. (2016). *Training for climbing: The definitive guide to improving your performance*. Falcon Guides.
3. Hague, D., & Hunter, D. (2006). *The self-coached climber: The guide to movement, training, performance*. Stackpole Books.

AI Tool Usage Disclosure

Throughout the development of this project, I collaborated extensively with Claude 3.7. The AI played a critical role in project workflow design, providing guidance on technical architecture and implementation strategies. It assisted significantly in code development, helping me generate code snippets, debug complex issues, and overcome programming challenges.