

Impact / Significance / Intro

Interlimb asymmetry has been suggested to negatively impact jump performance, yet the magnitude, threshold, and sex-specific effects remain unclear. This study applied Extreme Gradient Boosting (XGBoost), a machine learning approach, to predict jump height based on interlimb asymmetry levels in collegiate athletes.

Methods

- Eighteen national athletes (8 females, 10 males) performed weekly countermovement jumps over two years, totaling 2,772 trials.
- Interlimb asymmetry—defined as the percent difference in peak force between limbs—was categorized at 0%, 5%, 10%, 15%, and 20%.
- A 10-fold cross-validation XGBoost model was trained to predict jump height (cm) using age, sex, asymmetry, and countermovement depth (hyperparameters: eta = 0.03, max_depth = 10, nrounds = 200).
- Model performance was assessed via root mean squared error (RMSE) and coefficient of determination (R²).

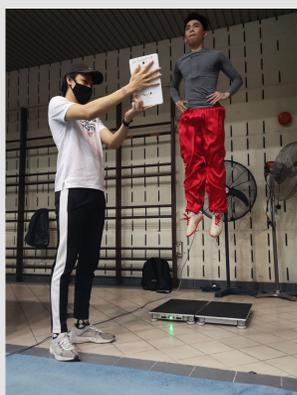


Figure 1. CMJ weekly testing set up and data collection (Left), and online data processing by the Hawkin Dynamics software (Right).

Positive improvements in JH over training time

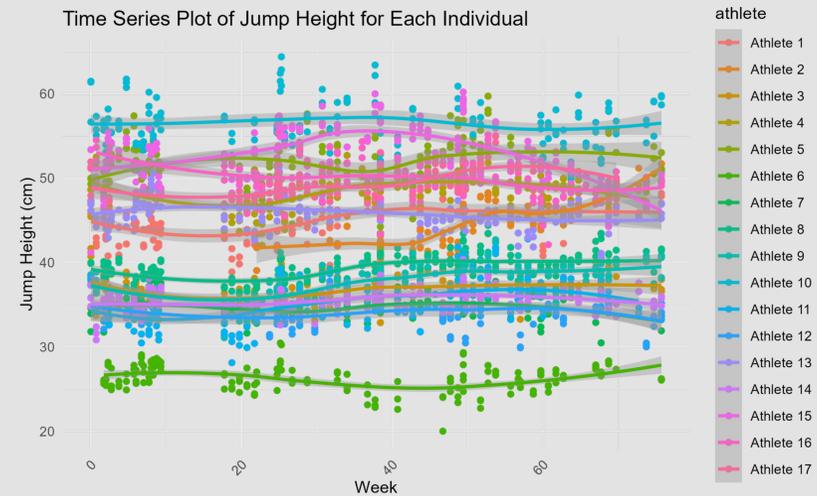


Figure 2. Jump Height responses to training time.

Machine Learning Algorithms can predict decreases in Jump Height from Interlimb asymmetry

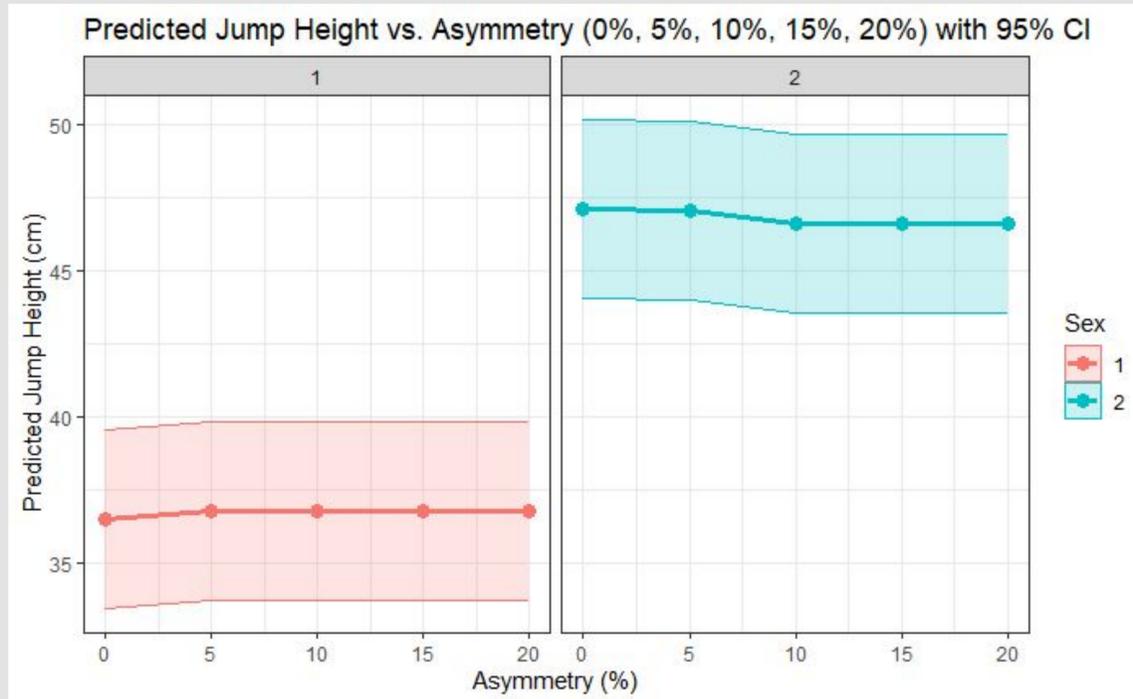


Figure 3. Predicted decreased Jump Height with increased interlimb asymmetry %.

Results

- XGBoost achieved high predictive accuracy (RMSE = 1.56 cm, R² = 0.966).
- Predicted jump heights revealed a nonlinear relationship between asymmetry and performance, with asymmetry beyond 10% producing no further decrements (suggesting a threshold effect).
- Males exhibited a more linear decline (approximately 1.5 cm reduction from 0% to 20% asymmetry), whereas females showed an initial reduction up to 5% followed by performance stabilization beyond 10%.
- These findings align with prior research on sex-based differences in neuromuscular strategies and lower-limb power.

Practical Applications

Strength and conditioning professionals should consider individualized asymmetry thresholds rather than universal cutoffs. Corrective strategies may be most beneficial when asymmetry exceeds 10% and is accompanied by demonstrable performance deficits. Incorporating machine learning into athlete monitoring systems can facilitate real-time performance tracking and data-driven decision-making in training and rehabilitation.

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