### Dynamic Threshold Modeling for Inter-Limb Symmetry-Based Injury Risk Prediction in U.S. Collegiate Athletes: A Novel Machine Learning Approach

**Abstract:**

Injury risk prediction has traditionally relied on static threshold models, particularly in assessing inter-limb asymmetry metrics such as force, impulse, and torque. However, increasing evidence suggests these static thresholds lack context sensitivity and fail to adapt to athlete-specific variability. This study proposes and validates a novel dynamic buffer thresholding framework combined with machine learning models to predict injury risk based on symmetry deviations. Our research utilizes U.S.-based collegiate athlete data, addressing a notable geographic gap in the literature, and demonstrates improved risk classification and early-warning capability over traditional cutoff-based models. We evaluate model performance across multiple quarters, track individual athlete risk progression, and introduce athlete-specific alerting thresholds. Our findings support a paradigm shift toward personalized injury monitoring in sports science.

**1. Introduction**

Injuries are a persistent concern in sports, affecting athlete longevity, team performance, and institutional cost. Inter-limb asymmetry, defined as a measurable difference between left and right limb performance metrics, has often been cited as a key indicator of injury risk. Most prior research, however, has utilized fixed cutoffs (e.g., 10-15%) to flag abnormal asymmetry, ignoring natural athlete variability and task-specific demands. Further, the majority of such studies have been conducted in European or Australian contexts, leaving a significant gap in U.S.-based athlete populations.

This study addresses both methodological and geographic gaps by developing a machine learning-based dynamic threshold model using performance symmetry data from collegiate athletes in the U.S. We propose a novel framework that continuously adjusts risk thresholds based on each athlete's baseline variability, and analyze its effectiveness in predicting injury risk over time.

**2. Related Work**

A growing body of research explores the relationship between asymmetry and injury risk. Studies such as "A Preventive Model for Muscle Injuries Using Machine Learning" and "Predictive Modeling of Hamstring Strain Injuries in Elite Australian Footballers" applied decision trees, boosting algorithms, and support vector machines to assess risk factors, yet used static thresholds and often overlooked asymmetry evolution over time.

Systematic reviews such as the one conducted by Claudino et al. (2019) emphasize the potential of AI in sports injury modeling, but note limited application in real-time or dynamic contexts. Meanwhile, Bittencourt et al. (2016) and Meeuwisse et al. (2007) argue for a shift from linear, reductionist models to complex, recursive systems that consider time-varying risk factors. Our study operationalizes these theoretical insights into a real-world, data-driven implementation.

**3. Methodology**

* **Dataset**: Performance data were collected from U.S. collegiate athletes, including symmetry metrics such as left/right force, torque, and impulse, across multiple sessions.
* **Symmetry Calculation**: Inter-limb symmetry ratios were computed and normalized.
* **Dynamic Buffer Thresholds**: For each athlete, a rolling baseline was established using previous session metrics. A risk threshold was defined as deviations exceeding ±1.5 standard deviations from the individual’s average.
* **Modeling**: Random Forest classifiers were used, with comparison across various resampling techniques (SMOTE, SMOTEENN, class weighting).
* **Temporal Analysis**: Data were grouped into quarters to assess risk evolution and seasonal variation.

**4. Results**

* **Improved Predictive Accuracy**: Models incorporating dynamic thresholds outperformed static-threshold counterparts in detecting high-risk athletes.
* **Feature Importance**: Metrics like AvgForceSymmetry, ImpulseSymmetry, and TorqueSymmetry were found most predictive.
* **Athlete-Level Trends**: Time-series tracking allowed identification of deteriorating symmetry before actual injury reports.
* **Resampling Techniques**: SMOTEENN yielded the best balance between precision and recall for minority class (High Risk).

**5. Discussion**

This study shows that dynamic thresholds provide greater sensitivity to individual athlete variability, outperforming rigid, population-based cutoffs. Unlike prior models that treat athletes as homogeneous groups, our approach respects the heterogeneity in adaptation, fatigue, and performance trends. By capturing temporal changes and personalized baselines, this model offers coaches and medical teams a more robust tool for intervention.

Our work also fills a geographic void by providing the first implementation of dynamic symmetry-based injury prediction in a U.S. collegiate population. As most previous research focused on Australian or European cohorts, this localization offers both cultural and methodological novelty.

**6. Limitations & Future Work**

* Limited biomechanical and psychological factors (e.g., joint angles, stress levels) were included; future models should expand feature sets.
* Real-time sensor integration is pending but represents a key direction for future validation.
* External dataset validation from other sports (e.g., basketball, rugby) is planned to generalize findings.

**7. Conclusion**

Our study introduces a personalized, dynamic thresholding framework for inter-limb symmetry-based injury prediction, grounded in machine learning and validated on a U.S. collegiate dataset. This work sets the stage for more individualized, adaptive approaches to injury monitoring and has strong potential to improve athlete care and reduce preventable injuries.

**References**