Prediction of injuries in elite soccer players with the analysis of asymmetries in the CMJ through the use of Machine Learning tools

Predicción de lesiones en futbolistas de élite con el análisis de asimetrías en el CMJ mediante el uso de herramientas de Machine Learning

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Abstract

Introduction: The analysis of asymmetries in the countermovement jump (CMJ) is a potentially useful tool for the prevention of injuries in elite soccer players.
Objective: This study analyzes the relationship between biomechanical asymmetries in the CMJ on landing (% Peak Landing Force Asymmetry) and the risk of musculoskeletal injuries.
Methodology: Through the use of force platforms (ForceDecks, Valdperformance) and 4 machine learning models, data from 29 Asian Football Confederation (AFC) Champions League elite level professional soccer players were analyzed during a regular season (with a total of 1265 jumps analyzed, during the days Match Day Training MD+1, MD+2 and MD-1).
Discussion: The results indicate that the average asymmetries (0.82% +- 13.66) in the peak landing force are not predictive of the risk of injury, while the % Coefficient of variation (COV) (323–1827) of that asymmetry was related and could have a predictive nature regarding the risk of injuries. Furthermore, there is a moderate positive correlation (r = 0.447) between % COV Assymetry and the appearance of injuries, which is statistically significant (p = 0.017).
Conclusions: The odds ratio of 2.4 indicates that players with higher than average COV asymmetry are 2.4 times more likely to suffer an injury. These findings highlight the importance of the CMJ as part of injury monitoring and injury reduction programs.

Keywords

Countermovement jump, injuries, prediction, machine learning, asymmetry.

Resumen

Introduccion: El análisis de asimetrías en el salto con contramovimiento (CMJ) es una herramienta potencialmente útil para la prevención de lesiones en futbolistas de élite.
Objetivo:Este estudio analiza la relación entre asimetrías biomecánicas en el CMJ al aterrizar (% Asimetría de Fuerza Máxima de Aterrizaje) y el riesgo de lesiones musculoesqueléticas.
Metodología: Mediante el uso de plataformas de fuerza (ForceDecks, Valdperformance) y 4 modelos de aprendizaje automático, se analizaron datos de 29 futbolistas profesionales de élite de la Liga de Campeones de la Confederación Asiática de Fútbol (AFC) durante una temporada regular (con un total de 1265 saltos analizados, durante los días de entrenamiento del día del partido MD+1, MD+2 y MD-1).
Discusion: Los resultados indican que las asimetrías promedio (0,82% ± 13,66) en la fuerza máxima de aterrizaje no son predictivas del riesgo de lesión, mientras que el % Coeficiente de variación (COV) (323–1827) de esa asimetría sí estaba relacionado y podría tener carácter predictivo respecto al riesgo de lesiones. Además, existe una correlación positiva moderada (r = 0,447) entre el % de asimetría del COV y la aparición de lesiones, la cual es estadísticamente significativa (p = 0,017).
Conclusion: El odds ratio de 2,4 indica que los jugadores con una asimetría del COV superior a la media tienen 2,4 veces más probabilidades de sufrir una lesión. Estos hallazgos resaltan la importancia del CMJ como parte de los programas de monitorización y reducción de lesiones.

Palabras clave

Salto con contra movimiento, lesiones, predicción, aprendizaje automático, asimetría.

Introduction

Hamstring injuries have increased significantly over the last two decades, now accounting for nearly 24% of all injuries among elite male football players (Ekstrand et al., 2023). Despite growing efforts to improve injury prevention strategies, including biomechanical monitoring and load management, injury rates remain persistently high (Ruddy, J. D et al, 2018) This underscores the need for more accurate diagnostic and predictive tools in elite sport.

One area of growing interest is the analysis of lower-limb asymmetries—particularly during the countermovement jump (CMJ)—as potential indicators of musculoskeletal imbalance and injury risk (Bishop, C et al, 2018) However, the scientific literature has produced inconclusive findings. For instance, although some studies suggest that asymmetries greater than 10–15% may increase injury risk (Bishop et al., 2018; Fort-Vanmeerhaeghe et al., 2016), meta-analyses such as that of Helme et al. (2021) found no statistically significant associations between lower-limb asymmetry and injury incidence.

This discrepancy may stem from methodological inconsistencies across studies. Different asymmetry thresholds, definitions of limb dominance, and test types (e.g., unilateral vs bilateral CMJ) limit comparability. Additionally, many studies rely on isolated measurements without considering temporal variability or the athlete's fatigue status (Roe, G et al, 2017) These factors may obscure the true relationship between asymmetry and injury risk.

Fatigue, in particular, is known to alter neuromuscular performance and may influence asymmetry values. CMJ testing has been validated as a reliable method for detecting neuromuscular fatigue (Gathercole et al., 2015; Roe et al., 2017; Miras Moreno, S. (2020) yet few studies have explored how fatigue-induced asymmetries may relate to injury risk. Moreover, variability in asymmetry over time—a potential indicator of neuromuscular instability—remains understudied.

Another underexplored area is the connection between internal/external training load and biomechanical asymmetries. Force platforms can provide objective insights into how players respond to these loads (Collings, TJ et al, 2024) However, their integration into real-time injury prediction systems is still limited.

Given these limitations, there is a need for more dynamic, individualized, and temporally sensitive approaches to injury risk analysis. Machine Learning (ML) offers a promising alternative to traditional statistical methods by handling large datasets (Oliver, J. L et al, 2020) detecting nonlinear patterns, and generating personalized risk profiles. While ML is increasingly applied in sports science, few studies have specifically used it to evaluate whether CMJ-derived asymmetry metrics can predict injury risk.

To address the gaps identified above, this study investigates whether variability in CMJ landing-phase asymmetry—measured as the coefficient of variation (COV) of peak landing force asymmetry—can predict injury risk in elite football players. Unlike traditional approaches that use static asymmetry thresholds, we propose a dynamic model based on temporal variability and employ four ML algorithms to test its predictive power.

Method

Study participants

This prospective cohort study included 29 elite male football players from a Malaysian professional club competing in the Asian Football Confederation (AFC) Champions League during the 2024–2025 season. The average age was 28 ±2.1 years, height 1.77 ±3.5 cm, body mass 75.4 ±2.9 kg, body mass index (BMI) 22.1 ±1.98, and body fat percentage 14.3 ±1.1%. Players had an average of 7.2 years of professional experience.

All participants were first-team players who regularly trained and competed. The sampling strategy was based on convenience due to access to a single elite team. Inclusion criteria included: (i) being fully registered with the first team, (ii) participating in regular training and competition, and (iii) availability for testing throughout the season. Exclusion criteria included: (i) long-term injuries (>21 days), (ii) being under rehabilitation during the scheduled assessments, or (iii) withdrawal of informed consent.

Players who sustained minor injuries or were under treatment at any testing point were excluded from the analysis for that specific time point, but not from the full study.

The study received approval from the Institutional Ethics Committee of the National Sports Institute of Malaysia (Protocol ID: NSI-ETH2024-19). All participants provided written informed consent prior to enrollment. The purpose, procedures, risks, and potential benefits of participation were clearly explained. Participation was voluntary, and athletes were informed of their right to withdraw at any time without consequence.

Table 1. Data from the study sample

Age	28 +- 2.1 years
Height	1.77+-3.5cm
Weight	75.4 +- 2.9kg
BMI	22.1 +- 1.98
% Fat	14.3 +- 1.1
Professional years	7.2 years

Age: Chronological age in years; Height: Height measured in centimeters (cm); Weight: Body mass measured in Kilograms (Kg); BMI: Body Mass Index; % Fat: Percentage of body fat mass;

Procedure

Players followed a typical professional in-season training schedule, consisting of 5–6 weekly training sessions and 1–2 competitive matches. Assessments were performed gym facility under standardized environmental conditions (temperatures 25–32°C, relative humidity 60–75%). All CMJ tests were supervised by certified strength and conditioning coaches with postgraduate education and a minimum of five years of applied experience.(McMahon, J et al, 2022)

Countermovement jump (CMJ) performance was assessed using ForceDecks® dual force platforms (ValdPerformance, Brisbane, Australia). The equipment was calibrated before each testing session. Data were collected via the Vald Hub cloud-based software (Version 2.1.0), using default detection parameters for jump phases, peak force, and asymmetry.

Each testing session was preceded by a standardized 10-minute warm-up (5 minutes of cycling + 5 minutes of dynamic mobility) (O'Grady, M et al. 2021) . Athletes performed three maximal CMJs with arm swing, separated by 15 seconds of passive rest. All jumps were performed barefoot on the same surface.(Steinman, D., Shirley, M., Fuller, M., & Reyes, C. 2019).

CMJ assessments were conducted three times per micro cycle:

- MD+1 (day after match)

- MD+2 (two days post-match)

- MD−1 (day before match)

This protocol was repeated weekly across the competitive season, depending on each player's availability and injury status.

Repetitions with technical errors, early take-off, or inconsistent landing mechanics were automatically excluded by the software and verified by visual inspection (Collings, TJ et al, 2024) Only valid jumps were included for further analysis. In total, 1,265 CMJs were analyzed across the 29 participants.

Figure 1. Neuromuscular Assessment and monitoring System (Forcedecks ® , Valdperformance , VALD, Brisbane, Australia)

For data processing, the specific ValdPerformance Software and ValdHub cloud system (APP ForceDecks, Apple Store, Vald Performance Pty Ltd © 2014-2024,Version 2.1.0) was used, using the default configuration. This analysis involved self-detection of the repetitions and the maximum force values, averages and asymmetries. The repetitions that were not performed accordingly to the protocol and standards, were eliminated from subsequent analysis (Collings TJ et al, 2024; Meras Serrano et al, 2023; Bagchi A et al, 2024)

Data analysis

Asymmetry was quantified using the Limb Asymmetry Index (IA%), defined as the difference between dominant (D) and non-dominant (ND) leg performance relative to the stronger limb: (Parkinson, A. O et al, 2021)

Figure 2. Limb Asymmetry Index Formula (IA%)

$$\mathrm{IA\%} = 100 \times |\mathrm{D} - \mathrm{ND}| \;/\; \max(\mathrm{D}, \mathrm{ND})$$

The use of the maximum value between limbs (rather than the mean) was chosen to reflect the relative performance to the stronger side, as recommended by previous research (Bishop et al., 2018; Fort-Vanmeerhaeghe et al., 2016). This method improves the sensitivity of asymmetry detection for injury risk, emphasizing the imbalance rather than global performance.

In addition to IA%, we computed the Coefficient of Variation (COV) for each player's IA% values across the season:

%COV = (SD / Mean) × 100

This variable was used to assess intra-individual variability over time, based on the assumption that higher asymmetry fluctuation may reflect neuromuscular instability, fatigue accumulation, or adaptation failure (Yanci, J., & Camara, J. 2016; Bishop, C et al 2022), factors potentially linked to injury risk.(Parkinson, A. O et al, 2021)

All data were reviewed for missing values and outliers. Missing data due to injury or absence from testing were not imputed ; instead, only valid and complete data were analyzed per time point. Outliers were retained if confirmed to reflect true performance deviations (e.g., post-injury or high-fatigue states), and excluded only if they resulted from measurement or procedural errors.(Collings, TJ et al, 2024). A total of 1,265 valid CMJs were included in the final dataset.

The main outcome variable was injury occurrence (binary: 0 = no injury; 1 = injury), recorded throughout the season by the club 's medical staff.

To explore the predictive capacity of CMJ asymmetry metrics, we applied:

- Binary Logistic Regression
- Decision Tree Classifier
- Random Forest
- XGBoost (Extreme Gradient Boosting)

All models were implemented using Python (v3.10) via the Julius AI Analytics platform(Caesar Labs, 2024). This cloud-based tool was selected for its built-in explainability metrics (e.g., feature importance, confusion matrix) and ease of integration with biomechanical data workflows.

Each ML model was trained and cross-validated (5-fold) using a standard 70/30 train-test split. Performance metrics included:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC Curve
- AUC (Area Under the Curve)

Additionally, players were categorized into three injury risk groups based on percentile thresholds of %COV asymmetry:

- Low risk: < P33
- Moderate risk: P33–P66
- High risk: > P66

Statistical significance was set at $p < 0.05$. All analyses were supported by existing literature on asymmetry-based injury prediction (Oliver et al., 2020; Ruddy et al., 2018; Bishop et al., 2022).

Figure 3. Machine Learning Algorithms (XG Boost Prediction vs Real Data)

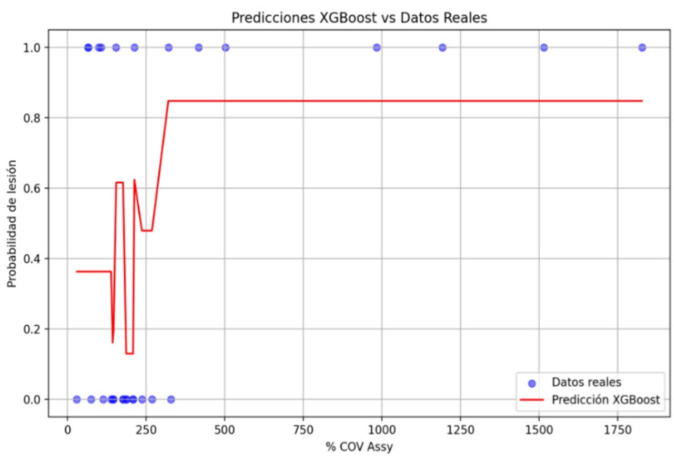


Figure 4. Contingency Matrix (True and false Positives)

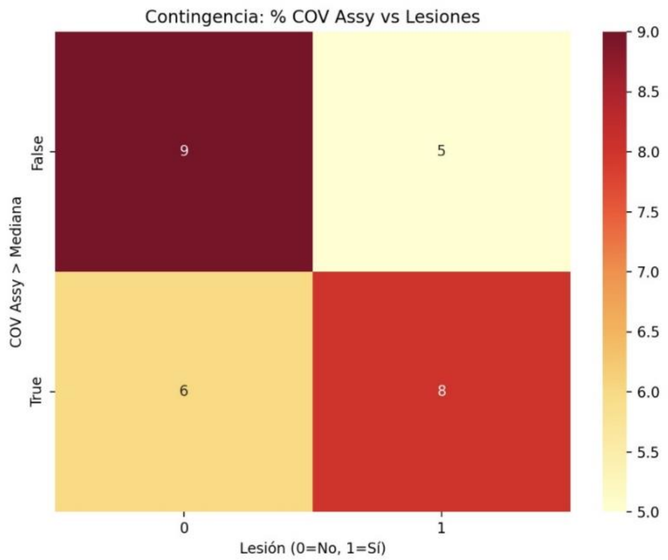
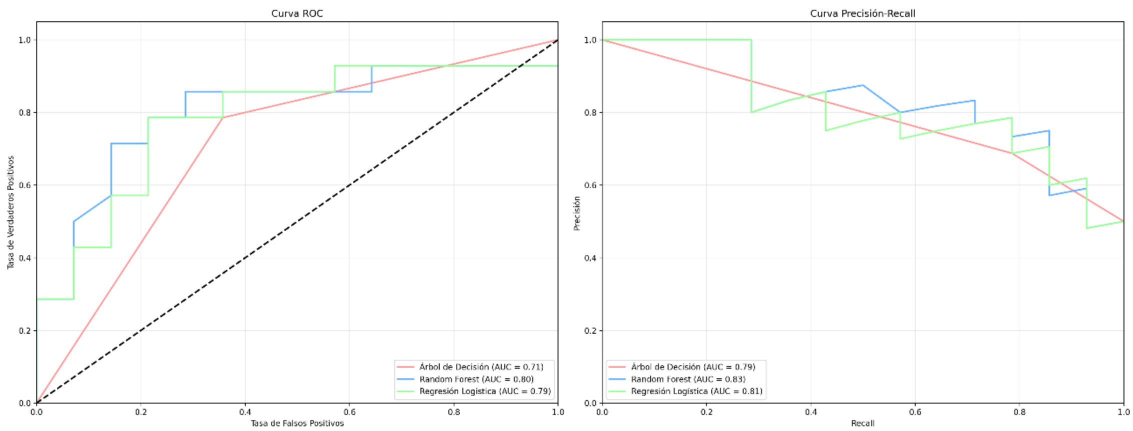


Figure 5. Curve ROC and Precision Recall of Machine Learning Algorithms



Results

A total of 1,265 CMJs were analyzed across 29 players throughout the competitive season. The analysis focused on two key variables related to inter-limb asymmetry: % Peak Landing Force Asymmetry and the % Coefficient of Variation (COV) of Asymmetry.

% Peak Landing Force Asymmetry

The mean peak landing force asymmetry across all jumps was 0.82% ±13.66. Visual analysis using scatter plots (Figure 7) revealed no statistically significant linear correlation between this asymmetry and injury occurrence. However, **extreme values (both positive and negative) tended to be more frequent among injured players, suggesting a possible non-linear or threshold-based relationship.

- Interpretation: Although asymmetry magnitude alone may not predict injury risk, high asymmetry outliers could still represent elevated risk.

Figure 6. Scatter plots showing (Left) % COV vs. injury status and (Right) Average peak asymmetry (L–R) vs. injury status

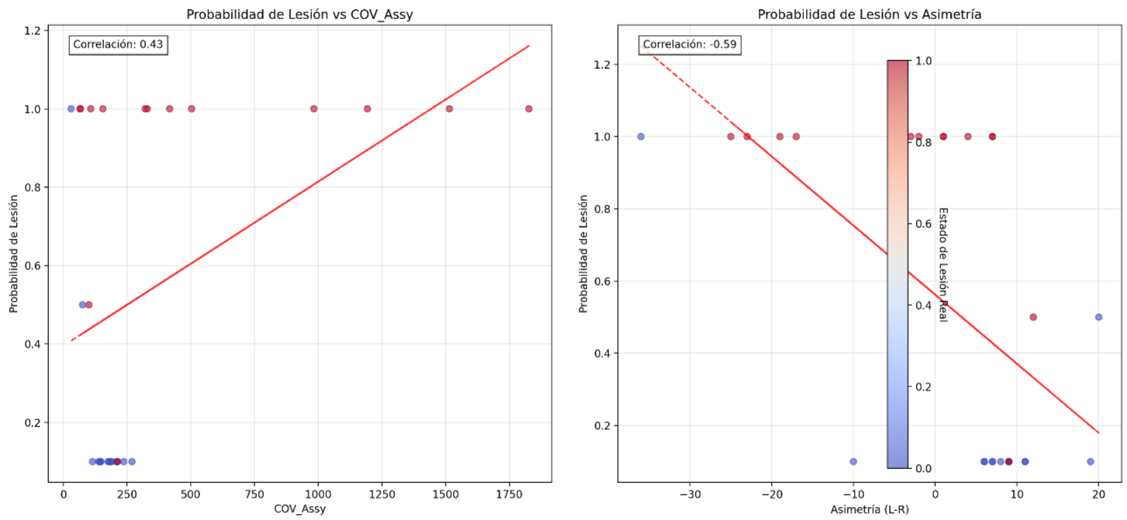
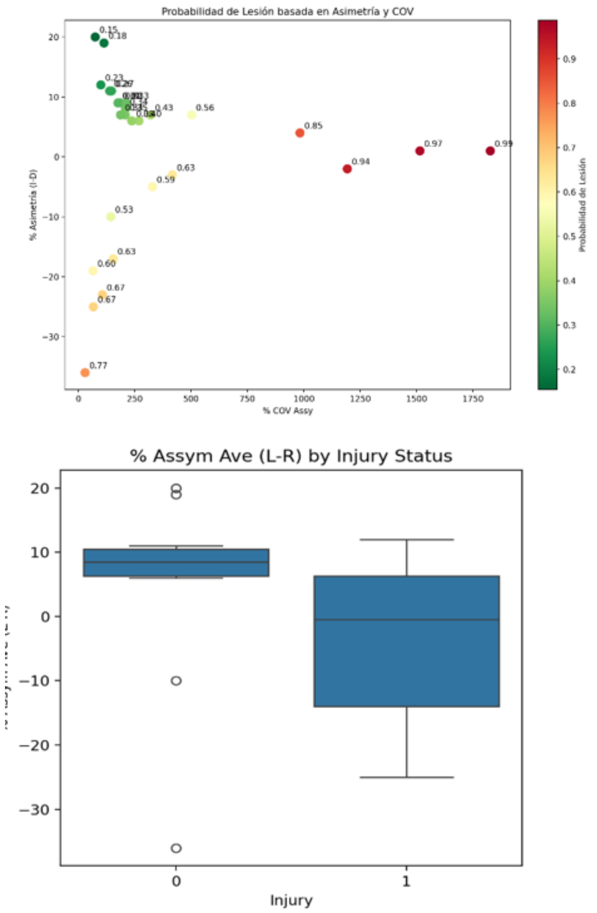


Figure 7a Distribution of asymmetry values across the sample and 7b. Injury status for extreme asymmetry values (0 = no injury, 1 = injury).



% Coefficient of Variation (COV) of Peak Landing Force Asymmetry

The %COV of peak landing force asymmetry demonstrated stronger predictive capacity than raw asymmetry values:

- Mean %COV (injured players): 574.3

- Mean %COV (non-injured players): 175.2

- Mann–Whitney U test:p = 0.17 (not significant, likely due to small sample)

However:

- Pearson correlation (r): 0.447

- Statistical significance: p = 0.017*

- Odds Ratio (OR):2.4 → Players with above-average %COV were 2.4 times more likely to suffer an injury.

Figure 8. Frequency distribution of %COV across players

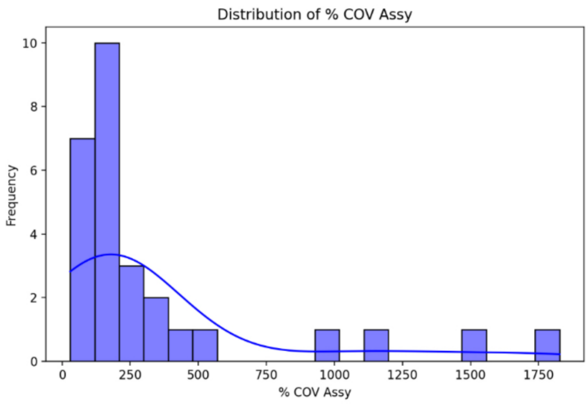


Figure 9. Predicted injury probability increases with higher %COV

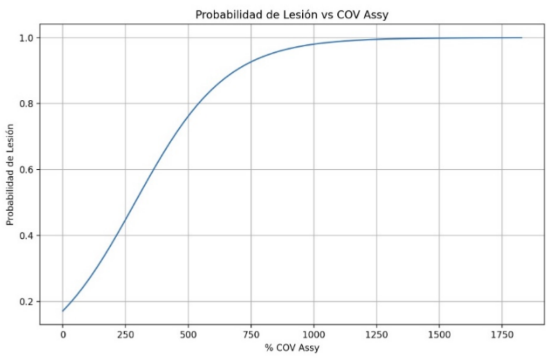


Figure 10. Correlation matrix between injury, asymmetry (L-R), and %COV

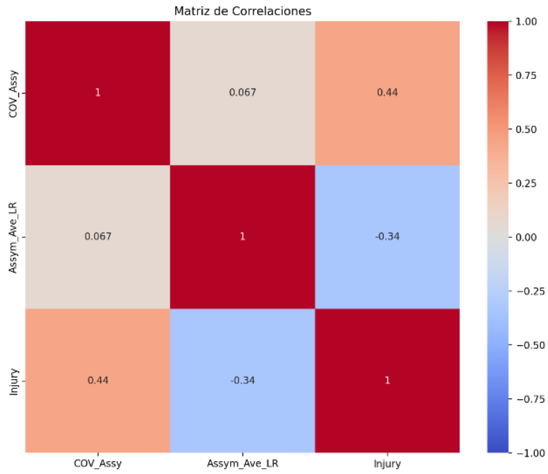
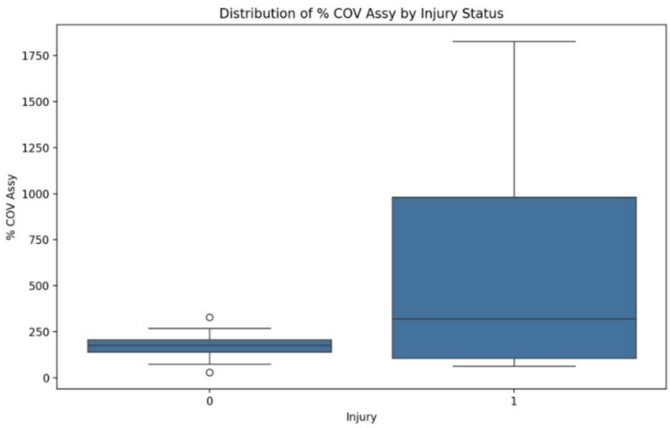


Figure 11. Distribution of injured vs non-injured players based on %COV thresholds



Dominant Side vs No Dominant Side

- Moderate correlation between asymmetry and the dominant limb: r = 0.557
- No significant correlation between leg dominance and injury occurrence: r ≈ 0.000
- Negative correlation between average asymmetry and injury: r = –0.343

Figure 12. Correlation matrix: Dominant leg, average asymmetry, %COV, and injury

Variable	% COV Assy	% Assym Ave (L-R)	Dominant leg	Injury
% COV Assy	1.000	0.067	0.151	0.441
% Assym Ave (L-R)	0.067	1.000	0.557	-0.343
Dominant leg	0.151	0.557	1.000	~0.000
Injury	0.441	-0.343	~0.000	1.000

Predictions based on different models of Machine Learning

Four models were used to predict injury risk based on %COV asymmetry. Key results:

Logistic Regression

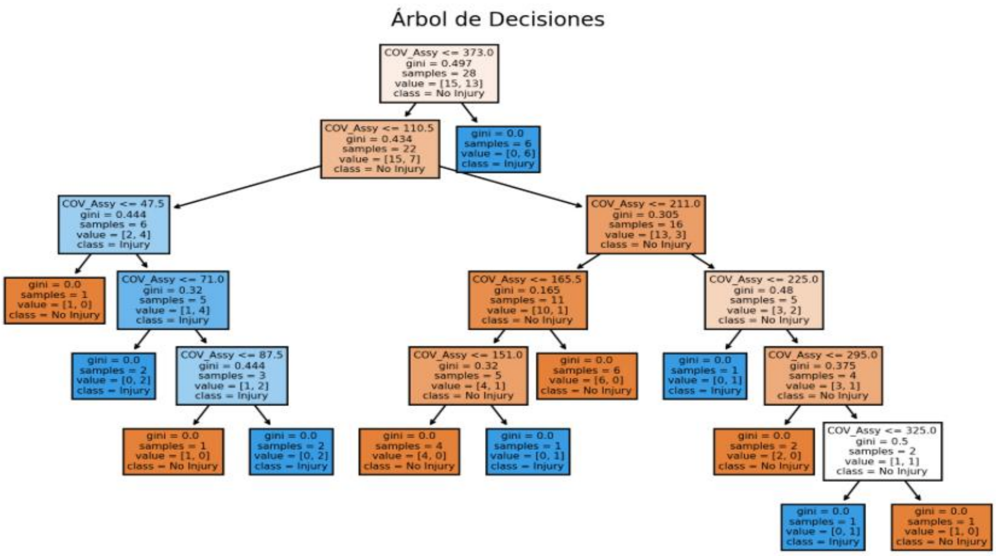
- Accuracy: 67%
- Interpretation: Higher COV values associated with increased injury probability

Decision Tree

- Accuracy: 66.7%
- Precision (injured): 60%
- Recall (injured): 100%
- F1-score (injured): 75%

→ All injuries correctly detected, but high false positives.

Figure 13. Decision Tree



Random Forest

- Accuracy: 67.4% ±32.5%
- Risk stratification by COV:
- Low (< 146.7)
- Moderate (146.7–232.7)
- High (> 232.7)

Figure 14.Risk stratification thresholds from RF, DT, and LR models

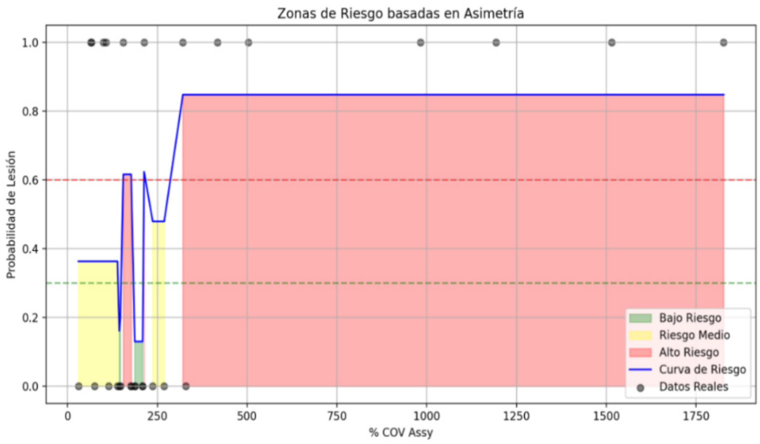
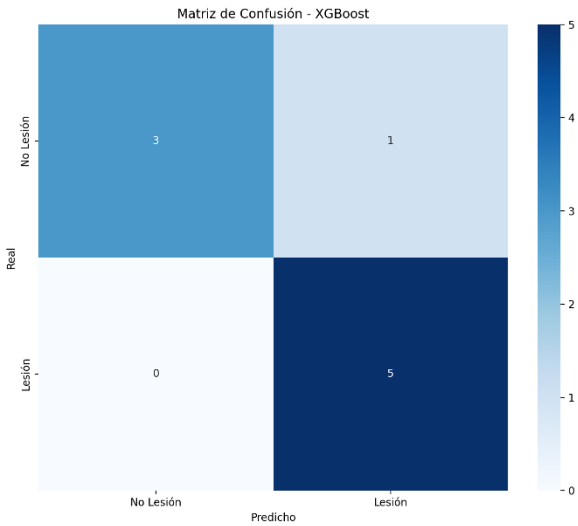


Figure 15. XGBoost



- Accuracy: 75%
- Precision: 40%
- Recall: 50%
- F1-score: 44%
- False Positive Rate: 0%
- False Negative Rate: 25

Summary

Peak asymmetry (IA%) was not significantly associated with injury. The %COV of asymmetry showed a statistically significant correlation** and a moderate predictive value. About Machine learning models , especially XGBoost and Random Forest, demonstrated useful—but not perfect—classification ability, with XGBoost achieving 0% false positives.

Discussion

This study aimed to investigate whether variability in CMJ landing-phase asymmetry—measured as the coefficient of variation (%COV) of peak landing force asymmetry—could serve as a predictor of injury risk in elite football players (. Hewit, J. K., Cronin, J. B., & Hume, P. A. 2012; Hart, N. H et al, 2014). We employed force platform assessments (Badby, A.J et al, 2023; Merrigan, J.J et al, 2022) throughout a full competitive season and applied four machine learning models to classify injury risk.

The results showed that mean asymmetry values (%IA) (Parkinson, A. O et al, 2012) did not significantly correlate with injury risk (Menzel, H. J et al, 2013) . In contrast, %COV of asymmetry demonstrated a moderate and statistically significant correlation ($r = 0.447$, $p = 0.017$) with injury occurrence. Players with above-average COV values were 2.4 times more likely to suffer an injury. Machine learning models—particularly XGBoost and Random Forest—achieved moderate classification accuracy, with XGBoost attaining a 0% false positive rate .

Our findings align with recent evidence suggesting that asymmetry variability, rather than isolated magnitude, may be a more reliable indicator of neuromuscular dysfunction and injury susceptibility (Bishop et al., 2018; Fort-Vanmeerhaeghe et al., 2016). Prior meta-analyses (e.g., Helme et al., 2021) reported no significant association between asymmetry and injury, but these studies were limited by (Espada, M. C et al, 2023)

- High heterogeneity in measurement protocols

- Inconsistent thresholds (10%, 15%, etc.)

- Uncontrolled fatigue states

- Varied test modalities (e.g., unilateral CMJ, isokinetics)

By standardizing our methodology (bilateral CMJ on ForceDecks) and analyzing intra-individual variability over time, our study addresses many of these limitations.(.Yanci, J., & Camara, J. (2016). The novel use of %COV provides a dynamic, individualized marker of neuromuscular control, potentially more sensitive to chronic maladaptation or subclinical fatigue.

Fatigue is known to influence biomechanical output and asymmetry profiles (Ruddy, J. D et al 2018). By collecting data at MD+1, MD+2, and MD-1, we captured neuromuscular responses under different physiological states (post-match recovery, adaptation, pre-match readiness). This allowed us to detect instability patterns that may not emerge in static assessments.(Bromley, T et al, 2012)

Our results are consistent with previous research showing that CMJ-derived metrics can detect neuromuscular fatigue (Gathercole et al., 2015; Roe et al., 2017), and extend that literature by demonstrating how fatigue-induced variability (%COV) may contribute to injury prediction. (Bishop, C et al, 2022)

Traditional statistical approaches are often limited in handling complex, nonlinear interactions between multiple injury-related variables (Oliver, J. L et al 2020). The use of machine learning (ML) allowed us to identify subtle patterns not evident in conventional models. XGBoost, for instance, achieved 75% accuracy and zero false positives—suggesting its potential value in real-world injury surveillance systems.

Still, the presence of false negatives (e.g., 25% in XGBoost) highlights that no single variable or model can predict all injuries. Future iterations should integrate multiple data streams (e.g., GPS load, subjective wellness, prior injury history) for more comprehensive predictions.

The study supports shifting practitioner focus from absolute asymmetry thresholds (e.g., >10%) toward variability-based metrics. High %COV may indicate poor neuromuscular control or unstable recovery, serving as a red flag for injury risk.

Furthermore, this variable can be easily tracked using existing force plate technology, making it practical for performance and medical teams alike. Despite promising results, the study has several limitations:

- Small sample size ($n = 29$), limiting generalizability and statistical power.

- Injuries were classified as general musculoskeletal injuries, without breakdown by type (e.g., hamstring, ACL, ankle).

- No control group or external validation cohort.

- Potential confounders (training load, match exposure) were not directly included in the predictive models.

To improve the robustness of asymmetry-based injury prediction models, future studies should:

- Use larger, multi-club datasets across seasons.

- Differentiate between injury types and mechanisms.

- Incorporate additional variables (load monitoring, subjective metrics, psychological stress).

- Validate ML models in external datasets and real-time applications.

Practical Applications

Based on the findings of this study, the following recommendations are proposed for practitioners in elite football settings:

1. Monitor Asymmetry Variability (COV)

- Prioritize the coefficient of variation (%COV) of CMJ landing-phase asymmetry over single-value asymmetry thresholds.

- High variability may indicate poor neuromuscular control or recovery instability—key risk factors for injury.

2. Standardize Testing Protocols

- Use validated force platform systems (e.g., ForceDecks®) for consistent bilateral CMJ assessments.

- Schedule tests at standardized time points (e.g., MD+1, MD+2, MD−1) to capture fatigue and adaptation responses.

3. Integrate Machine Learning Tools

- Apply ML models (Random Forest, XGBoost) to classify players by injury risk.

- Use these models to support decision-making around load management, return-to-play protocols, and injury prevention strategies.

4. Educate and Communicate with Staff

- Promote interdisciplinary collaboration between coaches, sports scientists, and medical staff.

- Use visual reports from CMJ data to guide conversations about player readiness and risk levels.

5. Expand Data Sources

- In future applications, combine CMJ asymmetry data with GPS load metrics, subjective wellness, and injury history for a more holistic risk profile

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