DOI 10.26773/smj.251007

ORIGINAL SCIENTIFIC PAPER

From Body to Combat: Physical Characterization of Fencers according to their Weapon

Jhon E. Roa[1], Nicol D. Arias[1], Javier Gaviria[1], Diego F. Orejuela[1], Isabel C. Rojas-Padilla[1]

[1]National School of Sports, Faculty of Education and Sports Sciences, Cali, Colombia

Abstract

Fencing is an Olympic sport with three modalities differentiated by the weapon used: épée, foil, and sabre. Each involves different physical demands due to the characteristics of the weapon, such as its weight and the specific combat technique required. The objective of this study was to develop a predictive model to determine the optimal fencing modality based on the athletes' anthropometric characteristics and physical capacities. The study was quantitative, cross-sectional, and observational, and was conducted with active fencers from the Valle del Cauca league in Colombia. Anthropometric (weight, wingspan, muscle mass, and fat percentage) and physical variables (measured using the McCloy battery) were evaluated, along with additional data such as age and VO_2 max. To improve the representativeness of minority classes, the SMOTE oversampling technique was applied. Five classification models (LDA, KNN, CART, NB, and SVM) were tested, the Decision Tree being the one that obtained the best performance after being optimized with Grid Search. The results showed that the percentage of muscle and body fat, as well as the squat with jump, significantly influence the identification of the weapon used, allowing for more specific and efficient training strategies according to the competition modality.

Keywords: *fencing, body composition, physical abilities*

Introduction

Fencing is an Olympic combat sport contested in three modalities—épée, foil, and sabre—differentiated primarily by the characteristics of the weapons, including weight (500–770 g) and technical and tactical demands. These distinctions influence movement patterns, physiological stress, and competitive strategies (Bottoms et al., 2023; Rincón et al., 2022; Wei & Wei, 2024). Major international events include the Olympic Games, next scheduled for Los Angeles 2028, and the World Championships, held in Milan, Italy (2023), with the upcoming edition in Tbilisi, Georgia (2025).

Although the same fundamental rules govern fencing, the demands of specific weapons create distinct performance profiles. Bout dynamic short, intermittent, high-intensity actions interspersed with brief recovery periods—predominantly tax the anaerobic lactic energy system with a significant phosphagen contribution (Cabuk et al., 2025). Strength, speed, and endurance have been identified as key determinants of performance (Ramos-Campo et al., 2025), yet their relative influence across modalities remains unclear. Research on sabre fencers has reported superior countermovement jump (CMJ) performance, suggesting greater reliance on stretch–shortening cycle mechanics (Gómez-Chibás et al., 2019), while lactate concentrations vary by weapon but generally do not alter the dominant energy pathway (Bahamondes-Avila et al., 2014).

Anthropometric attributes also contribute to weapon specialization. Body composition influences both force production and injury risk; optimal lean mass supports power generation, whereas excess fat mass may impair movement efficiency. Female fencers have been shown to possess higher adiposity than athletes in other combat sports, as well as a greater arm span relative to their height—morphological traits that may provide reach advantages (Bany & Lopuszanska-Dawid, 2025). However, comprehensive profiling that integrates physical capacities with anthropometric variables for each modality is lacking.

Correspondence:

Isabel Rojas
National School of Sports, Faculty of Education and Sports Sciences, Street 9 # 34-01, Cali, Colombia
E-mail: isabelcrojasp@gmail.com

This knowledge gap limits the development of weapon-specific conditioning programs and evidence-based talent identification. Standardized assessment tools, such as the McCloy battery, offer a potential framework for systematically evaluating these characteristics. Therefore, the present study aimed to develop a predictive model to classify the type of weapon used—épée, foil, or sabre—based on body composition and physical capacities in competitive fencers.

Methodology

Study Design

Quantitative cross-sectional study with observational design.

Context

The study was conducted in the fencing league of Valle del Cauca, Colombia, where fencers are regularly trained and participate in competitions at different levels. This league has a considerable number of athletes who practice the three weapon modalities (épée, foil, and sabre), which facilitate data collection in a competitive training context.

Participants

The sample consisted of active fencers from the Valle del Cauca league, selected using non-probabilistic sampling. The inclusion criteria were: (1) to have previous experience in fencing, (2) to be older than 15 years, (3) to be training regularly in any of the three weapon modalities without interruption for more than two years, (4) to have complete measurements and tests; as exclusion criteria, it was considered to have or have had a musculoskeletal injury that had kept the athlete out of training for a week or more, not to provide signed consent in the case of adults or signed informed consent and assent in the case of minors. According to these criteria, the sample consisted of 33 athletes.

Variables

Anthropometric and physical variables were evaluated for each participant. The variables included were:

Anthropometric: weight, height, wingspan, relative wingspan, formic index, Manouvrier index, adipose mass (kg), fat percentage, muscle mass (kg), muscle percentage, and bone mass.

Physical: variables obtained using the McCloy physical test battery, which included different endurance, strength, and speed evaluations.

Other variables, including age and VO2 max, were incorporated to analyze their influence on the prediction of weapon type.

The response variable was the type of weapon used, coded in three categories: 0 = sword, 1 = foil, and 2 = sabre.

Data

The data were collected directly from the fencers during measurement and physical evaluation sessions conducted at the league's facilities. Anthropometric values were measured by an ISAK Level II anthropometrist using calibrated equipment, including the TANITA scale, SECA measuring rod, LUFKIN tape measure, CERSCORF anthropometer, and adipometer. Physical tests were administered under controlled conditions, following standard McCloy battery protocols.

Bias

To address potential biases resulting from the disproportionate representation of participants in each weapon class, the Synthetic Minority Over-sampling Technique (SMOTE) was employed. SMOTE enabled us to generate synthetic data for the minority classes (foil and sabre), thereby reducing bias towards the majority class (épée) and enhancing the representativeness of the predictive models.

Experimental Procedure

Selection of participants: Active fencers from the Valle del Cauca league who met the inclusion and exclusion criteria were identified and selected for participation. Anthropometric variables were collected from each fencer, such as weight, height, wingspan, muscle mass, and fat percentage, among others. The measurements were performed by trained personnel using calibrated instruments to ensure the accuracy of the data, by the method of the International Society for the Advancement of Kineanthropometry (ISAK). The preparation for taking measurements was ensured, as participants wore appropriate clothing, were adequately illuminated, and were in a safe and ventilated space.

The physical capacities of the participants were evaluated using the McCloy test battery, which measures different physical performance parameters (strength, endurance, speed, etc.). This evaluation was performed under controlled conditions within the league's facilities, following standard protocols for each test. Additional variables, such as age and VO2 max, were recorded to explore their influence on predicting weapon type. The collected data were organized in a structured set, where the target variable "weapon" was coded as 0 (épée), 1 (foil), and 2 (sabre).

Data analysis

The data analysis was performed in several stages to identify the most appropriate model for the classification of the type of weapon:

Five classification models were tested: Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), Decision Tree (CART), Naive Bayes (NB), and Support Vector Machines (SVM). To evaluate the robustness of the models, Stratified K-Fold cross-validation with 10 partitions was used. This stratified technique ensures that each partition maintains the proportion of classes, providing an accurate assessment of the average accuracy and variability of each model.

Accuracy, recall, and F1-score were analyzed for each class and each model. Overall model accuracy was also reported as a summary metric.

The Decision Tree model, which showed the highest average accuracy, was optimized by hyperparameter tuning to maximize its performance. The Grid Search technique was used in combination with cross-validation, which enabled the identification of the optimal parameters for the model.

The final decision tree was visualized to facilitate the interpretation of the hierarchy and relevance of the predictor variables. Data analysis was performed in Python using libraries such as scikit-learn for preprocessing, class balancing, training, and model evaluation. Visualizations and classification reports provided a clear understanding of the accuracy of each model and the influence of anthropometric and physical variables on the prediction of weapon type.

Measures of magnitude and certainty derived from the test set confusion matrix were incorporated. Agreement beyond chance was moderate (Cohen's Kappa ≈0.41, 95%CI≈0.18-0.61), and the overall correlation between actual and predicted classes showed a similar pattern (MCC≈0.43, 95%CI≈0.12-0.64). The strength of association between predictions and actual classes was intermediate (Cramér's V ≈0.46, 95%CI≈0.28-0.66). The accuracy of 62% presented an IC95%≈0.43-0.79. F1s by class showed intervals per sample size and imbalance: sword 1.00 (≈0.72-1.00), foil 0.40 (≈0.15-0.68), and saber 0.57 (≈0.30-0.82). On average, macro F1 hovered around 0.66, and weighed F1 remained at 0.61 (95%CI≈0.40-0.78). Taking them together, these numbers fit the pattern already described: the tree hits clearly in épée, performs moderately in sabre, and encounters greater difficulty in foil. Although the ranges are wide, which is to be expected given the small sample size and unequal classes, the magnitude of the effect consistently falls within the intermediate range and is consistent with the observed accuracy.

Ethical considerations

This study was approved by the corresponding institutional ethics committee on September 23, 2024, following the principles outlined in the Declaration of Helsinki. All participants were informed about the study's objectives, procedures, and potential risks and benefits, and provided their informed consent. This included consent from the parents of underage athletes and adult fencers, as well as Informed Consent from the minors before they participated. Additionally, data confidentiality and the right of participants to withdraw from the study at any time without repercussions were guaranteed.

Results

This study focused on classifying weapon types in fencers (épée, foil, and sabre) using machine learning models, incorporating anthropometric and physical variables. The results of the techniques applied for model evaluation, data balancing, and hyperparameter optimization are presented below.

Given the imbalance in the classes of the dataset, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to generate additional instances of the minority classes (foil and saber), thus ensuring a balanced distribution. This balancing is crucial for improving the model's performance in classes with fewer samples, as it minimizes the bias towards the majority class (sword).

To evaluate the robustness of the models, Stratified K-Fold cross-validation with 10 partitions was used. Stratified K-Fold validation allows each partition to preserve the proportion of classes from the original set, which is especially important in multiclass classification problems. In this way, an accurate and consistent assessment of the average accuracy and variability of each model is obtained.

Five classification algorithms were evaluated using Stratified K-Fold validation. The mean accuracy and standard deviation results for each model were as follows:

Linear Discriminant Analysis (LDA): mean accuracy of 0.62 with standard deviation of 0.24. K-Nearest Neighbors (KNN): mean accuracy of 0.48 with standard deviation of 0.30. Decision Tree (CART): Average accuracy of 0.70 with standard deviation of 0.35, this being the best-performing model. Naive Bayes (NB): Mean accuracy of 0.58 with standard deviation of 0.33. Support Vector Machines (SVM): Extremely low accuracy of 0.09 and standard deviation of 0.14.

The high variability observed in some models (such as CART and NB) suggests that these models are sensitive to the composition of the partitions in the cross-validation, which could be related to the complexity of the dataset and the balance achieved with SMOTE.

Due to its outstanding performance, the Decision Tree (CART) model was selected for hyperparameter optimization using a grid search with cross-validation. The optimal hyperparameters found were max_depth: None (no restriction on tree depth). min_samples_split: 2 (minimum number of samples required to split a node). These parameters allowed the model to maximize accuracy by allowing deep splits and capturing more complex patterns within the data.

With the optimized CART model, the following classification report was obtained on the test set: Class 0 (Épée): Accuracy of 1.00, Recall of 1.00, and F1-Score of 1.00, indicating that the model correctly classifies all sword cases without errors. Class 1 (Foil): Accuracy of 0.50, Recall of 0.33, and F1-Score of 0.40. This reflects the model's lower ability to identify the foil class, possibly due to the similarity in some variables with other courses. Class 2 (Sabre): Accuracy of 0.50, Recall of 0.67, and F1-Score of 0.57, indicating moderate performance in predicting sabre, with some cases correctly identified.

The overall accuracy of the model was 0.62. The weighted average metrics: accuracy of 0.62, recall of 0.62 and F1-score of 0.61. These results indicate that the model is accurate in classifying the épée class but exhibits limited performance in the foil and sabre classes (Table 1).

Table 1. Accuracy of the model

Class	Precision	Recall	F1-Score
0	1	1	1
1	0.5	0.33	0.4
2	0.5	0.67	0.57
Accuracy			0.62

The optimized decision tree (Figure 1) revealed that the most relevant variables for classification are:

Muscle Percentage: this is the first division criterion, with a cut-off value at 46.993%. If the percentage of muscle is less than or equal to this threshold, the model proceeds to evaluate with the variable "Squat with Jump"; if it is higher, it considers the percentage of fat.

Squat with Jump and Fat Percentage: These variables were used in successive splits to improve the classification of each observation, establishing different cut-off values.

This hierarchical tree illustrates the significance of physical and anthropometric variables in distinguishing between different types of weapons. In particular, the percentage of muscle and body fat is decisive in the prediction, suggesting a relationship between body composition and the type of weapon used.

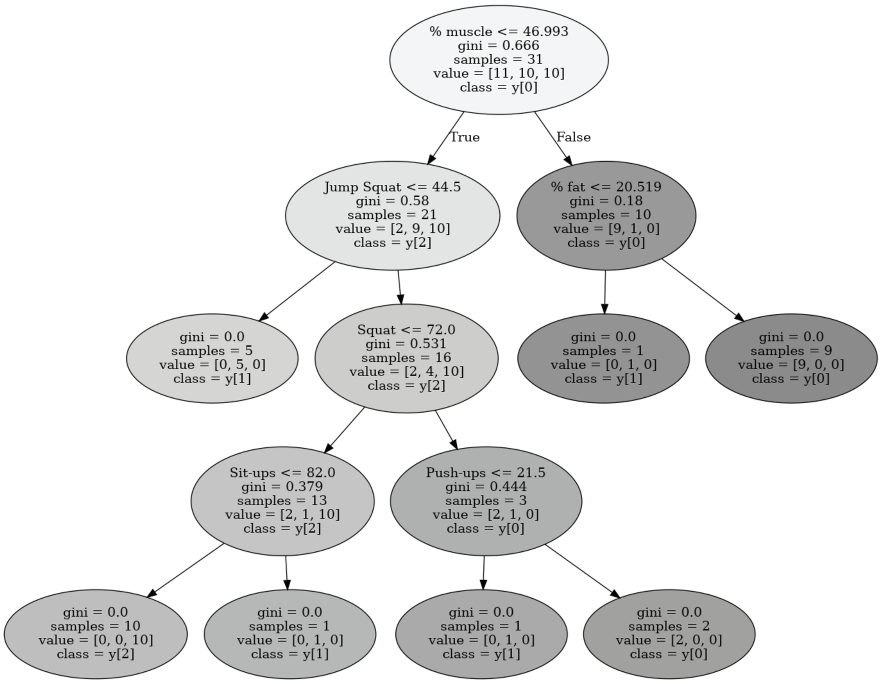

FIGURE 1. Optimized decision tree

Discussion

The present study developed and tested predictive algorithms to classify weapon types in fencing based on anthropometric and physical performance variables, with the decision tree model demonstrating the highest predictive capacity. This model achieved 100% recall for épée, 67% for sabre, and 33% for foil, with an overall accuracy of 62%. These results suggest that certain physical and morphological traits may be more distinctive for some weapons, particularly épée, than for others.

Our findings align with previous literature highlighting the role of anthropometric characteristics in talent identification for fencing. In Indonesia, lower-limb length, stature, body mass, body fat percentage, and BMI have been identified as the most relevant predictors (Rimasa, 2021). Similarly, Jagiello et al. (2017) reported that elite female Polish fencers exhibit arm spans that exceed their height, suggesting that limb length and adiposity may influence weapon specialization. In the present model, variables related to segment length and fat percentage also emerged as significant predictors, supporting the notion that morphological attributes play a role in the differentiation of weapons.

Body composition is a critical determinant in combat sports, influencing both performance and injury risk (Anastasiou et al., 2024). Reduced skinfold thickness has been associated with greater movement explosiveness and reduced physiological strain during bouts. Somatotype analysis has shown that elite fencers often exhibit endomorphic predominance, with a tendency toward mesomorphy in males (Zamudio, 1997). In contrast, Rincón et al. (2022) found mesomorphic predominance overall. In our study, épée fencers exhibited the highest body fat percentage, consistent with earlier observations on somatotype. These findings suggest that the proportions of muscle mass and bone mass are relevant discriminators in weapon classification.

A weapon-specific reach advantage was noted for foil in the present dataset, consistent with previous findings that arm spans exceed height in elite fencers. However, this variable was not selected as important in the decision tree model for foil classification, possibly due to limited variability within the sample.

Physiological profiling also supports weapon differentiation. Lactate concentrations across all weapons typically exceed 2 $mmol·L^{-1}$, confirming the predominance of anaerobic metabolism (Bahamondes-Avila et al., 2014). Sabre competition has been associated with lactate levels around 4 $mmol·L^{-1}$ (Turner et al., 2018), while épée bouts range between 2.7 and 3.6 $mmol·L^{-1}$ (Oates et al., 2023). Foil values are similar, with post-bout concentrations averaging 3.59 ± 1.16 $mmol·L^{-1}$ (Iglesias et al., 2023). These values place fencers near or above the onset of blood lactate accumulation (OBLA), indicating a substantial anaerobic glycolytic contribution across weapons. Muscle mass is especially relevant in this context, as it enhances glycogen storage and, consequently, anaerobic performance (Sarria et al., 2024). This relationship may partly explain the performance advantages of higher lean mass in foil athletes.

Despite these differences, some authors suggest that strength and conditioning programs should target overall physical development rather than weapon-specific energy demands (Cross et al., 2024), noting that differences in physical capacities may not necessitate entirely distinct conditioning regimens. Nevertheless, our model identified variables related to explosive strength, such as squat jump (SJ) and countermovement jump (CMJ) performance, as important predictors. Improving the stretch–shortening cycle (SSC) function has been shown to enhance the rate of force development (RFD) and explosive power (Gómez-Chibás et al., 2019). Sabre fencers, despite their higher-intensity bouts, may display deficits in elastic–explosive strength due to constant ground contact limiting tendon energy storage.

Speed, another critical determinant, is closely linked to strength. Optokinetic training has been shown to improve both selective and straightforward reaction times in fencers (Yao, 2022). Additionally, strength increases through high-load training have been correlated with speed gains (Wetscott, 2024). In this study, jump squat performance—a proxy for explosive lower-limb force—emerged as a significant variable in the model, consistent with the literature on the benefits of SSC training for fencing performance.

Aerobic capacity (VO_2max) is generally considered less decisive in fencing performance due to the sport's predominant anaerobic demands. While our model included VO_2max measured by the Leger test, it did not select it as a key variable. This aligns with findings that carbohydrate metabolism predominates in fencing (Bottoms, 2023). However, VO_2max values of ~74% during competition indicate that aerobic capacity still contributes to recovery between high-intensity exchanges, with its relevance varying according to competition format and weapon type. Endurance training, particularly intermittent and interval-based methods, has been recommended as a foundation for developing other capacities, such as strength, speed, and agility (Ramos-Campo et al., 2025).

Taken together, our findings indicate that anthropometric traits (especially limb length, muscle mass, and body fat percentage) and selected physical performance metrics (explosive strength and speed) are valid predictors of weapon type in fencing, particularly for épée. However, differences in physiological and performance profiles across weapons may not always justify entirely distinct conditioning programs. Future research should include larger and more diverse samples, integrate biomechanical analysis, and explore how technical–tactical demands interact with morphological and physiological determinants to refine weapon-specific talent identification and training strategies.

Limitations

One of the limitations of this study is the imbalance in the number of fencers with a specialty in each weapon who participated, since the analysis would be enriched with a similar number of participants for each weapon; on the other hand, it is essential to remember that this study was conducted with league fencers from the southwestern part of the country so that the conclusions will be a starting point but not a generalization of the Colombian population. Another significant limitation is related to the study's conclusion, as it cannot be generalized because only some of the possible variables that influence the field of interest in this study were considered.

Future research

It is recommended to recruit a similar number of fencers with a specialty in each of the three weapons to have an analysis with greater applicability; likewise, it is recommended to have the participation of fencers from different areas of the country to have a broader scope of the results. It is recommended for future studies to include not only physical capacities and anthropometry, but also other aspects such as biomechanical factors, reaction time, agility, and tactical decision, which will broaden the scope of the model.

Conclusions

According to the results, it can be affirmed that the percentage of muscle is vital for the three fencing modalities, since the model of 13 subjects classified 10 épée fencers, which indicates little dispersion of data in this variable. For this modality the athlete must have less than 20% of fat for the other weapons very few met this criterion, however its recall is not very high to determine if it influences the foil and sabre modalities, therefore it is recommended to investigate other tools and tests such as MRI and inertial sensors to strengthen these two fencing modalities further.

Thus, based on the decision tree (CART), the predictive model was the most accurate and we can conclude that the jump squat stood out as an essential variable to differentiate the type of weapon in fencing, reflecting its influence on the sabre, based on the abdominals were determinant for the sabre modality, allowing to have a reference point for the selection of this weapon. Arm flexions were not determinant in the model because only three participants were classified, indicating that this test is not adequate for weapon selection in fencing. However, in practice, they are crucial in both attack and defense, as the strength of the core influences the stability and handling of the weapon. This could be considered in other research to enrich the model and inform the use of the foil or the épée.

Finally, these findings may have practical implications for the training and selection of weapons in fencing, allowing coaches to identify the strengths and weaknesses of their athletes and guide their preparation more effectively, thereby enabling them to achieve a faster sporting form and enhance high performance in Colombian fencing. It is essential to acknowledge that these findings can help trainers guide the selection of a fencing weapon and facilitate follow-up for their athletes to improve, while also recognizing the individualization that sports require, as those conclusions cannot be generalized to inform Colombian fencers' final decisions.

Acknowledgements
To the fencers, coaches, and members of the PHANAS research hotbed.

Conflict of Interest
Authors declare no conflict of interest.

Received: 20 July 2024 | **Accepted:** 22 August 2025 | **Published:** 01 October 2025

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