



Advantages of Artificial Intelligence (AI) Technologies for Automating Physical Development Assessment.

Marina Kinkulkina ¹, Ekaterina Chebotareva ¹, Tatiana Izyumina ¹, Tatiana Avdeeva ¹,
Dmitry Zyuzin ¹, Hassan Shafaei* ³, ¹Victoria Zaborova ^{1,2}.

¹ Institute of Clinical Medicine, Sechenov First Moscow State Medical University, 119991
Moscow, Russia

² Moscow Institute of Physics and Technology, Institutsky lane 9, Dolgoprudny, Moscow
Region, 141700, Russia

³ Department of Physical Rehabilitation, massage and health-improving physical culture
named after I. M. Sarkizov-Serazini RSUFKSMiT, 105122, Moscow, Russia

Corresponding Author: Hassan Shafaei, hassanshafai37@yahoo.com, ORCID: 0000-0001-
5802-3385

Abstract

Physical development (PH) is a complex indicator that covers a set of anthropometric parameters. In the course of this work, the most important anthropometric parameters for athletes and swimmers were determined - different for men and women. So, for men, the most important indicators were shoulder width, arm length, height, age, body weight, hand length and chest circumference. And the necessary indicators for women were body weight, height, pelvic width, shoulder width, arm length, shoulder girth and chest volume. Moreover, body weight was more important for female swimmers than for male swimmers. Shoulder width played a more important role for men than for women. Thus, the novelty of the solutions lies in an integrated approach to the assessment and management of physical development using intelligent technologies.

Keywords: artificial intelligence, physical development, anthropometry

Introduction

Physical development (PH) is a complex indicator that characterizes the state of health of an individual or group of people at different ages of life. Physical development includes a set of anthroposcopic, anthropometric and anthropophysiological characteristics. This indicator changes dynamically in accordance with biological patterns and under the influence of environmental factors.

The anthropometric parameters and body composition of athletes may vary depending on their specialization and level of training [1,2]. This suggests that different sports, such as swimming and cross-country skiing, will have different effects on physical development parameters [3,4].



Swimming is a discipline that involves swimming various distances in the shortest amount of time. The huge density of water (1.0 g/cm^3) determines the features of a swimmer's motor activity. The horizontal position of his body is forced. The resistance of water to movement depends on the position of the body in the water, its changes in various phases of the motor cycle [5].

Swimming requires a fundamental restructuring of movement control based on the continuation of the entire experience of land movements. There are no antigravity reflexes in water, because movements are performed in hypogravity. The effect of reactive forces increases due to the lack of solid support.

Biomechanics of sports swimming technique reveals the patterns of interaction of the swimmer's body and its working links with the aquatic environment, the ratio of driving and braking forces, sources and ways of preserving mechanical energy in the movement system [5]. From a biomechanical point of view, the main task of a swimmer is to move his body along the water path as fast as possible. The direct cause of movement is the driving forces created by locomotor (rowing) movements of the arms and legs in the aquatic environment. Water serves as a support for movement. It also provides the main resistance to the swimmer's body, slowing down his progress.

The main source of driving forces is the internal forces of muscle contraction, the forces of muscle traction. Muscles are the engine of an athlete. In rowing movements, the main load falls on the large muscles of the extremities, which originate from the skeleton of the trunk: the latissimus dorsi, the pectoralis major, the large round, the quadriceps femoris, the gluteus maximus, and others.

Swimmers rely solely on the driving force of their bodies when moving through the water, thereby emphasizing the crucial role of strength. In addition, the importance of aerobic endurance varies depending on factors such as swimming style, intensity, and distance traveled [6]. In swimming, the relationship between strength and technique plays a key role, as swimmers have to contend with hydrodynamic resistance — resistance that increases in proportion to swimming speed, following the quadratic law [7]. Overcoming this resistance requires a combination of well-developed strength and impeccable rowing technique, as swimmers strive to minimize resistance and optimize their results in the water.

In this study, using the machine learning methods described in the previous article, we analyzed which anthropometric parameters are most important for monitoring and predicting success in swimming.

Materials and methods

To determine the indicators most necessary for studying the level of athletic training of swimmers, we used anthropometry. We have summarized the results of these measurements by constructing mathematical models.



Anthropometry was performed using an anthropometer, thick compasses, measuring tape, caliper and scales. Body weight (in kg) was determined on a medical scale. An anthropometer was used to determine (in cm) height, heights of anthropometric points, and lengths of body segments: hand, forearm, shoulder, foot, shin, hip, torso, as well as height and length of legs and arms. Using thick compasses, the width of the shoulders, pelvis, sagittal and frontal diameters of the chest, the diaphyses of the forearm, shoulder, hip, shin, foot and hand widths were determined. The girths of the trunk and limbs were determined with a measuring tape, and the skin-fat folds were measured with a caliper.

Measurement of girths. When measuring girths, the tape fit snugly to the skin of the measured area of the body, but did not compress the underlying tissues. At the same time, the arm was in a relaxed state and hung freely along the body. The study was conducted three times, followed by the calculation of the average value. When measuring girths (except for the head and neck), the tape was positioned perpendicular to the axis of the measured area (Table 1).

Table 1. Method of measuring torso and limb girths.

Location	Measurement technique
Hand	according to the projection of the 2nd and 5th metatarsal-phalangeal joints
Wrist	5 cm above the wrist joint
Forearm	5 cm below the projection of the elbow joint
Shoulder	the middle of the distance between the acromial process of the scapula and the ulnar process of the ulna
Head	above the eyebrows
Neck	below the laryngeal protrusion, the head was pointing straight ahead
Chest	fourth sternocostal joint after exhalation
Waist	the middle of the distance between the edge of the costal arch and the upper anterior crest of the ilium (on exhalation)
Buttocks	the largest protrusion of the buttocks
Femurs	along the subclavian fold, horizontally
Hip	the gluteal fold
Shin	the greatest protrusion of the calf muscle
Ankle	in the narrowest part of the shin, above the ankle joint
Foot	according to the projection of the 1st and 5th metatarsophalangeal joints



Measurement of skin-fat folds. The thickness of the folds (in mm) was measured with a caliper, which exerts constant pressure on the skin (10 g/cm^2). The skin and subcutaneous fat were captured with the thumb and forefinger, pulled back by 1 cm and a caliper was applied distal to the finger grip in the middle of the distance between the top and base of the resulting fold. The measurement was carried out 2-3 seconds after fixing the fold, with an accuracy of 0.5 cm, while the fold was not released.

After three measurements, the average value was determined (Table 2).

Table 2. Methodology for measuring skin-fat folds.

Location	Measurement technique
Hand	2 mm on the recommendation of the Moscow State University Institute of Anthropology
Forearm	inner surface
Shoulder at the back	the middle of the distance between the acromial process of the scapula and the ulnar process of the ulna, a fold along the arm
Shoulder in front	in a similar way, but on the front surface of the shoulder
Chest (male)	above the pectoralis major muscle
Xiphoid process	5 cm to the left of the sternal line when the fold is vertically gripped
Abdomen	to the right of the umbilicus
Anterior iliac spine	2-3 cm above the inguinal ligament along the mid-clavicular line, with the crest of the fold positioned horizontally
Shoulder blade	1 cm below the lower corner of the scapula, the fold was located parallel to the edge of the scapula, at an angle of 45 degrees to the horizontal
Hip in front	the middle of the anterior surface of the thigh between the inguinal fold and the patella
Shin	the posterior surface of the shin above the lateral head of the gastrocnemius muscle

Male swimmers

The table contains data on 163 men. Of these, 18 men have 3 years of athletic experience, 19 have 5 years of experience, 41 have 7 years of experience, 52 have 10 years of experience, and 33 have 12 years of experience (Figure 1).

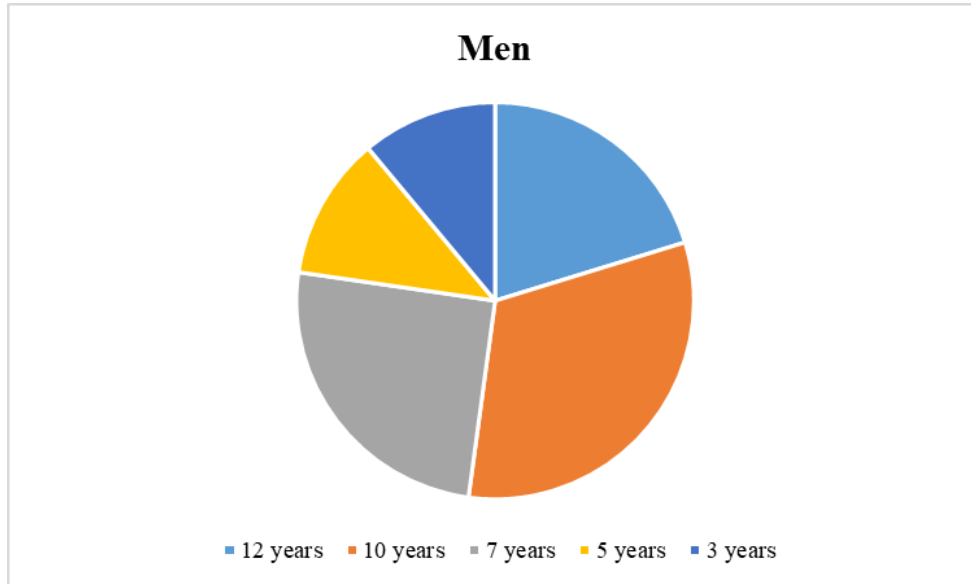


Figure 1. The ratio of male swimmers by the number of years of athletic experience.

Female swimmers

There were 80 women in the resulting table. 9 people have 12 years of athletic experience, 34 have 10 years of experience, 21 have 7 years of experience, 10 have 5 years of experience, and 6 have 3 years of experience (Figure 2).

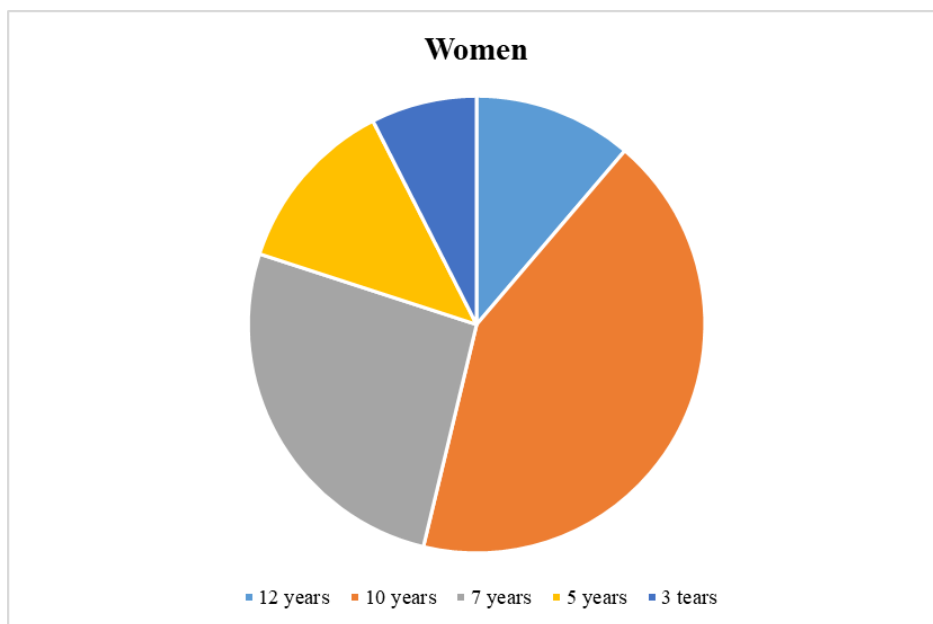


Figure 2. The ratio of female swimmers by the number of years of athletic experience.



After grouping the data, we started testing various machine learning methods. To begin with, we wrote a script in the Python programming language that collects anthropometric data of athletes and sportswomen from separate tables dedicated to one person into one of two summary tables — one for men and the other for women. The output was a table, each row of which corresponded to the anthropometric measurement of one person. Let's consider the obtained data of swimmers, divided by gender.

Results

Women, swimming.

To begin with, we used the linear regression method. In addition to the basic algorithm, we used the Gridsearch tool, which allows us to analyze network training parameters in order to get the most accurate data.

Such hyperparameters of the network as the type of regularization (l1 and l2) and the regularization coefficient C varied. The best result in the test sample was given by a network with l2 parameters and a coefficient of $C = 0.12$.

As a result, the resulting model gives an accuracy of about 42% on the deferred data (also from the original dataset, but previously unknown models). However, in practice, it turned out that this model in any control sample provides only variants of 7 and 10 years of athletic experience in predicting results, which, in this sample, is undoubtedly strategically correct, but is not ideologically correct (Figure 3).

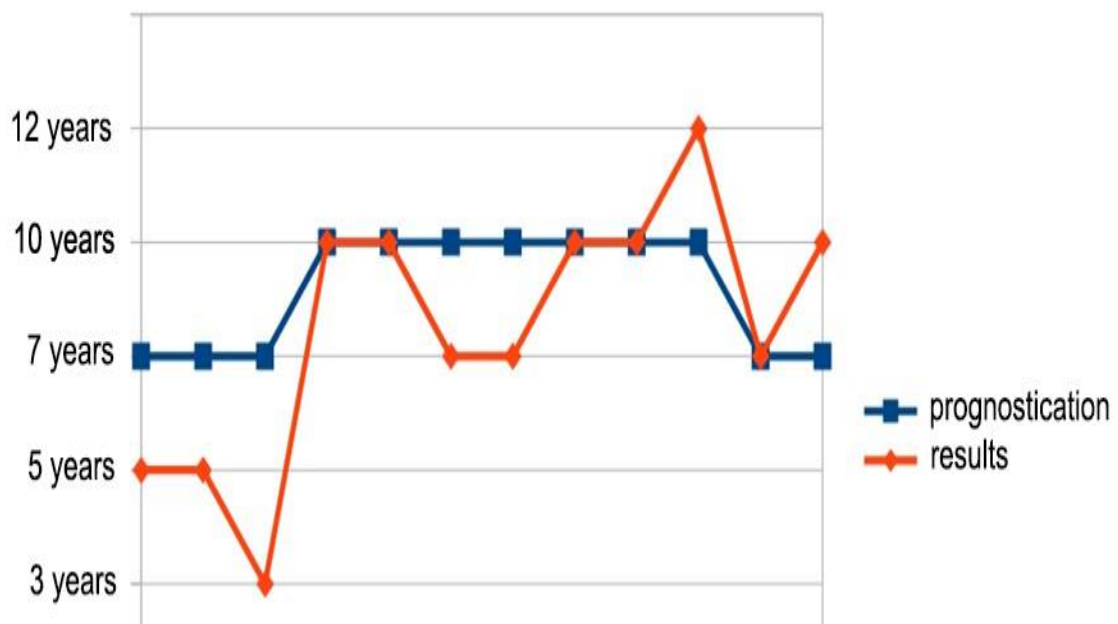


Figure 3. Prognostication of the best regression model.



Due to such features, we considered the model not very suitable for solving the problem of classifying athletes due to the tendency to such behavior (giving the most likely, rather than the closest result).

We used other learning models, such as the k nearest neighbors (kNN) method.

We also used Gridsearch for this method. We varied the number of neighbors and the presence/absence of weights depending on the distance. As a result, we got the best parameters when determining by 2 neighbors and weighing by distance.

The accuracy of the resulting kNN-based model on deferred data is 50%, and the graph is smooth. At none of the 12 points will the predicted value deviate from the real value by more than 1 grade (Figure 4).

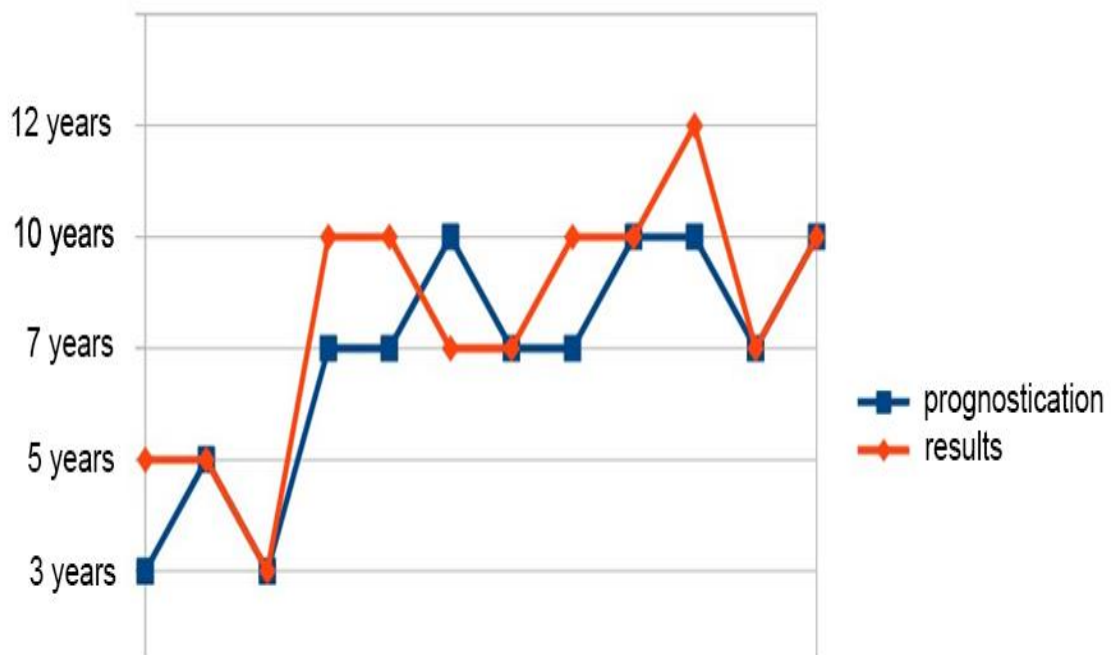


Figure 4. Prediction of the best kNN model.

We considered the training of this model to be successful, and the model itself suitable for the task of classifying athletes. It is likely that with an increase in the training sample, the accuracy of the prediction of this model will also increase.

For the model based on the "random trees" method, the criteria for constructing a tree (criterion), the maximum depth of the tree (max_depth) and the number of trees (n_estimators) in the decisive forest were varied. As a result of GridSearch's action, the optimal hyperparameter values were as follows: criterion = 'gini', max_depth = 4, n_estimators = 6.



As a result, the prediction accuracy was comparable to kNN – also about 50%, with an error of no more than 1 digit in the entire test sample (Figure 5).

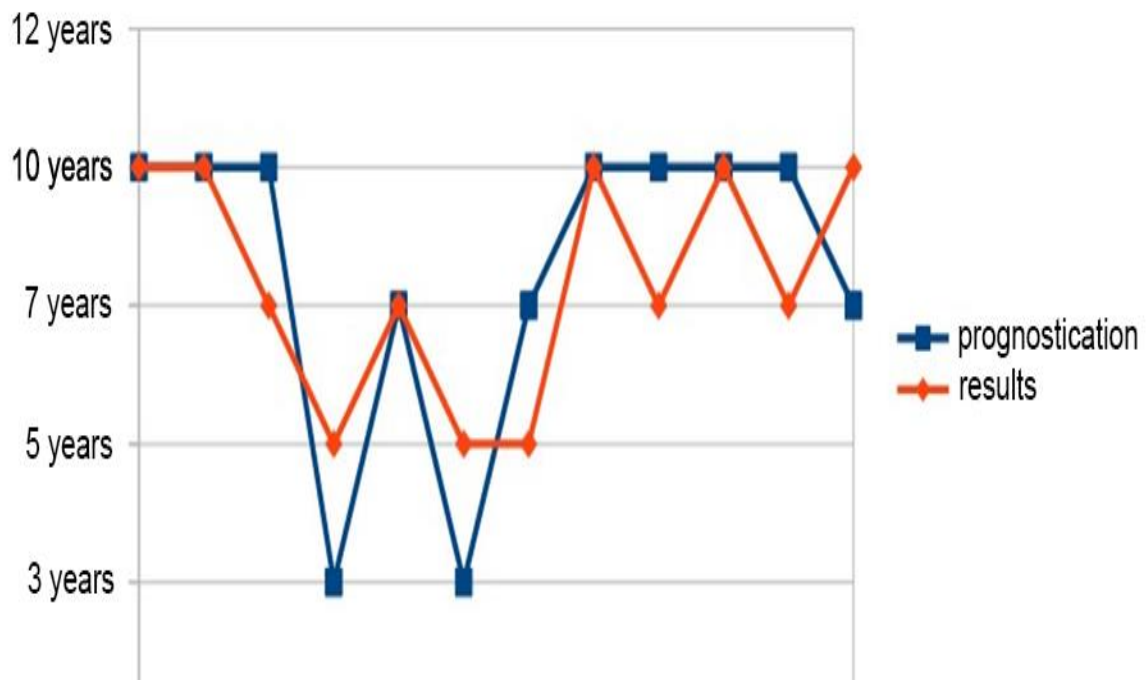


Figure 5. Prognostication of a random tree model.

Men, swimming.

Similarly to the data on women, we consistently launched the Gridsearch tool to search through the most optimal parameters of machine learning models.

The regression model on the male sample of swimmers suddenly showed a decent result relative to other models. The final accuracy on the deferred sample was 38%, while on the test sample it reached 76%. (Parameter C is 0.23, optimal L2 regularization, penalty parameter was 0.47).

Despite the high percentage in the training sample with a fairly low percentage in the delayed sample, the network produces a fairly reliable result if you allow a 1-grade bias and does not look much overfitted.

Next, we consider the results of training the k-nearest neighbors model.

According to the results of the selection of parameters, the optimal parameters were 4 neighbors and a majority vote, regardless of distance. In the control (delayed) sample, the accuracy of the method was 38%.

Getting into a class with an error of no more than 1 is more than 85%.

The graph shows that sometimes the models agree with each other, while sometimes the spread goes in different directions regarding the correct answer (Figure 6).

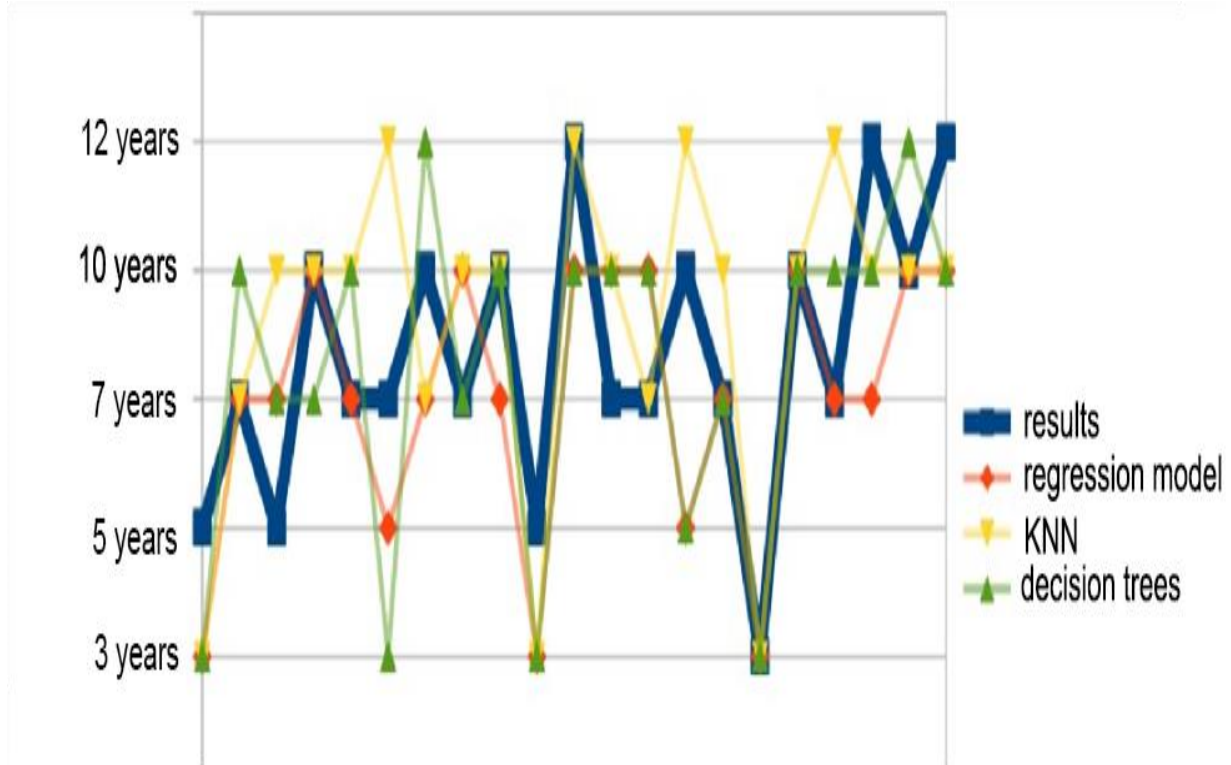


Figure 6. Summary graph of model testing in the control sample, swimming, men.

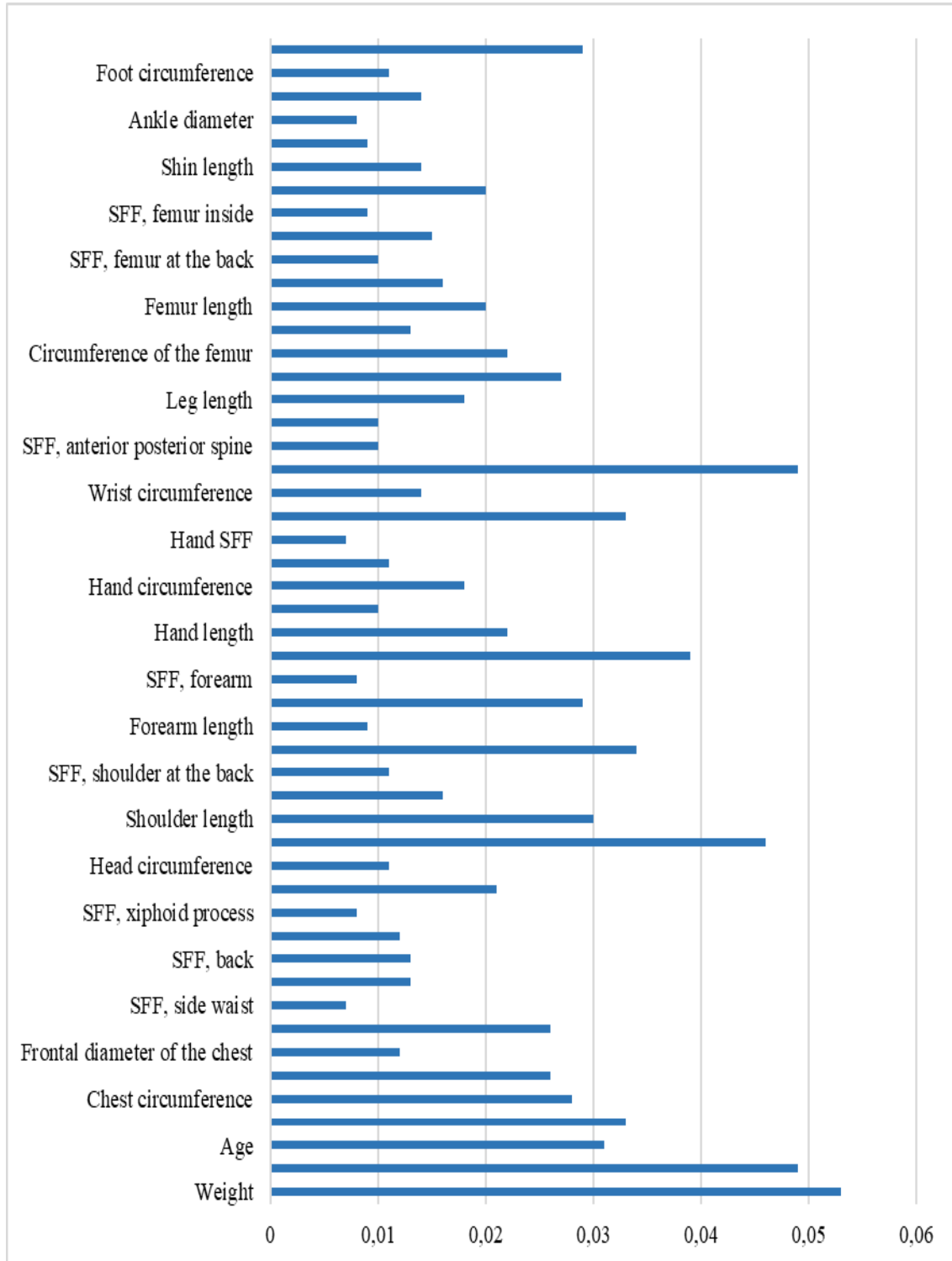
Evaluation of the importance of parameters.

Theoretically, it is classifiers based on decision trees that can most clearly assess the contribution of each parameter. This is due to their architecture and algorithms for building a decision tree — the most defining parameters are often located closer to the root in order to divide the data into classes as efficiently as possible. Also, when testing, the classifier based on trees showed good accuracy.

It is for the above reasons that it is proposed to use the proprietary `feature_importances_` method of the `ExtraTreesClassifier` class of the `sklearn` library to assess the importance of each parameter of anthropometric measurements in predicting athletes' results.

Women, swimming.

The best tree-based classifier obtained in this work evaluates the importance of the parameters in Figure 7.



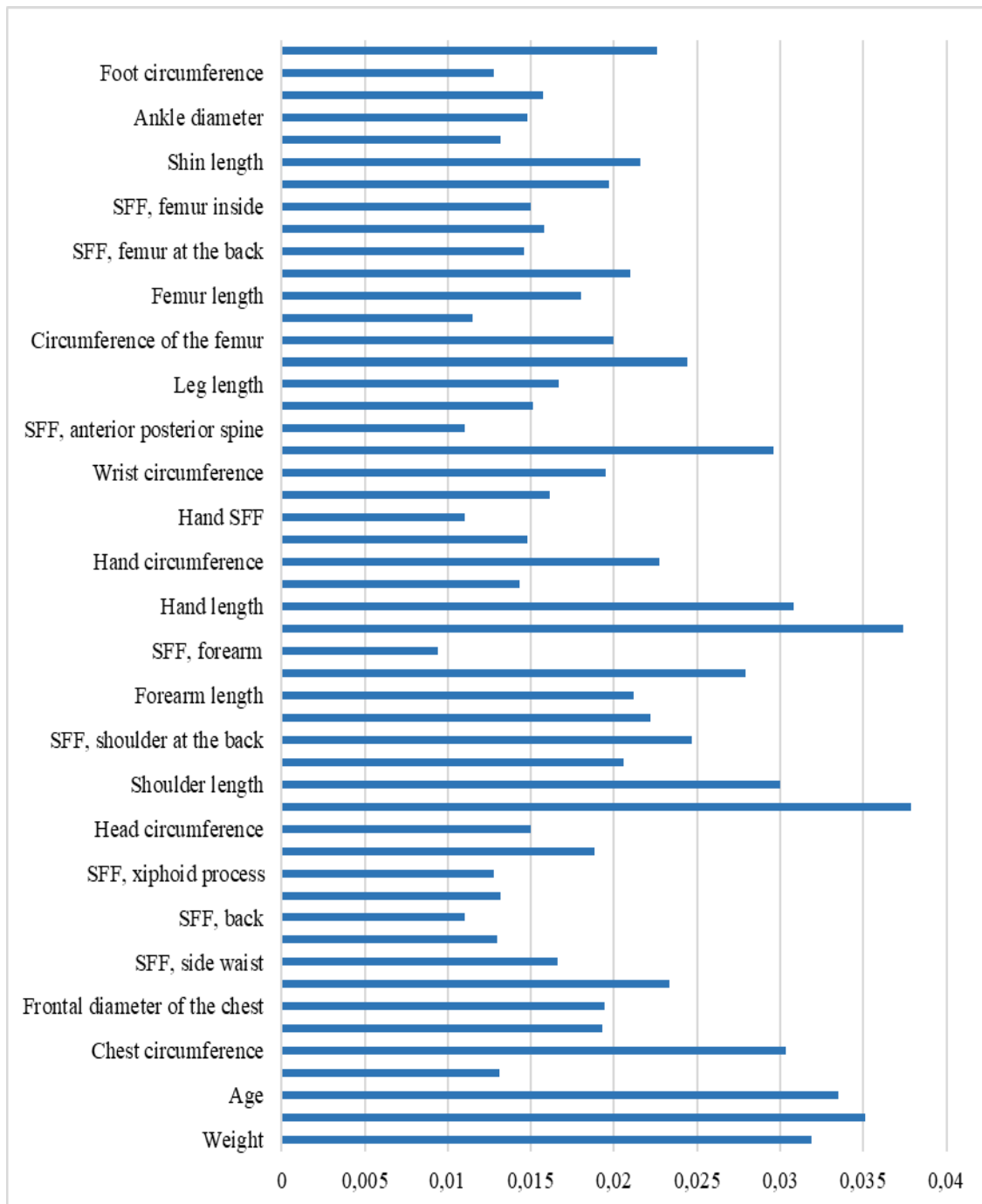
*SFF – skin-fat fold

Figure 7. The importance of anthropometric parameters, women, swimming.



Men, swimming.

We performed similar actions for the male part of the surveyed swimmers (Figure 8).

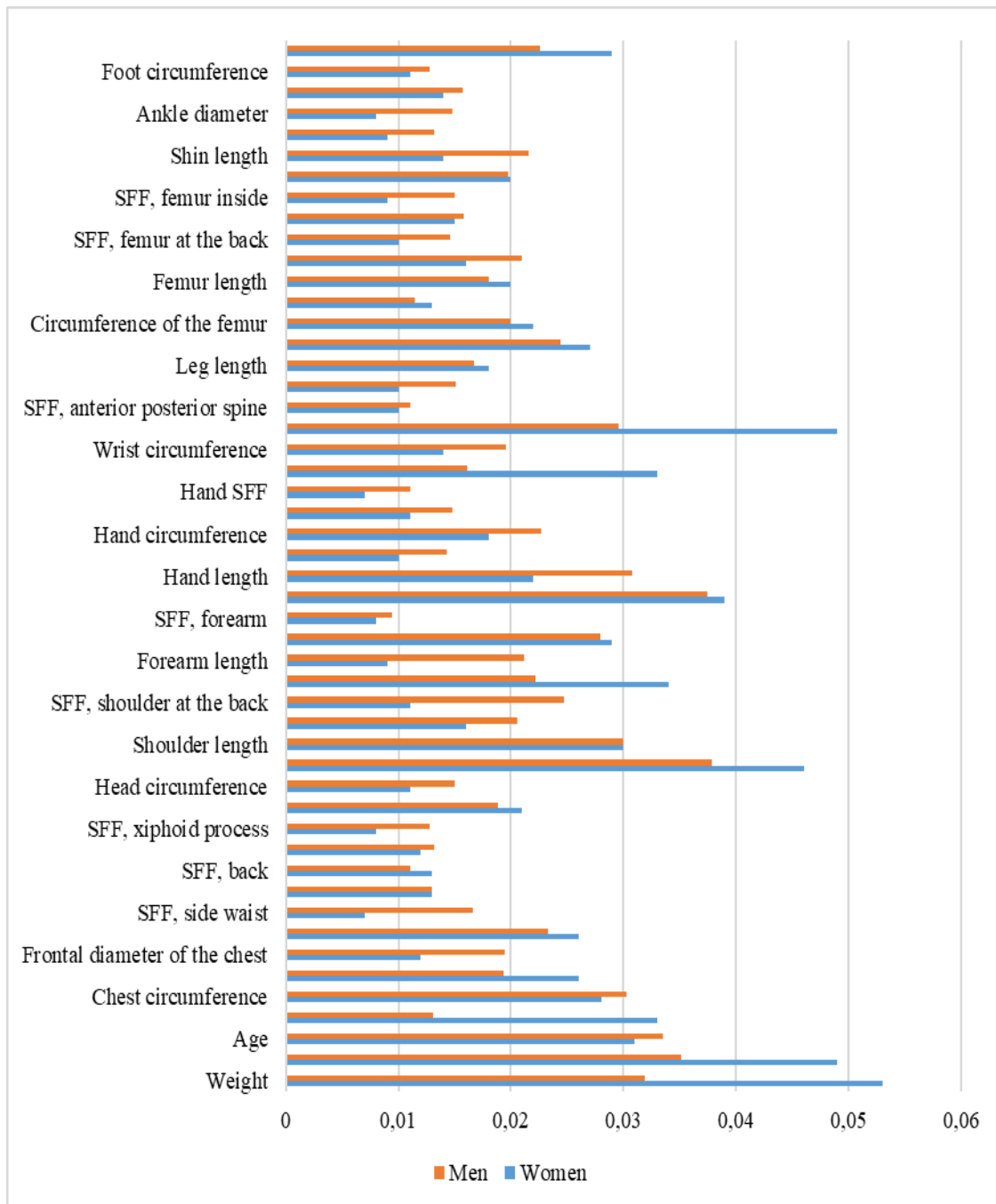


*SFF – skin-fat fold

Figure 8. The importance of anthropometric parameters, men, swimming.



The importance of parameters for men and women was also plotted on the same graph (Figure 9).



*SFF – skin-fat fold

Figure 9. Comparison of the importance of anthropometric parameters, men and women, swimming.



In the figure, you can see that mostly the same parameters are of similar importance for men and women when classifying them by the number of years of athletic experience.

There is a clear dependence on the parameters indirectly related to age. The explanation for this is the high level of athletes who participated in the testing. The same reason explains the low importance of fat folds for predicting results.

Nevertheless, there is some pattern observed in both men and women, namely, the parameter of the lengths and girths of the arm sections is predominantly higher than the similar parameter of the legs. The only obvious exception is the girth of the hips in women (much more important than the girth of the shoulders), which, in other ways, may also be a consequence of age-related changes in the body of girls.

Discussion

In this study, we examined the possibility of using expert systems to assess the level of training of athletes, taking into account changes in specific anthropometric parameters characteristic of a particular sport. There is a correlation between anthropometric parameters and the level of athletes and it is discernible on the available data sets.

To date, many studies have proposed new anthropometric measurements developed for a specific type of sport – football, wrestling, swimming, etc. [8,9,10]. Studies have established that anthropometric measurements developed for the general population of non-athletes are inapplicable to professionals and that those developed for athletes are very specific to a particular sport [11,12,13]. Therefore, before choosing adequate anthropometric measurements for their athletes, coaches and sports experts should take into account gender, race, age, nation, health status and competition level, protocols for skin folds and other anthropometric measurements, as well as other specific characteristics of the athlete population used to develop the chosen method [14].

In a comprehensive review of the literature, Franchini et al. It has been shown that such a sport as, for example, judo provides a high level of muscular strength, power and cardiorespiratory endurance to achieve success in competitions regardless of gender [15]. In this context, Dread et al. The physical fitness and anthropometric profiles of elite (international prize-winners) and sub-elite (national prize-winners) male judoka were compared [16]. The authors revealed that elite judoka were stronger and more powerful than their peers from the sub-elite. In addition, the same authors reported higher upper limb muscle mass in elite athletes compared to athletes from the sub-elite. Thus, monitoring the profiles of physical fitness and anthropometry on a regular basis during the training season for judoka seems to be critically important, since these characteristics affect the results during the competition [17].



There is also a relationship between anthropometric variables and results in Olympic rowing [18, 19]. The data showed that a taller rower with more muscle mass may have an advantage due to a longer lever arm, resulting in more power per stroke.

The results obtained in the Castañeda-Babarro et al study are partially consistent with the studies conducted in rowing, as a significant relationship was found between the anthropometric variables of athletes and their results [20,21]. It has been shown that indicators such as height, weight, body mass, and wingspan correlate with results in rowing, both Olympic and other sports, and traditional rowing, thus demonstrating the importance of these variables in their relationship to athletic performance in this particular sport [22].

Our results partially confirmed previous studies that reported differences in anthropometric indicators between elite swimmers and water polo players [23]. These studies consistently show that water polo players tend to be heavier and have higher body fat levels compared to elite swimmers. A comparative study of water polo athletes from 1980 to 1995 revealed interesting trends in body composition, revealing changes in height, limb length, waist circumference, shoulder width, and the ratio of muscle and fat mass over time [24]. The importance of body structure characteristics, which significantly affect the contractile potential of swimmers, regardless of gender, is determined by SMM, FFM and the ratio of muscle and fat. All these variables correlate with strength and energy production in sprint swimmers [25].

In addition to task-related parameters (i.e. variables evaluated during and related to actual swimming), body-related parameters (i.e. variables related to the swimmer himself) that are not specific to the swimming task indirectly correlate with swimming results, such as upper body strength on land. It has been reported to positively correlate with swimming speed [26]. It has been reported that anthropometric characteristics such as height, arm span, and hand surface area directly or indirectly affect swimming speed and other performance-related parameters [27,28].

Conclusion

Thus, the advantages of using modern artificial intelligence (AI) and big data technologies to automate the assessment of physical development:

1. Integration of multicomponent analysis of physical parameters.

Unlike standard methods based on static measurements (height, weight), the system analyzes complex data, including muscle mass, endurance level, coordination of movements, biomechanical characteristics and dynamics of changes in real time. This allows for a more accurate and objective assessment of physical development.

2. Predictive analysis and assessment of injury risks.



The use of predictive models to determine the likelihood of injury or overexertion based on data from past workouts and physiological indicators helps to prevent possible health problems. The introduction of such technologies reduces the risk of injury, which is especially important for professional athletes.

References

1. J.J. Ramos-Álvarez; J.J. Montoya.; C. Solís-Mencia; F. Miguel-Tobal.; P. López-Tapia; A.J. Sánchez-Oliver; R. Domíngue; J.M. Martínez-Sanz. Anthropometric Profile Assessed by Bioimpedance and Anthropometry Measures of Male and Female Rugby Players Competing in the Spanish National League. *Appl. Sci.*, 11, 11759. 2021.
2. S.Y. Lee; D. Gallagher. Assessment methods in human body composition. *Curr. Opin. Clin. Nutr. Metab. Care*, 11, 566–572. 2008] [U. Mulasi; A.J. Kuchnia; A.J. Cole; C.P. Earthman., Bioimpedance at the bedside: Current applications, limitations, and opportunities. *Nutr. Clin. Pract.*, 30, 180–193. 2015.
3. Schwesig R., Hartmann M., Leuchte S., Fischer D., and Kuß O., Validity of a complex soccer-specific field test and a non-specific sprint test-assessments for test and match performance, *Sportverletzung Sportschaden*. 2013.
4. Barfod, K.W.; Feller, J.A.; Clark, R.; Hartwig, T.; Devitt, B.M.; Webster, K.E. Strength Testing After Anterior Cruciate Ligament Reconstruction: A Prospective Cohort Study Investigating Overlap of Tests. *J. Strength Cond. Res*. 2019.
5. Pyne, D.B.; Sharp, R.L. Physical and energy requirements of competitive swimming events. *Int. J. Sport Nutr. Exerc. Metab.* 2014.
6. Samson, M.; Monnet, T.; Bernard, A.; Lacouture, P.; David, L. Comparative study between fully tethered and free swimming at different paces of swimming in front crawl. *Sports Biomech*. 2019.
7. Takagi, H.; Nakashima, M.; Sengoku, Y.; Tsunokawa, T.; Koga, D.; Narita, K.; Kudo, S.; Sanders, R.; Gonjo, T. How do swimmers control their front crawl swimming velocity? Current knowledge and gaps from hydrodynamic perspectives. *Sports Biomech*. 2023.
8. Oliver J. M., Lambert B. S., Martin S. E., Green J. S., and Crouse S. F., Predicting football players' dual-energy x-ray absorptiometry body composition using standard anthropometric measures, *Journal of Athletic Training*. 2012.



9. Riyahi-Alam S., Mansournia M. A., Kabirizadeh Y., Mansournia N., Steyerberg E., and Kordi R., Development and validation of a skinfold model for estimation of body density for a safe weight reduction in young Iranian wrestlers, *Sports Health*. 2017.
10. Faulkner J. A., *Physiology of swimming*, American Association for Health, Physical Education and Recreation. 1966.
11. Forsyth H. L. and Sinning W. E., The anthropometric estimation of body density and lean body weight of male athletes, *Medicine and Science in Sports*. 1973.
12. Oliver J. M., Lambert B. S., Martin S. E., Green J. S., and Crouse S. F., Predicting football players' dual-energy x-ray absorptiometry body composition using standard anthropometric measures, *Journal of Athletic Training*. 2012.
13. White J., Mayhew J. L., and Piper F. C., Prediction of body composition in college football players, *The Journal of Sports Medicine and Physical Fitness*. 1980.
14. Body Fat Evaluation in Male Athletes from Combat Sports by Comparing Anthropometric, Bioimpedance, and Dual-Energy X-Ray Absorptiometry Measurements. Marko Dimitrijevic, Verica Paunovic, Vladimir Zivkovic, Sergey Bolevich, Vladimir Jakovljevic, *BioMed Research International*, 2022.
15. Franchini, E.; Del Vecchio, F.B.; Matsushigue, K.A.; Artioli, G.G. Physiological profiles of elite judo athletes. *Sports Med. (Auckl. N. Z.)*, 2011.
16. Drid, P.; Casals, C.; Mekic, A.; Radjo, I.; Stojanovic, M.; Ostojic, S.M. Fitness and anthropometric profiles of international vs. national judo medalists in half-heavyweight category. *J. Strength Cond. Res.* 2015.
17. Kim, J.; Cho, H.C.; Jung, H.S.; Yoon, J.D. Influence of performance level on anaerobic power and body composition in elite male judoists. *J. Strength Cond. Res.* 2011.
18. De Laroche Lambert, Q.; Del Vecchio, S.; Leroy, A.; Duncombe, S.; Toussaint, J.F.; Sedeaud, A. Body and Boat: Significance of Morphology on Elite Rowing Performance. *Front. Sports Act. Living*, 2020.
19. Alföldi, Z.; Boryslawski, K.; Ihasz, F.; Soós, I.; Podstawski, R. Differences in the Anthropometric and Physiological Profiles of Hungarian Male Rowers of Various Age Categories, Rankings and Career Lengths: Selection Problems. *Front. Physiol.* 2021.
20. Arkaitz Castañeda-Babarro, Patxi León-Guereño, Aitor Viribay, Borja Gutiérrez-Santamaría, Iker López and Juan Mielgo-Ayuso. The Influence of Anthropometric Variables on the Performance of Elite Traditional Rowers. *Sports*, 2024.



21. Larrinaga, B.; Río, X.; Coca, A.; Rodriguez-Alonso, M.; Arbillaga-Etxarri, A. Anthropometric differences and maximal aerobic power among men and women in racing-boat rowing. *Arch. Med. Deporte*, 2023.
22. Majumdar, P.; Das, A.; Mandal, M. Physical and strength variables as a predictor of 2000m rowing ergometer performance in elite rowers. *J. Phys. Educ. Sport*, 2017.
23. Lozovina, V.; Pavčić, L. Anthropometric changes in elite male water polo players: Survey in 1980 and 1995. *Croat. Med. J.* 2004.
24. Avlonitou, E.; Ceorgiou, E.; Douskas, G.; Louizil, A. Estimation of Body Composition in Competitive Swimmers by Means of Three Different Techniques. *Int. J. Sports Med.* 1997.
25. Dopsaj, M.; Zuoziene, I.J.; Milić, R.; Cherepov, E.; Erlikh, V.; Masiulis, N.; di Nino, A.; Vodičar, J. Body Composition in International Sprint Swimmers: Are There Any Relations with Performance? *Int. J. Environ. Res. Public Health.* 2020.
26. Tan, J.Q.J.; Lee, M.J.C.; Boey, D.; Lum, D.; Barbosa, T.M. The Transfer of Dry-Land Strength & Power into Thrust in Competitive Swimming. *Sport. Biomech.* 2021.
27. Barbosa, T.M.; Bartolomeu, R.F.; Morais, J.E.; Costa, M.J. Skillful Swimming in Age-Groups Is Determined by Anthropometrics, Biomechanics and Energetics. *Front. Physiol.* 2019.
28. Morais, J.E.; Marques, M.C.; Rodríguez-Rosell, D.; Barbosa, T.M.; Marinho, D.A. Relationship between Thrust, Anthropometrics, and Dry-Land Strength in a National Junior Swimming Team. *Physician Sportsmed.* 2020.