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USE OF ARTIFICIAL NEURAL NETWORKS TO EVALUATE THE INTERACTION OF CONFOUNDING FACTORS WITH DISCRIMINATING FACTORS DURING THE SELECTION OF YOUNG ATHLETES FROM DIFFERENT SPORTS: A PILOT STUDY

UTILIZAÇÃO DE REDES NEURONAIS ARTIFICIAIS PARA AVALIAR A INTERAÇÃO DE FATORES DE CONFUSÃO COM FATORES DISCRIMINANTES DURANTE A SELEÇÃO DE JOVENS ATLETAS DE DIFERENTES MODALIDADES ESPORTIVAS: UM ESTUDO PILOTO

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ABSTRACT

Introduction: Multilayer artificial neural networks (MLP's) have proven to be effective in discriminating morphological and biomechanical specificities of young elite athletes. However, they have not yet verified the effectiveness of MLP's to identify the interaction of confounding factors, such as biological maturation (BM). BM influences morphological and biomechanical factors, so if MLPs have not considered this confounding factor they may group young athletes by maturational rather than sport characteristics. **Objective**: Analyze the morphological and neuromuscular discriminatory factors of young athletes of different sports using MLP's to assess the interaction with BM. **Methods**: This is a cross-sectional study. The sample consisted of 56 young national level Brazilian athletes (tennis, rowing, football, Brazilian jiu-jitsu (BJJ), swimming and volleyball) of both sexes (13.0±1.0-yrs). Measurements included standing and sitting height, leg length, BM (by peak height velocity, PHV), body composition (by DEXA), upper limb performance, handgrip and squat (SJ) and countermovement (CMJ) jumps. Analyses were performed using canonical correlations and MLP's. **Results**: BM, sitting height, bone density (BMD), CMJ and handgrip discriminated 39.3% of athletes ($F=2.432$; $p<0.001$). Specifically, sitting height, handgrip, CMJ and BMD produced the probability of discriminating volleyball athletes by 80%, football by 78.1%, BJJ by 55.5%, tennis by 33.9%, swimming by 30.9% and rowing by 16.6%. BM interacted positively in the discrimination process of athletes in 90% in football, in 80% in volleyball and in 54.5% in swimming. **Conclusion**: MLP's have been shown to be effective in finding the interaction of confounding factors. MLP's can be used to aid in the selection process of young athletes.

Keywords: Performance; Sport; Puberty; Biological Maturation.

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INTRODUCTION

Several programs have been successful in selection of young athletes using morphological factors, motor tests and physiological data for advancement to elite opportunities (PION *et al*., 2015; ZHAO *et al*., 2019). Elite sports schools implement athlete selection based on standards (i.e., morphological, motor and physiological) of established elite athletes of specific modalities to match performance capabilities (REES *et al.*, 2016). This process occurs through the observations of sports professionals, anthropometrics and physiologists, and is centered on periodic documentation of the performance characteristics (RIKBERG; RAUSEPP, 2011; PION *et al.*, 2014).

Predictive player and sport selection occurs in team, individual, combat, water, and resistance sports, among others (PION *et al.*, 2014). For example, young elite volleyball players have a better jumping ability and a higher stature when compared to their peers who have not reached the elite level (PION *et al.*, 2015). Young gymnasts have better jumping skills when compared to swimmers, handball players and tennis players of the same age (BENCKE *et al.*, 2002). For fencers, they are not superior in long jump capabilities when compared to weightlifters and fighters (KRISHNAN *et al.*, 2017).

It is noted that many sports are based on a complex and multidimensional performance profile (BUEKERS; BORRY; ROWE, 2015), making the selection of athletes focused on a multifaceted physical, physiological, psychomotor and psychological performance variables (WILLIAMS; REILLY, 2000). However, previous investigations using complex batteries of tests or discriminating models of young athletes have not fully considered the interaction and/or the influence of biological maturation on these morphological and neuromuscular parameters of performance (MALINA *et al.*, 2015; WONDISFORD, 2020).

Considering that biological maturation is not always synchronized with the movement patterns and body characteristics expected for a given chronological age group, the subjects may be biologically delayed or advanced, which can confound the judgment of those involved in athlete selection (MALINA *et al.*, 2015). Recently, it was observed that biological maturation has significant effects on upper and lower limb muscle strength in young elite athletes, and in addition, athletes with advanced biological maturation had advantages in relation to body morphology (ALMEIDA-NETO *et al.*, 2020a). Previous studies have found a biological maturation influence in relation to morphological and neuromuscular parameters in young non-athletes and athletes (BARROS *et al.*, 2017; SILVA; OLIVEIRA, 2010).

In a recent meta-analysis study, it was demonstrated that biological maturation is a determining factor for neuromuscular performance in young athletes (ALMEIDA-NETO *et al.*, 2021). However, in the application to athletics, using biological maturation for predictive purposes requires the use of specific tests such as x-ray of the hand-wrist or the use of generalized equations that require anthropometric data collection (LLOYD *et al.*, 2014). Due to these limitations, it may be valuable to explore ways to integrate biological maturation more systematically. Computerized artificial neural networks are used to assist professionals in various fields in decision making, reducing subjective bias, increasing the impersonality of the evaluator (HAYKIN, 2001). In sports, multilayer neural networks (MLP's) were useful to discriminate athletes from different sports (judo, volleyball, swimming, fencing, basketball and table tennis) through anthropometric characteristics (ZHAO *et al.*, 2019). Additionally, they showed the biomechanical pattern of rowing athletes (BENSISAID *et al.*, 2021) and androgenic hormones and biological maturation in relation to the neuromuscular performance of young athletes of both sexes (ALMEIDA-NETO *et al.*, 2020b; 2020c). However, MLP's have not yet been tested to verify the interaction of biological maturation with morphological and neuromuscular discriminant factors in young athletes.

Thus, it is likely that in addition to discriminating the main morphological factors for different sports, the MLP's are able to verify the interaction of confounding factors such as biological maturation. Thus, the implementation of the use of artificial neural network algorithms can help minimize human error, optimizing the selection and guidance of young talents in sports. Thus, we hypothesized that MLP's would be able to discriminate elite athletes from different sports by identifying the interaction of the confounding factor biological maturation. Given this, our objective was to use multilayer perceptron artificial neural networks to analyze the morphological and neuromuscular discrimination factors of young athletes from different sports, verifying the interaction of biological maturation as a confounding factor.

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MATERIALS AND METHODS

This is a cross-sectional study. This study used a sample of 56 young Brazilian athletes (74% male and 26% female)recruited from clubs in the city of Natal - RN in 2019. The sample included athletes from different sports:Rowing (10.5%, 5 male and 1 female), Brazilian Jiu-jitsu (BJJ) (15.8%, 8 male and 1 female), Soccer (19.3 %, 11 male), Swimming (19.3%, 7 male and 4 female), Tennis (15.8%, 9 male) and Volleyball (17.5%, 2 male and 8 female). According to the state federation of each sport, all athletes were ranked among the 20 best in their category (in Brazilian ranking) as well as being nominated for the best athletes of the year preceding this research in the Brazilian confederation of their respective sports. Based on information from the national confederations, and according to the classification by Matsudo, Rivet & Pereira (1987), the sample is classified as national level athletes.

We emphasize that an a priori sample calculation using the open source software G* Power® (Version 3.0; Berlin, Germany) was performed considering the effect size of 0.954 found by Pion et al. (2014) in a canonical correlation analysis to discriminate U13 category athletes from different sports through anthropometric and motor variables. Thus, we considered an $\alpha < 0.05$ and a β of 0.8 and arrived at a minimum sample size of five subjects per group (Power= 0.9).

The inclusion criteria were: (1) Being an athlete officially registered with a state sports federation. (2) Ranked among the best athletes in their respective categories. (3) Have a weekly training load of more than three days. Athletes who reported osteomioarticular injuries in the last six months prior to the research were excluded.

The research was approved by the Ethics and Research Committee of the Federal University of Rio Grande do Norte - Brazil (CAEE: 15865619.7.0000.5537) according to Resolution 466/12 of the National Health Council, on 12/12/2012, strictly respecting the national and international ethical principles of the Declaration of Helsinki. Additionally, the study complied with all the international requirements and standards of the STROBE checklist for observational studies of incidence and prevalence (VON ELM *et al.*, 2014). We emphasize, that we informed the participants and their respective guardians about the risks and benefits of participating in the research. Subsequently, all participants and their guardians signed the informed consent forms agreeing to participate in this research.

After signing the consent form, the athletes underwent a physical assessment that included variables of strength, anthropometry and body composition. All measurements were carried out at the Movement Laboratory (LABMOV) - UFRN.

Anthropometry

Anthropometric assessments were performed according to the International Society of the Advancement of Kinanthropometry protocols (KARUPAIAH, 2018). Body mass was measured using a digital scale with an accuracy of 0.1 kg (FILIZOLA®, São Paulo, Brazil). Height and sitting height were assessed using a stadiometer with an accuracy of 0.01 cm (SANNY®, São Paulo, Brazil). Leg length was calculated by subtracting sitting height from height (MIRWALD *et al.*, 2002). The perimeter was measured using an anthropometric tape (SANNY®, São Paulo, Brazil), and the bone diameters were measured using a caliper (SANNY®, São Paulo, Brazil).

Body composition

Body composition was assessed with dual energy x-ray bone densitometry (DXA) (LUNAR® / GE PRODIGY - LNR 41,990, United States) using specific algorithms for the pediatric population (enCORE, GE Healthcare®, version 15.0, Madison, WI, USA). This procedure is considered one of the most reliable standards for measuring body composition (KHADILKAR *et al.*, 2020). DXA used the following standardization during the evaluations: Full Body Evaluation, Voltage (kV): 76.0, Current (mA): 0.150, Radiation dose (μGγ): 0.4 (Very low, no health risk).

Upper Limb Performance and Handgrip

We used the medicineball throw test (MELLO *et al.*, 2016) to determine upper limb power (ULP). For the test we used a medicineball with a mass of two kilograms (Ax Sports®, Tangará, Brazil). The participant was instructed to hold the medicineball at the height of the sternum and after the evaluator emitted a sound signal or participant launched the medicineball horizontally. During the throw both hands held the medicineball and the trunk was not allowed to move. Each participant performed the test three consecutive times interspersed with three minutes of rest; the best result was considered for further analysis.

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Through the handgrip test (using a hydraulic dynamometer, JAMAR®, Cambuci, Brazil; calibrated before each evaluation) we evaluated the isometric strength of the upper limbs. During the handgrip test, the participants remained seated on an adjustable chair with backrest, keeping the right forearm flexed at 90° and the knees flexed at 90° with the feet fixed on the ground. Each participant performed three maximal isometric contractions (lasting 3-s) interspersed with one minute of rest, the best performance was used for further analysis.

Lower Limbs Performance

Using a force platform(with interrupt system) (CEFISE®, São Paulo, Brazil), we used protocols established by Bosco *et al.*, (1982) to evaluate squat jump (SJ) and countermovement jump (CMJ). Thus, we determined the performance of lower limbs. Prior to the evaluations, the subjects performed familiarization jumps of each type and were given feedback as needed to execute the protocol properly. Then, starting from an orthostatic position, held for three seconds, with the knees flexed at approximately 90º and the hands fixed on the waist, the subjects were instructed to perform a maximal vertical jump. For CMJ analysis the same recommendations were adopted, however, the subjects started in the upright position and performed a squat followed by the jump. A 10-minute recovery interval was observed between SJ and CMJ. For both tests, three attempts were made, interspersed with 60s of passive recovery and the best attempt was used for data analysis. We used the height of the jumps in centimeters as a parameter for the performance of the lower limbs.

Biological maturation analysis

Biological maturation was defined as years from attainment of peak height velocity (PHV; termed maturity offset), using the following equations (MIRWALD *et al.*, 2002):

(1) Maturity offset in males = – 9.236 + [0.0002708 * (Leg Length*sitting height)] + [–0.001663 * (Age* Leg length)] + [0.007216 * (Age*sitting height)] + [0.02292 * (Weight/ Height) * 100]

(2) Maturity offset in females = – 9.376 + [0.0001882 * (Leg Length * sitting height)] + [0.0022 * (Age * Leg length)] + [0.005841 * (Age* sitting height)] – [0.002658 * (Age* Weight)] + [0,07693 * (Weight/ Height) * 100]

Age at PHV was calculated as age at measurement - maturity offset. Three maturity categories were identified (MIRWALD et al., 2002): (1) Pre-PHV (Maturity offset<-1); (2) circum-PHV (Maturity offset ≥-1 to ≤+1); (3) Post-PHV (Maturity offset >+1). Categorizing the stages of maturation by means of predictive equations proved to be a valid method compared to the gold standard (hand-wrist X-ray) (ALMEIDA-NETO *et al.*, 2022).

STATISTICS ANALYSIS

All analyzes were performed using the statistical software R (version 4.1.1; R Foundation for Statistical Computing®, Vienna, Austria), and $p<0.05$ was considered significant.

Z-score identification

To normalize the results of all sports, the Z-score of the morphological and neuromuscular variables was used in all analyses, the data's weighted Z-Score can be found in ***Supplementary file 1***. To calculate the Z-score, the following were taken into account: (a) Gender (b) Age (c) Sport. The average variance of each measurement was verified by age group in the total sample and by age group within each specific sport, then the sample standard deviation was used for the calculation: ***Z score = (Va – VaG) / SdG***. *Where:* Va = Average of a single subject for the analyzed variable. VaG = Group average in relation to the analyzed variable. SdG = Standard deviation of the group in relation to the analyzed variable.

Data normality and discriminant analysis

The normality of the data was verified by the Shapiro-Wilk and Z-score tests for asymmetry and kurtosis (-1.96 to 1.96). Discriminant analyses were carried out with canonical correlations and cross-validations in relation to the selection of young athletes for their respective sports of origin, using the variables: morphological, neuromuscular and biological maturation. It should be noted that in addition to the use of the specific Z-score for each sex, the difference between males and females were controlled in the analyses by the arithmetic method of "Backdoor", allowing subjects of both sexes to be allocated in the same group in relation to their respective sports (PEARL, 2009). Sport was used as a dependent grouping variable, and the test results

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(morphological and neuromuscular) were used as a set of independent variables.

Programming of Artificial Neural Networks

Multilayer perceptron artificial neural networks (MLP's) were programmed with the objective of verifying the probability of correct prediction in relation to the discrimination of athletes for their respective sports based on the patterns of morphological and neuromuscular variables. MLP's were also programmed, to determine the interaction of biological maturation patterns and discriminating athletes for their respective sports. Subsequently, both MLP's were combined in a mixed model, aiming to assess the interaction of maturation together with morphological and neuromuscular variables to discriminate between athletes and their respective sports. MLP's have been programmed with back propagation algorithms to adjust synaptic weights. 100% of the sample was used for MLP's training and testing in 10,000 run times, the procedures were repeated five times in a row and the average results of the five repetitions were taken as the final result (CIABURRO; VENKATESWARAN, 2017). In all analyses, the test results (morphological, neuromuscular and biological maturation) were used as a set of independent variables and sports as a dependent grouping variable. The MLP's had a performance of 93.7%, which indicates good reliability (CIABURRO; VENKATESWARAN, 2017).

Mixed Analyzes

To prioritize which characteristics were more relevant for a respective sport in relation to the others, discriminant analyses in conjunction with MLP's were programmed to identify the percentage of importance of each variable individually (From Scores - Z). The MLP's had a performance of 90.2%, which indicates good reliability (HAYKIN, 2001; CIABURRO; VENKATESWARAN, 2017). In each analysis, athletes were grouped into two groups that served as a dichotomous dependent variable: (i) specific sport group. (ii) group all the remaining sports.

Technical error of anthropometrics

The technical error of anthropometric measurements was analyzed as follows: Acceptable for anthropometric measurements of body dimensions and circumferences ≤ 1.0% (PERINI *et al.*, 2005). The standard error was obtained from the product generated by dividing the standard deviation by the square root of the sample size of each group.

RESULTS

The sample characterization was presented descriptively by means and standard deviations of the variables (Table 1). Although the chronological age was similar between the sports groups, somatic maturation stages showed different numerical patterns for each sport group. Specifically, the classification varied between pre (for soccer and tennis) and circum-PHV (for BJJ, rowing, swimming and volleyball). Table 1 also highlights the patterns of the morphological and muscular strength variables between sports (technical error <1 % for all variables).

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Table 1. Sample characterization.

Variables	BJJ	Rowing	Soccer	Swimming	Tennis	Volleyball
Age (years)	13.4 ± 1.1	13.4 ± 1.1	12.9 ± 0.6	13.2 ± 1.1	12.4 ± 0.7	13.2 ± 1.0
Biological Maturation (PHV)	-0.5 ± 1.8	-0.7 ± 1.8	-1.2 ± 1.2	-0.4 ± 1.8	-1.4 ± 1.6	-0.4 ± 1.9
Stature (cm)	161.1 ± 10.8	161.0 ± 11.0	159.2 ± 10.9	159.9 ± 10.3	157.2 ± 10.9	160.1 ± 10.5
Sitting height (cm)	80.1 ± 9.0	79.7 ± 9.2	75.9 ± 9.9	79.3 ± 8.7	74.8± 10.0	79.4 ± 8.8
Leg length (cm)	80.9 ± 7.3	81.3 ± 7.6	83.3 ± 7.6	80.6 ± 7.2	82.3 ± 8.5	80.6 ± 11.1
Body Weight (kg)	51.9 ± 11.8	51.6 ± 11.6	48.5 ± 12.0	50.4 ± 11.2	46.2 ± 8.7	50.3 ± 11.1
Lean Mass (kg)	37.8 ± 9.0	38.0 ± 8.5	25.8 ± 7.7	36.4 ± 8.2	34.6 ± 7.2	36.4 ± 8.1
Fat Mass (kg)	12.5 ± 5.8	12.0 ± 5.7	11.3 ± 6.9	12.4 ± 5.8	10.1 ± 2.8	12.4 ± 5.9
BMD (g/cm²)	1.5 ± 0.4	1.5 ± 0.4	1.4 ± 0.4	1.5 ± 0.4	1.4 ± 0.3	1.5 ± 0.4
BMC (g)	2.3 ± 0.8	2.2 ± 0.8	2.1 ± 0.7	2.0 ± 0.8	2.2 ± 0.5	2.0 ± 0.8
Handgrip (kgf)	25.6 ± 8.5	25.8 ± 8.6	22.9 ± 7.7	24.6 ± 8.3	21.8 ± 6.5	24.5 ± 8.1
ULP (m)	3.3 ± 0.9	3.3 ± 0.8	3.1 ± 0.7	3.1 ± 0.8	3.1 ± 0.7	3.2 ± 0.8
CMJ (cm)	25.8 ± 5.2	25.8 ± 5.2	21.2 ± 4.6	25.3 ± 5.0	25.2 ± 4.3	25.3 ± 5.1
Squat jump (cm)	23.6 ± 4.8	23.6 ± 4.8	22.0 ± 3.9	23.2 ± 4.6	22.4 ± 3.8	23.3 ± 4.7
			Absolut Technical Error (Relative Technical Error %)			
Stature (cm)	0.3 (0.0)	0.2 (0.0)	0.1 (0.0)	0.1 (0.0)	0.3 (0.0)	0.2 (0.0)
Sitting height (cm)	0.0 (0.0)	0.1 (0.0)	0.1 (0.0)	0.2 (0.0)	0.1 (0.0)	0.0 (0.0)
Leg length (cm)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Body Weight (kg)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Handgrip (kgf)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
ULP (m)	0.1 (.03)	0.1 (.04)	0.1 (.04)	0.2 (.06)	0.2 (.06)	0.1 (.05)
CMJ (cm)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Squat jump (cm)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)

BJJ = Brazilian Jiujitsu. BMD = Bone mineral density. BMC = Bone mineral content. ULP = Upper limb performance. CMJ =Countermovement jump.

In relation to the analyzed variables, the discriminant analyses showed that the strongest set of variables to discriminate athletes to their respective sports were: sitting height, BMD, CMJ and Handgrip. The model with discriminant functions based on this set of variables managed to discriminate athletes by 37.5% for their respective sports ($F = 1.453$; $p = 0.02$) (Figure 1). However, after cross-validation, the model was only able to discriminate young athletes by 16.1%. When considering only the maturation to discriminate athletes to their respective sports, the discriminating function was more satisfactory ($F = 9.081$; $p < 0.001$) and to discriminate the subjects in 42.9% for their respective sports. which were unchanged after validation. By combining the variables maturation, sitting height, BMD, CMJ and Handgrip in the same model of discriminating functions, the model correctly discriminated athletes in their sports by 51.8% ($F = 2.432$; $p < 0.001$) dropping to 39.3% after cross-validation.

Figure 1. Discriminant analysis considering maturity, sitting height, BMD, CMJ and Handgrip. Function 1 = linear discrimination function of the random vector Y. Function 2 = linear discrimination function of the random vector X. 1= Brazilian Jiu jitsu. 2 = Rowing. 3 = Soccer. 4 = Swimming. 5 = Tennis. 6 = Volleyball.

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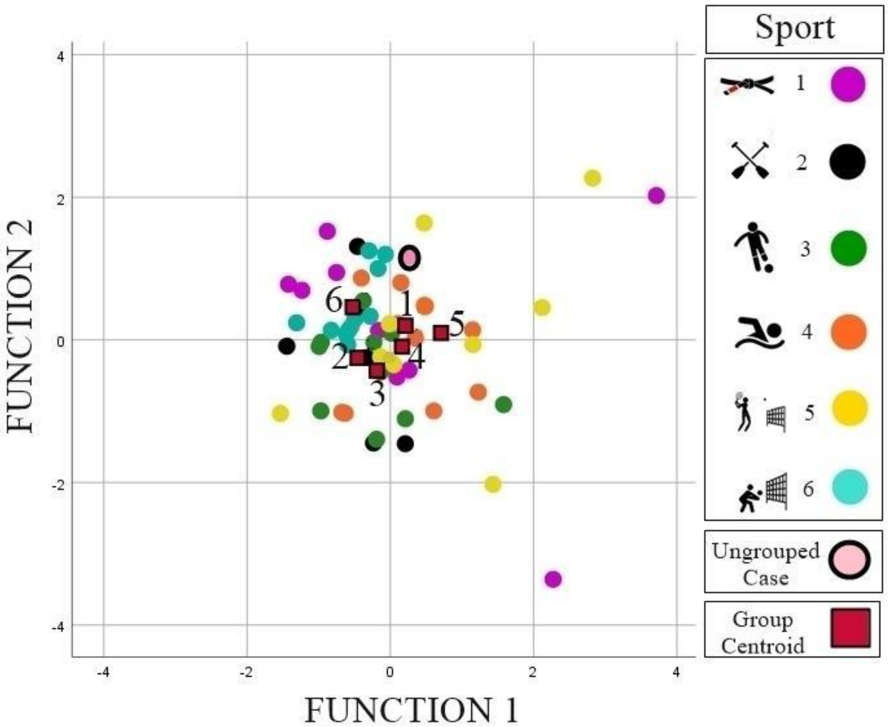

The analysis of MLP's, showed that the discrimination of young athletes for their respective sports through the model adjusted by the present study (sitting height, handgrip, CMJ and BMD), points out the probability of being 80% correct for volleyball, in 78.1 % soccer, 55.5% for the BJJ, 33.9% for tennis, 30.9% for swimming and 16.6% for rowing (Table 2). The neural networks analyses suggest that the biological maturation interacted in the process of discrimination of athletes (90% for soccer, in 80% for volleyball and 54.5% for swimming). The combined model proposed presently using biological maturation stages indicated the probability of discriminating young athletes correctly was 83.4% for soccer, 78.0% for volleyball, 54.3% for swimming, 53.3% for tennis, 35.5% for BJJ and 20% for rowing.

Table 2. MLP's analysis for the probability of correct answers in relation to the discrimination of young athletes and the interaction of biological maturation with the model of discriminating factors.

Group	Model	BM interaction with the discriminant model	Model + BM
BJJ	55.5 %	00.0 %	35.5 %
Rowing	16.6 %	00.0 %	20.0 %
Soccer	78.1 %	90.0 %	83.4 %
Swimming	30.9 %	54.5 %	54.3 %
Tennis	33.9 %	00.0 %	53.3 %
Volleyball	80.0 %	80.0 %	78.0 %

BJJ = Brazilian Jiu jitsu. Model = Analysis of artificial neural networks of the multilayer typeperceptron based on the variables: sitting height, handgrip, countermovement jump and bone mineral density. BM = biological maturation (PHV).

Handgrip proved to be a discriminating characteristic for BJJ athletes while upper limb performance and lean mass were identified as the main discriminating factors for rowers (Table 3). For soccer, BMD and CMJ were the main discriminating factors. In swimmers, the length of the lower limbs and the SJ are the main discriminating factors. For tennis players, the handgrip and upper limb performance were discriminating factors for the sport while height and the length of the legs discriminated in volleyball athlete. The probability of discriminating ranged from 77.8% and 97.4% in these MLP analyses.

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Table 3. Discriminating factors and their importance for each sport.

Groups	Discriminating Factors		% Importance (MLP's)		F		p
	Factor 1	Factor 2	Factor 1	Factor 2	Factor 1	Factor 2	
BJJ	HG	---	93.7%	---	17.375	---	0.003
Rowing	ULP	LM	86 %	90.3%	15.845	16.379	<0.005
Soccer	BMD	CMJ	79.5 %	87.6%	4.591	19.301	<0.001
Swimming	LL	SJ	88.9%	97.2%	3.751	15.419	<0.00001
Tennis	HG	ULP	77.8%	88.3%	11.370	14.090	<0.0001
Volleyball	Stature	LL	97.4 %	85.6 %	3.456	2.510	<0.005

BJJ=Brazilian Jiu jitsu. MLP's = % of importance estimated by artificial multilayer perceptron neural networks. HG = Handgrip. ULP = Upper limbs performance. LM = Lean Mass. LL = Leg length. BMD =Bone mineral density. CMJ= Countermovement Jump. SJ = Squat Jump.

DISCUSSION

This study aimed to use artificial neural networks to analyze the morphological and neuromuscular discrimination factors of young athletes from different sports, as well as to analyze whether biological maturation interacts with the discrimination process of athletes from different sports. Thus, our initial hypothesis was confirmed by demonstrating that artificial neural networks were effective at discriminating young athletes and to support the interaction of biological maturation in this process.

As far as we know, this is the first study to use MLP's to assess the interaction of biological maturation with morphological and neuromuscular factors in young athletes. It should be noted that MLP's are non-linear models that aim to examine with high precision the importance of certain factors within a predetermined model, forecast strength of a dependent variable in relation to an independent variable and/or the interaction of a determined variable within of a predetermined model (TINO; BENUSKOVA; SPERDUTI, 2015). In this sense, artificial neural networks have learning capacity and can identify the interaction of patterns of a given covariate on the analysis variables (HAYKIN, 2001).

Thus, in the present study, biological maturation, body morphology and neuromuscular performance were identified as factors discriminating athletes in their respective sports by 39.3%. Morphological characteristics, such as the height and length of the upper and lower limbs, were suggested by Ziv & Lidor (2009), as discriminating factors for young athletes specialized in basketball. Similarly, Hohmann *et al.*, (2018) identified the importance of the same factors for swimming athletes and Lidor *et al.*, (2007) suggested that for volleyball, the same patterns are significant for the discrimination of athletes.

The present study identified that, when considering biological maturation, it was possible to discriminate in more than 42% young Brazilian athletes from six different sports. These findings occurred at random, demonstrating that there were young athletes from the same group with similar patterns of maturation stages. Thus, in more than 40% of the cases, the athletes were directed to the same group of origin, which suggests that the selection of these subjects was possibly influenced by their biological advantages from a maturational perspective.

Biological maturation is the biological mechanism responsible for the improvement of several systems (i.e., neurological, muscular, endocrine, etc.) that interacts with the growth process (i.e., increase in body dimensions), influencing morphological characteristics (i.e., height, length of upper and lower limbs, predominance of lean mass, etc.) (WONDISFORD, 2020). Moreover, Malina *et al.* (2015) argue that during the selection of young athletes, biological maturation is a factor that can confuse those involved in the process, especially when considering that, in relation to chronological age, subjects may be biologically delayed, synchronized or advanced (LLOYD *et al.*, 2014). In general, it is natural that subjects in advanced stages of biological maturation have advantages of morphological characteristics in relation to their delayed biological maturation counterparts (MALINA *et al.*, 2015). Therefore, there are no guarantees that these performance advantages will remain until the young athlete reaches adulthood. Many young people with advanced biological maturation, classified as promising athletes, end up stagnating when their late maturing peers catch up maturational (Malina, 1994; WONDISFORT *et al.*, 2020).

In addition, when considering a specific analysis of MLP's, the present research found that biological maturation interacted significantly on the process of discriminating against 54% of swimmers, 90% of soccer athletes and 80% of volleyball athletes. This may be justified due to the advancement of biological maturation being related to upper and lower limb performance in adolescent athletes (ALMEIDA-NETO et al., 2020b; 2020c). Moreover, several studies indicate that biological maturation is associated with morphological advantages (height, wingspan and lean mass) and the increase in muscle strength of the body segments (LLOYD et al., 2014; SCHEFFLER; HERMANUSSEN, 2018; DANTAS *et al.*, 2018).

In the findings of the present study, MLP's identified that a model of selection of athletes based on the sitting height, handgrip, CMJ and BMD proved to be effective in discriminating over 35% of BJJ athletes, more than 53% of swimming athletes and tennis and more than 78% of soccer and volleyball athletes. Zhao *et al.* (2019) showed morphological characteristics (chest width, length of lower limbs, thigh circumference, etc.) to be discriminating factors for the identification of young Chinese athletes from six different sports (judo, fencing, table tennis, swimming, volleyball and basketball). Hunter *et al*. (2015) observed that the length of the Achilles tendon was associated with the performance of runners. In volleyball, young athletes with superior performance have greater body stature (RIKBERG; RAUDSEPP, 2011). It is noteworthy that the model under discussion used by the present study and the models used by the previous investigations did not consider the influence of biological maturation on the morphological factors associated with the discrimination of elite athletes.

In addition, the present study is the first to investigate discriminating models in adolescents rowing athletes. However, the discriminant model based on sitting height, handgrip, CMJ and BMD only achieved 16.6% rate of discriminating rowing athletes. This may be explained by the characteristics of the sport, that despite having a significant demand for handgrip, athletes do not rely on maximal strength of lower limbs (CMJ) and do not perform activities of joint impact (i.e., such as running and jumping) that cause the increase in BMD (HARUN; NASRUDDIN; SYAHROM, 2020). Thus, the discriminant model used in the present study, demonstrated a strong classification performance in athletes of modalities (BJJ, volleyball, soccer, tennis and swimming) who frequently use the strength of lower limbs and joint impact activities.

When considering the high cost invested in the selection of elite athletes, it is important that coaches make the least number of mistakes possible (MALINA *et al.*, 2015; PION *et al.*, 2015). Thus, the selection of athletes requires a high precision and with tools that are accessible to coaches (PION *et al.*, 2017). The analysis of maturation stages can be carried out in a practical way and can significantly assist in the selection process of young athletes, due to the effect of biological maturation on morphological characteristics and muscle strength levels (LLOYD *et al.*, 2014; MALINA *et al.*, 2015).

In the present research, the mixed analyses of discriminating factors together with MLP's, indicated that neuromuscular and morphological factors have different degrees of importance for each analyzed modality. The main factors identified for each sport were: handgrip for BJJ, upper limbs performance and lean mass for rowing, BMD and CMJ for soccer, leg length and SJ for swimming, handgrip and upper limbs performance for tennis, stature and length of the legs for volleyball performance. The results of the present study corroborate previous research that identified characteristics regarding the importance of morphological and neuromuscular patterns for different sports. Zhao *et al*. (2019) suggested that young athletes of judo, basketball and volleyball have among the most important characteristic of dynamic strength of the back, and swimmers have a smaller width of the iliac crest and a greater Achilles tendon length as the most important characteristics for performance. Likewise, quadriceps strength is an important factor for fencing athletes and sprinters (MOROUÇO *et al.*, 2011; TURNER *et al.*, 2014).

Limitations and key-points

Despite the relevance of the results, the main limitation of the manuscript is that the neural networks were not trained with a distinct sample, using the same subjects in cross-validation causes the model to overlap with the sample, which makes it impossible for us to generalize the results to other samples. Furthermore, the sample size is small to allow us to make generalizations of the findings to larger groups. However, the sample calculation performed a priori indicated that the sample size was adequate for a pilot study. And our main goal was to expose that artificial neural networks are efficient in assisting in the selection of elite athletes. Thus, the present study brings as a key-point, the use of artificial intelligence as a useful tool to help sports professionals identify discriminating factors in young athletes, and to verify possible covariates that may interact with such discriminating factors. This can be useful for profiling sports using processes of selecting and guiding athletes in the sport.

CONCLUSION

Artificial neural networks are useful to identify discriminating factors in young elite athletes, as well as to determining the interaction of covariates in such discriminating factors. Thus, as neural networks can be used to assist in the process of selecting and mentoring young talent in sport. This may assist in minimizing human failure by analyzing morphological and biomechanical factors that have particularities specific to different sports. Furthermore, as artificial neural networks can help identify the interaction of confounding factors such as biological maturation that is related to body morphology and biomechanical performance independently of sports practice.

REFERENCES

ALMEIDA-NETO, P. F. D., MATOS, D. G. D., BAXTER-JONES, A. D., Batista, G. R., Pinto, V. C. M., Dantas, M., ... & Cabral, B. G. D. A. T. (2020a). The effectiveness of biological maturation and lean mass in relation to muscle strength performance in elite young athletes. **Sustainability**, 12(17), 6696. DOI: 10.3390/su12176696.

ALMEIDA-NETO, P. F. D., DE MATOS, D. G., PINTO, V. C. M., DANTAS, P. M. S., CESÁRIO, T. D. M., DA SILVA, L. F., ... & CABRAL, B. G. D. A. T. (2020b). Can the neuromuscular performance of young athletes be influenced by hormone levels and different stages of puberty?.**International Journal of Environmental Research and Public Health**, 17(16), 5637. DOI: 10.3390/ijerph17165637.

ALMEIDA-NETO, P. F., SILVA DANTAS, P. M., PINTO, V. C. M., CESÁRIO, T. D. M., RIBEIRO CAMPOS, N. M., Santana, E. E., ... & Tinoco Cabral, B. G. D. A. (2020c). Biological maturation and hormonal markers, relationship to Neuromotor performance in female children. **International Journal of Environmental Research and Public Health**, 17(9), 327. DOI: 10.3390/ijerph17093277.

ALMEIDA-NETO*, P. F. D., OLIVEIRA*, V. M. M., DE MATOS, D. G., DOS SANTOS, Í. K., BAXTER-JONES, A., PINTO, V. C. M., ... & CABRAL, B. G. D. A. T. (2021). Factors related to lower limb performance in children and adolescents aged 7 to 17 years: A systematic review with meta-analysis. **Plos One**, 16(10), e0258144. DOI: 10.1371/journal.pone.0258144.

ALMEIDA NETO, P. F. D. (2021). Title in portuguese: Relação da maturação biológica e de parâmetros hormonais e morfológicos com a força muscular de membros superiores e inferiores de jovens atletas. Title in English: **Relation of biological maturation and hormonal and morphological parameters with upper and lower limb muscle strength in young athletes** (Master's thesis, FederalUniversity of Rio Grande do Norte).

ALMEIDA-NETO, P. F., DE MEDEIROS, J. A., MEDEIROS, R. M. V., BAXTER-JONES, A., DE MATOS, D. G., AIDAR, F. J., ... & DE ARAÚJO TINOCO CABRAL, B. G. (2022). Reliability of biological maturation analyses performed by equations predicting skeletal age and peak height velocity with hand and wrist X-ray results. **American Journal of Human Biology**, e23775. DOI: 10.1002/ajhb.23775.

BARROS, J. D. S. V., DE LIMA, M. V. M., & SAMPAIO, A. N. (2017). Analysis of motor capacities in the maturational stages of female adolescents. **JournalHuman Growth Develop**, 27(2), 206-212. DOI: 10.7322/jhgd.125018.

BENSISAID, K., ABABOU, N., ABABOU, A., ROTH, D., & VON MAMMEN, S. (2021). Tracking rower motion without on-body sensors using an instrumented machine and an artificial neural network. Proceedings of the Institution of Mechanical Engineers, Part P: **Journal of Sports Engineering and Technology**, 17543371211014108. DOI: 10.1177/17543371211014108.

BENCKE, J., DAMSGAARD, R., SAEKMOSE, A., JØRGENSEN, P., JØRGENSEN, K., & KLAUSEN, K. (2002). Anaerobic power and muscle strength characteristics of 11 years old elite and non-elite boys and girls from gymnastics, team handball, tennis and swimming. **Scandinavian Journal of Medicine &Science in Sports**, 12(3), 171-178. DOI: 10.1034/j.1600-0838.2002.01128.x.

BOSCO, C., VIITASALO, J.T., KOMI, P.V., LUHTANEN. (1982). Combined effect of elastic energy and myoelectrical potentiation during stretch-shortening cycle exercise. **Acta Physiologica Scandinavica**, 114, 557-565. DOI: 10.1111/j.1748-1716.1982.tb07024.x.

BUEKERS, M., BORRY, P., & ROWE, P. (2015). Talent in sports. Some reflections about the search for future champions. **Movement & Sport Sciences-Science &Motricité**, (88), 3-12. DOI: 10.1051/sm/2014002.

CIABURRO, G., & VENKATESWARAN, B. (2017). Neural Networks with R: Smart models using CNN, RNN, deep learning, and artificial intelligence principles. Packt Publishing Ltd. ISBN: 978-1-78839-787-2.

DANTAS, M. P., SILVA, L. F., GANTOIS, P., SILVA, L. M., DANTAS, R. N., & CABRAL, B. T. (2018). Relationship between maturation and explosive strength in young rowers. **Motricidade**, 14(S1), 112-121.

HAYKIN, S. (2001). **Neural networks. Principles and practice** 2 ed. [S.l.]: Bookman. ISBN: 9788573077186.

HARUN, M. N., NASRUDDIN, F. A., & SYAHROM, A. (2020). Rowing biomechanics, physiology and hydrodynamic: A systematic review. **International Journal of Sports Medicine.**

HOHMANN, A., NEUMANN, T., & FRANKEL, J. (2018). **Prognostic validity of swim-specific performance prerequistes in elite crawl sprint**.

HUNTER, G. R., MCCARTHY, J. P., CARTER, S. J., BAMMAN, M. M., GADDY, E. S., FISHER, G., ... & NEWCOMER, B. R. (2015). Muscle fiber type, Achilles tendon length, potentiation, and running economy. **The Journal of Strength & Conditioning Research**, 29(5), 1302-1309. DOI: 10.1519 / JSC.0000000000000760.

KARUPAIAH, T. (2018). Limited (ISAK) profiling the International Society for the Advancement of Kinanthropometry (ISAK). **Journal of Renal Nutrition and Metabolism**, 3(1), 11-11. DOI: 10.4103/2395-1540.232541.

KHADILKAR, A., CHIPLONKAR, S., SANWALKA, N., KHADILKAR, V., MANDLIK, R., & EKBOTE, V. (2020). A cross-calibration study of GE lunar iDXA and GE lunar DPX Pro for body composition measurements in children and adults. **Journal of Clinical Densitometry**, 23(1), 128-137. DOI: 10.1016/j.jocd.2019.03.003.

KRISHNAN, A., SHARMA, D., BHATT, M., DIXIT, A., & PRADEEP, P. (2017). Comparison between Standing Broad Jump test and Wingate test for assessing lower limb anaerobic power in elite sportsmen. **Medical Journal Armed Forces India**, 73(2), 140-145. DOI: 10.1016/j.mjafi.2016.11.003.

LLOYD, R. S., OLIVER, J. L., FAIGENBAUM, A. D., MYER, G. D., & CROIX, M. B. D. S. (2014). Chronological age vs. biological maturation: implications for exercise programming in youth. **The Journal of Strength & Conditioning Research**, 28(5), 1454-1464. DOI:10.1519 / JSC.0000000000000391.

LIDOR, R., HERSHKO, Y., BILKEVITZ, A., ARNON, M., & FALK, B. (2007). Measurement of talent in volleyball: 15-month follow-up of elite adolescent players. **Journal of Sports Medicine and Physical Fitness**, 47(2), 159.

MALINA, R. M. (1994). Physical growth and biological maturation of young athletes. **Exercise and Sports Sciences Reviews**, 22(1), 280-284.

MALINA, R. M., ROGOL, A. D., CUMMING, S. P., E SILVA, M. J. C., & FIGUEIREDO, A. J. (2015). Biological maturation of youth athletes: assessment and implications. **British Journal of Sports Medicine**, 49(13), 852-859. DOI: 10.1136/bjsports-2015-094623.

MATSUDO, V. K., RIVET, R. E., & PEREIRA, M. H. (1987). Standard score assessment on physique and performance of Brazilian athletes in a six tiered competitive sports model. **Journal of Sports Sciences**, 5(1), 49-53. DOI: 10.1080/02640418708729763.

MELLO, J. B., NAGORNY, G. A. K., HAIACHI, M. D. C., GAYA, A. R., & GAYA, A. C. A. (2016). ProjetoEsporteBrasil: physical fitness profile related to sport performance of children and adolescents. **Revista Brasileira de Cineantropometria & Desempenho Humano**, 18, 658-666. DOI: 10.5007/1980-0037.2016v18n6p658.

MIRWALD, R. L., BAXTER-JONES, A. D., BAILEY, D. A., & BEUNEN, G. P. (2002). An assessment of maturity from anthropometric measurements. **Medicine and Science in Sports and Exercise**, 34(4), 689-694.

MOROUÇO, P., NEIVA, H., GONZÁLEZ-BADILLO, J. J., GARRIDO, N., MARINHO, D. A., & MARQUES, M. C. (2011). Associations between dry land strength and power measurements with swimming performance in elite athletes: a pilot study. **Journal of Human Kinetics**, 29, 105.

PEARL J. (2009). *Causality*. [S.l.]: **Cambridge university press**. ISBN: 978-0521895606.

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PERINI, T. A., OLIVEIRA, G. L. D., ORNELLAS, J. D. S., & OLIVEIRA, F. P. D. (2005). Technical error of measurement in anthropometry. **Revista Brasileira de Medicina do Esporte**, 11, 81-85. DOI: 10.1590/S1517-86922005000100009.

PION, J., FRANSEN, J., LENOIR, M., & SEGERS, V. (2014). The value of non-sport-specific characteristics for talent orientation in young male judo, karate and taekwondo athletes. **Archives of Budo**.

PION, J., SEGERS, V., FRANSEN, J., DEBUYCK, G., DEPREZ, D., HAERENS, L., ... & LENOIR, M. (2015). Generic anthropometric and performance characteristics among elite adolescent boys in nine different sports. **European Journal of Sport Science**, 15(5), 357-366. DOI: 10.1080/17461391.2014.944875.

PION, J., HOHMANN, A., LIU, T., LENOIR, M., & SEGERS, V. (2017). Predictive models reduce talent development costs in female gymnastics. **Journal of Sports Sciences**, 35(8), 806-811. DOI: 10.1080/02640414.2016.1192669.

REES, T., HARDY, L., GÜLLICH, A., ABERNETHY, B., CÔTÉ, J., WOODMAN, T., ... & WARR, C. (2016). The great British medalists project: a review of current knowledge on the development of the world's best sporting talent. **Sports Medicine**, 46(8), 1041-1058. DOI: 10.1007/s40279-016-0476-2.

RIKBERG, A., & RAUDSEPP, L. (2011). Multidimensional performance characteristics in talented male youth volleyball players. **Pediatric Exercise Science**, 23(4), 537-548. DOI: 10.1123/pes.23.4.537.

SCHEFFLER, C., & HERMANUSSEN, M. (2018). Growth in childhood and adolescence. **The International Encyclopedia of Biological Anthropology**, 1-11. DOI: 10.1002/9781118584538.ieba0537.

SILVA, D. A. S., & OLIVEIRA, A. C. C. D. (2010). Impact of sexual maturation on upper and lower limb strength on adolescents. **Revista Brasileira de Cineantropometria & Desempenho Humano**, 12, 144-150. DOI: 10.5007/1980-0037.2010v12n3p144.

TINO, P., BENUSKOVA, L., & SPERDUTI, A. (2015). Artificial neural network models. In Springer Handbook of Computational Intelligence (pp. 455-471). **Springer**, Berlin, Heidelberg. DOI: 10.1007/978-3-662-43505-2_27.

TURNER, A., JAMES, N., DIMITRIOU, L., GREENHALGH, A., MOODY, J., FULCHER, D., ... & KILDUFF, L. (2014). Determinants of Olympic fencing performance and implications for strength and conditioning training. **The Journal of Strength &Conditioning Research**, 28(10), 3001-3011.

VON ELM, E., ALTMAN, D. G., EGGER, M., POCOCK, S. J., GØTZSCHE, P. C., VANDENBROUCKE, J. P., & STROBE INITIATIVE. (2014). The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement: guidelines for reporting observational studies. **International Journal of Surgery**, 12(12), 1495-1499. DOI: 10.1016/j.ijsu.2014.07.013.

WILLIAMS, A. M., & REILLY, T. (2000). Talent identification and development in soccer. **Journal of Sports Sciences**, 18(9), 657-667. DOI: 10.1080/02640410050120041.

WONDISFORD, F. E. (2020). Puberty cases. In essentials of endocrinology and metabolism (pp. 279-287). **Springer**, Cham. DOI: 10.1007/978-3-030-39572-8_30.

ZHAO, K., HOHMANN, A., CHANG, Y., ZHANG, B., PION, J., & GAO, B. (2019). Physiological, anthropometric, and motor characteristics of elite Chinese youth athletes from six different sports. **Frontiers in Physiology**, 10, 405. DOI: 10.3389/fphys.2019.00405.

ZIV, G., & LIDOR, R. (2009). Physical attributes, physiological characteristics, on-court performances and nutritional strategies of female and male basketball players. **Sports Medicine**, 39(7), 547-568. DOI: 10.2165/00007256-200939070-00003.