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ORIGINAL

PREDICTION OF SPORTS TALENT IN YOUNG THROWERS USING MACHINE LEARNING

PREDICCIÓN DEL TALENTO DEPORTIVO EN JÓVENES LANZADORES UTILIZANDO MACHINE LEARNING

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ABSTRACT

The objective of this study is to detect any performance factors in athletics throws between 1997 and 2015 in 662 throwers (15.67 ± 1.01 years of the National Program for Sports Technification of the Royal Spanish Athletics Federation using Machine Learning methods by means of algorithms (Logistic Regression, Random Forest and XG Boost). When examining the importance of the variables with reference to performance, the triple jump (0.20) stands out over the rest of the variables: backward overhead shot throw (0.14), arm span (0.11), vertical jump (0.10), body mass (0.20), height (0.07) and flexibility (0.03). In each discipline the triple jump takes the lead in shot put (0.20), discus (0.21) and hammer (0.29) throws, while backward overhead shot throw does in javelin, the variables rearranging themselves in a particular way depending on the discipline. These findings enable the early detection of potential talents as well as their subsequent sport specialization.

KEY WORDS: athletics, performance, strength, talent detection.

RESUMEN

El estudio aborda la detección de factores de rendimiento en los lanzamientos atléticos utilizando técnicas de Machine Learning, en 662 lanzadores (15,67 ± 1,01 años) del Programa Nacional de Tecnificación Deportiva de la Real Federación Española de Atletismo entre 1997 y 2015, mediante diferentes algoritmos (Logistic Regression, Random Forest y XGBoost). Al medir la importancia de las variables en función del rendimiento, el triple salto (0,20) destaca sobre el resto de variables: lanzamiento dorsal (0,14), envergadura (0,11), salto vertical (0,10), masa corporal, estatura (0,07) y flexibilidad (0,03). En cada disciplina, el triple salto encabeza la importancia en los lanzamientos de peso (0,20), disco (0,21) y martillo (0,29), mientras que el lanzamiento dorsal lo hace en la jabalina (0,20). Las variables se reordenan de forma particular modificando su importancia para cada disciplina. Estos hallazgos permiten mejorar la detección inicial de posibles talentos, así como su posterior especialización deportiva.

PALABRAS CLAVE: atletismo; rendimiento; fuerza; detección de talento.

1. INTRODUCCIÓN

In the athletics field like in other sports disciplines, talent detection is a complex process whose aim is to detect the potentially distinctive features in athletes to achieve success. Since resources are scarce, it is essential to adequately combine fitness qualities and motor skills such as strength, power, balance or timing requiring near-perfect technique (Judge et al., 2010) since excelling requires demanding, hard work all over the years. Hence, early detection processes have become vital as a part of success (Maszczyk et al., 2011; Ortigosa-Márquez et al., 2018).

Traditionally, coaches have periodically monitored progress during the training sessions by using these data to successfully predict performance, frequently based on their own experience, the fruits of practice. As regards throws, explosive field and power tests have become a recurrent source of information even though it has been suggested that there is no correlation between novel and experienced throwers´ performance (Maszczyk et al., 2014) due to the fact that performance is a part of a complex scheme (García-Martín et al., 2016; Musa et al., 2019).

The study of performance factors in sport has been approached by taking into consideration anthropometric, physiologic, psychological, biomechanics and fitness variables and the use of descriptive statistics and linear models, the statistical analysis being unable to describe the relationship between dependent and independent variables (Maszczyk et al., 2011). We can currently count on models which have generated efficient, computerized decision systems, which, for instance, have been used to place team players in the most adequate field position (Woods et al., 2018) or to determine the performance factors to adapt training loads for 400m hurdles runners (Przednowek et al., 2017) for a better performance and to decrease the risk of injury.

Techniques like Machine Learning enable us to establish new correlations between the data due to its capability to discriminate relevant from irrelevant information, only by taking the first one into consideration (Musa et al., 2019). Thus, new prediction models for shot put throwers (Tuo & Li, 2020) or 400m. hurdles runners (Przednowek et al., 2016) have been found recently. These techniques have become a successful tool to optimise training by selecting the suitable training loads (Przednowek et al., 2017), by choosing the most yielded exercises (Flores & Redondo, 2020), by reducing training time (Bunker & Thabtah, 2019) and by adhering to optimal tailored training or the analysis of sports performance (Soto-Valero, 2018). To the authors´ knowledge, there appears to be a lack of non-conventional studies researching performance factors aimed at talent detection and selection processes among young throwers. For that reason, the purpose of this study was to identify some of the most decisive factors for young throwers´ performance and to improve the early talent detection and selection processes among throwers and specially in each discipline by using new technologies providing the use of more precise data.

2. METHODS

2.1. Experimental approach to the problem

This study is part of a Ph.D. thesis focused on the quantification and control of the performance variables in elite young throwers. Having examined the effects of relative age (Redondo et al., 2019), this study was designed in order to analyse the variables enabling us to determine the specific performance among U-18 throwers. The subjects under study were selected in some of the 106 National Training Camps of the Royal Spanish Athletics Federation (RFEA) pursuing the National Sport Technification Program (PNTD) annually held from 1989 by the Superior Sports Board (CSD). Participants were convened to those camps held three times a year during school holiday periods.

In those, standardized tests were conducted preceded by a warm-up and following a graduate in Physical Activity and Sports Sciences´ instructions easing young throwers´ familiarisation with the protocol of each discipline. Tests were always carried out in the same order: anthropometric measurements, acceleration capacity, vertical jump, triple jump and flexibility.

This research was conducted in observance of the principles established by the Declaration of Helsinki developed by the 18th World Medical Association (Helsinki, Finland, June 1964) and revised by the 64th General Assembly (Fortaleza, Brazil, October 2018), being adopted on April 16th, 2021, by the Bioethics Committee for Scientific Research at León University, Castilla y León, (Spain). Legal guardians gave written informed consent prior to athletes´ participation in several tests and all contestants were provided with an explanation of testing protocols before data collection.

2.2. Participants

As shown in table 1, the participants of this study were 662 throwers (393 males and 269 females) aged 15.67 ±1.01.

Table 1. Description of the participants under study (aged mean ±SD)

DISCIPLINES	GENDER	N	AGE (YEARS)
Shot put	Female	67	15.65±0.95
	Male	102	15.59±1.04
Discus throw	Female	55	15.53±1.06
	Male	112	15.81±1.01
Hammer throw	Female	79	15.59±0.97
	Male	106	15.65±1
Javelin throw	Female	68	15.62±1.03
	Male	73	15.83±1.05

2.3. Performance variables in throwers

2.3.1. Anthopometric measurements

Anthropometric variables were obtained according to the technical guidelines and protocols of the International Society for the Advancement of Kinanthropometry (Esparza Ros et al., 2019). The measurements and collection of these variables were conducted individually by collegiate doctors selected for each camp by the RFEA. Parents´ size was taken from the reports collected at the beginning of the activity along with the required written consent.

2.3.2. Acceleration capacity (30m sprint)

The subjects performed 3 maximal 30-m sprints on a synthetic track with a flying start. There was a 3-minute recovery period between the 30-m sprints. Timings were taken using an electronic timing system (Prosport TMR ESC 2100, Tumer Engineering, Ankara, Turkey), only the shortest time being used in the analysis.

2.3.3. Vertical jump

Vertical jump performance was assessed using a portable force platform (Newtest, Finland) (Bosco et al., 1983). Players performed countermovement (CMJ) according to Bosco et al., (1983). Each subject performed 3 jumps with a 3-minute recovery time between each attempt. Athletes were encouraged to jump as high as possible; the highest one being then recorded in centimetres for the analysis.

2.3.4. Triple jump

Athletes jumped forward three following times as far as possible from the standing position using both feet, the last one landing on a sandpit. The length of the jump was determined by using a tape measure, affixed to the ground from the starting point to the closest indentation on the sand. Each subject was given 3 trials with a 3-minute recovery time, the distance of the best jump being measured in metres and centimetres to the nearest 1 cm in accordance with the regulations of the International Association of Athletics Federations (IAAF, 2019)

2.3.5. Backwards overhead shot throw (Dorsal)

Athletes performed 6 backward overhead shot throws (Ekstrand et al., 2013) under the IAFF regulations according to their category and gender (IAFF, 2019) with an approximate 3-minute recovery after each attempt. Athletes started by standing facing away from the throwing direction, with their feet shoulder width apart, flexing their knees and hips till placing the weight between their legs and throwing it over their heads with an abrupt leg, trunk and arm stretch. The longest distance was recorded to the nearest with a tape measure spread along the ground from the throwing line to the mark made by the shot on the grass or sand nearest to the throwing point.

2.3.6. Flexibility

The flexibility of the coxo-femoral joint was measured by means of the sit-and-reach exercise (López-Miñarro et al., 2009). The forward reach scores were recorded, the best one being used for analysis after two attempts.

2.3.7. Personal best (IAAF PB)

Personal best (PB) is the best result achieved along the year season in official competitions and recognised by RFEA during the season in which the athlete participated in technification activities. Data gathering was extracted on the one hand from the yearbooks published from 1997 to 2004 by RFEA and on the other hand from the top list issued from 2005 to 2015 on the internet official site. The performance records were converted into points according to IAAF scoring tables, the official tool to compare athletes´ performance across the different athletic events (Spiriev & Spiriev, 2017).

2.4. Statistical analysis

Decision-trees methods, which have been proved to be robust models (Biau et al., 2008), were employed to measure feature importance. Robustness is a required condition, given the fact that our dataset contains a high number of variables (11) compared to the number of samples (662). In regard to data visualization, a principal component analysis (PCA) was carried out (O'Donoghue, 2008).

PCA relies on the hypothesis that our label can be described as a linear combination of our features, based on either the covariance or the correlation matrices. PCA has recently become a very popular topic in the research on elite athletes (Gløersen et al., 2018). To understand those linear dependencies mentioned before, a correlation matrix was also introduced. In order to measure the variable importance in a dataset, three decision-tree-based algorithms (Breiman, 2001) to the data were fitted.

During the fitting process the out-of-bag error for each data point is tracked and averaged over the forest. The previous algorithms do not rely on whether the problem is a classification or a regression one; i.e., they do not rely on the nature of our label. In this case, a continuous label was provided, and hence, the error estimations were given by the mean squared error loss-function. To be more precise, Logistic Regression, Random Forest and Extreme Gradient Boost models are trained to provide estimations of feature importance, and results are assembled by the same criteria.

The scalar magnitude problem of each of the components was solved by standardizing the quantitative variables by scaling them to the unit interval, and the categorical ones were numerically encoded, since the categorical information did not require an extensive natural language processing analysis to be able to find a similarity coefficient between labels (Singh & Singh, 2020). The performance of the models was evaluated using Phyton programming language with several libraries (pandas: 1.4.0; scikit-learn: 1.0.2; numpy: 1.22; matplotlib: 3.5.1; seaborn: 0.11.2).

3. RESULTS

Figure 1 shows the relationship between categories and IAFF scores in the different disciplines. It can be observed that the dataset does not contain a large number of outliers, most of them being in the hammer throw discipline, making results consistent.

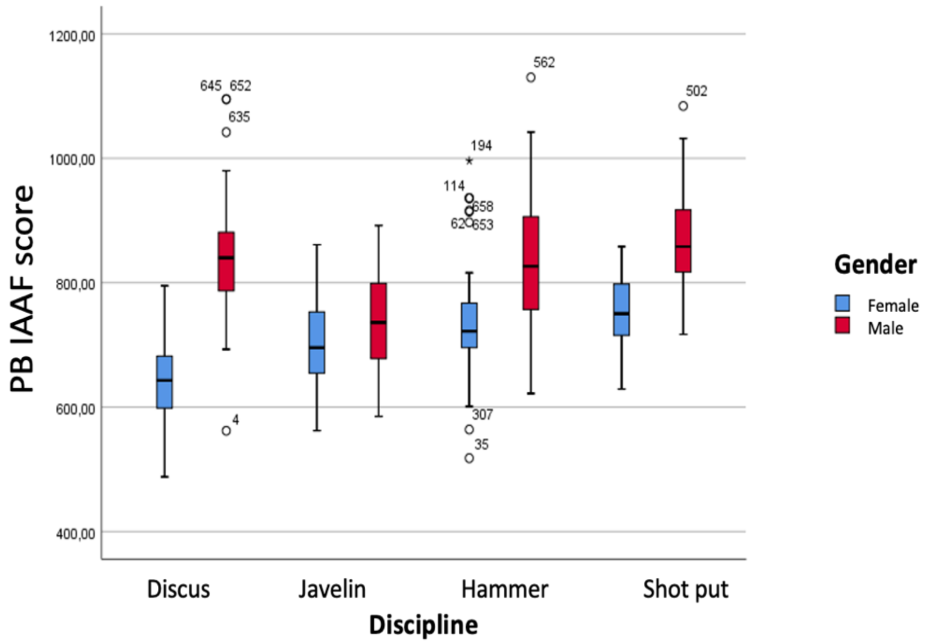

Figure 1. Distribution of athletes according to gender, category and performance.

Figure 2 represents a matrix showing the linear dependence among the different variables. The three linearly correlated variables with the PB IAFF scores are backward overhead shot throw (0.54), Triple Jump (0.53) and Vertical Jump (0.49).

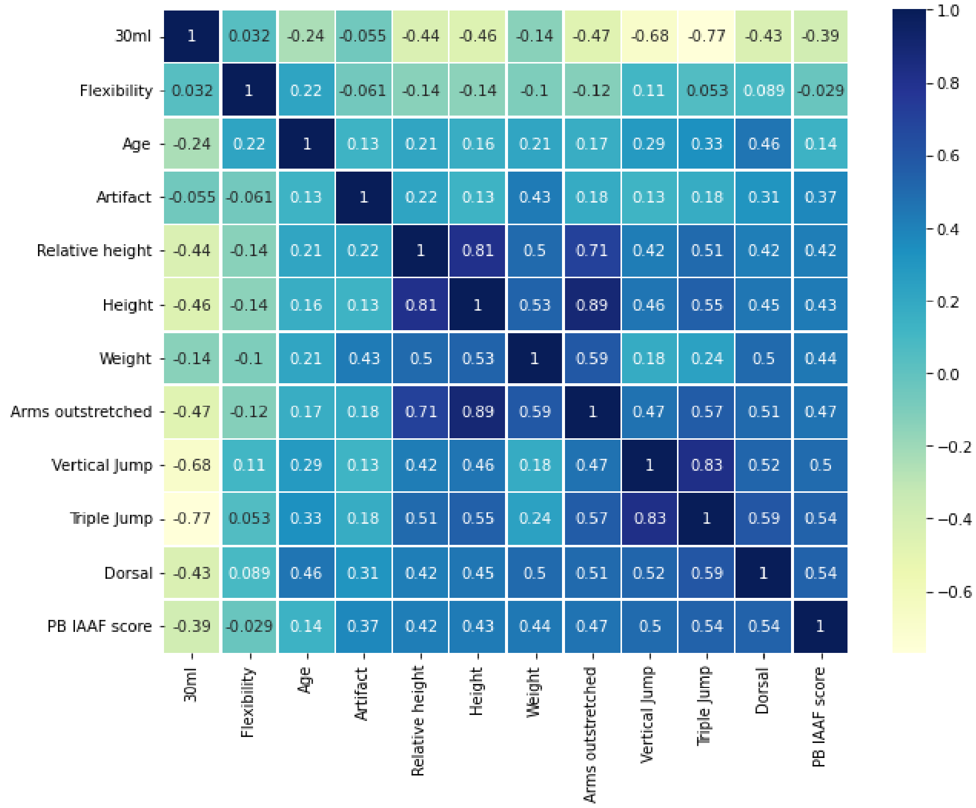

Figure 2. Correlation heatmap showing the linear dependence among variables.

There is a strongly positive correlation between triple jump and vertical jump (0.83), which might lead us to remove one of these variables according to their respective linear coefficients with respect to the PB IAAF score. However, by taking a closer look at the joint distribution of both variables (Figure 3), a certain degree of skewness is shown, and hence, we decide to preserve both of them.

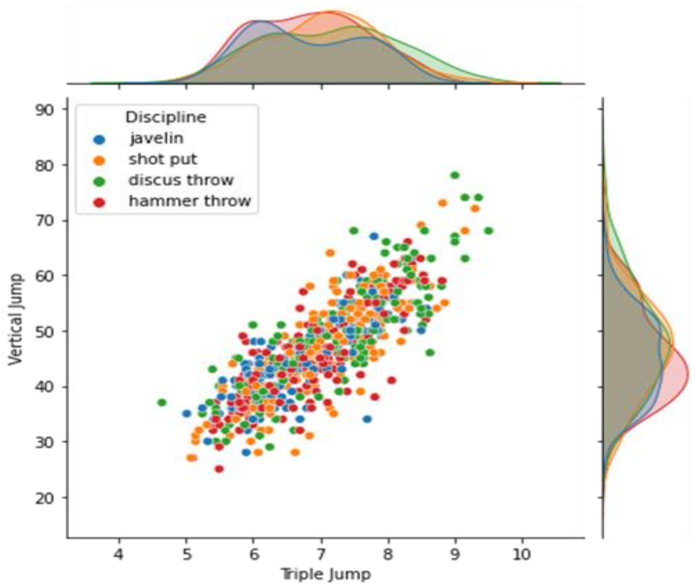

Figure 3. Paired distribution of vertical jump and triple jump, grouped by discipline.

Similarly, as shown in figure 4, a strongly negative correlation between 30m sprint and triple jump (-0.77) can be observed. Taking a closer look at the paired distribution of both variables, with respect to the discipline and the PB IAFF score, a certain degree of skewness is shown, and hence we decide to preserve both of them.

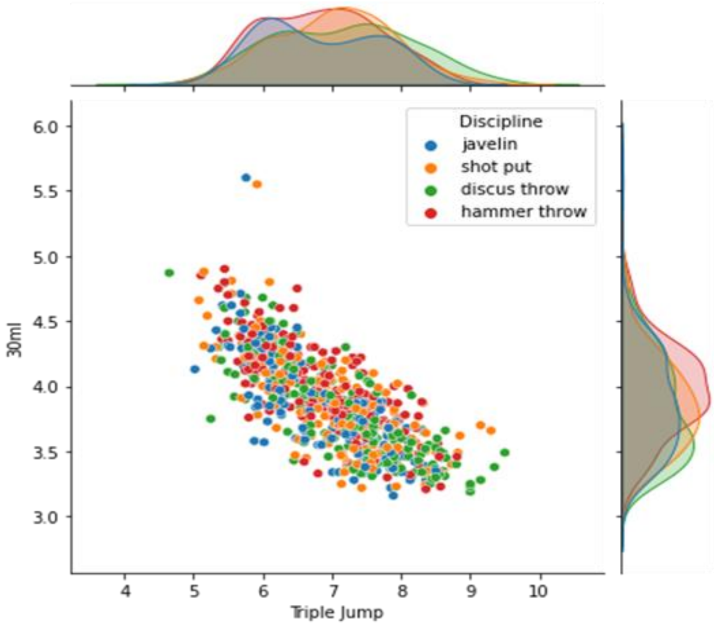

Figure 4. Paired distribution of 30m sprint and triple jump, grouped by discipline.

3.1. Modelling feature importance

In this section, a quantitative tool for measuring feature importance is shown for the next eleven variables: age, artifact, height, relative height, weight, arm span, 30m, flexibility, backward overhead shot throw, vertical jump and triple jump. As it was previously mentioned, three models are tested to provide an effective measure of feature importance, and results are aggregated by model and feature (Figure 5).

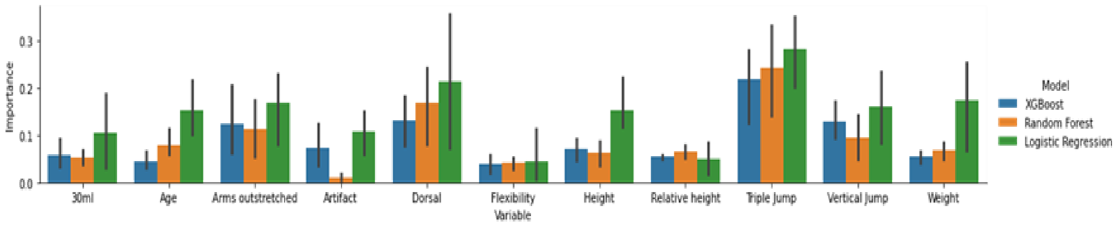

Figure 5. Feature importance distribution by model.

As one can easily see, Logistic model is slightly more "optimistic" than other estimators in most variables, Random Forest and XGBoost having most of their punctuations in common. This is the result of the nature of a different model: while Logistic is a single algorithm, Random Forest and XGBoost use decision trees with two different regularisation techniques: bagging and boosting respectively. Considering the performance of the three estimators, they are assembled by the weighted mean, obtaining a single numeric representation of feature importance (figure 6). It is particularly important to point out the overwhelmingly strong significance of Triple Jump feature.

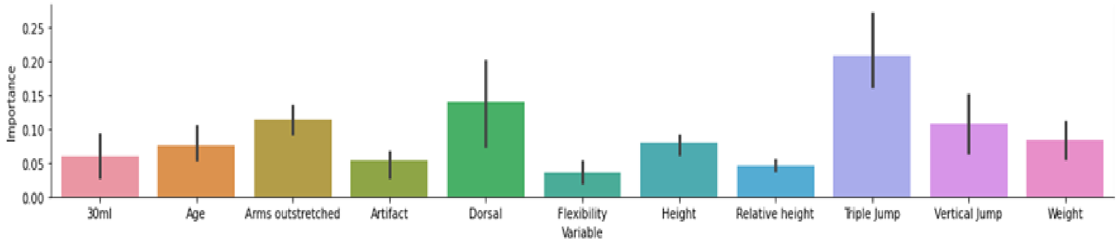

Figure 6. Feature importance distribution grouped by model.

Figure 6 clearly shows the importance of each variable for all disciplines. Triple Jump (0.20) is highlighted among the rest of variables, a specific test in which explosivity and strength are measured. In second place are backward overhead shot throw (0.14), arm span (0.11) and vertical jump (0.10), all of them of the same nature except for Arm span, which is at the same time strictly correlated to athletes' gender and category. On the other hand, flexibility (0.03) turns out to be the least relevant according to this analysis.

This analysis, however, is not capable of detecting the significance of each variable in each discipline, and in spite of the fact that all these disciplines belong to the same area, they have their own characteristics. To achieve this, feature importance is now aggregated by model, feature and discipline (Figure 7).

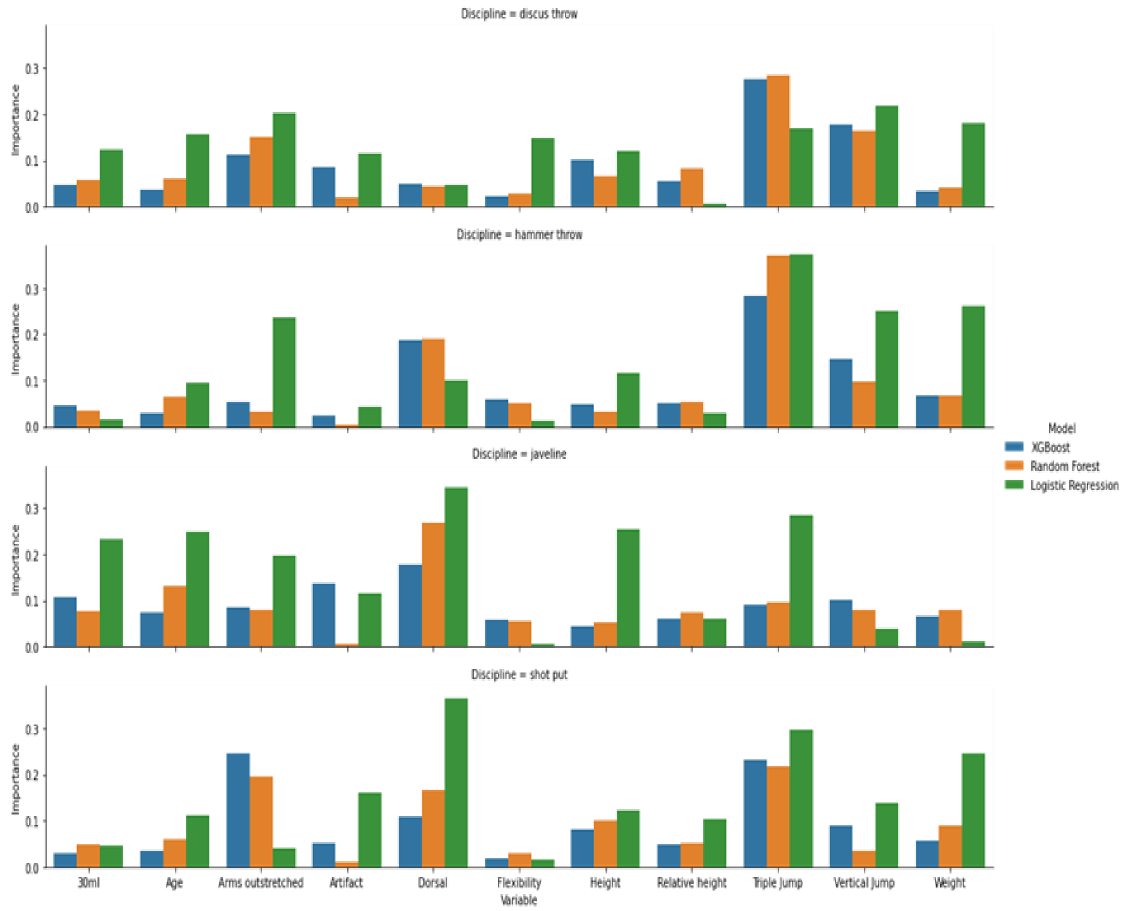

Figure 7. Feature importance distribution according to discipline.

As it has been discussed in Figure 7, Logistic model is more sensitive to potential outliers, a technical factor that makes Random Forest and XGBoost more reliable. It is also important to recall that models show a very different distribution according to discipline in variables such as arm span and weight. Once more, assembling estimators by using the weighted mean of the performance of each model, a simplified outlook of the results is shown (Figure 8).

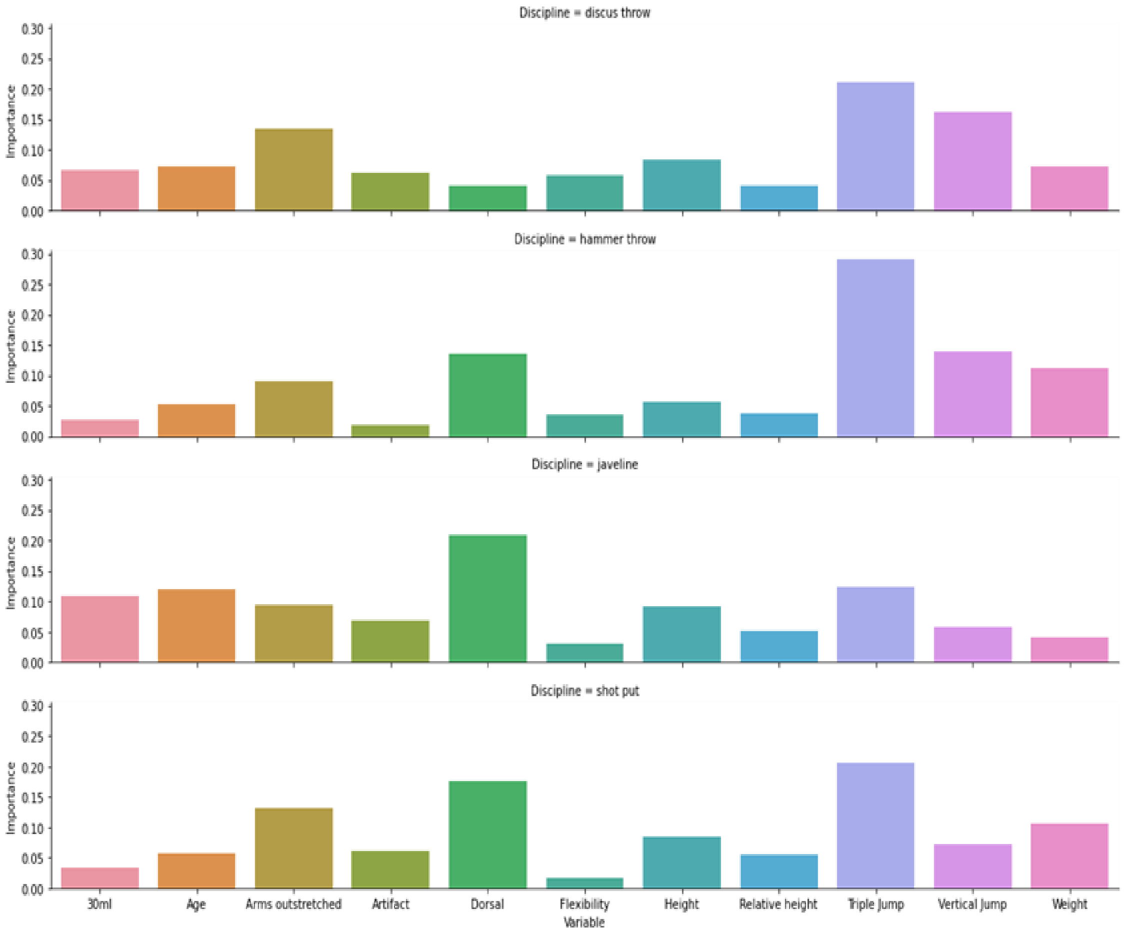

Figure 8. Feature importance distribution aggregated by variables and differentiated by discipline.

4. DISCUSSION

This study approaches a new insight into sport talents´ early selection by analysing the performance factors in elite young throwers. Findings support the authors´ hypothesis on the possibility of detecting sport talent by means of new technologies, the result of advances in computing, far away from the linear regression inconsistency due to data deviation. Thus, our study confirms the authors´ explanations of IAAF scoring tables, stating they do not try to make a comparison between male and female performance since the model itself enables the differentiation between male and female performance due to obvious biological differences (Spiriev & Spiriev, 2017). The analysis of the main components has provided a real breakthrough of two variables that explain 81% of the variability of the data by themselves: age and discipline. In accordance with these results, young throwers are claimed to achieve better results just because they grow older, that not being the direct cause. Analysing our results, performance could be highlighted as being closely related to age, due to the development of other factors such as anthropometric features and physical qualities such as strength and speed, strongly associated with age (Cobley et al., 2009). We should not forget the efficient improvement of specific motor skills provided by learning (Davids et al., 2000), which could be influenced by the more participation in technical training camps supervised by highly qualified technicians and the transfer of greater skills and experience resulting from the competition itself (Folgar et al., 2014; Pamucar, 2020).

Triple jump is shown to be the most important variable in determining throwing performance in relation to the results obtained by Kyriazis et al., (2009), who did find a strong correlation between jumping ability (Kyriazis et al., 2009) and performance contrasting with the conclusions of Aoki et A., (2015), who did not find a significative correlation between jumping ability and performance in throws specifically and generically (Aoki et al., 2015). On the other hand, backward overhead shot throw became the second most significant variable, supporting the suggestions by Zaras et al., (2019), who revealed that a 2% increase in backward overhead shot throw plus a 5% increase in the thickness of the vastus lateralis muscle could improve performance by 6.9% (Zaras et al., 2019). According to the study, arm span appears to be the third most important variable, being the most outstanding one of anthropometric variables, agreeing with Dayal (2007) among throwers´ morphologic features, stating they must be tall and heavy with their upper limbs relatively longer than their lower ones (Dayal, 2007). In the same vein, the research carried out by Till et al., (2015) resulted in the fact that the selected athletes have certain anthropometric features in common in relation to their performance (Till et al., 2015): being tall to increase the release height of the artifact. Similarly, Zaras (2021) highlights the increase of the release height in throws and downplays body mass (Zaras et al., 2021).

Concerning the various disciplines, triple jump has been observed to be the most prominent performance factor in hammer throw, according with Tuo & Li (2020), who confirmed that triple jump is closely related to performance in this discipline by establishing a neural network (Akman et al., 2016; Tuo & Li, 2020). Likewise, as regards Reis and Ferreira (2003) jumping exercises should be used in training sessions to improve the shot putters´ explosive leg-power though they themselves do not appear to have a strong correlation with this discipline (Reis & Ferreira, 2003). Their findings suggested a combination of variables with strength exercises, throws and jumps to predict performance with the highest accuracy. As for the results in discus, the most significant variables were the triple jump followed by arm span, height and weight; backward overhead shot throw surprisingly being next to last; those results agreeing with Maeda et al., (2018), who place great importance on arm span and weight (Maeda et al., 2018).

Findings evince that the most prominent variables for hammer throw are triple jump, vertical jump, backward overhead shot throw and the thrower´s body mass. In relation to triple jump (Sung & Lee, 2011), our results contrast with those by Sung & Lee (2011); highlighting that backward overhead shot throw performance is closely related to hammer throw performance in addition to the importance of body weight justified by the increase in body mass, significantly contributing to performance in this discipline (Terzis et al., 2010). In contrast with the former disciplines, backward overhead shot throw is the most remarkable variable to achieve a longer distance in javelin followed by triple jump, seemingly agreeing with Ihalainen (2018), who outlined the strong correlation between performance and horizontal jumps, the triple jump showing a narrower correlation with personal best and concluding 20m flying sprint in field test battery not to be necessary, which was also remarked in our results in the case of 30m (Ihalainen, 2018).

5. CONCLUSIONS

The current study has identified the importance of variables closely related to performance for the development and improvement of young throwers´ detection. Triple jump backward overhead shot throw, athlete´s arm span and vertical jump have revealed themselves to be efficient markers of throwers´ potential performance. These field tests can be easily performed as neither specific equipment, which might be expensive or complex, is needed and is available for trainers and athletes nor their execution or measurement present any technical difficulty. Machine Learning techniques used in this research have been able to determine the performance factors among young throwers. Trainers should take these exercises into account in conjunction with morphologic features and select athletes with the aim of training throwers and subsequently orienting them to throwing disciplines so as to get their highest performance level, taking the specific characteristics of each discipline into consideration. Consequently, throwers could be selected for each discipline: shot put, discus, hammer and javelin.

5.1. Improvement proposals

Since the IAFF score tables have no correlation with each other as far as performance and gender are concerned, the variables under study could be thought to behave differently according to gender. Additionally, although the subjects in the study are elite athletes, their performance is non-identical and hence, it could be fruitful to address the study considering different performance levels in search of sport prediction, which would imply studying the behaviour of the variables in relation to performance level, defining different ranges of sport success. And lastly, owing to the direct dependence of the most important variables on strength and muscle power, regarding new variables would be convenient to establish a more accurate prediction model.

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