Building Tomorrow's Champions: A Vision for Olympic Education at the School Level through Virtual Foresight and Sport-Specific Fitness Profiling
Construir a los campeones del mañana: Una visión de la educación olímpica en la escuela a través de la prospectiva virtual y la elaboración de perfiles de aptitud física específicos para cada deporte

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Abstract. The aim of this study is to determine the sport-specific fitness profile with the virtual prediction method and to contribute to the determination of tomorrow's champions with the Olympic Training Module carried out in primary school. In this context, 97 (53 boys, 44 girls) primary school students aged between 10-11 (years) participated in the study. The participants were tested for reaction time, hand grip strength, standing long jump, 30 m sprint, medicine ball throwing and hitting the target at a distance of 5 meters. After all tests were performed, the test results were classified as good (1), fair (2) and poor (3) according to gender. The accuracy between all classifications and performance tests was analyzed with MATLAB 2022B application. Accordingly, male participants' reaction time was 94.34%, handgrip strength 98.11%, standing long jump 100%, 30 m sprint 98.11%, medicine ball throwing 94.34%, and hitting the target from a distance of 5 meters were classified with 100% accuracy. Reaction time of female participants was 95.45%, handgrip strength 100%, standing long jump 100%, 30 m sprint 97.73%, medicine ball throwing 97.73%, and hitting the target from 5 meters distance with 100% accuracy. In addition, performance parameters were significantly different between the groups (p<.001). As a result, it was determined that performance classification using machine learning modeling was performed with great accuracy. Therefore, the results of our research can be used in talent selection and guidance of individuals of this age to the appropriate sports branch.
Key Words: Olympic Education; Virtual Foresight; Fitness Profiling; Children

Resumen. El objetivo de este estudio es determinar el perfil de forma física específico del deporte con el método de predicción virtual y contribuir a la determinación de los campeones del mañana con el Módulo de Entrenamiento Olímpico realizado en la escuela primaria. En este contexto, 97 (53 niños, 44 niñas) estudiantes de primaria con edades comprendidas entre 10-11 (años) participaron en el estudio. Los participantes fueron sometidos a pruebas de tiempo de reacción, fuerza de agarre de las manos, salto de longitud de pie, sprint de 30 m, lanzamiento de balón medicinal y golpeo de la diana a una distancia de 5 metros. Una vez realizadas todas las pruebas, los resultados se clasificaron como buenos (1), regulares (2) y malos (3) en función del sexo. La precisión entre todas las clasificaciones y las pruebas de rendimiento se analizó con la aplicación MATLAB 2022B. En consecuencia, el tiempo de reacción de los participantes masculinos fue del 94,34%, la fuerza de agarre de la mano del 98,11%, el salto de longitud de pie del 100%, el sprint de 30 m del 98,11%, el lanzamiento de balón medicinal del 94,34% y el golpeo al blanco desde una distancia de 5 metros se clasificaron con una precisión del 100%. El tiempo de reacción de las participantes femeninas fue del 95,45%, la fuerza de prensión de la mano del 100%, el salto de longitud de pie del 100%, el sprint de 30 m del 97,73%, el lanzamiento de balón medicinal del 97,73% y el acierto en el blanco desde una distancia de 5 metros con una precisión del 100%. Además, los parámetros de rendimiento fueron significativamente diferentes entre los grupos (p<.001). Como resultado, se determinó que la clasificación del rendimiento mediante modelos de aprendizaje automático se realizó con gran precisión. Por lo tanto, los resultados de nuestra investigación pueden utilizarse en la selección de talentos y la orientación de individuos de esta edad hacia la rama deportiva adecuada.
Palabras clave: Educación olímpica; Prospectiva virtual; Perfiles de aptitud física; Niños

Introduction

In many ways, sport is a beautiful field to showcase human talents and reveal their achievements. Success in sport requires high motivation, a rich training environment and objective competition (Baker et al., 2020). In an era defined by rapid technological advancements and an ever-evolving educational landscape, the development of an Olympic education system at the school level is a compelling and visionary endeavor (Hwang & Henry, 2023). As society continues to emphasize the importance of holistic growth and well-rounded individuals, the incorporation of Olympic values, principles, and sports into the education system stands as a promising opportunity (Teetzel, 2012; Ryskaliyev et al., 2020). Within this context, the establishment of

a Virtual Foresight Laboratory and the systematic identification of physical fitness among school children in various sports are pivotal components that can revolutionize the way we nurture young talents, instill essential life skills, and contribute to the greater goal of producing well-prepared athletes and responsible global citizens.

This extensive program offers a multidisciplinary approach to education, focusing not only on intellectual development but also on physical well-being, character development, and values founded in the Olympic spirit (Knijnik & Tavares, 2012; Ryskaliyev et al., 2020). It aims to combine the worlds of academia and athletics. The Virtual Foresight Laboratory in particular enhances the educational experience by enabling creative ways to teach knowledge and

promote a deeper awareness of the relevance of the Olympic Movement (Real, 1996). Through these laboratories, knowledge can be disseminated to a large number of people, equality of opportunity in education can be increased, and a culture of technological education can be created (Carruth, 2017).

In this context, the creation of virtual laboratories can also benefit children to participate in talent selection from an early age. Every child has a unique genetic makeup (Rees et al., 2016). Sports performance is not instantaneous and sometimes requires long periods of time (Till & Baker, 2020). Early talent selection will also contribute positively to children's future performance (Hancock et al., 2013). Especially in students between the ages of 7 and 8, since strong hypotheses emerge about which branch their basic motoric characteristics will be for which branch, Olympic education can also be supported by making talent selection in this period and planning certain trainings in advance (Burgess & Naughton, 2010).

The problem of talent identification is seen in another way; the main issue is to try to design sporting structures that allow, on the one hand, to increase the number of participants in sport and, on the other hand, to improve sporting outcomes, such as the nation (Green, 2005). And from this perspective, the research conducted attempts to analyse, among other things, the economic cost of Olympic medals (e.g. Hogan & Norton, 2000; Kuper & Sterken, 2003), where the research is seen to be as follows: In the field of expertise development, identification or talent development there is normally a tendency to be mono-disciplinary and a geneticist or environmentalist vision is normally adopted (Phillips, Davids, Renshaw & Portus, 2010). To advance knowledge on expertise and talent development, a multidisciplinary and integrative perspective needs to be adopted, where different perspectives and sciences contribute to the methodologies and outcomes. This way of understanding shows that more value should be placed on the talent identification process than understanding it as the possibility of identifying a future athlete through the application of tests and understanding it as the development of a perfect tool for assessing people's performance. To give more value to the individual path followed by each athlete and to the delicate moments to develop the training process suitable for each age. Calvo L., et al. (2012).

This article explores the possibility of a comprehensive learning experience that combines the depth of classroom instruction with the physical skills and sportsmanship of Olympic participants. The article addresses the fascinating area of Olympic education at the school level. In doing so, we hope to highlight the many benefits of the system and draw attention to the opportunities it offers for the development of the next generation of athletes and responsible global citizens. In addition, we will explore how modern technology can be used to assess and maximize the physical fitness of children in a variety of sports, providing a glimpse into how data-driven insights can revolutionize talent identification and development. This study was conducted to create a sport-specific fitness profile by examining 7-to 8-year- old students by gender and grade level variables on various physical parameters such as reaction time, grip strength, standing long jump, 30-meter sprint, medicine ball throwing, and hitting the target from 5 meters, and to create a vision for the creation of virtual labs related to Olympic education by looking at performance classification.

Material & methods

This section includes the research model, research group, data collection tools and data analysis.

Research Model

In this study, survey method, one of the quantitative data collection techniques, was used (Keppel, 1991). Accordingly, 97 primary school 3rd grade students aged between 10-11 (years), studying in schools located in rural (2 schools) and city center (2 schools) in Almaty, Kazakhstan, participated in the study. Participants who a) were actively continuing their education, b) were in the specified age range and grade level were included in this study. Participants who a) had special learning disabilities, b) needed special education, c) had cardiovascular disease, d) had developmental disorders, e) had active infections, f) had thyroid-like developmental disorders, g) had chronic diseases, h) took regular medication that would affect their performance positively or negatively were not included in the study.

G-Power (version 3.1.9.7) was used to determine the minimum sample size for this study. For power analysis, t tests (Means: Difference from constant (one sample case), A priori: compute required sample size- given α, power, and effect size were used. Accordingly, when $\alpha=0.05$, power $(1-\beta) =0.80$, and effect size 0.35, it was calculated that there should be at least 90 participants (Actual Power= 95.0%). In this context, a total of 97 participants (53 males, 44 females) from 4 different schools were included in our study.

After determining the research sample, the participants were informed about the purpose, importance and method of the study. In this context, the participants and their legal representatives signed a "Voluntary Consent Form" indicating that they voluntarily participated in the research. All necessary permissions were obtained from the relevant Ministry and school administration. This study was conducted in accordance with the principles set out in the Declaration of Helsinki. For this research, necessary permissions were obtained from the Kazakh Academy of Sports and Tourism Local Ethics Committee of the Health Sciences with the Number 2022/51 Ethics Committee.

Data Collection Tools

In order to determine some motoric performances of the participants, standing long jump, throwing a ball to a 5-meter target, throwing a medicine ball, hand grip strength,

30 m sprint, reaction time were determined. Participants were given the opportunity to do stretching movements for 5 minutes after a 5-minute warm-up. Performance tests were then performed.ç

Standing Long Jump

The test was conducted in a controlled research laboratory so that the environmental conditions were similar between participants. A pre-prepared black mat was used on which the starting point was drawn. The mat was 4.5 m in length and 0.60 m in width, drawn at 0.5 cm intervals. The participant was asked to jump from the starting point to the longest point they could jump. The participant was given 3 repetitions and the best value was recorded (Porter et al., 2010).

Throwing a Small Ball for Accuracy From 5 M

Participants were asked to shoot at a 1x1 m platform located 5 meters away. Each shot was counted until they hit the platform. Accordingly, participants who hit the platform with their first shot received 0 points. Subsequent throws were counted and continued until a hit was made and recorded (van den Tillaar & Ettema, 2003).

Handgrip Strenght Test

The standard procedures recommended by the American Society of Hand Therapists (ASHT) were followed to determine the hand grip strength of the participants. Measurements were performed with a Tkaei digital hand dynamometer. The dynamometer was adjusted according to the participant's hand size (Ruiz et al., 2006). The elbow joint was in 90° flexion and the shoulder joint was in 10° abduction. The wrists were in flexion between 0-30° and ulnar deviation of 0-15° (España-Romero et al., 2010). Participants took 2 trials with 1 min rest intervals and the best value was recorded.

Medicine Ball Throw Test

Participants were asked to throw a medicine ball weighing 1kg, maintaining its round shape and having a good grip surface to the farthest distance. First, the researcher in charge demonstrated how to perform the test. The participant held the ball in front of them with both hands and placed it on their lap. With the command "throw", the participants were instructed to lift the ball up to their chest and throw it forward with their last strength.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

$$Precision = \frac{TN}{TN + FP}$$

$$F - score = \frac{2TP}{2TP + FP + FN}$$

Each participant was given two throws and rested for 1 min between throws. Participants' best distances were recorded in cm (Davis et al., 2008).

30 M Sprint Test

Sprint time was measured using a two-port photocell (Speed Test 6.0 CEFISE, Nova Odessa, SP, Brazil) with an accuracy of 0.01. The starting position was positioned so that the big toe of the leading foot was 0.5 m behind the starting line. The first photocell was placed at a distance of 0 m and the second at a distance of 30 m. Participants were allowed to run this distance twice and their best time was recorded in seconds. A rest interval of 1 min was given between the two runs (Martins et al., 2021).

Reaction Time Test

The participants' simple visual reaction time was determined with the MOART Lafayette Reaction Meter. Participants were measured by pressing the button on the bottom panel of the device with the index finger of the hand to the complex light stimuli. Measurements were made for dominant hands. After the participants were given the opportunity to experiment, they were asked to perform 3 repetitions and the best value was recorded (Turna, 2020).

Data Analysis

In the study, the performance parameters were arranged in mathematical order (best to worst) and classified as good (1), moderate (2) and poor (3). The MATLAB R2022B program was used to determine the appropriateness of the classification. The test of correspondence between the classification data and the performance parameters was determined using the Optimizable Enseble method. the 10-fold cross-validation method was used. As a result, the performance metric values for accuracy, sensitivity, precision, latency and F-score were given by the complexity matrix (Figure 1). The results of ROC triangulation of the analysis results are also presented to determine the discriminatory power of the test and to determine the appropriate positive threshold.

Figure 1. TP (True Positive)-positive class predicted by the classifier (grade 1), False Positive (FP)-incorrectly predicted by the classifier (class 1), False Negative (FN) - negative class predicted incorrectly by the classifier (class 2) and TN (True Negative) − are negative class (class 2) values that the classifier predicts correctly. The equations given below are used to calculate performance metrics.

SPSS 25 (IBM, USA) package program was used for statistical analyses. Normality analysis of the data was tested with Kolmogrov Simirnov test. Levene's test was performed for homogeneity of variances. The data were found to be normally distributed and One Way Anova Test was

used for the analysis of demographic characteristics and performance tests between classifications. In the study, the significance level was determined as 0.05.

Results

Table 1.
Comparison of participants performance parameters according to classification by gender

Parameters	Gender	Group 1 x±S.D.	Group 2 x±S.D.	Group 3 x±S.D.	F	p
Reaction Time (sec)	Male	143.94±8.32	135.05±1.79	128.02±2.13	41.832	p < .001
	Female	18.45±2.28	26.25±2.59	31.75±5.00	79.607	p < .001
HGS (kg)	Male	19.36±1.67	16.05±0.16	12.40±1.86	100.323	p < .001
	Female	16.85±2.67	13.82±0.39	11.02±0.92	64.476	p < .001
SLJ (cm)	Male	147.81±12.40	127.18±2.61	115.50±4.37	53.777	p < .001
	Female	136.40±12.07	117.86±2.97	102.07±7.52	60.545	p < .001
30 m sprint	Male	6.01±0.07	6.28±0.10	7.00±0.45	31.857	p < .001
	Female	6.25±0.10	6.58±0.04	7.04±0.30	24.644	p < .001
MBT (m)	Male	6.06±1.60	5.08±1.33	4.32±2.86	14.053	p < .001
	Female	4.93±6.02	4.16±1.43	3.15±3.79	72.796	p < .001
Hit the target from 5 m	Male	7.40±0.54	5.55±0.52	2.38±1.13	76.931	p < .001
	Female	3.22±0.44	2.00±0.51	1.21±0.46	148.595	p < .001

HGS: Hand Grip Strenght, SLJ: Standing Long Jump, MBT: Medicine Ball Throwing

Table 1 shows the statistical analyses between the classifications made for the performance parameters of the participants. According to this, male and female participants' reaction time (Fm=41.832, pm<.001; Ff=79.607, pf<.001), hand grip strength (Fm=100.323, pm<.001; Ff=64.476, pf<.001), standing long jump (Fm=53.777, pm<.001; Ff=60.545, pf<.001), 30 m sprint (Fm=31.857, pm<. 001; Ff=24.644, pf<.001), medicine ball throwing (Fm=14.053, pm<.001; Ff=72.796, pf<.001), and hitting the target from a distance of 5 meters (Fm=76.931, pm<.001; Ff=148.595, pf<.001).

Table 2.
Optimizable Ensemble classification results of male participants' performance parameters

Parameters	Class	N (truth)	n (classified)	Accuracy	Precision	Recall	F1 Score	Overal Accuracy
Reaction Time (sec)	1	42	41	98.11%	1.00	0.98	0.99	
	2	5	6	94.34%	0.67	0.80	0.73	94.34%
	3	6	6	96.23%	0.83	0.83	0.83	
HGS (kg)	1	23	22	98.11%	1.00	0.96	0.98	
	2	8	9	98.11%	0.89	1.00	0.94	98.11%
	3	22	22	100%	1.00	1.00	1.00	
SLJ (cm)	1	27	27	100%	1.00	1.00	1.00	
	2	16	16	100%	1.00	1.00	1.00	100%
	3	10	10	100%	1.00	1.00	1.00	
30 m sprint (sec)	1	6	6	100%	1.00	1.00	1.00	
	2	16	15	98.11%	1.00	0.94	0.97	98.11%
	3	31	32	98.11%	0.97	1.0	0.98	
MBT (cm)	1	22	23	94.34%	0.91	0.95	0.93	
	2	10	10	96.23%	0.90	0.90	0.90	94.34%
	3	21	20	98.11%	1.0	0.95	0.98	
Hit the target from 5 meters	1	5	5	100%	1.00	1.00	1.00	
	2	9	9	100%	1.00	1.00	1.00	100%
	3	39	39	100%	1.00	1.00	1.00	

HGS: Handgrip Strenght, SLJ: Standing Long Jump, MBT: Medicine Ball Throwing

Table 2 shows the metric values of the performance parameters of the male participants classified by the Optimizable Ensemble method. Accordingly, the validation rate of reaction time was 98.11%, 94.34%, and 96.23% in the 1st, 2nd, and 3rd classification, respectively. The confirmation rate of hand grip strength was 98.11%, 98.11%, and 100% in the 1st, 2nd, and 3rd classification, respectively. Standing long jump had the highest verification rate for each group (100%). The 30-meter sprint performance verification rate was 100%, 98.11%, and 98.11% in the 1st, 2nd, and 3rd classification, respectively. The accuracy rate of medicine ball throwing performance was 94.34%, 96.23%, and 98.11% in the 1st, 2nd, and 3rd classification, respectively. The accuracy rate for hitting a target 5 meters away had the highest accuracy rate (100%). Figure 2 shows the ROC curves of all performance parameters according to the classification level, respectively.
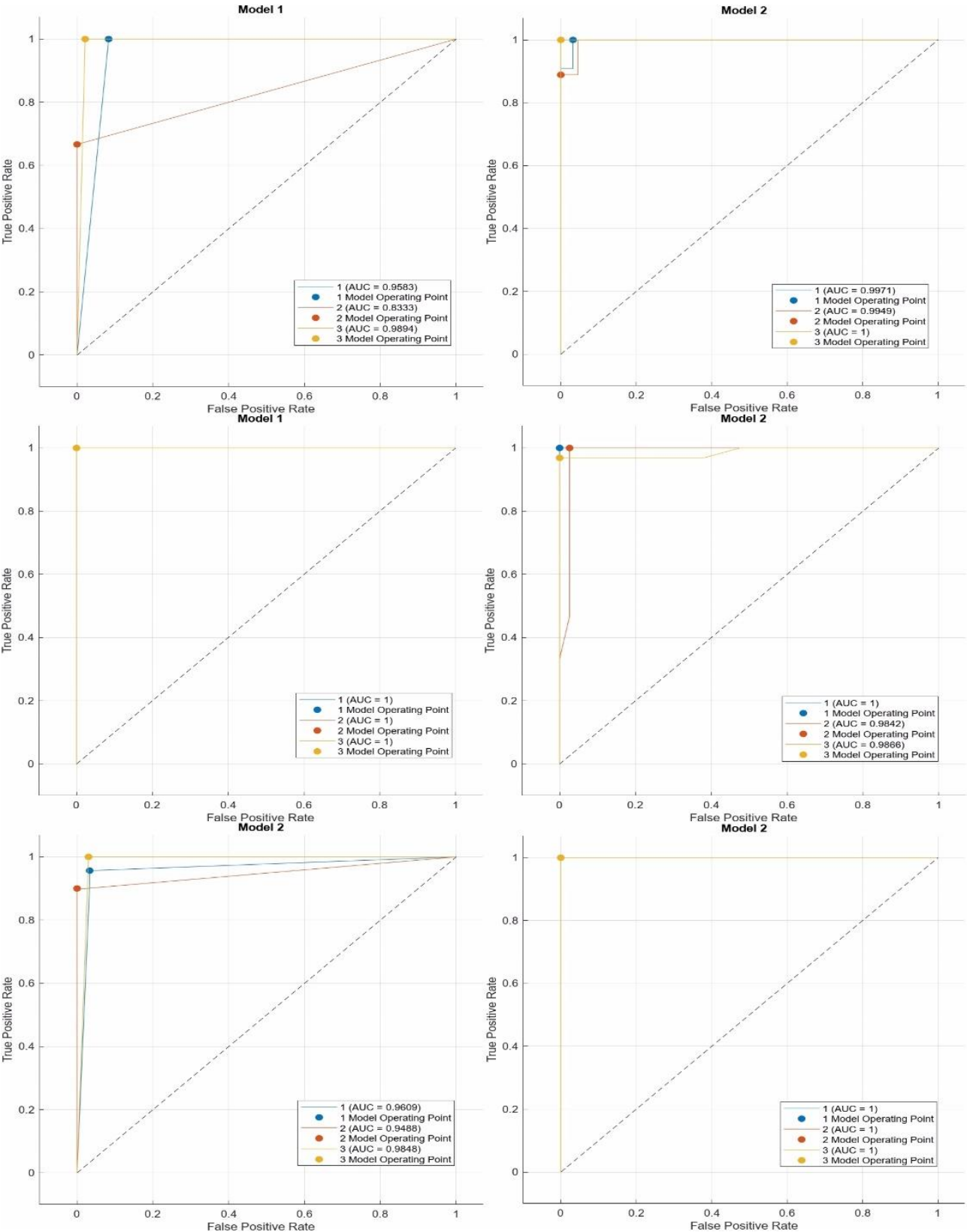
Figure 2. ROC curves of the performance classifications of male participants: Respectively from top to bottom, from left to right, respectively; Reaction time, Handgrip Strength, Standing Long Jump, 30 m Speed, Health Ball Labor, and hit the target from 5 meters

Table 3.
Optimizable Ensemble classification results of female participants' performance parameters

Parameters	Class	N (truth)	N (classified)	Accuracy	Precision	Recall	F1 Score	Overal Accuracy
Reaction Time (sec)	1	35	36	97.73%	0.97	1.0	0.99	
	2	4	4	97.73%	0.75	0.75	0.75	95.45%
	3	5	4	97.73%	1.00	0.80	0.89	
HGS (kg)	1	7	7	100%	1.00	1.00	1.00	100%

	2	17	17	100%	1.00	1.00	1.00	
	3	20	20	100%	1.00	1.00	1.00	
SLJ (cm)	1	15	15	100%	1.00	1.00	1.00	
	2	15	15	100%	1.00	1.00	1.00	100%
	3	14	14	100%	1.00	1.00	1.00	
30 m sprint (sec)	1	5	6	97.73%	0.83	1.00	0.91	
	2	6	5	97.73%	1.00	0.83	0.91	97.73%
	3	33	33	100%	1.00	1.00	1.00	
MBT (cm)	1	13	12	97.73%	1.00	0.92	0.96	
	2	7	8	97.73%	0.88	1.00	0.93	97.73%
	3	24	24	100%	1.00	1.00	1.00	
Hit the target from 5 meters	1	9	9	100%	1.00	1.00	1.00	
	2	14	14	100%	1.00	1.00	1.00	100%
	3	21	21	100%	1.00	1.00	1.00	

HGS: Handgrip Strenght, SLJ: Standing Long Jump, MBT: Medicine Ball Throwing

Table 3 shows the metric values of the performance parameters of the female participants classified by the Optimizable Ensemble method. Accordingly, the validation rate of reaction time was 97.73% in the 1st, 2nd, and 3rd classification. The confirmation rate of hand grip strength was 100% in the 1st, 2nd, and 3rd classification. Standing long jump was 100% in 1st, 2nd, and 3rd classification. 30-meter sprint performance verification rate was 97.73% for 1st, 2nd, and 3rd classification and 100% for 3rd classification. The validation rate for medicine ball throwing performance was 97.73% for classification 1, and 97.73% for classification 2, and 100% for classification 3. The accuracy of hitting a target 5 meters away was 100% for the 1st, 2nd, and 3rd classification. Figure 3 shows the ROC curves of all performance parameters according to the classification level respectively.
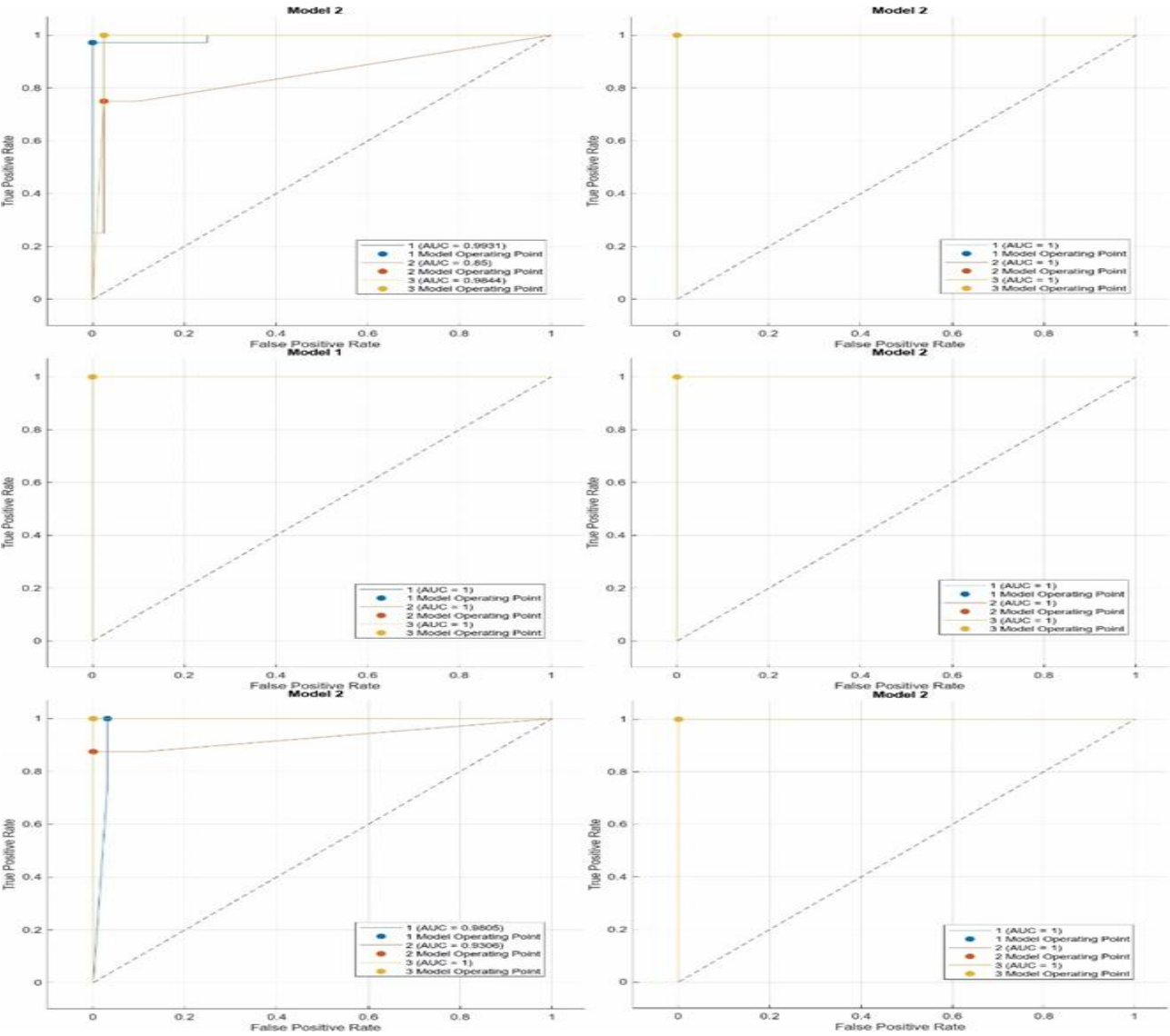

Figure 3. ROC curves of the performance classifications of female participants: Respectively from top to bottom, from left to right, respectively; Reaction time, Handgrip Strength, Standing Long Jump, 30 m Speed, Health Ball Labor, and hit the target from 5 meters.

Dicussion

The present study aimed to utilize machine learning modeling for sport-specific fitness profiling and performance classification among primary school students aged 7-8 years. The research involved 97 participants, with gender-based classifications, and assessed various physical parameters, including reaction time, hand grip strength, standing long jump, 30-meter sprint, medicine ball throwing, and hitting a target at a distance of 5 meters. The results of this study demonstrated high accuracy in performance classification, with implications for talent identification and sports branch guidance for individuals in this age group.

The utilization of machine learning modeling for performance classification yielded highly accurate results for both male and female participants. Notably, reaction time, hand grip strength, standing long jump, 30-meter sprint, medicine ball throwing, and hitting the target from a distance of 5 meters were all classified with remarkable accuracy. These findings suggest that machine learning can effectively distinguish between different performance levels among primary school children. This is a significant advancement in the field of talent identification, as it provides a data-driven and objective approach to evaluating and categorizing young athletes.

The early identification of sports talents includes finding the right sport and is of great importance for both scientists and practitioners. When the literature is examined, there are some studies in this context (Keogh et al., 2003; Gil et al., 2014; Mkaouer et al.,; 2018Larkin et al., 2023). Keogh et al. (2003) devised a comprehensive testing battery to discern the differences between regional representative and local club-level female field hockey players. Their study revealed several key factors that contributed to distinguishing players at different performance levels. Regional representative (Rep) players exhibited lower body fat percentages and demonstrated superior performance in various physical and skill-related tests, including sprinting speed, agility (both with and without dribbling), aerobic fitness, lower body muscular power, and shooting accuracy. However, no significant distinctions were found in height, body mass, speed decrement during repeated sprints, handgrip strength, or pushing speed. These findings emphasize the importance of assessing body composition, speed, agility, dribbling control, aerobic and muscular power, and shooting accuracy in talent identification programs for female field hockey, as they serve as valuable indicators of player potential and performance (Keogh et al., 2003).

Our study and Keogh et al.'s (2003) study both delve into talent identification within the realm of sports but differ in methodology and context. The former employs machine learning for performance classification among primary school students in various sports-specific fitness tests, striving to enhance talent selection. In contrast,

Keogh et al. (2003) target female field hockey players, employing anthropometric and physical performance measures to differentiate regional representatives from local club-level athletes. Despite their distinctions, both studies underscore the pivotal role of specific physical and performance parameters in talent identification. Our study showcases the effectiveness of machine learning in achieving high classification accuracy, offering an objective approach for assessing young athletes' potential. Conversely, Keogh et al. (2003) highlight the significance of factors such as body composition, speed, agility, endurance, and skill accuracy in profiling female field hockey players, demonstrating their relevance for talent identification programs. In essence, both studies contribute valuable insights to talent identification in sports, with implications for future research and talent development initiatives. Mkaouer et al.'s (2018) study focused on the identification of critical physical and basic gymnastics skills necessary for talent selection and the enhancement of performance in men's artistic gymnastics. Their research involved 51 boys actively competing at the national level in gymnastics, with a mean age of 11.03 years. The study incorporated anthropometric measurements and a comprehensive physical test battery aligned with the International Gymnastics Federation's (FIG) age group development program. The physical attributes assessed encompassed muscle strength, flexibility, speed, endurance, and muscle power. Principal components analysis was employed to discern the most influential factors. The key findings underscored the significance of power speed, isometric and explosive strength, strength endurance, and dynamic and static flexibility as the pivotal physical fitness elements in the talent selection process for young male artistic gymnasts. These findings have significant implications for the effective identification, selection, and development of gymnastic talent (Mkaouer et al., 2018). Mkaouer et al.'s (2018) study and our study share a common focus on talent identification in sports but differ in their respective approaches and sports contexts. While Mkaouer et al. concentrate on men's artistic gymnastics and delineate crucial physical and skill-related attributes for talent selection, our study employs machine learning techniques to classify primary school students' performance across various sports-specific fitness tests. Both studies highlight the significance of specific physical attributes in talent identification, with Mkaouer et al. emphasizing the importance of power speed, strength endurance, and flexibility in young male gymnasts. In contrast, our study underscores the effectiveness of machine learning in achieving high classification accuracy in a broader context. Ultimately, both studies contribute valuable insights to talent identification, offering distinct methodologies and applications within the realm of sports talent development. Gil et al.'s (2014) investigation into talent identification within a professional soccer club sheds light on the distinct characteristics and selection criteria for outfield players

(OFs) and goalkeepers (GKs) aged 9–10. OFs displayed advantages in age, leanness, and various performance tests when compared to a control group (CampP). The study underscores the importance of velocity and agility as pivotal factors in player selection, with selected OFs being not only older but also excelling in agility and endurance.

In contrast, GKs exhibited different anthropometric traits, including height, weight, and body fat percentages, and their physical test performances were comparatively weaker. Selected GKs were older, taller, more mature, and showed better results in handgrip and jump tests. Ultimately, this research highlights the role of specific anthropometric attributes, agility, and age in the selection process for soccer players (Gil et al., 2014). Gil et al.'s (2014) study and our study both delve into the realm of talent identification but in distinct sports contexts and through different methodologies. Gil et al. primarily explore talent identification in professional soccer, focusing on age, leanness, and performance attributes of outfield players (OFs) and goalkeepers (GKs). They highlight the critical role of velocity and agility in player selection, with specific anthropometric and physical performance differences between the two positions. In contrast, our study employs machine learning modeling to classify the performance of primary school students across various sports-specific fitness tests. The study demonstrates the effectiveness of this virtual prediction method for talent selection and guidance. While Gil et al.'s research is sport-specific and emphasizes the role of certain physical attributes, our study takes a broader approach and emphasizes the use of machine learning for performance classification. Both studies, however, contribute to the understanding of talent identification and selection in sports, albeit through different lenses and methodologies. In the study by Larkin et al. (2023) examining talent-identified youth sport academy athletes, normative values were established in relation to gender, age, and sport. The research spanned five years and involved 794 youth athletes attending specialized school sports academies. The findings revealed that as athletes grew older, there was a consistent increase in anthropometric measures such as height and body mass, irrespective of gender. Additionally, with advancing age, athletes generally exhibited higher vertical jump abilities, faster sprint performances, and improved physical endurance. These trends were further influenced by sport-specific differences. Overall, the study's results offer valuable age, gender, and sport-specific normative data for talent-identified youth athletes, serving as representative performance profiles that can be beneficial for coaching staff in making performance comparisons and informed decisions (Larkin et al., 2023). Larkin et al.'s (2023) study and our study both revolve around the context of talent identification and the establishment of performance profiles, albeit in different settings and with distinct methodologies. Larkin et al. conducted a five-year investigation into talent-identified youth sport academy athletes, emphasizing age, gender, and sport-specific

normative values. They found consistent growth in anthropometric measures and improved physical performance with age across gender groups. In contrast, our study employed machine learning modeling to classify the performance of primary school students across various sport-specific fitness tests, providing a tool for talent selection and guidance. While Larkin et al.'s research offers comprehensive normative data for youth athletes, our study focuses on performance classification using technology. Both studies, however, contribute to understanding talent identification and performance evaluation in youth sports, with Larkin et al.'s work providing a broader normative context, and our study offering a technological approach to performance assessment.

The study also highlighted notable gender differences in performance parameters. Male participants generally exhibited higher accuracy rates in reaction time, hand grip strength, and medicine ball throwing, while female participants excelled in the 30-meter sprint and hitting the target at a distance of 5 meters. These differences underscore the importance of considering gender-specific training and development strategies in youth sports. Coaches and educators can use these insights to tailor their programs to the specific needs and strengths of male and female athletes. Dencker et al. (2006) examined 248 children (140 boys and 108 girls), aged 8-11 years. Both Dencker et al.'s (2006) study and the research presented in our study focused on aspects related to physical fitness and performance evaluation in children, although they differed in their primary objectives and methods. Dencker et al. investigated factors influencing aerobic fitness, particularly in terms of gender differences and body composition among children aged 8-11. They emphasized the significance of body composition as a predictor for VO2peak, highlighting the impact of lean body mass and physical activity (Dencker et al., 2006). In contrast, the study outlined in our research aimed to determine sport-specific fitness profiles in primary school students aged 7-8 using machine learning modeling, with a focus on talent selection. While Dencker et al. delved into the physiological aspects of aerobic fitness and gender disparities, the latter study employed technological tools to assess a broader range of physical performance parameters and their utility in identifying potential young athletes. Both studies contributed to our understanding of physical development in children, with Dencker et al. focusing on determinants of aerobic fitness, while our study emphasized the application of technology and machine learning for talent identification in youth sports. Mayhew and Salm (1990) conducted a study that aimed to determine if the differences in anaerobic power between males and females could be attributed to variations in body composition, strength, and neuromuscular function. In their research, 82 untrained men and 99 women were assessed through measures of body composition, somatotype, isometric strength, neuromuscular function, and anaerobic power tests. The study revealed significant distinctions between men and women in strength, power,

and neuromuscular measurements, as well as various anthropometric dimensions. While strength and anthropometric factors played a role in anaerobic power, relative fat exerted varying degrees of influence on sprint and jump performances depending on gender. Although controlling for anthropometric, strength, and neuromuscular differences reduced the differences between the sexes, it did not eliminate them, suggesting the involvement of factors beyond lean body mass, leg strength, and neuromuscular function in explaining gender differences in explosive power (Mayhew & Salm, 1990). On the other hand, our study presented research centered on determining sport-specific fitness profiles in primary school students aged 7-8 using machine learning modeling for talent selection. While both studies touched upon physical fitness and performance assessment, Mayhew and Salm (1990) investigated gender differences and their determinants, while the latter study employed technology to assess performance parameters and their role in talent identification among youth, making them distinct in their focus and methodology. Maud and Shultz's study compared anaerobic power and anaerobic capacity between young active men and women, finding significant differences in various parameters such as body height, weight, percent fat, anaerobic power, and anaerobic capacity when recorded in absolute terms or relative to body weight. These differences were reduced when adjusted for body weight and further diminished when corrected for fat-free mass (FFM) (Maud & Shultz, 1986). In contrast, our study focused on determining sport-specific fitness profiles in primary school students aged 7-8, primarily using machine learning modeling for talent selection. While both studies examined aspects of physical fitness, they differed in scope and methodology. Maud and Shultz delved into gender-related differences in anaerobic power and capacity in young adults, emphasizing the impact of body composition. In contrast, the latter study concentrated on assessing a range of physical performance parameters in children, aiming to identify future athletic talents using technology. Thus, the studies were distinct in their objectives and target populations.

The results of this study have important implications for talent selection and youth sports development. By employing machine learning modeling, it becomes possible to identify and nurture young talents more effectively. The accuracy of performance classification can guide coaches and sports organizations in making informed decisions about which sports branches young athletes may excel in. This, in turn, can lead to a more targeted and personalized approach to talent development, optimizing the chances of identifying future champions.

There are several limitations to this study. Firstly, the study's sample size consisted of 97 primary school students aged between 7-8 years (53 boys and 44 girls), which may be considered relatively small in the context of sports science research. This limitation could impact the generalizability of the findings to a broader population of young athletes. Secondly, the research focused exclusively on a specific age group (7-8 years old), which may restrict the applicability of the findings to different developmental stages within the youth sports population, neglecting potential variations in physical attributes and performance potential across age groups. Thirdly, the study assessed a limited set of performance parameters, including reaction time, hand grip strength, standing long jump, 30 m sprint, medicine ball throwing, and hitting a target at a distance of 5 meters. While these parameters are important, they do not cover the full range of physical attributes influencing sports performance, such as flexibility, agility, and endurance. Fourthly, the exclusive use of MATLAB 2022B for data analysis might pose accessibility challenges for practitioners and educators looking to implement similar assessments. Therefore, the practicality and user-friendliness of the chosen software tool should be considered for real-world applications. Lastly, the study did not delve into the practical feasibility of implementing such models in actual school or sports settings, and ethical considerations related to the assessment and classification of young athletes were not explicitly addressed. Recognizing these limitations is essential for a nuanced interpretation of the study's scope and implications, and future research in this field should aim to address these limitations for improved talent identification and sports-specific fitness profiling techniques in youth sports contexts.

Building on the success of our machine learning-based performance classification model, future research endeavors should aim to expand its application to a broader spectrum of age groups and sports disciplines. Exploring the longitudinal impact of early talent identification and guidance through the Olympic Training Module on individuals' sports careers and overall development warrants further investigation. Additionally, incorporating psychosocial and mental resilience factors into the talent selection process can provide a more holistic approach to nurturing young athletes. Furthermore, the integration of emerging technologies, such as virtual reality and augmented reality, can enhance the training experience and enable more comprehensive foresight in talent development. Collaborations with educational institutions, sports organizations, and experts in various fields can facilitate a multidisciplinary approach to optimize the implementation of these findings in educational and sporting contexts.

The findings of this study hold significant educational implications for primary school settings. The use of machine learning modeling for performance classification offers a data-driven and objective method for identifying and nurturing young talent in sports. Educators, school administrators, and sports instructors can integrate these insights into physical education curricula to identify students' strengths and guide them toward suitable sports disciplines. This approach promotes a more personalized and effective educational experience, aligning with the vision of Olympic education at the school level. Moreover, it underscores the importance of early exposure to diverse

sports and tailored training modules, fostering a holistic approach to children's physical development. Collaboration between educational institutions and sports organizations can facilitate the implementation of these educational strategies, ultimately contributing to the development of tomorrow's champions.

Conclusions

In summary, this study has demonstrated the potential of machine learning modeling in the generation of sport-specific fitness profiles and performance classification in primary school children. The high accuracy achieved in discriminating performance levels underlines the effectiveness of this approach. The observed gender differences underline the need for tailored training programs. The results presented in this study can serve as a valuable tool for talent selection and youth sport development, helping to identify and nurture future champions in the world of sport. As the field of sports science continues to evolve, machine learning is likely to play an increasingly important role in shaping the future of sports talent identification and development.

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