Journal of Advanced Sport Technology 7(1):33-44.

Received:March,12,2023 Accepted: June,9,2023

Original Research

Wearable Measurement Unit for Objective Assessment of Catching and Underhand Throwing Development

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ABSTRACT

Developing fundamental movement skills (FMS) as the building blocks of complex sports skills and daily physical activity is crucial. The mechanically optimal performance can be determined by qualitative changes in the sensitive aspects of the skill. Accurate scoring of this process is time-consuming and requires minimum training and experience. Thus, this study was designed to evaluate the feasibility of using wearable inertial units (IMUs) based on artificial intelligence algorithms (AIA) for objective assessment of catching and throwing skills.Thirteen children aged 4 to 10 years (age = 7±1.84) (boys = 53%) were asked to do at least ten repetitions of two hands ball catch and underhand throw according to the Test of Gross Motor Skills Development- third edition (TGMD-3). Trials were captured with video recording and three IMUs, simultaneously.

Dynamic Time Warping (DTW) and K-Nearest Neighbor (KNN) artificial intelligence algorithms automatically classified IMU signals. The intraclass correlation coefficient (ICC) was calculated between expert scores and the artificial intelligence algorithm. All tests were done at a 95% confidence interval. The classification accuracy of the KNN algorithm (k=7) for two hand catch was 73%, ICC =0.51 (CI=0.25-0.69), and for underhand throw was 70%, ICC= 0.559, (CI=0.314-0.717). The algorithm accuracy when using lower back sensor data was 72% for the tow-hand catch and 78% for the underhand throw. The scoring time was reduced from 5 minutes per skill (in an expert-oriented way) to less than 30 seconds (using artificial intelligence). A close examination of the artificial intelligence classification revealed several aspects of performance that did not play an influential role in trials but were artificially consistent with the TGMD-3. Locating the sensor in the waist area for these two skills will save the cost and time in screening plans. This instrument assessment provides instant feedback, is portable, economical and easy-to-use, and is suitable for educational setting. In the future, more research should be conducted on IMUs' real-world applications by teachers, researchers, clinicians, and coaches.
Keywords: Test of Gross Motor Development, Wearable Inertial Measurement Unit, Artificial Intelligence Algorithms, Fundamental Movement Skills, Motor Development Assessment

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INTRODUCTION

According to the metaphor of the Mountain of Motor Development, refining FMS and acquiring motor competence as a precursor to complex sports skills should happen in childhood [1]. In fact, higher levels of proficiency in the FMS in mid to late childhood, allow individuals to prepare for participation in sports events by participating in a variety of motor activities. Further, systematic review studies found a causal relationship between FMS and an active lifestyle [2, 3].

Catching and underhand throwing as a critical subset of FMS are vital skills for participation in various sports; softball pitching, bowling ball delivery, field hockey drives and passes, underarm volleyball serve, badminton underarm clear, basketball, handball, rugby, baseball, and goalkeeping [4, 5]. Catching requires a precise spatial and temporally coordinated action adjusting to the direction, speed, weight, and size of the incoming ball [6]. It is necessary to adjust the person's posture before starting the movement of hands [7]. Moreover, underhand throw is a complex skill that requires coordination between four components: hands, trunk, feet, and wrists [5]. Due to the intricate nature of FMS, it comes as no surprise that these skills are poorly executed by children [6].

Therefore, they are included in most tests of motor development; such as the Bruininks-Oseretsky Test of Motor Proficiency, TGMD, the Peabody Developmental Motor Scales, and the Movement Assessment Battery for Children [7]. Recently, there have been great efforts to assess motor skills using technological tools. For an effective population screening, researchers have sought to overcome the limitations of process-oriented tests; video recording, post hoc analysis, and a trained examiner. In fact, by maintaining relative accuracy, they tried to improve the efficiency of process-oriented tests of motor skills in schools and sports fields.

The IMU is the practical electronic system for determining the velocity, position, and attitude of a moving object. In these systems, three axes accelerometer, gyroscope, and magnetometer measure linear accelerations and angular velocities, and orientation of motion things, respectively. Moreover, the IMU is inexpensive, small-size, and has high-power batteries [8]. A recent application of the IMU is in diagnosing developmental disorders [9] and elderly clinics [10]. This technology, while reaporting accurate and objective information, do not limit to any disease, gender, or age groups [8].

Many skills such as walking [11], running [12], hopping [13], long jumping [14], and overhand throwing [15, 16] and the tests like The Dragon Challenge [17], Locomotor subtests of TGMD-2 [18] and TGMD-3 (seven skills) [19] were examined. The results indicated the advancement of the goals achieved by using IMU.

Non-academics, however, cannot process large volumes of accelerations and angular velocities data. Therefore, it is necessary to find an automatic scoring algorithm to facilitate evaluation by all types of users; diagnostic clinics, physical educators, kindergarten teachers, and sports talent coaches. By extracting patterns and identifying trends from complex and ambiguous data, AIA helps humans to make a decision. This method eliminates the time-consuming kinematic feature selection phase.

Classification AIA help understand and compare the results of the instrument-based evaluation and current methods by extracting the essential parameters in the data of the IMU [15, 19]. Recently researchers have shown that it works even faster and more accurately than human perception during the real-time assessment of FMS [15, 20].

On the other hand, new approaches seek to reduce the number of IMUs to minimize setup and data upload time [21, 22]. For example, Lander et al. (2020) initially used 17 sensors to evaluate seven skills of the TGMD-3 test and then reported the results with high accuracy using just four sensors [19]. Walking reliability was assessed by placing only one accelerometer on the L5 in seven life periods (young to old age groups). The multiple entropy analysis determined that the trunk movement changes are the progress indicator of perfection or decline in walking [9].

Underhand throwing (like pitching motion) involves a series of movements that transfer energy from the lower body to the upper body and finally to the ball. The most effective throwing occurs when all body parts work together to produce maximum velocity. The acceleration of the proximal segment is transferred to the distal and, at the same time, as the distal acceleration reaches the peak, the proximal acceleration decreases. Energy should be transmitted like a chain from the legs, trunk, shoulder, and elbow to wrist; it is called a "kinematic chain" [23].

Grimpampi et al. (2016) proposed that the ability to throw overhand is linked to an increase in the speed of the trunk and pelvis rotation. A greater "yaw" and the maximum forward-backward movement of the trunk leads up to increase the speed of ball. Consequently, the speed at which the trunk and hips rotate is a right way to assess a person's level of motor development. A detailed examination determined that the rotation speed of the pelvis compared to the trunk was a more accurate indicator in distinguishing the stages of motor development in children [16]. Therefore, these measurements can be used to categorize children according to their level of proficiency and are useful in assessing fundamental motor skills. Indeed, the absence of trunk or hip rotation is seen as a sign that someone is at a beginner level of overhand throw [16]. The role of pelvis movements in the skillful execution of motor skills is undeniable but has not been measured with an IMU until now.

As a result, to evaluate FMS using IMU as efficiently as possible, there are challenges in determining the minimum number of sensors needed and the best location to install the sensors. Therefore, the current study aims to determine the optimal number and place for evaluating the development of the two-hand catch and underhand throw by IMU and using AIA.

MATERIAL AND METHODS

Participants

This study, In terms of the purpose, is developmental. Because of advancing, and evaluating products that must meet the criteria of internal consistency and effectiveness [24]; carried out in cross-sectional design [25]. According to the spread of the coronavirus at the time of data collection and the results of the study by Grimpumpi et al. (2016), 13 children aged 4 to 10 years (M=7±1.84 y) were asked to perform at least ten trials of each skill [16]. The researchers made an effort to recruit children from different socio-economic levels and different regions of Gorgan City in the Golestan province of Iran.

All children present in this study did not have motor or cognitive disabilities. Also, the level of their developmental coordination disorder was checked using the responses of the children's parents to the developmental coordination disorder questionnaire (DCDQ) [26]. First of all the purpose and procedures of the study, the questionnaire, and the consent form for participating in the study, were emailed to the parents. Unwillingness to continue the tests was the criterion for withdrawing from the study. Due to the coronavirus, the parents wanted the tests to be conducted at their location of residence, and their children were not allowed to leave the house.

All ethical principles were followed, including confidentiality. The Ethics Committee of the Research Institute of Physical Education and Sports Sciences of Iran (blinded) approved this study: ethical code IR.SSRI.REC.1400.1219. Furthermore, the University of Tehran institutional review board approved the protocols being used in the study.

Instruments

The inertial sensors used in this study were manufactured by Shokofa Tavan Vira (Tehran University Science and Technology Park- ID 140084). Row data were captured at a 25 Hz sampling frequency on the 9 DOF, incorporating a three-axis accelerometer (±1.5 g), three-axis gyroscope (±250°/s), and three-axis magnetometer (±48 Gauss). The sensor weighs 21 g and has dimensions (48 × 41 × 18 mm) including the plastic frame. The sensor's raw data is downloadable via a USB output [15].

The locations of the sensors were as follows: A sensor between the 4th and 5th lumbar vertebra; to perform the catching skill: in the proximal area of the wrists and to perform the underhand throw skill: a sensor on the proximal area of the wrist of preferred hand, and a sensor above the outer ankle of the leg opposite the throwing hand [27]. All of them were fixed on the child's body via a plastic frame with a 3 cm wide elastic band and Velcro. The X, Y, and Z axes represent the body's linear acceleration forward/backward, up/down, and left/right, respectively. The yaw, pitch, and roll angular velocities were evaluated around vertical, lateral-central, and anterior-posterior axes, respectively.

TheTGMD-3 was used to measure the process of performing the skills of catching with two hands and underhand throwing. This test is used as a gold standard to check the level of motor proficiency of children aged 3 to 10 years at the international level [28]. Three criteria for catching with two hands and four criteria for underhand throwing are evaluated as 0 and 1 by the experienced examiner. The examinerof this study was well familiar with the procedures of TGMD [29]. Previously the reliability and validity of TGMD-3 were approved in Iran [30].

Data collection

Before starting the data collection process, using the application program of the gross motor skill animation, both skills were shown to the child several times. Children had the opportunity to perform the skill once or twice before the official assessment so that the examiner can make sure that the children have a correct understanding of the performance.

Then according to the skill type, the sensors were placed in their location. In order to comply with ethical standards, the waist sensor was placed on its location by the parents under the supervision of the examiner.

Participants were asked to perform each skill at least ten times. At the same time, the examiner's assistant captured trails from the side view with a mobile camera (p1080 & 30f/s). All the data of IMU were stored by MATLAB/R2016a software.

Preprocessing

Then, the expert evaluated each performance; one for each successful criterion and zero for failure to observe the standard of TGMD-3. All the scores were stored in the data bank. The matrix received from the sensors was also coded and stored in another data bank. For a better intuitive understanding, graphs of IMU signals' linear acceleration and angular velocity were plotted. In this step, the data recorded asynchronously with the subject's performance were dropped out.

An infinite impulse response (IIR) low-pass filter was used at a cutoff frequency of 2.5 Hz for the accelerometer and 50 Hz for the gyroscope to remove the noise signals. The Max Abs Scaler function was used to normalize each data series to remove the effect of physical fitness and child characteristics. Considering that each data series was normalized using its maximum absolute value, all data were placed between -1 and 1.

Extracting data and scoring algorithm

First, the signals were labeled according to the obtained performance score in the TGMD-3 criteria (zero or one). However, the complete set of recorded data of each throw or catch includes twelve-time series of the 3-axis signals of the magnetometer, accelerometer, and gyroscope. Even in this study, with a small sample size and relatively low sampling frequency, there were more than 20000 data. Therefore, the data were clustered using the K-Medoids and Density-based spatial clustering of applications with noise (DBSCAN) algorithms. Cluster analysis proved that each criterion could be categorized. As a result, the correct sequence of peaks in each signal was identified (Figure 1).

It should be noted that the primary goal of the signal analysis was to find the movement pattern for the FMS. Therefore, the "Dynamic Time Warping" and "k nearest neighbor" (KNN) algorithms were used for automatic data classification. The KNN algorithm classifies the considered signal in its class based on the nearest neighbors. First, 20% of the total data was separated for testing. Then, 20% of the remaining data was allocated for validation. The rest data were used for training. According to the validation phase, k was chosen between 3 and 7.

Data processing and algorithm evaluation

In this step, the minimum difference between test and training signals was calculated, and then the signals were classified. Two issues were assessed: false acceptance, in which an “incorrect” performance was classified as “correct”, and false rejection, in which a “correct” performance was classified as “incorrect”. The accuracy of the algorithm was measured by using the data that had not been used during the training of the model. At this stage, the output indicates the score of the TGMD-3 criteria of tow hand catch and underhand throw.

Statistical analysis

A multi-fitness metric should be used when evaluating machine learning models. To evaluate the model's performance, training, and prediction times, as well as accuracy, and F1 score, were computed. Essentially, F1-score is a harmonic mean between precision and recall (equal balances between precision and recall are desirable). F1 scores are unaffected by class distributions, so it is a good performance metric for unbalanced datasets [31].

An intraclass correlation coefficient (ICC) was calculated between the expert rater and the automated algorithm to test the reliability between the raters. In the present study, the two-way mixed effects model was chosen. An absolute agreement was also used for the definition option [32]. The classification of the ICC reliability output is done as follows: poor=less than 0.5, average = between 0.5 and 0.75, good=

between 0.75 and 0.9, and excellent= more than 0.9. An ICC minimum of 0.6 is required for screening human movements [33].

RESULTS

Demographics

Thirteen typical children aged 4 to 10 years participated in this study (boys = 53%); with the Average of age=7±1.84 y, height=129.46±7.17 cm, weight=28.15±3.53 kg, and DCDQ=63.4±32/6.

Motor skills according to the tgmd-3

Two hand catch: The hands placed in front of the body in 79% of the trials were performed with and the elbows flexed during the preparation stage. While in only 29% of performances, the elbows were extended to catch the ball. Also, in 67% of ones, the ball is caught by hands only. In total, there were 28 proficient performances (successful in all three criteria), 36 semi-proficient trials (successful in just two of the criteria), and 46 beginner performances (failed in at least two criteria).

Underhand throw: In 67% of the performances, swinging the hand down and back until reaching the back of the body was preferred. Stepping forward with the foot opposite the throwing hand was followed in 48% of performances. Regarding the third criterion (ball is tossed forward hitting the wall without a bounce), because no sensor was placed on the ball, the power of judgment was low; As a result, the classification of this criterion was not done. The continuation of the hand movement after releasing the ball up to the level of the chest was seen in 87% of cases. Overlay if the performance gets a score of one in each of the four criteria, it is marked as "proficient" no. = 55 (45%), and if three criteria are displayed, "semi-proficient" no. = 29 (24.1%) and if less than three criteria are displayed "Beginner" no. =36 (%30) is displayed [19].

Sensor wear

According to the preprocessing, 110 trials out of the 137 of catching skills and 120 tests out of the 131 underhand throw performances entered the data processing stage. Figure 1 shows the sequence of correct peaks based on the clustering of angular velocity data.

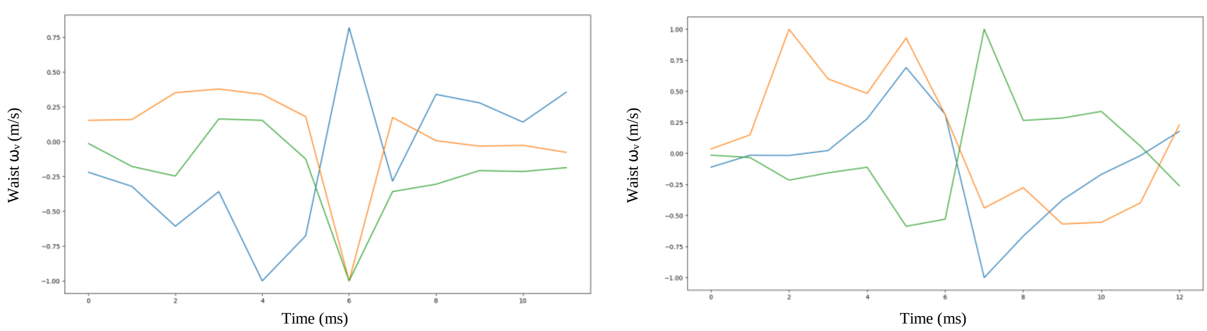

Figure 1: These graphs demonstrate represents a sample of gyroscope data on the x-axis, y-axis, and z-axis for the low back sensor (right= two-hand catch, left= underhand throw). The sequence of peaks is referenced as a feature of the skills.

Data distance was calculated using the DTW algorithm, and automatic classification was performed using the K-NN algorithm. To test the algorithm, a random selection of 20% (tow hand catch=28, underhand throw=21) of data points were performed before processing. Then 20% (tow hand catch=22, underhand throw=26) of data points were randomly divided for the K validation stage. The remaining data were used for algorithm training. This algorithm used K=7 to accomplish the classification task. The results were classified by considering type one and two errors. In total, the classification accuracy was 73% for tow hand catches, and 70% for underhand throws. Based on the results of similar articles, which found that the low back area sensor was critical in distinguishing the developmental level of FMS in children; table 1 compares the classification accuracy of using only one sensor with that of three sensors at the same time.

Table1: Results of the testing of the signals against its model; comparison between all sensors (A) and low back sensor (L)

	TGMD-3 criteria	A % Accuracy	L % Accuracy	A F1 score	L F1 score	A % Accuracy	L % Accuracy
Two hand catch	Hands placed in front of the body and the elbows flexed during the preparation stage.	86	79	.92	.87	73	72
	Arms extend while reaching for the ball as it arrives.	64	61	.16	0		
	Arms extend while reaching for the ball as it arrives.	68	75	.79	.84		
Underhand throw	Preferred hand swings down and back reaching behind the trunk.	62	67	.75	.79	70	78
	Steps forward with the foot opposite the throwing hand.	62	83	.64	.64		
	Ball is tossed forward hitting the wall without a bounce.	-	-	-	-		
	Hand follows through after ball release to chest level.	85	85	.92	.92		

The scoring time per skill was reduced from 5 minutes (in an expert-oriented way) to less than 30 seconds (using artificial intelligence). The ICC of tow-hand catch was 0.514, CI=0.254-0.684 with a 95% confidence interval (Pvalue <0.001); underhand throw was 0.559, CI=0.314-0.717 with a 95% confidence interval (Pvalue <0.001). According to the mentioned values, these are average agreement coefficients.

DISCUSSION

In children's FMS, skill refinement is a crucial part of motor development. The mechanically optimal performance can be determined by qualitative changes in the sensitive aspects of the skills [34]. This process requires a lot of time and experience to evaluate; consequently, this study aims to determine the feasibility of assessing FMS quality using commercially available and affordable technologies. The two hands catch and underhand throw skills were evaluated using IMU and AIA according to the criteria of the TGMD-3. It takes only three sensors to achieve 73% and 70% accuracy in classifying tow hand catch and underhand throw criteria, respectively. Signal processing techniques were used to obtain this result without the intervention of an expert evaluator; therefore, this level of accuracy is promising.

The secondary goal of this study was to investigate the ability of the waist sensor in the measurement in comparison with the data from three sensors in classification. It is interesting to note that the accuracy of the classification using low back sensor data not only did not drop significantly But also increased (tow hand catch=72%, underhand throw=78%). A close examination of the artificial intelligence classification revealed several aspects of performance that did not play an influential role in trials but were artificially consistent with the TGMD-3. Locating the sensor in the waist area for these two skills will save the cost and time in screening plans.

During the preparation stage of catching, the subjects' hands were in front of their bodies in 79% of performances, and their elbows were flexed. There were 58 runs (48.3%) in which the expert evaluator observed the elbows being extended to catch the ball. In 67% of trials, the ball was caught with their palms. In 81 (67.5%) underhand throw performances, "Preferred hand swings down and back reaching behind the trunk" was observed. Also, stepping forward with the opposite leg of the throwing hand scored one in 58 (48.3%) performances. The classification accuracy of them was the same. In 105 (87.5%) trials, the fourth criterion (continuation of hand movement up to chest level) was skillfully displayed. The algorithm correctly classified this criterion with 85% accuracy.

The present study follows Lander et al. (2020) in examining the catching pattern with two hands. 30% of the subjects of that study showed the criterion of the preparation stage correctly while extending the elbows was seen in 87% of their performances. That study showed 90 and 100 percent classification accuracy for criteria one and two [19]. This study found that the classification accuracy for criterion one was 86%, which is very similar to the Lander's; however, for criterion two, it dropped sharply to 64%.

In a similar study, Children with varying levels of motor development showed no difference in three kinematic synergies that emerged during two-hand catching, according to Balali et al. (2020). Based on the developmental sequence model and the TGMD-2, participants were grouped. There were no differences in the number and strength of synergies between their development levels. According to the tasks, the children demonstrated different kinematic synergies. Three specific synergy groups were formed: reaching-oriented synergy, catching-oriented synergy, and retaining-oriented synergy [20].

Underhand throwing is a complex skill that requires coordination between four components: hands, trunk, feet, and wrists [5]. From the motor control or development perspective, understanding the processes such as trunk rotation, stepping, hand movement, and ball release facilitates understanding developmental changes in children's motor skills. The previous study investigated the relationship between age and level of training and skills among girls aged 9-11 years (25 beginners, 14 softball league players, and 9 participants in softball training classes). Data analysis showed that in the specific group, regardless of age, the performance of underhand throwing was similar. But, the throwing experience differentiated four motor components of performance among girls. In addition, different experiences (league training or formal practice) caused significant differences in trunk rotation and ball release technique [5].

In the present study, the beginners threw without taking a step and with still feet. Some semi-skilled children would throw by taking a step to the side with the foot compatible with the throwing hand. Generally, the use of the opposite arm and leg pattern was seen when the child was correctly using the weight transfer process and benefiting from foot placement for better hip and opposite shoulder rotation. Therefore, placing the foot without the energy transfer process did not help to perform skillfully. As a result, despite the fact that in the TGMD standards, putting the leg opposite the throwing hand forward has a point, but this action must be done in harmony with the movement of the hip rotation and its physical aspects.

The current study's strong point is that it could explain why the automatic scoring algorithm's accuracy decreased noticeably in some criteria. This is probably due to the use of a pattern that is more efficient than the one intended by TGMD-3.

A similar study discussed the importance of the order in which body parts are activated during the pitching motion in softball and baseball. In the ball speed (62%); the supporting role of the trunk and lower limb movement in energy transfer was the cause of such acceleration and finally increased ball release speed in the skilled group. Energy should be transmitted like a kinematic chain [23].

Their results suggested that energy is transferred from the lower body to the upper body, and then to the ball, and that maximum velocity is achieved when all body parts work together effectively. The researchers found a specific sequence of proximal to distal segmental motions among intermediate and advanced windmill softball pitchers, but not among novice pitchers. That study suggested that larger; more proximal segments should reach their peak angular velocities first, followed by smaller, more distal segments, with the wrist/hand stabilizing just before ball release. However, the natural whipping motion of the windmill pitch means that this sequence may not be evident until just before ball release [23].

Another advantage of using automated algorithms was reducing time spent on scoring. A typical process takes at least five minutes (uploading videos of the trials, reviewing the videos several times, and entering the scores in a computer) per trial. Instead, the automatic processing was done all these stages in less than 30 seconds. This time was only reported in the study by Bisi et al. They reduced the 15-minute evaluation time of six locomotor subtests of the TGMD2 to just two minutes (excluding time for downloading sensor data) (25). Consequently, it provides immediate feedback, in addition to being portable, cost-effective, and easy to use, making it suitable for educational settings and the FMS screening plans.

The accuracy of criteria-based classification should be viewed cautiously in light of the limited number of performances. Additionally, there may have been some crucial information that was not collected at a sufficient rate. As a result of the spread of Coronavirus at the time of data collection, the researcher had to use the simplest classification algorithms available, given the lack of subjects. In the proposal, deep-learning algorithms will be used to analyze data in the project. A movement schema can then be created using artificial neural networks to model raw data according to the criteria specified in TGMD. The field of pattern recognition has been impacted significantly by deep learning in the last few years (35); in some cases, these models have also been used to detect human activity [36, 37]. Therefore it is recommended that more subjects be used in future research, as well as more accurate algorithms.

CONCLUSION

In conclusion, a reliable and practical method of evaluating the fundamental movement skills of tow hand catch and underhand throw were achieved through the use of artificial intelligence applied to the signal processing of one sensor. In this way, children's skills can be monitored and evaluated objectively. Locating the sensor in the waist area for these two skills will save the cost and time in screening plans. Furthermore, the time required for process-oriented analysis of movement skills for research, clinical, sports, and educational purposes was significantly reduced while maintaining relative accuracy.

Author Contributions: Conceptualization, methodology, SH, MSH, HV; formal analysis, SH, HV investigation, SH; resources, SH, MSH, HV ; data curation, SH; writing—original draft preparation, SH, MGH; writing—review and editing, SH, HV, MGH; supervision, MSH,DH, ; project administration, MSH,MGH, HV,DH. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the University of Tehran Science and Technology Park under Grant number 140084; the National Sports Technology Innovation Center of Iran under Grant number 11/25845/10.

Institutional Review Board Statement: The Ethics Committee of the Research Institute of Physical Education and Sports Sciences of Iran (blinded) approved this study: ethical code IR.SSRI.REC.1400.1219. Furthermore, the University of Tehran institutional review board approved the protocols being used in the study.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.
Data Availability Statement: Data will be available at request.

Acknowledgments: The authors are thankful to all the participants and their families for their participation in this study.

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واحد اندازه‌گیری پوشیدنی برای ارزیابی عینی رشد دریافت کردن و پرتاب از زیر شانه

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چکیده:
رشد و تکامل مهارت های حرکتی بنیادی به عنوان بلوک های سازنده مهارت های ورزشی پیچیده و فعالیت بدنی روزانه بسیار مهم است. عملکرد بهینه مکانیکی را می توان با تغییرات کیفی در جنبه های حساس مهارت تعیین کرد. امتیازدهی دقیق این فرآیند زمان بر بوده و به حداقل آموزش و تجربه نیاز دارد. بنابراین، این مطالعه به منظور ارزیابی امکان‌سنجی استفاده از واحدهای اینرسی پوشیدنی بر مبنای الگوریتم‌های هوش مصنوعی برای ارزیابی عینی مهارت‌های گرفتن با دو دست و پرتاب از زیرشانه طراحی شد.
از ۱۳ کودک ۴ تا ۱۰ ساله (۱/۸۴±۷=سن) (پسران = ۵۳٪) خواسته شد که مطابق با ویرایش سوم آزمون رشد مهارت‌های حرکتی درشت حداقل ۱۰ دو مهارت دریافت با دو دست و پرتاب از زیر شانه را اجرا کنند. اجراها به شکل همزمان با استفاده از حسگر اینرسی پوشیدنی و دوربین فیلم برداری ضبط شدند. الگوریتم‌های هوش مصنوعی پیچش زمانی پویا و K-نزدیک‌ترین همسایه به‌طور خودکار سیگنال‌های حسگر ها را طبقه‌بندی کردند. ضریب همبستگی درون طبقاتی (ICC) بین نمرات خبرگان و الگوریتم هوش مصنوعی محاسبه شد. تمامی آزمون ها با فاصله اطمینان ۹۵ درصد انجام شد. دقت طبقه‌بندی الگوریتم (k=۷) ۷۳٪ و ICC=۰/۵۱ (CI=۰/۲۵-۰/۶۹) و پرتاب از زیر شانه=۷۰٪ و ICC=۰/۵۶، (CI=۰/۳۱-۰/۷۲) بود. دقت الگوریتم هنگام استفاده از داده‌های حسگر کمر ۷۲ درصد برای دریافت توپ با دو دست و ۷۸ درصد برای پرتاب از زیر شانه بود. زمان امتیازدهی از ۵ دقیقه به ازای هر مهارت (به روش متخصص محور) به کمتر از ۳۰ ثانیه (با استفاده از هوش مصنوعی) کاهش یافت. بررسی دقیق طبقه‌بندی هوش مصنوعی چندین جنبه از عملکرد را نشان داد که نقش تأثیرگذاری در کارآزمایی‌ها نداشته اما به‌طور مصنوعی با TGMD-۳ سازگار بودند. قرار دادن سنسور در ناحیه کمر برای این دو مهارت باعث صرفه جویی در هزینه و زمان در طرح های غربالگری می شود. این ارزیابی ابزاری علاوه بر قابل حمل بودن، مقرون به صرفه بودن و استفاده آسان، بازخورد فوری را ارائه می دهد و آن را برای محیط های آموزشی مناسب می کند. در آینده، تحقیقات بیشتری باید در مورد کاربردهای حسگر اینرسی در میادین اصلی توسط معلمان، محققان، پزشکان و مربیان انجام شود.

کلمات کلیدی: آزمون رشد مهارت های حرکتی درشت، واحد اندازه‌گیری اینرسی پوشیدنی، الگوریتم‌های هوش مصنوعی، مهارت‌های حرکتی بنیادی، ارزیابی رشد حرکتی