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A novel method for clustering basketball players with data mining and hierarchical algorithm

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Abstract The issue of talent identification in basketball is significantly underrepresented in the existing literature, despite its undeniable significance in the field of sports. The objective of this research is to use artificial intelligence algorithms in the talent detection procedure for basketball athletes. The timely identification of specific aptitudes in teenage athletes is a critical determinant of their prospective achievements. This research used player clustering techniques that included both individual and group talents in order to establish a talent detection approach for foundational age groups. The present investigation was carried out on a sample of 70 participants, ranging in age from 14 to 16 years. The algorithm described in this study demonstrated the improved performance in hierarchical clustering by using a combined strategy. This resulted in a greater level of accuracy when compared to comparable research endeavors. The primary objective of this approach is to provide a proficient aide for coaches and talent scouts. The findings of this study demonstrate a clustering accuracy of over 94 percent when categorizing players according to their talents and abilities, as compared to the evaluations provided by experienced coaches involved in this research endeavor. In summary, the present methodology shows a greater degree of precision in comparison to approaches used in analogous research investigations.
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Keyword: Clustering, Hierarchical Algorithm, Talent, Artificial Intelligence, Recognition.

1 Introduction

One further obstacle encountered by talent identification methods pertains to their capacity to predict and effectively choose persons with exceptional abilities. Regrettably, several talent identification models and patterns have shown restricted prognostic capability, hence raising considerable inquiries about their efficacy and believability.

In recent decades, there has been a growing recognition of the importance of anthropometric traits in determining the performance of top athletes. Consequently, these qualities have garnered considerable interest in the field of sports science. Nevertheless, the

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attainment of championship objectives cannot be exclusively achieved based on anthropometric characteristics alone. It is important to take into account other elements such as biomechanical, physiological, and psychological variables. Variables pertaining to physical readiness, individual abilities, and psychological skills are significant determinants that have a substantial impact on the achievement of athletes. A comprehensive comprehension of these elements could prove to be advantageous in the identification of athletic aptitude and the cultivation of its growth.

Undoubtedly, the concurrent and parallel consideration of several factors for a human might be intricate and susceptible to errors. Pattern-based models that depend on artificial intelligence algorithms have many advantages. One such advantage is their capacity to efficiently handle substantial amounts of data. Additionally, these models possess the ability to assess circumstances in a manner that closely resembles human cognitive processes. This facilitates the establishment of a cohesive methodology grounded on scientific principles for talent identification within the realm of basketball coaching and scouting.

Nowadays, the necessity of using AI algorithms, substituting them for statistical methods and diving into qualitative and quantitative data have been thoroughly specified [1]. AI algorithms create an organized insight and raise the human ability to describe and elaborate on different phenomena [2]. In recent years, the behaviour analysis of players in sports has been a hot topic in machine vision, on which different studies have been focused [3]. One of the active subjects in this field is talent identification in sports. The final goal of talent identification and selection is to develop the potential of selected persons with the help of and in collaboration with experienced trainers, scheduled exercises, regular matches, and facilities, motivating toward further development and fostering of talents.

To this end, first, the methodology of this research work is described. In this study, by gathering data associated with 70 basketball players aged from 14 to 16 according to those metrics explained in the following and using the proposed algorithm, these players are divided into 5 clusters concerning their talents and capabilities.

So far, several studies have been conducted on sports talent identification. The prerequisite of talent discovery is to consider all aspects affecting this task. The main challenge in this type of talent identification is how a wide range of available data that may include different physical, skill, and mental dimensions of a player can be modelled. The first step to mitigate this challenge is collecting information about all players' dimensions and normalizing this data [4].

Therefore, clustering initially aims to select the appropriate player to focus on and invest in them. In other words, clustering allows players possessing talent in a specific sport properly use the facilities provided in sports clubs. In addition, it can redirect those players in a specific sport for whom a bright future cannot be imagined in that sport to another sport. Also, players for whom a stable future cannot be imagined are determined [5].

The goal of talent identification is to gain more achievements in different sports. In team sports such as basketball, however, it can help better analyze players in the field from different aspects and finally intelligently choose the correct line up for achieving team success [6]. Hence, this topic has increasingly gained the attention of scholars, and new solutions have been presented.

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2 Literature review

It should be said that AI will change the sports world in the future and generally increase sport quality. Some algorithms used in the talent discovery process are reviewed in the following [7]. Regarding the continuous development of AI techniques and various research works in this field, using these techniques and evaluating their effects on sport evolution, especially in team sports, creates great opportunities to evaluate players during training and predict their future performance. The field of AI and applied techniques have attracted the interests of the information technology industry and, in particular, society because of the large amount of data in this field and the need for converting them into useful knowledge and practical solutions.

Researchers have presented a new approach for selecting sports talents using statistical regression equations based on computer programming to model the activity of athletes. For example, the mathematical modelling of athlete jumping and its analysis in a system helps coaches expand their skills in selecting elite athletes [8].

Norikazo proposed a talent identification model for players aged around 18. This model used the analysis of variance (ANOVA) test for players' physical features, including body height, weight, bone age, choice reaction time, pace, and stamina. In this study, 62 youth soccer players participated. These players were divided between professional, college, and local teams based on their performance at 18 years old. Lastly, it was specified that youth players with fast leg and hand movement should be recognized as potential professional players [9].

Another study was conducted using an expert system under the title of sports talent identification. This study presented a model for 14 specific sports (speed jumping, kicking-based martial arts, push/pull-based martial arts, soccer, tennis, handball, volleyball, swimming, sport, ball throwing, and gymnastic). This web-based method was quantified for sports collection with the help of fuzzy logic based on the knowledge of many experts in human sports with a set of eleven tests, including various motor skills assessments, morphological measurements of players, and functional tests with their importance preference [10].

To this end, another study was conducted in Turkey, presenting a similar structure to the latter; the only difference was that the presented structure was not web-based and only focused on basketball players. This study aimed to develop a decision support structure through a fuzzy multi-variable decision-making algorithm to select eligible players and help them become future professional players. This model was tested in the sports and youth services center in Turkey with the participation of seven teenage basketball players aged between 7 and 14. In this study, data were gathered about players' physical attributes and technical skills. Then, the fuzzy analytic hierarchy process (FAHP), a suitable method to get opinions from experts and specialists, was employed for the general ranking of players using the technique for order of preference by similarity to the ideal solution (TOPSIS) [11].

A new method based on the combination of YOLO and deep fuzzy LSTM network is proposed. YOLO is utilized for detecting players in the frame and the combination of LSTM and Fuzzy layer is used to perform the final classification. The reason behind using LSTM along with fuzzy logic refers to its inability in coping with uncertainty which led to the creation of a more transparent, interpretable, and accurate predictive system. The proposed model was validated on SpaceJam and Basketball-51 datasets [12].

A new method work aims at using the Bayesian networks to model the joint distribution of a set of indicators of players’ performances in basketball in order to discover the set of

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their probabilistic relationships as well as the main determinants affecting the player’s winning percentage. [13]

A new method was expressed using the K-nearest neighbours (KNN) algorithm to evaluate the closest talent to the desired position in soccer. The method presented in this study was a suitable tool to examine what soccer position is the best option for a player considering his/her skills and attributes. The features required for a player in different points of the field were gathered from the combination of information presented by different papers in the literature where soccer experts have specified those specific physical and technical features each player should have to play in a given position [14].

Indian researchers researched to identify, enhance, and select sports talents for cricket. The result was a web-based system named "C-TIES," which is a cricket talent knowledge base from opinions of experts and specialists in cricket gathered using ordered weighted averaging (OWA) operator and relative fuzzy linguistic quantifier (RFLQ). This system classified the talent level of cricket players into five classes by applying the normalized adequacy coefficient (NAC). Subsystems for strengthening exceptional talents also used suitable algorithms based on OWA, RFLQ, and NAC to detect the weak points of a player and select the most talented player from a large group. This study decreased the time for identifying players' weak points and delivered a short list of talented players by decreasing the standard deviation [15].

Lozada et al. proposed the establishment of performance indicators for the player based on a multivariate statistical analysis called i-sport. The principal component analysis (PCA) and factor analysis (FA) were performed to determine each player's physical, technical, and general scores, and copula modelling was proposed to develop a coherence and consistency index extending the Z scoring methodology. These indices were employed to introduce a web-based expert system for real-time sports data analysis through R language, a powerful tool to identify soccer talents. Figure 1 illustrates the complete cycle of this information system called i-sport, enabling the continuous monitoring and comparison of players through a simple and appropriate method.

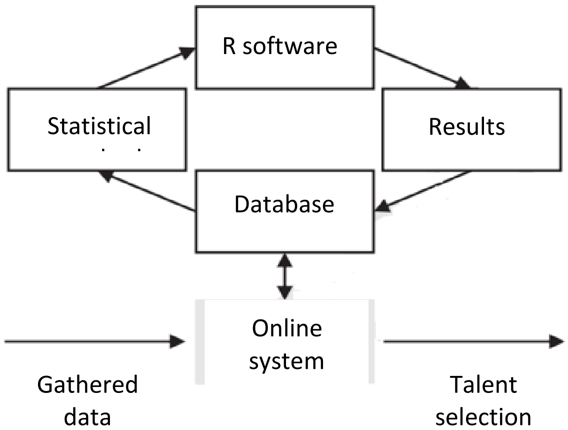

Fig. 1 Complete cycle of i-sport

i-sport identifies the main aspects and unique talents performing higher than average and increases the sports knowledge of athletes in the learning phase in every school, city, or region [16].

Some researchers developed a system based on classified information about taekwondo athletes through covering and embedded states, decision trees, and support vector machine

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(SVM) learning algorithms. These algorithms and methods were applied to evaluate different factors in classification, and this study mainly contributed to providing a support system to select talented athletes. For feature selection and classifiers, a new but simple method was proposed for the fair selection of athletes using decision trees and a support vector machine, providing coaches and sports managers with additional information about the most useful features for talent discovery. The studied field was the previous year's data of athletes from the national Ecuador taekwondo team. The feature analysis of these athletes led to identifying the required features and selecting the best candidate. It can be concluded that the proposed talent identification system can help determine the best athletes for the next competitions in this sport, in addition to delivering managers and coaches with correct information about athletes [17].

Table 1 demonstrates a set of AI algorithms and methods used in some studies on talent identification. The table below presents the sports investigated, along with the age of the players involved in the study. It also includes the number of features extracted from the players and references the research algorithm described in the background section of the study, providing a concise summary of the research process.

Table 1 Some important algorithms utilized with the number of features in specific sports

Algorithm	**Number of features**	**Age range**	**Sport**
Statistical regression	1	Without limitation	Jumping sports
Expert and fuzzy system	11	8-16	14 types of sports
Data mining	23	13 on average	Handball
ANOVA	6	18	Soccer
Multivariable fuzzy logic	4	16 on average	Basketball
Fuzzy logic	28	Without limitation	Cricket
K-nearest neighbor algorithm	10	8-31	Soccer
Multivariate statistical analysis	8	up to 16	Soccer
Decision tree and support vector machine	4	Without limitation	Taekwondo

Sports video analysis has indeed become a very active research area in recent years, with researchers from computer vision and sports communities working together to build datasets and develop new methodologies. Identifying the movements of athletes in recorded videos is a crucial aspect of analyzing sports videos in many previous studies [18-20]. This importance arises from the fact that recognizing group actions facilitates coaches in making better decisions and enables players to comprehend their performance in carrying out the strategies devised by them. Moreover, identifying individual actions can prove beneficial for training players by correcting minor errors in their actions. Overall, sports action recognition has great potential to contribute to the development of the sports industry and enhance people's experience of watching and playing sports [21]. Accordingly, although the focus of this paper is on recognizing the action of basketball players, studies conducted in this field of sport for action recognition are summarized in the following for better understanding.

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3 Proposed algorithm

For clustering 70 players participating in this study, which have similar attributes and features due to engaging in the same sport, the proposed algorithm first receives the intended dataset. It then applies a differential evolution (DE) algorithm to select influential features from the set of player features. In the next step, data are divided into training and test datasets. Finally, the players are clustered using a hierarchical clustering approach. Figure 2 indicates a structural schematic of the proposed algorithm.

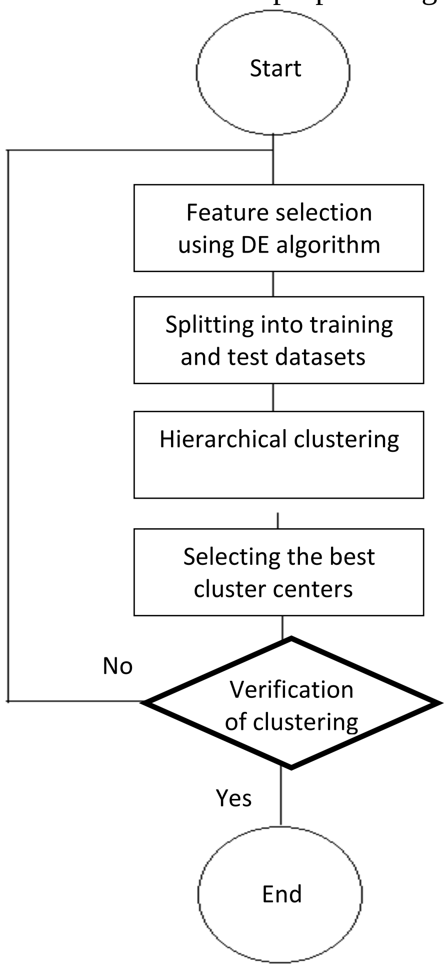

Fig. 2 Proposed algorithm structure

Existing data are randomly divided into two sets to create the training and test datasets. During training, the best cluster canters are selected. The optimality of these centres is determined during the test. The proper clustering condition is no significantly varying distance within clusters in the test step. If the cluster centres are not determined correctly, then clustering is performed again to specify the best cluster canters and realize the appropriate clustering.

In this study, 80% of the data are used for training and 20% for testing. Generally, feature selection aims to eliminate ineffective features. By neglecting these features, the size of the dataset is reduced, and the algorithm performance is improved. Therefore, selecting the most influential features is necessary. Hence, this paper employs the DE algorithm for feature selection. This algorithm consists of five steps: initial population generation, initial population fitness, mutation, crossover, selecting the superior population, and finally, evaluation.

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In the first step, the number of variables is assumed to equal the number of features extracted from players. For this reason, D is 61, and the variable equals 0 or 1. Zero denotes that the feature is not selected, and one denotes that the feature is selected. Generating the initial population is expressed by Eq. (1).

$$(X_{id}) = x_{imin} + ð_i(x_{imax} + x_{imin}) \qquad i = 1 \ldots NP \tag{1}$$

where $ð_i$ is a random number in this problem. Also, x_{imin} and x_{imax} are the upper and lower bounds of the feature value. Eq. (2) converts the continuous range of [0,1] into a binary value.

$$X_i^{t+1} = \begin{cases} 1 & r < S_i \\ 0 & r \geq S_i \end{cases} \tag{2}$$

$$S_i = \frac{1}{1+e^{-X_i^t}} \tag{3}$$

In the fitness evaluation of the DE algorithm, SVM is used to measure the error of feature selection as follows:

$$Err = \frac{M}{Total} \tag{4}$$

where M represents the number of samples.

The sequential selection algorithm is utilized for selecting the differential vector in which the population members are ranked based on their position. The probability of population selection is given by:

$$P_k = \frac{N_{max} - R_{k+1}}{\sum_{i=1}^{N_{max}} i}, \tag{5}$$

where P_k is the selection probability of the kth population, N_{max} is the last assigned rank, and R_k is the rank of the last population.

Then, roulette wheel algorithm is used to calculate the cumulative probability distribution and select the corresponding vector. In the mutation operation, the test vector for each member of the population is generated by mutating an objective vector and weighted difference. Lastly, the mutation vector is combined with the parent vector to produce the new generation. After feature selection using DE algorithm, the number of features is reduced to 32.

After selecting features, the agglomerative hierarchical algorithm is employed for data clustering. The similarity metric used is the Euclidean distance calculated by Eq. (6).

$$ED = \sqrt{(x_1 - x_2)^2} \tag{6}$$

In the first step, there is a table where the columns represent the samples, and the rows represent the features. First, a value with the lowest Euclidean distance (similarity index) from the first variable is found and placed in a cluster with this variable. This process continues to place those data with the lowest similarity index in new clusters, and clusters generated in this process involve to be cumulated with new variables. The termination

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condition of the algorithm is the number of target clusters as 5. In order to preserve the coherence of the clustering tree and avoid the creation of some individual subtrees, the proposed algorithm examines the general status of the tree. If subtrees are produced individually, they are connected based on the similarity index to complete the tree-making process [22]. The number of sub-clusters may increase in this process; for this reason, a measure of discrepancy between clusters should be defined to determine what clusters must be cumulated or separated. In most methods, this measure is defined as a link metric. In the proposed algorithm, determining the distance between clusters is performed using the minimum method, and each pair of clusters with the minimum distance are linked. Those clusters whose integration lowers the minimum distance are combined in each step.

4 Experiments

4.1 Dataset

The present study evaluates 70 male Iranian basketball players aged 14-16, considering the mental skills, technical skills, physical fitness, and anthropometric characteristics of players under the same standard conditions. In order to obtain more accurate results, players are divided into two groups, each with 35 individuals, according to the conditions described below.

First group:

- At least one year of experience in an under-14 or under-17 club team (professional or amateur)
- Continuous basketball training for at least five years
- Training three times a weak continuously
- Accounted for potential and promising basketball players by three reliable coaches

Second group:

- Interested in continuing basketball professionally
- At least one year of training experience in sports halls
- At least 1 or 2 basketball training sessions per month academically

Some researchers introduce elite athletes at the highest possible level in their age group. Also, they consider sub-elite athletes as individuals playing in local clubs.

Considering differences in physical fitness, cognitive skills, and anthropometric characteristics between players engaging in different sports, the age of general and special training will be different in the talent identification process [23]. Table 2 examines some sports from this perspective.

Table 2. Age of starting the fitness and special trainings in the talent identification process and the age of reaching the peak of performance in different sports

Sport	Age of starting general trainings	Age of starting special trainings	Age of achieving the performance peak
Basketball	10-12	14-16	22-28
Soccer	10-12	14-16	22-26
Handball	10-12	14-16	22-26
Boxing	13-15	16-17	22-26
Badminton	10-12	14-16	20-25
Cycling	12-15	16-18	22-28
Weight lifting	14-15	17-18	23-27

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4.2 Performance evaluation

In order to evaluate the proposed algorithm, different measures are used to measure the performance of the proposed method. The errors due to data clustering, running time, accuracy, and algorithm validation are assessed.

In Eqs. (7), (8), and (9), TP refers to the player of the same cluster detected correctly, whereas FN indicates the cluster member place detected incorrectly. Furthermore, FP is not the cluster member player that is wrongly identified as a member of the cluster, and TN is not the cluster member player that is correctly assigned to the cluster [24].

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{7}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{8}$$

$$Specificity = \frac{TN}{FP + TN} \tag{9}$$

Although R is a relative measure for evaluating the proper fitness of the model for dependent variables, MSE represents an absolute measure for calculations [25]. In addition, MSE denotes mean squared error and is given by Eq. (10), specifying how the results obtained from the proposed model are comparable with those of others.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{10}$$

5 Results

The structure of examined data, the proposed algorithm, and evaluation metrics are described in the previous section. This section presents the results obtained from implementing the proposed algorithm using MATLAB software and compares the results with several similar datasets. Fig. 3 shows the dendrogram of data clustering performed in this study, where the vertical axis denotes the Euclidean distance, and the horizontal axis represents the player number. Regarding the previous studies and the opinions from experts and coaches who participated in this study, five clusters, including 1 (elite), 2 (good), 3 (higher than moderate), 4 (moderate), and 5 (weak), are defined, and players are assigned to each cluster.

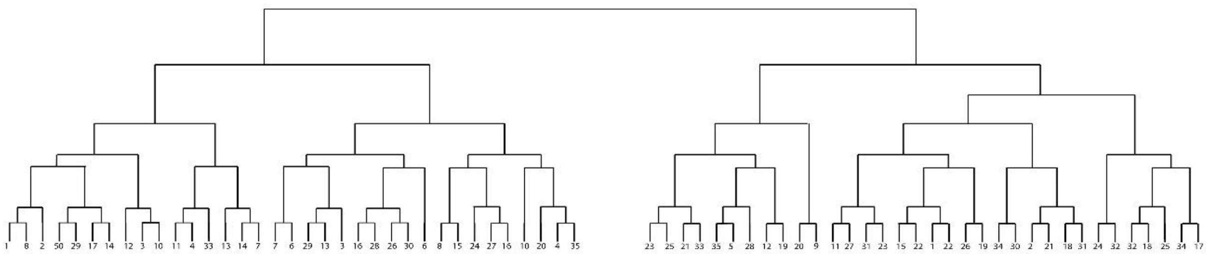

Fig. 3 Hierarchical clustering dendrogram

One of the fundamental metrics to evaluate algorithms is their error [26]. It is understood that lower error indicates the optimal performance of the proposed algorithm and its considerable

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capability in correctly clustering information. Diagram 1 demonstrates the error resulting from clustering.

Diagram 1 Error resulting from data clustering

We have presented all the data extracted from the players in various tests using diagrams 2 to 7. The results of the two research groups are depicted in distinct colors: blue represents the first group, and red represents the second group. Significant disparities are evident in the diagrams, which may arise from a variety of factors, including skills acquired during training and the players' latent talent.

Diagrams 2 to 7 indicate the differences in the skill level of players in the first group compared to those in the second group. Those players who have continuously trained and found the opportunity to play in club teams impressively differ in skills from players who have not experienced these conditions. For this purpose, it is tried to perform the correct clustering and thorough talent identification with the lowest error considering all influential factors jointly.

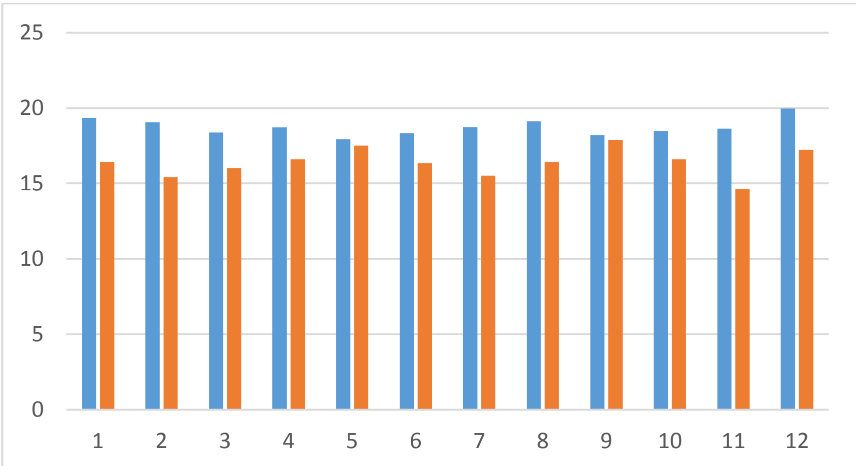

Diagram 2 Comparison of average mental skills using the OMSAT-3 questionnaire (blue: first group; red: second group)

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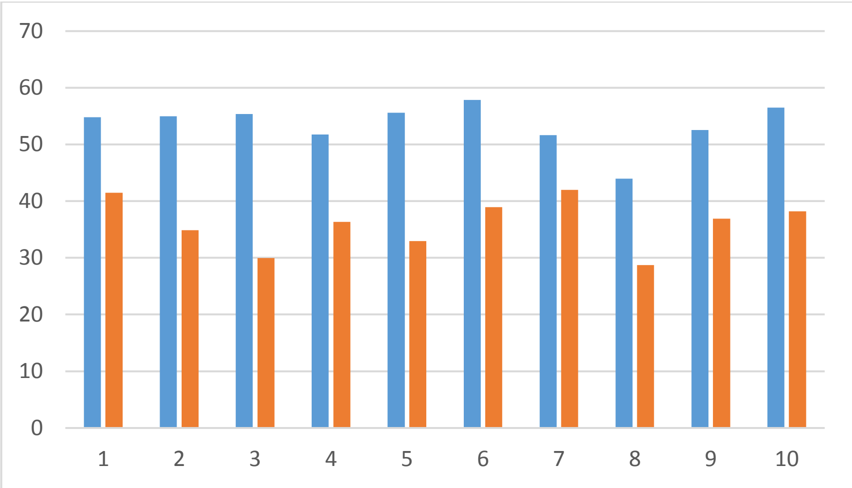

Diagram 3 Comparison of average physical skills (blue: first group; red: second group)

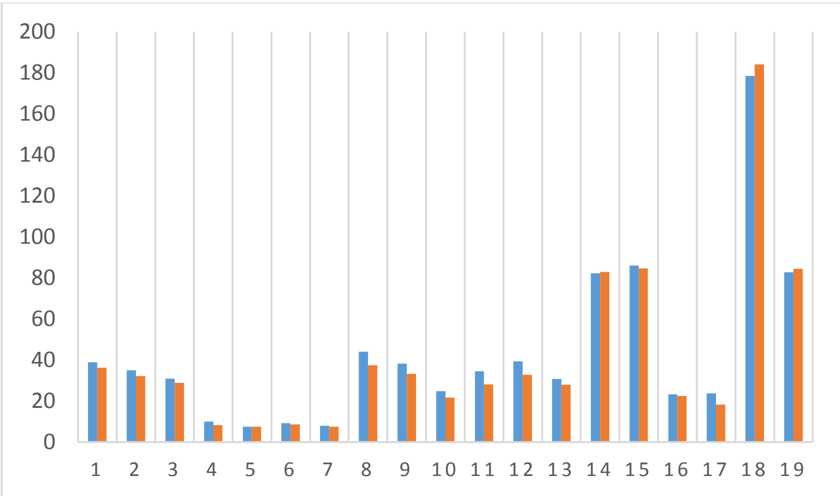

Diagram 4 Comparison of average anthropometric characteristics (blue: first group; red: second group)

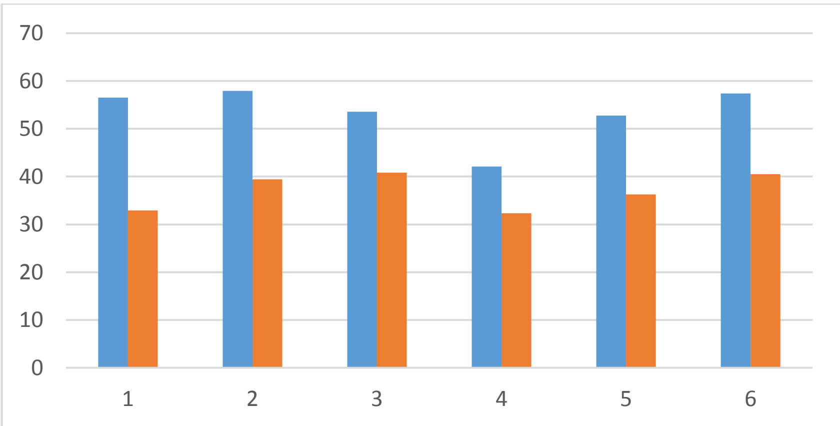

Diagram 5 Comparison of average technical skills (blue: first group, red: second group)

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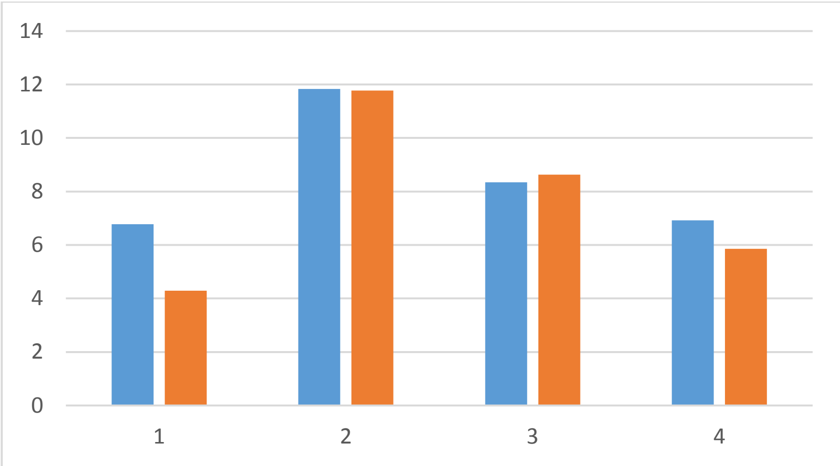

Diagram 6 Comparison of average Kinect outputs (blue: first group; red: second group)

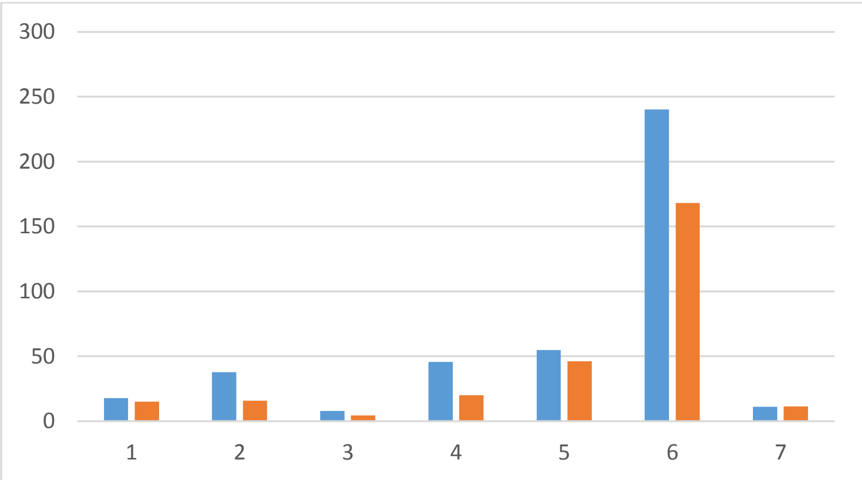

Diagram 7 Comparison of average results extracted from videos (blue: first group; red: second group)

In the clustering process, the elite cluster outlines players capable of joining professional clubs in premier leagues and national teams if adequate time and financial investments are allocated to them. Thus, for players with weak and very weak talent in a given sport, their potential talent should be evaluated in other sports.

The above evaluations are compared with the opinions of three professional coaches. Table 3 demonstrates the high accuracy of the proposed algorithm, as its results are in good agreement with those obtained from expert opinions.

Table 3 Comparison of the talent identification system with coaches' opinions

Cluster No.	Cluster name	Number of players based on opinions of coaches	Number of players in the system output	Accuracy (%)
1	Elite	8	7	87.5
2	Good	17	16	94.11
3	Moderate	11	11	100
4	Lower than moderate	18	19	94.7
5	Weak	16	17	94.11

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6 Conclusion

This paper aims to apply AI algorithms for clustering basketball players based on measuring their skills and capabilities. Generally, it should be noted that AI will evolve the sports world soon and will increase the quality of sports activities. For example, data from team players will be employed to analyze their performance. This paper has proposed an approach to place players in similar clusters by combining information about mental skills, physical fitness, individual skills, and anthropometric characteristics, as well as using various tools, such as Kinect and videos. In 2011, the concept of floating players in the field was introduced, which replaced the concept of specialized position for each player by determining the position of players in the next match based on their performance in previous matches. This concept justifies deploying players' full potential and improving team performance by updating clusters. In this study, results have been obtained from evaluating 70 under-14 and under-17 basketball players for two years; half have engaged in this sport professionally.

Table 3 compares the proposed algorithm with other clustering counterparts. Results indicate the superiority of the proposed algorithm in terms of accuracy and clustering error. Also, the running time of the proposed algorithm is lower than other algorithms.

Results show that in male basketball, influential factors, such as mental skills, anthropometric characteristics, physical fitness, technical skills, and during-match activities, can be employed to introduce talent identification patterns. Moreover, concerning the well-known features in each section and their high compatibility with conducted research, it can be said that the proposed method delivers much better solutions than other clustering algorithms.

It is recommended that future researchers develop intelligent talent identification processes for different sports using AI algorithms and examine other factors affecting talent discovery, such as hereditary and genetic factors and blood tests.

Table 4 Comparison of the proposed algorithm with some clustering algorithms

Algorithm name	Accuracy (%)	Clustering error (%)	Running time
Proposed algorithm	94.08	5.92	2.41274
Hierarchical	90.15	9.85	1.98425
Distribution-based	92.78	7.22	4.85714
K-means	93.91	6.09	2.18746
SOM	93.5	6.5	2.45715

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