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Use of AI methods to assessment of lower limb peak torque in deaf and hearing football players group

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Abstract: Monitoring and assessing the level of lower limb motor skills using the Biodex System plays an important role in the training of football players and in post-traumatic rehabilitation. The aim of this study is to build and test an artificial intelligence-based model to assess the peak torque of the lower limb extensors and flexors. The model was based on real-world results in three groups: hearing (n=19) and deaf football players (n=28) and non-training deaf pupils (n=46).

The research used a 4-layer forward CNN neural network with two hidden layers with typical normalization for small data sets and Multilayer Perceptron (MLP) based on MatlabR2023a software with Neural Networks and Deep Learning toolkits and semiautomated learning algorithm selection using ML.NET

The 70-90% accuracy shown in the article is sufficient here. AI provides a highly accurate, objective and efficient means of assessing neuromuscular performance, which can improve injury prevention and rehabilitation strategies.

The high accuracy shows that AI-based models can help with this, but their wider practical implementation requires further cross-disciplinary research. AI, and in particular MLP and CNN can support both training methods and various gaming aspects. The contribution of the research is to use an innovative approach to derive computational rules/guidelines from an explicitly given dataset and then identify the relevant physiological torque of the lower limb extensors and flexors in the knee joint. The model complements existing methodologies for describing physiology of peak torque of lower limbs with using fuzzy logic, with a so-called dynamic norm built into the model.

Keywords: Biodex, soccer, hearing-impaired and deaf football players, deaf non-training, computational model, artificial intelligence.

1. Introduction

Monitoring and accurately assessing the level of motor skills of athletes plays a key role in the initial sports selection process as well as in the training of athletes at every stage of their sports career. Success in sports depends on the innate motor skills possessed by the athlete, but it also depends on the impact of training on the change of the athlete's biomechanical variables. In order to assess training changes, a repeatable, cyclical, objective and reliable assessment of biomechanical variables, motor skills and cardiorespiratory capacity is needed [3, 12]. In football, the strength and dynamics of the lower limbs are very important. The research results indicated that muscular thighs allow players to generate high muscle torque. This skill is also very important when jumping, kicking, turning and changing the speed of movement [9]. Measurements of the level of lower limb motor skills can be performed as vertical jump tests, e.g. CMJ or SJ on a dynamometric platform, or as isokinetic tests assessing the strength of the lower limb extensors and flexors in the knee joint, e.g. at the Biodex System [28]. Assessment of changes in the level of the peak torque value of the lower limb extensors and flexors in the knee joint can help develop an effective training program focused on improving the locomotor speed and explosive power of the lower limbs of athletes, e.g. soccer players [16]. Explosive strength training allows for the improvement of the force-time characteristic, as an increase in the speed of force development and the generation of greater power of the lower limbs [21]. Studies [13] have shown, among other things, the key role of knee extensor training in achieving sprint performance, especially when taking into account peak torque values in the assessment of sprint and jumping performance [33, 38]. According to Wrigley, isokinetic tests of lower limb extensors and flexors in the knee joint are sufficiently reliable to examine the variability of strength in soccer players. Isokinetic measurement of peak knee flexion and extension torque is considered reliable if performed at an appropriate angular velocity in relation to the assessment of the intended effect: strength, speed or endurance, which is related to the specificity of the soccer game and position on the soccer pitch [16, 39]. Regular assessment of the peak torque of the extensors and flexors of the lower limbs in the knee joint allows determining the appropriate value of the training load of the lower limbs and the knee joint, which can be very important for preventing injuries and training injuries [18]. Pietraszewska et al. in their studies drew attention to the relationship between the value of the moment of force of the extensors and the value of the moment of force of the knee joint flexors [22]. The H/Q ratio is important for maintaining knee stability during dynamic activities: dynamic take-off, change of direction, braking while running, kicking the ball, etc. It is assumed that H/Q ratio values exceeding 60% can effectively prevent injuries and damage to the anterior cruciate ligament (ACL) and hamstring strains. According to Kim and Hong [19], soccer players with an H/Q ratio exceeding 60% are less likely to suffer from non-contact lower limb injuries. In the event of an injury or contusion, knowledge of the values of biomechanical variables related to the athlete's lower limbs may be an important part of the rehabilitation process, as a rehabilitation target value [26]. The key challenge of modern science is the objectivity of the evaluation of the results of research. In sports, in the case of analyses performed using artificial intelligence, the drawback is the relatively small groups, numbering a dozen or so to several dozen athletes.Small group sizes require appropriate selection of artificial intelligence methods and techniques and their precise tuning. Using AI-based models to assess the peak torque of lower limb extensor muscles in football players may enable increased precision and repeatability of assessments, provide more objective measurements, and may support personalization of training and enable continuous monitoring of the impact of training on the values of morphological and biomechanical variables of the athlete. Artificial intelligence (AI) can provide useful tools to support the research already conducted (Figure 1) [15, 35, 39]. Despite the popularity of AI methods (especially machine learning - ML), the potential associated with them in the computational analysis of footballer evaluation has not been fully exploited so far [40, 10]. A review of the 6 largest bibliographic databases using keywords (artificial intelligence, football, evaluation and similar) yielded 39 publications (2004-2023), which can be divided into several thematic groups: video analysis (including strategies and styles of players and entire teams), analysis of the impact of individual characteristics on the characteristics of players' game, and reviews of the impact of introducing AI/ML to team games such as football. The most interesting seems to be the review by Lee et al. on the post-pandemic transformation of football articles thanks to AI. The identified changes occurred in three areas: social and technological changes, approaches to performance training, and injuries to body parts [20].

The aim of this study is to build and test an AI-based model for assessing the peak torque of the lower limb extensors and flexors of soccer players.The summary of the main findings and contributions of the research will show the potential and possibilities of supporting the assessment of footballers using the Biodex system and AI-based analysis. This will allow for the continuation of research on larger, more homogeneous groups of footballers at different levels, including those with deficits, and the development of a unified research method based on the wider use of AI. We expect to improve the accuracy of predictions, automate the inference process, and in time: discover new, as yet unknown associations and mechanisms underlying them.

It should be noted that the mathematical models used so far have failed to create a model of a champion athlete based on anthropometric data, body composition, running speed, lower limb power, cardiorespiratory capacity and other tests. Perhaps advanced artificial intelligence models will enable defining the boundary conditions of an ideal athlete's figure.

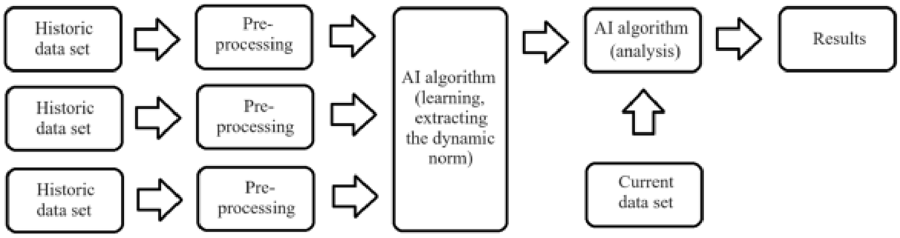

Figure 1.Diagram of established AI model.

AI methods for assessing lower limb peak torque in deaf and hearing football players have several advantages. They can increase the accuracy and consistency of measurements, minimising human error and subjective bias. AI can also process large data sets quickly, enabling real-time analysis and comparisons between groups. Disadvantages, however, include potential biases in AI models, especially if they are trained on limited or unrepresentative data. In addition, the cost and complexity of implementing AI systems can be a barrier to widespread use in sport.

2. Materials and Methods

2.1. Material

The model was based on real-life results in a group of hearing (Polish extra football league and third league of football) and hearing-impaired and deaf football players of Polish national team of Polish Deaf Sport Association. None of the participants had any history of musculoskeletal injuries and were allowed to participate in the study. In this way, the following study groups were collected:19 hearing male soccer players (Group 1),28 deaf male soccer players (Group 2), 46 deaf non-training male pupils (Group 3), a total of 93 men (Table 1).The research was approved by the Bioethics Committee of the Nicolaus Copernicus University in Toruń, Collegium Medicum in Bydgoszcz (approval No. 330/2014 dated April 29, 2014).

Table 1.Participants' characteristics.

Parameter/variables	Group 1 (n=19)	Group 2 (n=28)	Group 3 (n=46)
Age [years]			
Mean	19.6	20.1	21.6
Standard deviation (SD)	2.0	3.5	4.4
Body height [cm]			
Mean	173.2	174.9	175.5

Standard deviation (SD)	9.8	4.5	6.4
Shin length [cm]			
Mean	38.4	38.7	39.3
Standard deviation (SD)	2.5	2.9	2.8
Body mass [kg]			
Mean	66.9	70.4	72.9
Standard deviation (SD)	17.4	9.6	8.5
Dominant leg			
Left (L)	3 (15.8%)	4 (14.3%)	7 (15.2%)
Right (R)	16 (84.2%)	24 (85.7%)	39 (84.8%)

2.2. Methods

This article is an interdisciplinary development of research [30, 31] - concerning a social group that has been overlooked in academic research - deaf football players and physically inactive deaf students. The results of the study were compared with the authors' own findings and those of scientific publications that dealt with deaf football players [11, 13, 22, 27, 30]. At this studies [11, 13, 22, 27, 30], in terms of body height, body mass, muscle mass between the study groups, no statistically significant differences were observed. Statistically significant differences appeared in the study of peak torque of lower limbs ($p<0.001$) is in favor of the hearing football players.

Weaker muscles and muscle imbalance result in poorer stability and an increased risk of injury. One of the most suitable devices for testing muscle strength is the Biodex System 4 Pro equipment (Biodex Medical System, Shirley, NY, USA), who was used to measurements at this study. The device was calibrated, in accordance with guidelines described in the test protocol, before each series of daily measurements. Before the test commencement, the participants was immobilized in such a way as to isolate the movement in the examined join, preventing any support from other body parts (blocking belts running crosswise throught the chest, a horizontal belt running over the hips, a belt running over the thigh to stabilize the lower limb movement in sagittal plane). An additional blocking of upper body segments was provided by the grip of upper limbs against the seat frame. The measuring transducer rotation axis was set to match the joint rotation axis. The examination was performed separately for the right and left lower limbs. Before torque recording, each participant was acquainted with isokinetic movement specifity and the test protocols. During all measurements, the subjects received verbal and visual encouragment to maximize their potential. The isokinetic test was conducted in the concentric muscle work mode. The following measurements were performed: isokinetic measurements, concerning the peak torque of knee joint extensors and flexors (left and right, separately) at 3 angular velocities: 60, 180, and 300 deg·s-1. The movement was executed from 90^0 to the physiological extension of lower limb in the knee joint (0^0). For each of the angular velocities, 5 repetition were recorded for the knee joint, with no breaks between repetitions. There was a 60-second break between the 3 series of tests. The break between the isokinetic tests of right and left lower limb lasted 5 minutes.

2.2.1. Data set

An MS Excel spreadsheet (Microsoft, Redmond, USA) was used to store the data. Data set auditing was provided to remove incomplete, outlier and uncertain data. The data collected was analyzed using descriptive statistics. Data was acquired using the Biodex System 4 Pro isokinetic (eccentric and concentric) neuromuscular assessment and training kit. The data concerned the peak torque of test subjects' lower limb from all three study groups (groups 1-3).

The Biodex System 4 Pro makes it possible to assess the athlete's exposure to injury risky examining peak torque ratio of extensors and flexors - separately - of the left and right lower limb. Each participant in the study took part in a lower limb assessment during five forward and backward repetitions:

- Extension: movement at the knee joint in the sagittal plane from 90 to 0 degrees (straightening),
- Flexion: movement in the other direction to lateral movement (bending).

The following parameters were assessed and analyzed in the study using three movement speeds in isokinetic mode with restriction: 60 degrees/s, 180 degrees/s and 300 degrees/s (angular velocity):

- PEAKTQ (R, L): peak torque value for both lower limbs: R – right, L – left [Nm],
- PEAKTQ/BM: ratio of peak torque to body weight [Nm/kg],
- H/Q: the ratio of concentric hamstring peak torque during lower limb flexion to concentric quadriceps peak torque during lower limb extension [%] [22].

2.3. Statistical analysis

Statistica 13 software (StatSoft, Tulsa, USA) was used to statistically analyse the results of the study. The distribution of the data was checked each time using the Shapiro-Wilk test. If the data had a near-normal distribution then description by mean and SD (standard deviation) and parametric tests were used in further analyses. If the data had a distribution that deviated from normal then further analyses used description by minimum value, lower quartile (Q1), median, upper quartile (Q3), maximum value and non-parametric tests. Correlations between values from the measurements and results from the model were calculated using the non-parametric Spearman's test (Spermann's Rho value was used as the basis for assessment). The threshold for statistical significance in the study was set at $p \leq 0.05$.

2.4. Computational analysis

In addition, the data collected was are also used in predictive models to assess future values of certain key measurements. The learning dataset, after normalization and scaling of both input and output signals, were randomly divided into two subsets: a learning set (70% of all samples/records) and a validation set (30% of all samples/records). Normalization and scaling were necessary for an equal influence of the value ranges of all signals processed by AI algorithms later during their work.

In this part of the study, four approaches were chosen to solve the modeling problem based on the authors' knowledge and experience, taking into account their simplicity, ease and widespread applicability (also to ensure comparability of results with those of other studies):non-linear polynomial regression, multilayer perceptron (MLP (as an example of traditional neural network, convolutional neural network (CNN) as an example of deep neural networks), semi-automatic approach based on ML-NET built in Visual Studio 2022 (Microsoft)

Polynomial regression assumes that a higher polynomial degree achieves a better fit of the model to the non-linearity of the samples, increasing the computational complexity of the modeling. Assumed correlation coefficient: at least 0.8 with the complexity of the approximating function difficult to estimate.

The study also used a data-driven approach (i.e. without the need for rules, just based on the relationships between inputs and outputs extracted automatically by the network). Three different approaches were compared to solve the same problem. First of them was Multilayer Perceptron (MLP) based on MatlabR2023a software with Neural Networks and Deep Learning toolkits (MathWorks, Tulsa, USA). The second approach was Convolutional Neural Network (CNN) based on MatlabR2023a software with Neural Networks and Deep Learning toolkits (MathWorks, Tulsa, USA). The third approach was semiautomated learning algorithm selection using ML.NET (57 algorithms were tested).

MLP often provides the best results with the simplest possible structure (three-layer) with minimum root mean square error (RMSE) optimization, backpropagation (BP) algorithm, and naive initialization technique. The advantages of this solution are: ease of implementation, fast convergence, sufficient performance, no prior knowledge.

The selection of a steep transfer function (sigmoid) ensures better transfer of differences with a higher number of categories, which is important for the study's required data characterization.

The research used a 4-layer forward CNN neural network with two hidden layers with typical normalization for small data sets. The selection of hyperparameters in CNN thanks to more hidden layers (two instead of one) may give better results than in three-layer MLP in the case of complex input patterns, because after passing through convolutional layer(s), the input vector is extracted into a more complex feature map (activation map).

ML.NET is a free library for machine learning on the .NET using, among others,C# language. Allows you to train networks for classification and/or prediction purposes without the need for programming, ensuring that many (from several dozen to several hundred) training algorithms and network structures can be tested for one problem. From the above for some reasons, it can provide a faster check of a large solution space, also as a preliminary study.

The choice between the above four approaches was based on an assessment of the following factors for each approach: complexity of the task, time limitations, available (limited) resources, required accuracy.

A total of 140 models were run. Main evaluation criteria for the performance of the models were RMSE value and accuracy.

The number of neurons in input layer of ANN is adjusted to the number of input parameters, and the number of neurons in output layer is adjusted to the number of output parameters. However, the number of neurons in the hidden layer (in the case of MLP) or the number of neurons in hidden layers (in the case of CNN) are selected experimentally based on the knowledge and previous experience of the research team and by the successive approximation method in search of the global maximum. This approach requires the examination of many neural networks (even several hundred).

Network training was performed by repeating patterns used for learning and modifying the network weights accordingly, until the target RMSE is reached within a certain number of epochs (number of epochs not exceeding 1000). Accuracy of network training in the study was defined as the part (fraction) of data for which model reports correct data in the training data set. Therefore, an accuracy of 90.00% means 90 correct results (classification, prediction) for every 100 test examples.

The computational modeling shown in the study becomes cost-effective and usefull when previously used descriptive traditional statistical tools do not produce statistically significant results or have insufficient accuracy. This means that the relationships between input data sets and output data sets are highly non-linear and difficult to describe using mathematical functions. However, it should be noted that full use of the possibilities of computational analysis requires not only knowledge and experience, but also experimental confirmation of assumptions, which is very time-consuming and requires checking many algorithms and model structures, including tuning hyperparameters. Sometimes you have to check over 100 models to find one good solution. From the above reasons, this article presents only the results achieved by the best models.

We used RMSE as a useful loss function, the use of which is appropriate when large errors are more costly and it is important to minimize them.

3. Results

The main part of the results includes a comparison of a selection of the best models used for solving our problem and is presented in Table 2. We ran more than 100 different computational models as part of the study, but only the best of these are presented in Table 2. It is worth noting that only "pure" approaches were used to compare the models, i.e. hybrid models (i.e. combining different methods and techniques) were not used. For the utility of this study, the threshold of accuracy considered sufficient was estimated to be 80%.

Table 2. Comparison of the outcomes of the models used in the article.

Model	**Accurracy (learning) [%]**	**Accurracy (testing) [%]**	**RMSE**
MLP 12-15-1	83.22	85.21	0.001
CNN 12-15-15-1	80.16	81.33	0.002
ML.NET SdcaMaximumEntropyMulti	73.22	75.58	0.01
Regression (polynomial)	Spearmann's Rho value: 0.712 ($p<0.05$)		

3.1. MLP and CNN

Aforementioned comparison shows that the MLP-based solution for the dataset under study proved to be the most accurate. This solution offered a quick and easy problem solving that could be used in systems similar to real-time systems (maximum learning time was 100 seconds, average: 31.61 seconds). However, appropriately checked and selected data (input and output) must be ensured, but full explicit knowledge concerning rules/mechanisms linking the both data sets (input and output) is not required. Above approach allows the solution to be quickly adapted to further/other data, including from other Biodex System or another group of tested players. This may be significant due to possible high volatility of parameters in different groups of athletes, resulting not only from age, level of advancement or disability, but also from the division into groups training intensively and training amateurs. It is worth emphasizing that the use of networks with significantly different data (with the same number of input and output data) will require training the MLP network on new data, which can be automated (e.g. during a technical break of the Biodex device).

Unfortunately, changing the size of the data (both input and output) will require changing the structure of ANN (respectively input and output layer). The number of such cases may be large, e.g. new parameters or new measurement devices included in the analyses. This always requires testing the accuracy of the measurements, i.e. checking how quickly the network learns from new data, also during normal operation. A similar principle is to monitor RMSE and accuracy values as part of maintaining an ML system.

Various activation functions and their combinations for MLPs and CNNs were experimentally verified with the best results achieved for the sigmoidal activation function, particularly due to the greater flexibility of such networks. The observations confirm that the research problem posed in the article is complex, and modeling, optimization and prediction in training players will be a computational difficult task requiring further research (Table 3). As part of the study, we performed hyperparameter tuning, including the choice of the number of layers and selection of the number of neurons in the hidden layer(s), as well as the selection of the activation function. Each ANN layer contains neurons with a sigmoid activation function, chosen mainly because it is characterized by a high degree of flexibility. Using other activation functions gave much worse results.

Table 3. The five best MLP network models (best in bold).

Structure of ANN	Activation function (hidden layer)	Activation function (output layer)	Accuracy (learning) [%]	Accuracy (testing) [%]	RMSE
MLP 12-10-1	Sigmoid	Sigmoid	81.33	82.07	0.01
MLP 12-12-1	Sigmoid	Sigmoid	82.04	84.11	0.01
MLP 12-15-1	**Sigmoid**	**Sigmoid**	**83.22**	**85.21**	**0.001**
MLP 12-18-1	Sigmoid	Sigmoid	81.25	83.02	0.01
MLP 12-20-1	Sigmoid	Sigmoid	80.74	82.17	0.01

Scikit-learn 1.3.2 was used to verify the models in the Python environment (Figure 2). It is a statistical tool popular among ML developers to compare models solving a particular computational problem. It is easy to use and has lower variance estimates compared to other methods.

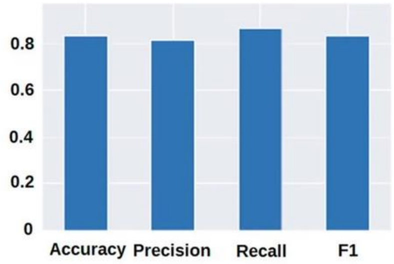

Figure 2. Outcomes of validation and performance comparison.

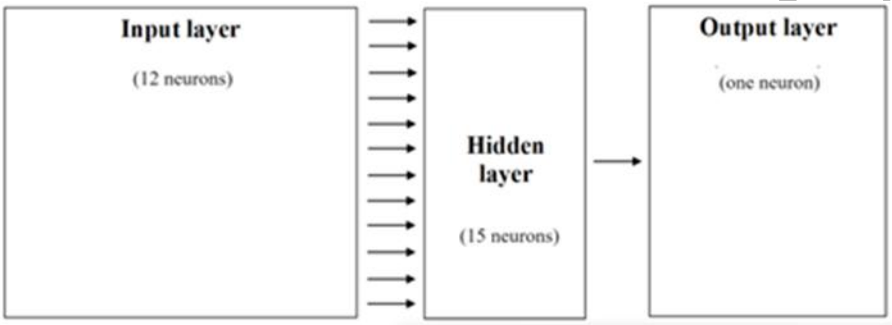

Figure 3. Diagram of established best model.

Simple, useful AI algorithms, currently implemented and tuned manually, are more accessible, simpler, more transparent in operation (especially in edge computing applications) and more readily used than complex, time-consuming to implement AI systems.

3.2. Polynominal regression

For polynomial regression calculated correlation values were too low (below the assumed threshold of 0.8), although various techniques considered effective were used: spline smoothing, moving average and weighted average.

3.3. ML.NET

The results of the study for ML.NET are presented in the tables 4-6.

Table 4. Classification Group 1.

Parameter	Best algorithm	Accurracy [%]	Remarks
Length of shin	SdcaMaximumEntropyMulti	48.29	To low accuracy

SdcaMaximumEntropyMulti is a linear model for solving multi-class classification problems. For a given number of classes and number of features, it assigns to each class a vector of coefficients and a variance, for a given probability of observing the class.

Table 5. Classification Group 2.

Parameter	Best algorithm	Accurracy [%]	Remarks
Length of shin	LbfgsMaximumEntropyMulti	95.33	Next was FastForestOva (51.72%)
Free Fat Mass (FFM)	SdcaMaximumEntropyMulti	51.25	
R PEAK TQ AWY	SdcaMaximumEntropyMulti	75.58	
L PEAKTQ/BM TWD	LbfgsMaximumEntropyMulti	54.17	

LbfgsMaximumEntropyMulti is a generalization of linear logistic regression, with logistic regression being designed for binary classification, while this model supports multiple classes.

Table 6. Classification Group 3.

Parameter	Best algorithm	Accurracy [%]
Length of shin	SdcaMaximumEntropyMulti	59.27
FFM	SdcaMaximumEntropyMulti	72.52
R PEAK TQ AWY	SdcaMaximumEntropyMulti	73.56

The use of artificial intelligence methods, in particular algorithms such as LbfgsMaximumEntropyMulti and SdcaMaximumEntropyMulti, provides high accuracy (70-95%) in the assessment of lower limb peak torque in both deaf and hearing football players. The algorithms are designed to process large data sets and capture complex relationships between variables such as shin length, fat-free mass (FFM) and relative peak torque (R PEAK TQ AWY). By analysing these parameters, AI can accurately predict muscle performance and torque generation in athletes. The LbfgsMaximumEntropyMulti algorithm, known for optimising model performance, works to classify and predict based on input data, while SdcaMaximumEntropyMulti enhances the generalisation capabilities of the model. These models effectively deal with multidimensional data collected from athletes, enabling precise peak torque assessment.

The proposed models have shown their effectiveness. The contribution of the study is in its use novel approach to extract computational rules from explicitly provided data and then to identify relevant mechanisms in healthy and deficient individuals. The model complements existing methodologies to describe physiology, possible pathological mechanisms and methods of restoring full fitness (including through rehabilitation) using e.g. fuzzy logic.

4. Discussion

Radivoje et al. research has shown that motor factors constitute an significant parameters in assessment a football player's performance to make the team's success in the match more probable [25]. Tests to determine the peak strength moment and lower limbs' power form the basis of research related to sport, training and the rehabilitation process. This is complemented by cardiorespiratory fitness tests. This article, due to the size of group 2 (28 Deaf soccer players), plays a special role in linking the analyzes carried out with this social (sports) group. Deaf athletes can achieve similar training effects, but this requires a much longer training period or special training conditions that are impossible to achieve due to the lack of inclusiveness of hearing sports. The slowed physiological development of the respiratory system of deaf people and the lack of verbal contact with the sports and training environment cause the sport of deaf people to be separated from the sport of hearing people and paralympians.

The research team's work will aim to create a universal AI model of strength and cardiorespiratory fitness, defining a range of values characteristic of non-trainees, recreational trainers and professional trainers. It will most likely be necessary to define such a model depending on the sport practiced. It is possible that in the case of deaf people, a separate AI model will be required.

Leveraging AI transformation of the training process can improve and accelerate analysis through better use of knowledge extracted from data and predictive abilities (Table 7).

Table 7. SWOT (strengths and weaknesses, opportunities, threats) analysis of AI-based assessments of selected parameters of soccer players (own version).

	Positive	**Negative**
Internal	**Strengths** Improved possibilities of data analytics Injuries prediction Training and performance adaptation and optimization Historical and predictive analysis	**Weaknesses** Integration of data sets AI complexity Algorithm bias Privacy, including sensitive personal data
External	**Opportunities** Improved training and performance Integration of various approaches	**Threats** AI reliability and transparency of decision-making process Low social awareness and lack of acceptance

Integration of solutions based on AI increases the possibility of accuracy, relevance and repeatability.

The study on the use of AI methods to assess lower limb peak torque in deaf and hearing football players is based on the need to understand the differences in neuromuscular performance that may exist due to sensory differences. From a mechanical point of view, the peak torque of the lower limb is crucial for explosive movements, balance and overall athletic performance, which are fundamental in football. Deaf athletes can rely more on visual and proprioceptive feedback to compensate for the lack of auditory cues, potentially affecting their neuromuscular control and force generation. Artificial intelligence provides a sophisticated tool to capture and analyse subtle changes in muscle activation and torque output that traditional methods may miss. By using AI to analyse large data sets, it is easier to identify patterns and trends that differentiate the performance of deaf and hearing athletes. What's more, AI's ability to analyse real-time data allows for continuous monitoring of athletes, providing more comprehensive insight into how peak torque changes with fatigue, training load or injury risk. This is crucial as neuromuscular adaptations can differ between it highlist the two groups due to their dependence on different sensory stimuli during movement. The AI-based approach provides high precision, minimizing the subjectivity of human assessments, which is particularly valuable to comparing different populations, such as deaf and hearing players.

The extracted feature sets serving as learning sets indicated that it was easier to capture and group differences in groups 2 and 3 than in group 1, as reflected in the accuracies presented in Table 4 (for group 1) and Tables 5 and 6 (for groups 2 and 3) respectively. At the same time, this may imply that the variation of parameters in group 1 is much greater than the variation of parameters in groups 2 and 3, and therefore indicates the need for further research into the so-called dynamic norm in healthy players. At the same time, this represents an advantage of our method in the adopted application, as the accuracies in the hearing deficit groups are high and sufficient.

In addition, the study can help optimise training programmes by identifying specific neuromuscular deficits in each group, leading to targeted strength training interventions. Overall, the ability of artificial intelligence to process and interpret complex neuromuscular data opens up new possibilities for understanding performance differences rooted in sensory differences, helping clinicians and coaches to adapt their approaches more effectively.

4.1. Limitations of the study

There are several limitations and challenges as outlined in Table 8 that researchers and practitioners should be aware of.

Table 8. Limitations and challenges (own analysis) [2, 6, 29].

Limitation	Detaileddescription
Low data quality and quantity	The quality of Biodex system data can be affected by various factors (equipment calibration, participant effort and environment al conditions). In addition, combining data from different

	Biodex devices into a single set may require comparison of their parameters and calibration. The resulting variability in data quality can affect the reliability of AI models, requiring careful standardization and quality control measures.
	The size of the dataset(e.g. big data or small data set) can influence both to the treatment of the dataset, as well as the choice of a particular AI method (some of them require datasets of 5000-10000 records for correct operation.
Limited generalization	AI models trained on specific data sets may have limited generalizability to different populations, styles of play or levels of competition - for the aforementioned reasons, it is crucial to validate models cross different groups of footballers to ensure their wider applicability.
Dynamicnature and variability	Soccer is a dynamic sport with rapidly changing conditions during a match (in different phases of the game, along with changing players), which may not be captured by AI models based on static assessments.
	Biomedical parameters can vary significantly between individuals due to factors such as age, fitness level, injury history and genetics, which need to be taken into account to provide accurate and meaningful assessments.
Validation	ecessary to ensure that AI-assisted assessment are validated against established gold standards or traditional measurement methods to ensure the accuracy and reliability of AI models.
Model interpretability	AI models (especially ML) lack transparency (i.e. understanding how models arrive at specific predictions) and interpretability – ensuring this is key to gaining the trust of coaches, players, clinicians and decision-makers.
Integration with on-field performance	Directly linking biomechanical parameters from the Biodex to on-field performance indicators is difficult due to the complexity of football movements and the multitude of factors affecting the performance of individual players, including adapting to their position on the field of play, stage of the match, weather conditions, etc.
Need to monitor long-term effects	Long-term monitoring using AI methods can face challenges in maintaining participant engagement and compliance and preventing data gaps.

Addressing the aforementioned limitations requires a coherent strategy (definition of goals and steps to reach individual outcomes), an interdisciplinary approach involving computer scientists, sports scientists, biomechanists, data scientists and ethicists. Further research and technological advances are needed to meet the intended requirements and increase the effectiveness of AI-based assessments in the context of footballers' biomedical parameters.

4.2. Future research directions

The datasets associated with training, matches and individual players are growing rapidly as a result of both the increase in demand and the ability to use them effectively, with accuracies of 70% to 95% being achieved [AWAN, VAN den Tilar]. Further research can contribute significantly to understanding players' physical conditions, injury prevention, and performance optimization (Table 9).

Table 9. Directions for further research (own concept) [5, 7, 8].

Direction	Detailed subsequent tasks
Further integration of AI algorithms with Biodex data	1. Investigate the feasibility and limits of integrating AI algorithms (including ML) with Biodex system data to analyse and predict specific biomedical parameters related to football performance. 2. Develop more complex, dedicated models that can better interpret Biodex measurements to comprehensively assess muscular strength, balance and stability, also in relation to age, gender, sophistication and, in patients, the degree of deficit and stage of rehabilitation.
Performance monitoring and enhancement	1. Using AI to monitor and improve performance by analyzing Biodex data against previously used and newly developed (using AI) key indicators in football. 2. Developing models that correlate Biodex-derived parameters with actual on-field performance indicators (e.g. sprint speed, agility and jumping ability). 3. Validate AI models against traditional assessment methods, compare them to established standards to ensure their reliability and accuracy in predicting biomedical parameters. 4. Collaboration between sports scientists, biomechanists, data scientists and football specialists to develop optimal assessment methods.
Profiling	1. Explore the integration of other sensor technologies, such as wearables, to complement Biodex data with more comprehensive analysis. 2. Explore the use of AI to create comprehensive profiles (including biomechanical) for football players based on Biodex assessments and simultaneous analysis of multiple parameters to gain a more holistic understanding of players' physical conditions.
Optimization of training and rehabilitation programs	1. Obtain AI-based personalized training program recommendations (adjustments to intensity, frequency and type of exercise, including based on the aforementioned biomechanical profiles of individual athletes). 2. Dynamic adaptation of training programs taking into account the changing physical condition of the athletes during the season.
Prediction and prevention of injuries	1. Predicting injury risk based on Biodex assessments, including analysis of muscle imbalance patterns, joint stability, etc. 2. Developing real-time monitoring systems that use Biodex data and AI algorithms to provide feedback to coaches and medical staff, helping them identify potential injury risks and implement preventative measures.
Longitudinal studies	1. Tracking changes in biomedical parameters to model the natural progression of athletes' fitness and potential indicators of fatigue or overtraining. 2. Identify patterns and trends that may indicate specific health or performance issues.

Monitoring player training load is key to improving injury prevention strategies, especially in sports that require a computational assessment of the number of repetitions, type and intensityof loads during exercises and matches with 80-87% accuracy [1, 4, 32, 34, 11]. A hybrid approach may be useful, using various methods and techniques of artificial intelligence, increasing not only the accuracy of predictions, but also extending the functionalities, e.g. by trend determination - such approaches include fuzzy logic or multifractal analysis [14, 17, 23, 24, 36].

5. Conclusions

A modern training programme in team sports must be based, on the one hand, on the individualisation of training, adapting training methods, training measures and training loads to the current psycho-physical performance of the athlete and, on the other hand, to the needs and requirements of the team as a whole. Artificial intelligence can link the links of individual physiological and biomechanical studies into a chain of interconnected relationships, while at the same time enabling training methods, including rest and recovery, to be adapted to the individual needs of the athlete. An overall assessment of our research shows that AI-based models can help with this, but their wider practical implementation requires further interdisciplinary research. AI, and in particular MLPs and CNNs, can support both training methods and different aspects of games.

A study on the use of AI methods to assess lower limb peak torque in deaf and hearing football players offers valuable information for clinicians and researchers. The 70-90 % accuracy shown in the article is sufficient here. AI provides a highly accurate, objective and efficient means of assessing neuromuscular performance, which can improve injury prevention and rehabilitation strategies, which may be related to balance, coordination or communication styles. The approach also demonstrates the potential of AI to offer personalised feedback and training adjustments for athletes with different physical or sensory abilities. Future research could extend this approach by investigating the role of AI in assessing other functional parameters, such as endurance or agility, in a wider population of athletes. In addition, larger, more diverse datasets should be used to ensure the generalisability of AI models and minimise bias. Finally, future research could explore the long-term impact of AI-based interventions on athlete performance and injury outcomes, providing a deeper understanding of their practical applications in sports science.

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