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Machine learning Methods for Performance Forecast and Assessment of Female Handball Players

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Abstract

System learning algorithms are used to carry out tasks that people find difficult to do. The evaluation and forecasting of the performance of precise fitness sports using players as a resource is becoming more and more important in both league and practice scheduling. When it becomes Due to the use of conventional methods, the variety and difficulty of particular sorts of sporting events, and the usually time-variant interactions among them, sports are difficult to research and predict. Strong Machine Learning (ML) algorithms can analyse gamers' physical requirements with remarkable accuracy

In order to develop a more effective tool and uncover the key variables affecting projected results in female handball athletes, this study aims to compare several machine learning (ML) approaches to predict specific participant achievement kinds. The simple type of regression in machine learning (ML), i.e. Simple Linear Regression (SLR), Classification Tree (CT), Support Vector Regression (SVR), and Neural Networks that employ Radial Basis Function (RBFN), were used to predict the performance abilities of female handball players in the Squat Jump (SJ), Squat Jump on Toes (SJT), Sprint over a ten-m distance (SP10), and a Handball Sport-Skill Test (HSST). For each ML version, 117 occurrences of training samples with a maximum of 23 feature values have been recorded.

With R-squared values ranging from 0.86 to 0.97, the results showed that the RBFNN outperformed superior models and switched from red to green when forecasting players' performance. Using numerous common performance criteria, such as mean squared errors (SE) and implied absolute errors, we also assessed all of the fashions (AE). Finally, by upgrading the superior instrument, important factors affecting expected achievement had been assessed. The results are encouraging and intriguing for future researchers, despite this being the earliest and most preliminary attempt to use ML in the problem of sports, namely handball.

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Index Terms: Squat Jump, Handball Sport-Skill Test, Machine Learning, and Handball.

I. INTRODUCTION

Handball is recognized as an activity that targets endurance, agility, strength, and sporadic pace, with the game's sporadic talents including quick defense and assault [1]. Additionally, due to the performance-based nature of handball, an athlete's ability basic athleticism and includes mechanical, strategic, and psychological components.

Modest regulations have resulted in a substantial improvement in the skills needed and relevant to players during the previous few years. Handball appears to have evolved into a rapid and strong sport where players are expected to perform better with self-controlled run, strain, bounce, shot, move, and block skills. Therefore, it can be quite important to evaluate the statistics from a few practise experiments for the assessment of actual game experience in that area. Sporting ability Examination and methods enable want committees, walking shoes, and sports managers to evaluate players' capability objectively. As a result, gamers' potential and talent have become crucial components of taste and education. The most important aspects of sport and exercise biomechanics, technology advancements, and psychobiology have all been evaluated by researchers using a variety of approaches and procedures [2].

Artificial intelligence and its methods are commonly utilised to expand strong solutions to complicated problems since their small error rate and great accuracy rate. Deep Learning, a branch of machine learning and ML, is used in several fields to improve solutions to challenging issues. When predicting outcomes, ML frequently draws on prior experience, and the dataset's traits and capabilities are a major factor in determining prediction accuracy. Studies employing ML approaches on handball activity are extremely rare. The following is provided as the work's final components. Related studies were noted in Section II. The suggested method is provided in Section III. The findings were discussed in Section IV's aspect. Findings and suggestions for the future are presented in Section V's conclusion.

II. RELATED WORK

In order to read the performance of game enthusiasts in particular sports disciplines and video games similar volley ball, basketball, handball, cricket, swimming, football, and so on, several professionals and experts developed prediction models using expedient learning. (2020) [1] Jovanovich, Set al. 20 female respondents between the ages of 16 and 25 were used in the experiments. The results demonstrated an R-squared price of .876. Tests on gamers' reaction-agility and the Illinois trial were safeguarded. The achievement in the sport of handball is driven by expectations rather than convictions, according to Gomez-Lopez, M. et al. (2020) [2]. The example now featured 444 elite competitors, 233 of whom were younger men and 211 of whom were younger women. Popa, D. et al. (2020) [3] point to the relationship between self-regulation techniques, mindfulness practice, and success. 288 Romanian handball representatives are in the examination. The population was made up of 70% women and 30% men, with ages ranging from 12.01 - 14. The variables explained 86.9 percent of the deviation in sports accomplishment in a ordered two-step regression.

S. Hermassi et al (2017). [4] seventy-two young handball players whose ages range from 15.2 to 16 were the subjects of research. Young handball players were studied for four years, with average performance measurements of the lower limbs. On different days, they evaluated the gamers' performance times. A variety of tests, including squat dives, counter-motion jumps, a five-meter sprint, a ten-meter dash, and a handball ability test, were conducted, with the results timed using digital timing entries. This model exactly predicted the average performance of the players, with R-squared values among 0.52 and 0.679.

D. Sekulic and others (2019). [5] Conducted studies on 32 male futsal players with ages ranging from 26 to 31 and heights varying from 182.13 to 187 cm.

Ninety-nine centi metres, with a frame mass of seventy seven. 40 to 80 kilo grams, five. Players' times for tests like the 10-meter dash, alternate-course speed test, and reactive agility test (RAG) were recorded using an energy regulator 300.

R. Soslu et al (2016). [6] Showed research on 23 male basketball troupes whose ages ranged from 23-26.7, their body heights from 197.1 to 206.1, and their frame masses from 95 to 95. One hundred and three. Basketball players weighing three kgs were taken into consideration for anthropometric average performance methods, vertical jump dimensions, race performance calculation, anaerobic average performance dimensions of isokinetic knee strength, and muscle power. The experiments were conducted during a week during which the participants showed little interest in other preparation or competitions. The results of tests like the T-drill and the Wingate Anaerobic Test have been reported.

All of the aforementioned Tests are designed to use ML prototypes to develop player demonstrations of specific talents in specific gaming environments as well as to assist mentors in selecting appropriate options in terms of squad or character participant willpower [7–10]. There have only been a select few research published on the use of artificial intelligence models to sports expertise. Each leisure also features great physical capabilities, conditions, and structures. The many and dynamic layout of athletic displays calls for the best ML version in order to resolve specific activities, video games, and sporting events [11–14]. This is the only study to employ machine learning to forecast expression, as far as we can reasonably expect displays made by handball players. Additional research may be necessary for a variety of games, age groups, and genders.

In this paper, four Machine Learning models are used to forecast the women's handball players' performances and allow coaches to precisely evaluate player performance before games. Additionally, significant factors influencing the notion of display capabilities have been addressed to enhance the participant execution. The purpose and issues of this evaluation may be described as follows: To put a few machine learning (ML) strategies into practice in order to select the ideal gift for the skills under consideration and to conduct a related exam with incredible measures.

(i) To keep in mind a variety of players' skills and abilities while making a prognosis.

(ii) To foresee the capacity of gamers in four areas and to assist mentors in effectively addressing gamers' effective desire for video games.

(iii) To identify the variables that affect the skills under examination and help coaches focus on crucial

III. SUGGESTIVE METHODOLOGY

A. DATA SET

Pertaining to fifty two gamers, age between 20 and 26 years, height between 164 and 170 centimetres' and weight between 60 to 80 pounds. BMI ranges from 23.4 to 25.7. We have gathered M2 from kaggle Repository. Psychometric data and socioeconomic statistics had been gathered throughout time intervals. A total of 23 attributes (table.1) quality measurements, and 117 incidences' were recorded for the ML Models in the context of collected samples. All participants' performance was noted for two distinct time periods, and the values from the data set are displayed.

Nine skin fold locations (upper arm middle front, upper arm middle back, lower shoulder blade, belly, linear axillaries, upper leg, and anterior calf) were chosen, and they were measured in accordance with the recommendations in [15]. By paying attention to the players' height and weight measures, Quetelet's Index (QI) can be created. Equation 1 uses the gadget's useful resource to express it.

$$\text{Quetelet's Index (QI)} = \frac{m}{h^2} \qquad \text{(Eq.1)}$$

Where "m" denotes "w" stands for the players' weight in kilos, while "h" stands for their height in metres. Bar-or [16] determined the top pressure, normal pressure, relative regular pressure, and relative peak. energy using the Wingate test. The speediness was tested on 20-meter straightaway track, and measurements at 10 and 20 metres were taken. Experiments have been repeated multiple times for minutes-long periods of time for any athlete. The fastest time changed into recorded for the test distances of 10 metres and 20 metres [17]. There was a Handball Sport-Skill Test in accordance with the approvals made by Iacono et al. [17]. Squat Jumps and SJ will be performed for each athlete with a 60 second break among tests.

Three (SJT) measurements on a piezoelectric force plate had been performed, and Moir's [18] best leap had been recorded. Jumping up and down from a squat position, the second interest interval on feet.

Machine Learning Models

SLR, CT, SVR, and RBFNN are the four top ML models that were taken into account in this study for player capability predictions and analyses.

SLR (Simple Linear Regression)

One of the most significant and vital ML prognostication trends is SLR. It is specifically used for entries that have a linear relationship between their capabilities and incidences.

For a 'Z' labeled dataset $(p_i, q_i)_{i=1}^{z}$ Equation 2 depicts the general linear regression model, where "Z" defines the size of all the facts, "pi" means the input vector, and "qi" denotes the output vector.

$$f_{v,a}(p) = vp + a \qquad \text{(Eq.2)}$$

Fv,a(p) is an N-directional tensor, v is a linear combination of

Classification Tree (CT)

For each forecast and class issue, this version provides a tree form. The terminal nodes mark the end of the CT, which starts at the basis node. Every terminal node can be categorised solely based on its content. Using decision trees reduces the amount of time needed for computation. The training facts and set of features may be used to obtain timber of various categories. In order to reach the top of the line type trees for class problems, there are a number of methods, including ID3, entropy, and Gini, which can produce more accurate and superior results than others. In prognostication domains, the SE is utilised to pinpoint the most crucial factor, which the degree of imperfections in the materials; fewer flaws signify a greater effective and equipped node One way to express SE is in Equation 3.

$$SE = \frac{1}{M}\sum_{b=1}^{M}(z_u - \mu)^2 \qquad \text{(Eq.3)}$$

Zu represents the tagged occurrences, M represents the overall occurrences, and represents the most frequent occurrence among all tags.

SVR (Support Vector Regression)

SVR is changed version of SVM that uses responses rather than really binary outputs to produce predictions for prediction problems. SVR allows for a stronger connection between input properties and the analysis of nonlinear data. It reduces the classifier's margin by producing a subset of facts factors from the input facts that may be closer to the hyper plane. Equation 4 represents the full-size SVR equation.

$$S(v) = \sum_{g=1}^{z}(\alpha_g^{*} - \alpha)n.(v_g, v) + a \qquad \text{(Eq.4)}$$

α_g^{*} n is the kernel technique, and are multipliers for locating local maximum and minimum of the function.

Radial Basis Function Network

This version's of From the idea of typical approximation, purpose is derived. This model differs from other models in the hidden layer evaluation tool. Weights are used in this variant is determined using radial foundation function and the Euclidean space (RBF). Euclidean distance is represented by Eq 5 and the radial basis is defined by Eq6, respectively.

$d_q = \sqrt{\sum_{p=1}^{z} f_p - u_{pq}^2}$ (Eq. 5)

Where "f" stands for input records and "u," accordingly, denotes the weight of a hidden neuron.

$\phi = e^{\frac{-d^2}{2\sigma^2}}$ (Eq.6)

The Gaussian curve's radius is indicated by the symbol > zero, and d represents the radial distance specified in Eq. 5.

Equation 7 is used in this version's output calculation.

$O(f) = \Sigma_{p=1}^{M} u_p \phi$ (Eq.7)

O(f) denotes the output of the version, "M" the dependencies of radial foundation functions, and "up" the weights, taken into account in the initial examination to project players' capacities. The lowest results were provided by CT, which received an R-squared rating of 0.10. SLR and SVR produced fairly similar R2 rating findings of 0.708 and -0.67. SVR additionally reduced the divergence. The second study to forecast player talents took into account the performance attribute of female handball players, in particular SJT. The RBFN produced inexperienced results for R-squared rating, SE and AE of 0.97, 0.0043, and 0.0076. In the third evaluation, SP10 was predicted, and CT (0.287, 0.1/2, and 0.1298) had the best SE and AE results as well as the lowest R-squared score.

IV. RESULTS AND DISCUSSION

Two different approaches were used to conduct observations: first, finding and obtaining the notable and green analysis model and grades for the female athletes; second, outlining the most crucial factors influencing the performance of the outperformed model that is the athlete's potential for the ability under consideration. Four distinct health events, including a squat jump , squat jump on toes , a sprint over a 10-m distance, and a handball sport-skill test, have been taken into consideration to predict the skills of female handball players. All occurrences have been scaled using min-max scaling to reduce the difficulty of the data and upsurge the analytical accuracy of the ML models. In Equation 8, the Min-Max Scaling formulation is unique.

$N_p = \frac{M_p - \min(M)}{\max(M) - \min(M)}$ (Eq.8)

Scaled price is denoted thru Np, data point is given via Mp, lowest and maximum values are provided for the corresponding abilities through the use of minimum (M) and maximum (M).

The four stated ML models In phase three(B), each health-related scenario was independently taught to apply 80% of the cumulative occurrences of the very last 23 talents. Following the correction of the attributes, end-most measurements were made using 10-fold go-validation, and 20% of the dataset's untrained examples were used for testing. R2 score, SE, and suggest AE were utilised as the major parameters to examine how well each model performed in this test. The R-squared rating, which quantifies how far a record appears to deviate from its projected price, is a statistical practice used to assess the relationship between examined and predicted data. It uses advise squared errors as its basis. The straightforward R-Squared score method in Equation 9 is given.

$$R^2 = 1 - \frac{\Sigma(e_p - \hat{e}_p)}{\Sigma(e_p - \overline{e_p})} \qquad \text{(Eq.9)}$$

Examined facts are shown by the resource ep, predicted rate is provided by the usable resource ê, and as a result, the average cost of all located facts is indicated by the symbol.

The remainder of the determined defects multiplied by the square root of the flaws and forecasted values is known called SE. The SE components are already stated in Equation 3. AE is not the Unusual of total mistakes that might be measured founded on the records' residual data

$$AE = \frac{1}{n}\sum_{i=1}^{n}|x_i - x| \qquad \text{(Eq.10)}$$

In which n stands for average errors and indicates the difference between the actual and expected statistics. Four observations, especially an SJ, SJT, SP10, and HSST, have been made in the performance evaluation of four aspects, in my opinion. To determine the more sophisticated iteration of the thought-about ML styles. SJ in particular has developed into a standout performer among female handball players.

In fact, the largest prediction was made using the RBFN in the most recent observation, which became the HSST. Table 2 displays the final outcomes of four machine learning (ML) models when four player abilities are compared to three standard performance metrics (R2 score, SE, and AE) (SJ, SJT, SP10, and HSST). Figures 1, 2, and 3 display a graphical comparison of the four ML models to the performance metrics R2 rating, SE, and AE outcomes.

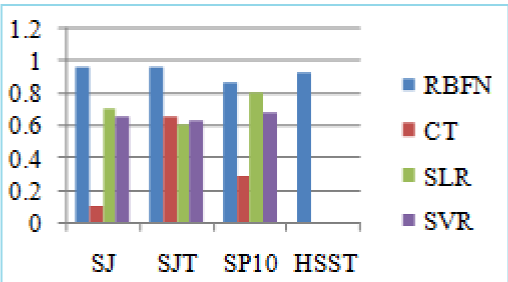

Figure 1: 4 ML models are comparison

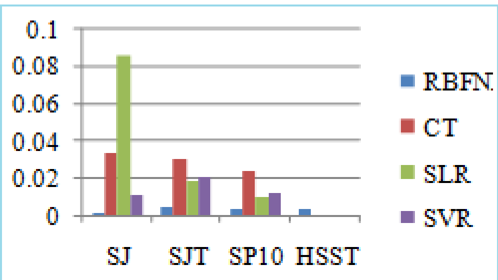

Figure 2: 4 ML models are comparison

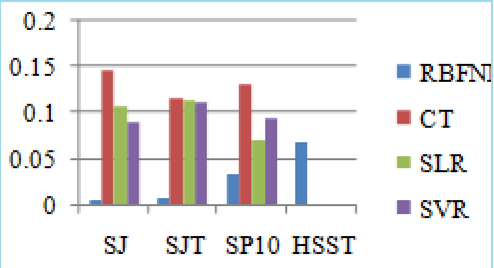

Figure 3: 4 ML models are comparison

Table 2: Results from each of the four ML models

Test		Method	RBFN	CT	SLR	SVR
SJ		SE	0.0018	0.034	0.0866	0.011
		AE	0.0038	0.1459	0.108	0.0891
		R2 score	0.97	0.11	0.708	0.67
SJT		SE	0.0045	0.031	0.019	0.020
		AE	0.0077	0.1158	0.1132	0.1112
		R^2 score	0.97	0.66	0.61	0.63
SP10		SE	0.0035	0.025	0.0094	0.012
		AE	0.0317	0.1299	0.0693	0.0927
		R^2score	0.85	0.287	0.80	0.68
HSST		SE	0.0032	N. A.	N. A.	N. A.
		AE	0.0676	N. A.	N. A.	N. A.
		R^2 score	0.94	N. A.	N. A.	N. A.

V. CONCLUSION AND FUTURE SCOPE

Prior to choosing a game, it is crucial to evaluate the skills and general performance of athletes. Numerous factors affect an athlete's total performance, making it impossible to forecast which factors are important and irrelevant. Coaches can schedule additional training sessions for weak performers by identifying the insignificant criteria that will help them understand the pros and drawbacks of the players. This can even assist the coaches in selecting the top players for the last team practice. The most effective huge methods of acting expectations for difficult and complex tasks are most likely ML models as predictive strategies. Results of this investigation shown that it is feasible to install nonlinear connections for one sort of body-related and exercising restrictions in female handball athletes using an ML version, particularly a radial base characteristic neural network.

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