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Performance Prediction and Evaluation in Female Handball Players Using Machine Learning Models

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ABSTRACT Machine learning models are implemented to perform tasks that human beings have difficulty completing. The analysis and prediction of players' performance of specific athletic tasks have increasing importance in both game and training planning. The diversity and complexity of specific types of athletic performance and the mostly nonlinear relationships between them make analysis and prediction tasks complicated when using conventional methods. Therefore, the use of effective machine learning models may contribute to the ability to achieve high accuracy predictions of players' athletic performance. The aim of this study was to evaluate different machine learning models for predicting particular types of athletic performance in female handball players and to determine the significant factors influencing predicted performances by using the superior model. Linear regression, decision tree, support vector regression, radial-basis function neural network, backpropagation neural network and long short-term memory neural network models were implemented to predict the performance of female handball players in countermovement jumps with hands-free and hands-on-hips, 10 meter and 20-meter sprints, a 20-meter shuttle run test and a handball agility specific test. A total of 23 properties and measurements of attributes and 118 instances of training patterns were recorded for each machine learning models. The results showed that the radial-basis function neural network outperformed the other models and was capable of predicting the studied types of athletic performance with R^2 scores between 0.86 and 0.97. Finally, significant factors influencing predicted performance were determined by retraining the superior model. This is one of the first studies using machine learning in sport sciences for handball players, and the results are encouraging for future studies.

INDEX TERMS Artificial intelligence, athletic performance, machine learning models, radial-basis function neural network.

I. INTRODUCTION

Handball is known as a sport that requires strength, coordination, power, and a discontinuous tempo, with intermittent game characteristics involving a fast-paced defence and attack [1]. In addition, the game is performance-oriented, and it contains technical, tactical, and psychological elements [2]. In recent years, as a result of new rules and an increment in training and game playing frequency in elite women's handball, the physical demands applied to the players have rapidly changed [3]–[5]. Handball has become a fast and intensive sport in which athletes with better sprint, push, jump, shot, shift and block abilities are expected to perform better. Therefore, it is very important to analyze the data from different exercise tests for the prediction of real game performance in the field.

Sport performance analysis and techniques allow sports scientists, coaches, and athletes to analyze athlete performance objectively. Thus, performance analysis has become an important component of training [6], and it has a vital role in planning training and competition strategies [3], [7]. Scientists have developed several systems and methods to evaluate the most important parameters of sports performance biomechanics, physiology, and behavioral neuroscience.

Artificial intelligence (AI) technology has been widely used in the last decade in almost every field of science and in our daily lives in areas ranging from education [8] to health [9], [10] and space research [11], [12]. AI and

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its corresponding technologies have gained importance as they provide effective and robust solutions to problems with high accuracy and few errors. As a field of AI, machine learning (ML), and a subset of ML, deep learning (DL) that uses multiple layers in its structure, are also applied within these fields, and their reliability has been proven [12]–[14]. ML uses previous experiences to make a connection with the future, and the success of the model is highly related to the characteristics of the dataset [8]. In recent years, several experiments using different ML models have been performed in sports [15]–[25].

Mezyk and Unold [15] combined fuzzy logic and ML to model swimming training. The classification accuracy of their proposed methodology reached 68.66%.

Ofoghi *et al.* [16] implemented ML techniques for selecting athletes in cycling as well as for strategic planning. They implemented a statistical approach, K-means and a naive Bayes classifier for inter-omnium analysis, and Bayesian belief networks with discrete optimization techniques for intra-omnium performance analysis.

Hore and Bhattacharya [17] used naive Bayes, support vector machines (SVMs), multilayer perceptron feed-forward networks, and random forests to build a sustainability model for the National Basketball Association (NBA) players. They concluded that SVMs produced superior results than the other models, with an accuracy of 85.65%.

Musa *et al.* [19] implemented a variation of k-nearest neighbor and linear regression to classify high-potential archers using physical fitness indicators.

Musa *et al.* [20] conducted another study on the scouting of high-performance archers. They implemented artificial neural network and k-nearest neighbor models. They used the selected performance parameters of 50 archers. The obtained results showed that the artificial neural network model achieved a higher accuracy (92%) than the other models.

Jesus *et al.* [21] implemented and compared a linear model and artificial neural network to predict the backstroke start performances of ten male backstroke swimmers. They concluded that the artificial neural network outperformed the linear model.

Maanijou and Mirroshandel [22] proposed a method to predict soccer player rankings based on an expert system and ensemble learning. Twenty features of soccer players were considered, and a comparison was performed by considering benchmarkML models such as multilayer perceptron, support vector machines, naive Bayes, logistic regression, etc. They concluded that the proposed method achieved the highest accuracy (60%).

Anik *et al.* [23] proposed another method based on feature elimination and machine learning implementation to predict the performances of cricket players. The machine learning step of the proposed method consisted of linear regression and a support vector machine with linear and polynomial kernels. The highest prediction accuracies obtained for batsmen and bowlers were 91.5% and 75.3%, respectively. ML was also implemented in a cricket game by McGrath *et al.* [24].

Zhou *et al.* [25] conducted research to predict countermovement jump heights by using machine learning models. Decision tree, random forest, and linear regression models were implemented to train selected features of athletes. Evaluation was performed by considering three metrics; namely, the R^2 score, root mean square error (RMSE) and mean absolute error (MAE). The obtained results demonstrated that linear regression outperformed the other considered ML models.

All the abovementioned studies aimed to implement ML models to make predictions of players' performances of specific abilities in different branches of sport, as well as to help coaches make appropriate decisions regarding team or individual player selection.

Only a limited number of studies have been conducted about the use of machine learning models in sport sciences. Each sport has a unique structure, physical ability, and requirements. The diverse and complex structure of athletic performances requires an appropriate machine learning model for particular tasks and particular sports to be determined. To the best of our knowledge, this is the first study to use machine learning models to predict specific performances in handball players. Further studies might be needed for different sports, age groups and sexes.

In this paper, we present the implementation of six ML models to predict the performances of women handball players, and to allow coaches to estimate the player performance before games accurately. In addition, significant factors influencing the considered performance skills, were determined to improve the player performance.

Based on the abovementioned information and a literature review, the aim and contribution of this study can be described as follows:

- To implement several ML models to determine the optimal model for the considered skills and perform a comparative evaluation using different metrics.
- To consider multiple performance skills of athletes for the prediction.
- To predict athlete performance in six skills and to assist coaches with the efficient selection of athletes in games.
- To determine the factors that affect the considered skills and assist trainers in focusing on significant factors to improve athlete performance of particular skills.

The rest of the paper is organized as follows: Section 2 introduces the materials and methods used in this research and Section 3 presents the obtained results. The discussions and conclusions are presented in Section 4 and Section 5, respectively.

II. MATERIALS AND METHODS

A. DATASET

Data were collected from 59 players (age: 20.7 ± 5.4 years, height: 164.0 ± 6.7 *cm*, bodyweight: 62.8 ± 10.0 *kg* and

TABLE 1. All attributes of the dataset.

Attributes	
Age (years)	Triceps Skinfold Thickness (ST) (mm)
Subscapular Skinfold Thickness (mm)	Wingate Average Power (AP) (kg)
Body Weight (kg)	Biceps Skinfold Thickness (mm)
Abdominal Skinfold Thickness (mm)	Wingate Relative Average Power (rAP) (kg.W-1)
Body Height (m)	Medial Calf Skinfold Thickness (mm)
Thigh Skinfold Thickness (mm)	Wingate Peak Power (PP) (kg)
Body Mass Index (BMI) (kg/m2)	Suprailiac Skinfold Thickness (mm)
Midaxillary Skinfold Thickness (mm)	Wingate Relative Peak Power (rPP) (kg.W-1)
10 meters sprint run (SP10) (s)	Countermovement jump / hands-on-hips CMJH (cm)
Chest Skinfold Thickness (mm)	Handball Agility Specific Test (HAST) (s)
20 meters sprint run (SP20)(s)	Counter-Movement jump / Hands Free CMJF (cm)
Shuttle run (SR) (km h-1)	—

BMI: 23.2 ± 2.7 $kg.m^2$) from the North Cyprus Women's Handball Super League. Prior to the study, Near East University Ethics Committee approval ($ProjectNo.\ YDU/2017/51-467$) was obtained. The study was conducted according to the Declaration of Helsinki, and all participants gave their consent after being informed about the study. For athletes who were younger than 18 years of age, consent was given by their guardians. Data, including demographic characteristics and physiological measurements, were recorded for two periods. In total, 23 properties (Table 1), and measurements of attributes were recorded for the ML models, and 118 instances were recorded for training patterns. Each measurement was recorded for each player at the same time during two different periods, and a multivariate dataset was created. The dataset that was created did not contain any time information.

Nine skinfold sites (biceps, triceps, subscapular, suprailiac, chest, abdominal, midaxillary, thigh and medial calf) were determined, and the measurements for these sites were performed according to the American College of Sports Medicine (ACSM) guidelines [26] by using a Holtain skinfold caliper. Body Mass Index (BMI) was calculated by using body height and weight measurements [27]. BMI formula is shown in Equation 1.

$$BMI = Weight/Length^2 \tag{1}$$

where body weight is measured in kilograms (kg) and body height is measured in meter (m).

The endurance shuttle run performed as described by Leger and Gadoury [28]. Using the Wingate test, average power, relative average power, peak power, and relative peak power were recorded according to Bar-Or [29].

Speed was measured on a 20-meter straight track, and data were recorded at 10 and 20 meters. Tests were repeated three times for each athlete with intervals of two minutes. The fastest time was recorded for the 10 meter (SP10) and 20 meter (SP20) test times [30].

The handball agility specific test (HAST) test was performed as described by Iacono *et al.* [30]. Countermovement jumps with free hands (CMJF) and countermovement jumps with hands-on-hips measurements (CMJH) were performed on a force plate three times for each athlete with a one-minute break between tests (Bertec Corporation, Leeds, UK), and the highest jump was calculated as described by Moir [31]. Table 1 shows all the attributes of the dataset in detail.

B. MACHINE LEARNING MODELS

Several machine learning models, including deep learning approaches, have been proposed for classification and prediction problems. Some of them can be used for both domains, while some are specific to one domain. In this research, the six most fundamental benchmark ML models were considered for the prediction and analysis of athlete performance. These models were the linear regression (LR), decision tree (DT), and support vector regression (SVR) models and three neural network models, namely, the backpropagation neural network (BP), radial-basis function neural network (RBFNN) and deep long short-term memory neural network (LSTM) models.

1) BACKPROPAGATION NEURAL NETWORK

BP is the most popular and widely used neural network model for both classification and prediction problems [8]. As with other neural network models, it tries to simulate the biological aspects of the human brain. It has input and output layers with a defined number of neurons according to the application, as well as a minimum of one hidden layer. The number of neurons in the hidden layer and the number of hidden layers are determined by trial and error.

Training of the backpropagation neural networks is based on weight updates, and the error, which is obtained by comparing actual and target outputs in the output layer is propagated back for weight updates according to Equation 2.

$$w_j^{k+1} = w_j^k + lr(y_i - \hat{y}_i^k)x_{ij} \tag{2}$$

where ${w_j}^{k+1}$ and ${w_j}^k$ are new and previous weights respectively, lr is the learning rate parameter, y_i and $\hat{y}_i^k$ are observed and desired outputs respectively, and x_{ij} is the input instance.

2) RADIAL-BASIS FUNCTION NEURAL NETWORK

The objective of an RBFNN is derived from the theory of function approximation [32]. The uniqueness of an RBFNN is due to the process performed in the hidden layer. Initially, clustering is applied to determine the clusters of patterns in the input space. Then, the Euclidean distance is computed between the data point and the center of each neuron, which is the cluster center, and the weight is computed by applying a radial basis function (RBF) to the distance. The equations of Euclidean distance and radial basis function are given in Equation 3 and Equation 4, respectively.

$$r_j = \sqrt{\sum_{i=1}^{N} (x_i - w_{ij}^2)} \tag{3}$$

where x and w denote the input data and center of cluster (weight of hidden neuron), respectively.

$$\phi = e^{(\frac{-r^2}{2\sigma^2})} \tag{4}$$

where $\sigma > 0$ represents the radius of the bell-shaped Gaussian curve, and r is the Radial distance which was defined in Equation 3.

The output of RBFNN is calculated in similar way to BP, as described below in Equation 5.

$$y(x) = \sum_{i=1}^{M} w_i \phi \tag{5}$$

where $y(x)$, M and w_i denote the output of the network, number of basis functions and the weights respectively. The general topology of RBFNN is shown in Figure 1.

An RBFNN is similar to BP in terms of input and output layers, but it differs with regard to its hidden layer. It only has a single hidden layer that is activated by radial-basis functions, and it does not require any other activation functions as in BP.

The RBFNN has several advantages over traditional neural networks. Faster convergence and effective error minimization due to the single hidden layer are the main advantages of an RBFNN; however, it is also important to note that the analyses and the interpretation of the hidden layer responses of an RBFNN are easier than those of the hidden layer in multilayer perceptron (MLP) and backpropagation.

RBFNNs have been implemented in several comparative studies aimed at performing classification and/or prediction problems [33]–[35].

3) DECISION TREES

A DT is a hierarchical form of instances and attributes that is used for both classification and prediction problems [36]. It has a tree form that starts with a root node and ends with decision nodes. Each decision node is a predicted or classified value.

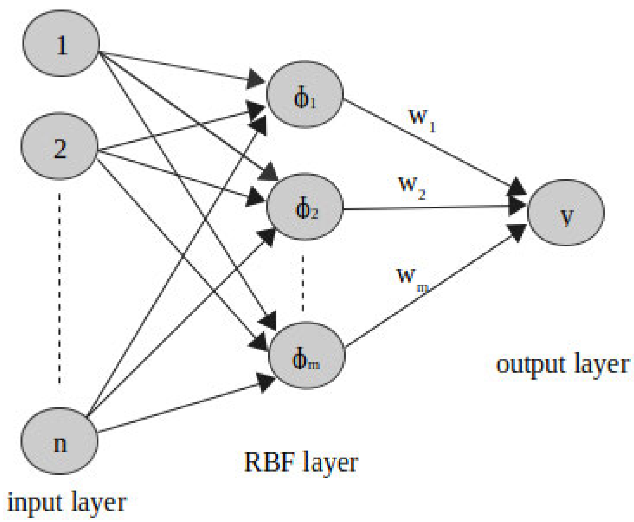

FIGURE 1. General topology of radial-basis function neural network.

In labeled data, a decision tree allows us to make predictions on samples of an example given a feature vector. Once a decision tree is constructed, it requires very little computational time. However, the construction of the tree from training data is a complex process, and many decision trees can be constructed from a set of features. Therefore, several algorithms, such as gini, entropy, and ID3, have been proposed to construct optimal decision trees for classification problems that can produce more accurate results than others. Proposed algorithms aim to split the set by the most informative attribute at the node into the most subsets. In prediction applications, the mean squared error (MSE) is used to determine the most informative attribute, which provides the degree of impurity, where a smaller degree of impurity represents a more efficient node. The formulae of MSE is given in Equation 6.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \mu)^2 \tag{6}$$

where N is the number of instances, y_i is the labeled instances and μ is the mean of all labeled examples.

4) LINEAR REGRESSION

LR is one of the basic ML models for prediction. It is widely used for the prediction of data that specifically has a linear relationship between its attributes and instances [37]. The general expression of Linear Regression is given in Equation 7 for an N labelled dataset $(x_i, y_i)_{i=1}^N$, where N is the size of the data, x_i is the feature vector, and y_i is the target.

$$f_{w,b}(x) = wx + b \tag{7}$$

where $f_{w,b}(x)$ is a linear combination of features of example x, w is a D-dimensional vector of parameters and b is a real number.

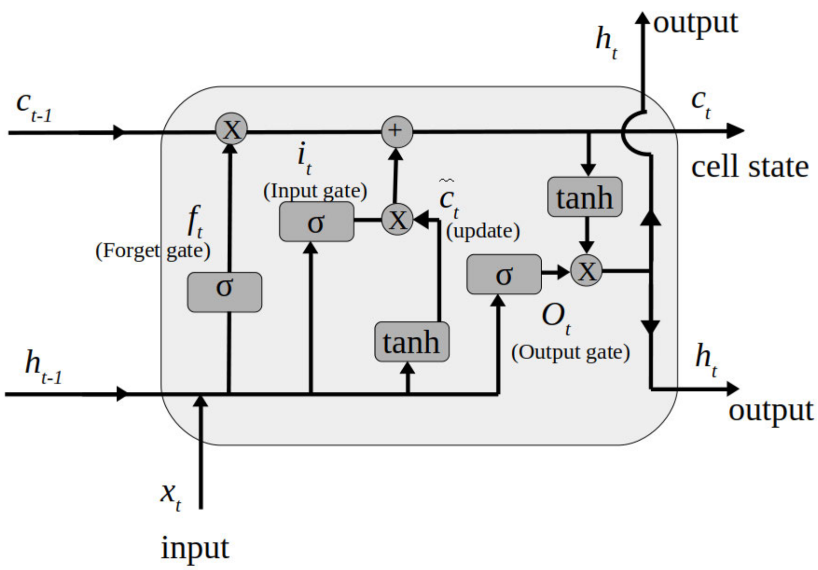

FIGURE 2. General structure of an LSTM cell.

5) SUPPORT VECTOR REGRESSION

SVR is a modified version of the support vector machine that accepts real-valued inputs to produce outputs for prediction problems instead of binary outputs [38]. SVR maps input features into a higher dimension and makes the prediction of nonlinear data possible. It creates a subset of the support vectors from the input data, and minimizes the distance between the input data points and hyperplane by the level of ϵ. Several kernel functions, such as radial-basis functions and polynomial functions, can be used in SVR. The standard SVR equation is given in Equation 8 below.

$$f(x) = \sum_{i=1}^{N}(\alpha_i^* - \alpha)k.(x_i, x) + b \tag{8}$$

where α_i^* and α are Lagrange multipliers and k is the kernel function.

6) LONG-SHORT TERM MEMORY NEURAL NETWORK

LSTM is a type of recurrent neural network that remembers its previous experiences and initiates recent experiences accordingly. It is frequently used for prediction problems, particularly those with a large number of hidden layers such as deep LSTM [39].

The architecture of an LSTM cell, which is responsible for the dependencies between the features in the input data, consists of three gates: an input gate, a forget gate and an output. A forget gate is used to remove irrelevant information from the cell, the input gate is responsible for the addition of new information into the cell, and the function of the output gate can be described as fitting the information flowing from other gates. Basic equations for the gates and the final output are given in Equation 9 and Equation 10, respectively.

$$Z_t = \sigma(w_z[h_{t-1}, x_t] + b_z) \tag{9}$$

where Z and b_z represent the gate and bias for corresponding gate z; w denotes the weights for corresponding gate z, and h_{t-1} and x_t represent the output of previous block and the input of corresponding block, respectively. σ represents the Sigmoid function.

$$h_t = o_t * tanh(c^t) \tag{10}$$

where h_t and o_t represent the outputs of the memory cell and output gate respectively. c^t denotes the candidate for the cell state. The general structure of LSTM cell is shown in Figure 2.

C. DESIGN OF EXPERIMENTS

Experiments were performed in two different ways, first to determine and obtain the optimum prediction model and rates for the female athletes and then to specify the most important factors (measurements and attributes) affecting the prediction accuracy of the superior model, i.e., the performance of athletes for the considered skill.

Six experiments were performed to predict the performance of female athletes in six different exercise protocols, namely, a countermovement jump with free hands (CMJF), a countermovement jump with hands-on-hips (CMJH), a 10-meter sprint (SP10), a 20-meter sprint (SP20), 20-m endurance shuttle run (SR) and a handball agility specific test (HAST).

All instances were normalized by min-max normalization to reduce the complexity of the data and to increase the prediction performance of the machine learning models. The equation of Min-Max normalization is given in Equation 11.

$$Z_i = \frac{x_i - min(X)}{max(X) - min(X)} \tag{11}$$

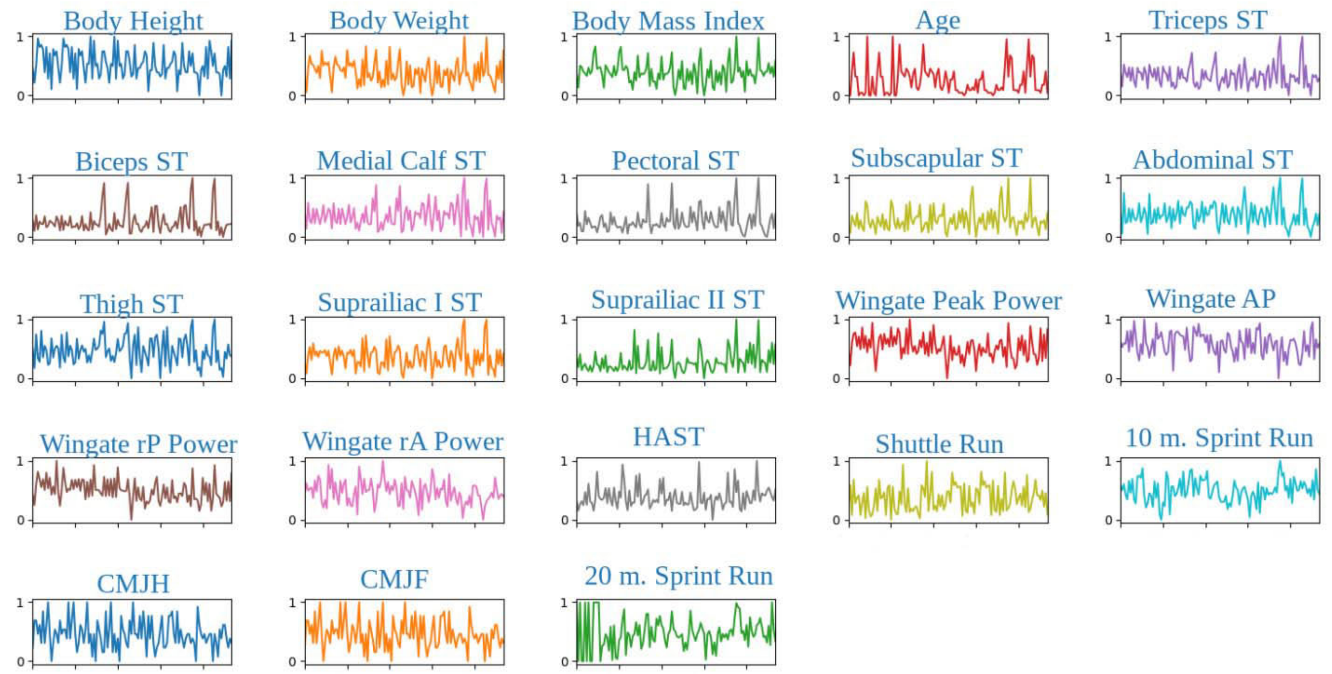

FIGURE 3. **Visualization of normalized attributes of dataset.**

where Z_i is the normalized value, x_i is the data point and $min(X)$ and $max(X)$ denote the minimum and maximum values of the corresponding attributes respectively. Figure 3 presents a visualization of the normalized data for each attribute separately, to demonstrate how the data were fed to the ML models. The y-axis represents the normalized value between 0 and 1, and the x-axis represents the instances for all subfigures.

Each exercise protocol was trained separately by the six ML models mentioned above by using 80% of the total instances of the remaining 22 attributes. All attributes (measurements) except the target exercise protocol were included in the training set to predict the observed skills. Five-fold cross-validation was used in preliminary experiments, and the hold-out method, which is based on the training of randomly selected instances, was used for hyperparameter tuning for each model to minimize computational cost. Final experiments were performed by 5-fold cross-validation after the tuning of the parameters, and 20% of the total instances, which were untrained samples of the dataset, were used for testing. The average R^2 score, MSE, and MAE of all test folds were considered as final results. A validation set was not considered during the training of models to avoid reducing the number of instances in the dataset.

Evaluation was performed by three metrics: R^2 score, mean squared error (MSE), and mean absolute error (MAE), which are the main indicators of model evaluation in prediction problems. The R^2 score is a statistical technique used to evaluate the relationship between observed and predicted data using variance, which is the measure of how much a data point tends to deviate from its mean. The basic formula of the R^2 score is given in Equation 12.

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)}{\sum (y_i - \bar{y}_i)} \tag{12}$$

where y_i, $\hat{y}$ and $\bar{y}$ represent observed data, predicted value and the mean value of all observed data, respectively.

MSE is the average of the square of the errors obtained from the difference between the observed values and the predicted ones. The formula for MSE was given in Equation 6. MAE is the mean of absolute errors, which can be measured by the difference between the observed and predicted data. The formula of MAE is given below in Equation 13.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |x_i - x| \tag{13}$$

where n represents the number of errors and $|x_i - x|$ denotes the absolute error between the observed and predicted data. Generally, the model with the highest R^2 score and lowest MSE and MAE is the most effective and therefore demonstrates the best prediction ability.

In neural network models, inputs and outputs are common and constant; in this study, there were 23 inputs and one output, because there were 23 attributes and a single prediction value.

Three hidden layers were used in the backpropagation neural network, and the learning rate and momentum factor were set to 0.00099 and 0.90, respectively. The convergence of the BP was stopped after 1000 iterations. In the radial-basis function neural network, the learning rate was set to 0.09, and

20 clusters were used. The maximum number of iterations was set to 6000. In the LSTM model, three LSTM layers were used, and the maximum number of iterations was set to 100.

In the DT model, the mean squared error was used to form the tree for prediction, while other criteria were used for classification. In SVR, the radial-basis function kernel was used, and the γ and ϵ values were initially set as 0.005 and 0.01, respectively. Then, the parameters were searched and tested for optimum results.

All parameters were decided by trial and error during the experiments as there were no exact determination criteria for the ML models.

After obtaining the prediction results, the change in prediction level (Δ) in the superior model of each measurement was performed for the considered skills separately. Measurement of the change in prediction level was calculated as a percentage by decreasing a single, different attribute (i.e., an athlete's measurements) for each training and obtaining the prediction level of the superior model without this attribute. The decrement of the prediction level was recorded, and the highest decrement percentage represented the most relevant factor influencing the considered skill.

III. EXPERIMENTAL RESULTS

A. PREDICTION EXPERIMENTS

As mentioned above, six experiments were performed separately to determine the superior of the considered models in performance predictions of six skills, namely, a countermovement jump with free hands (CMJF), a countermovement jump with hands-on-hips (CMJH), a 10-meter sprint (SP10), a 20-meter sprint (SP20), a 20-m endurance shuttle run (SR), and an agility test (HAST).

The first experiment was performed to predict the CMJF of female athletes, and the decision tree produced the worst results in this experiment with an R^2 score of 0.10. LR and SVR produced close results for R^2 score (0.707 and 0.660, respectively); however, SVR minimized the error, *MSE*, and *MAE*, between the predicted and observed data more effectively than LR. On the other hand, for the neural network algorithms, BP produced the lowest R^2 score (0.58), followed by deep LSTM (0.62). The highest R^2 score for both neural network algorithms and all models in this experiment, was obtained from the RBFNN (0.969). The *MAE* and *MSE* results for neural network models were also similar to the obtained R^2 scores, and the lowest *MAE* and *MSE* results were achieved by RBFNN, and followed by deep LSTM and BP, respectively.

In the second experiment, CMJH was considered for prediction, and similar to the CMJF, the RBFNN produced superior results for R^2 score, *MSE*, and *MAE* (0.96, 0.042, 0.0075, respectively). All other models produced close results when the R^2 scores are considered. DT followed RBFNN with an R^2 score of 0.65, and SVR, deep LSTM, LR and BP achieved 0.63, 0.61, 0.61 and 0.59 R^2 scores, respectively. LR outperformed the other four models when the *MSE* results were considered. In *MAE* results, RBFNN was followed by a neural network model, deep LSTM (0.0846). The lowest *MSE* and *MAE* results were obtained by BP for this experiment (0.023 and 0.1170, respectively).

In the third experiment, SP10 was predicted, and the lowest R^2 score and highest *MSE* and *MAE* results were obtained by the DT (0.286, 0.024, and 0.1297, respectively). The RBFNN and LR produced closer results in this experiment, but the RBFNN achieved the highest R^2 score and lowest *MSE* and *MAE* results (0.867, 0.0034, and 0.0316, respectively). However, the result of RBFNN was the minimum highest result obtained in this study, and the increase LR result for this experiment showed that the considered skill has a more linear relation to the attributes than the other skills, particularly to SP10. Other neural network models, BP and deep LSTM, achieved 0.72 and 0.64 R^2 scores. Even SVR achieved a higher R^2 score than deep LSTM; the error minimization was performed more effectively by deep LSTM than SVR.

In the SP20 experiment, the RBFNN again outperformed the other models by obtaining an R^2 score of 0.970 and an *MSE* and *MAE* of 0.0021 and 0.0596, respectively. The deep LSTM obtained lower *MAE* and *MSE* results than LR, however, LR achieved better performance for R^2 score (0.78). The other neural network model, BP, performed the lowest performance for all metrics in this experiment. SVR and DT produced close results to each other for all metrics; however, they were not capable of outperforming other models.

In the SR experiment, neural network models, RBFNN, BP, and deep LSTM, achieved higher R^2 scores than other models (0.95, 0.64, 0.54, respectively). DT and SVR produced close results for R^2 score (0.49 and 0.45, respectively). When the *MSE* results were considered, the lowest *MSE* was obtained by RBFNN (0.0020), followed by BP (0.019). Even deep LSTM produced a higher R^2 score than SVR, SVR achieved lower *MSE* than deep LSTM in this experiment. The *MAE* results fluctuated when compared to *MSE* results. RBFNN achieved lowest *MAE* result (0.044) and contrary to *MSE* results, followed by deep LSTM, DT, BP and SVR (0.1054, 0.108, 0.1178, 0.1269, respectively). LR was unable to make predictions in this experiment. Therefore, LR was indicated as not applicable (NA) in the SR experiment.

In the last experiment, which was the HAST, the highest prediction was again obtained by the RBFNN; however, the other models were unable to make connections between instances and attributes to make predictions. RBFNN achieved 0.93 R^2 score and, 0.0033 and 0.0674 *MSE* and *MAE* results, respectively. The other neural network models, BP and deep LSTM, produced R^2 scores of 0.113 and 0.160, respectively. Even the deep LSTM produced lower *MSE* than BP; BP outperformed deep LSTM when the *MAE* results were considered. The DT, LR, and SVR could not produce positive predictions, and low *MSE* and *MAE* results.

Table 2 shows all the results obtained in this research. Bold values within Table 2 indicate the highest R^2 score and the minimum *MSE* and *MAE* values for each experiment. Figure 4, Figure 5, and Figure 6 show the graphical

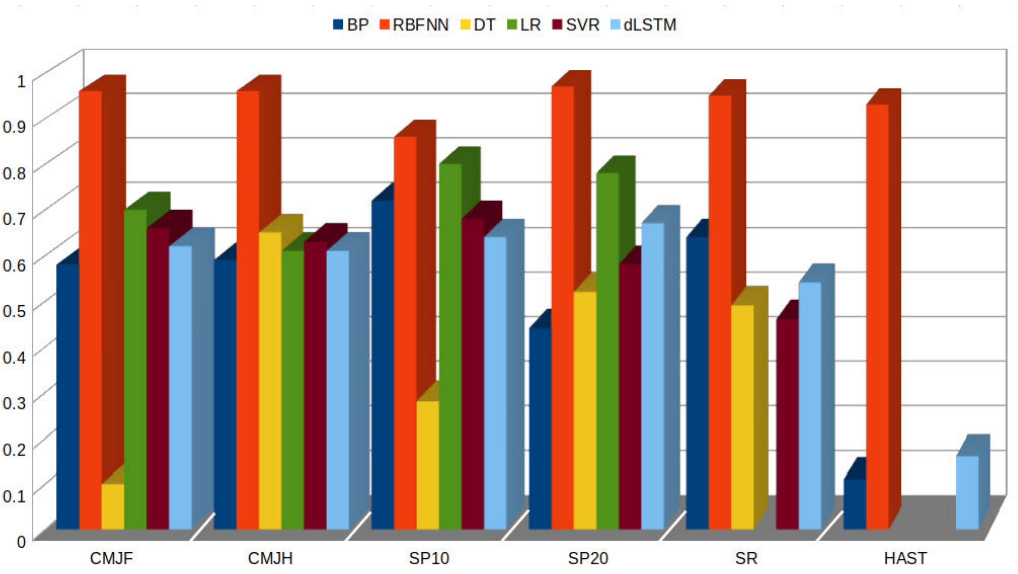

FIGURE 4. Comparison of models according to the obtained R^2 scores.

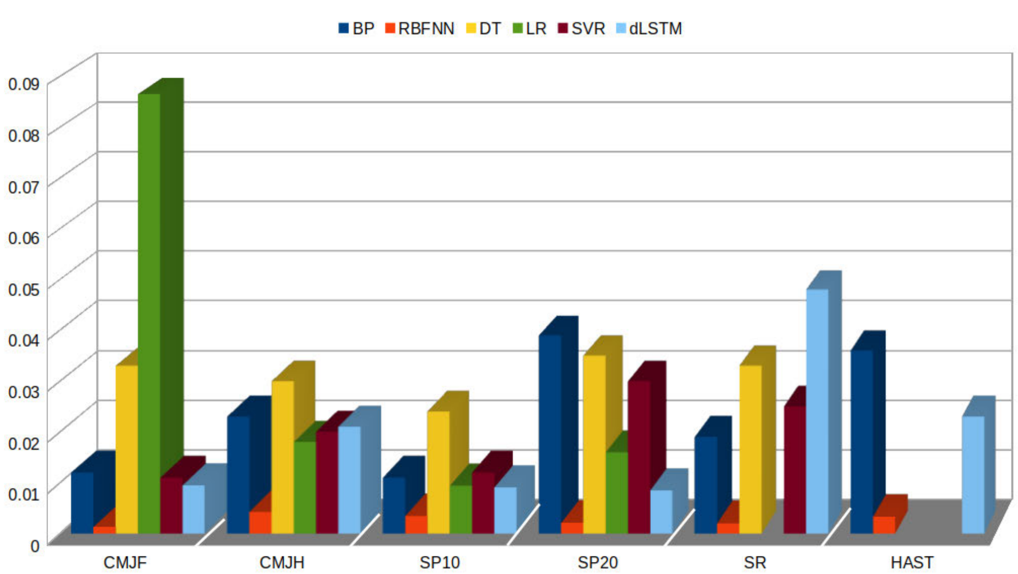

FIGURE 5. Comparison of models according to the obtained *MSE* results.

comparison of the models according to the obtained R^2 score, *MSE*, and *MAE* results, respectively.

The RBFNN showed the best predictions for all parameters studied. Figure 7 shows the RBFNN predictions and real measurements for all parameters.

B. DETERMINATION OF FACTORS

After determining the superior model implemented in this study by considering the highest prediction rates, the most influential factors on the considered skills were calculated separately by training the radial-basis function neural network without one attribute each time. The process of training RBFNN was repeated until all measurements were removed one by one and tested with the other 21 measurements for target performance. Therefore, the effect of each measurement on the prediction level, R^2 score, hence the impact on performance, was observed.

As mentioned above, the change in prediction level (Δ) was calculated as a percentage by decreasing a single, different attribute (i.e., an athlete's measurements) for each training and obtaining the prediction level of the RBFNN without this attribute. The highest decrement percentage represented the most relevant factor influencing the considered skill.

In the CMJF experiment, it was calculated that the R^2 score of RBFNN (0.96) decreased to 0.32 (Δ: 66.66%) without considering the CMJH in training. This indicated that the most important factor was CMJH in the prediction level of

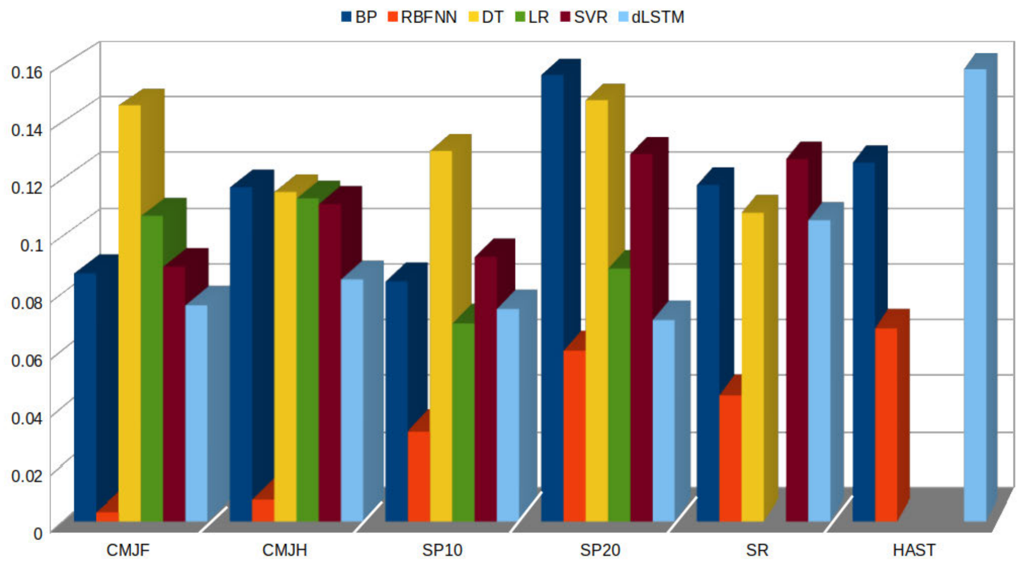

FIGURE 6. Comparison of models according to the obtained *MAE* results.

TABLE 2. General results for all experiments.

Skill	Metric	BP	RBFNN	DT	LR	SVR	dLSTM
CMJF	MSE	0.012	**0.0013**	0.033	0.0865	0.011	0.0095
	MAE	0.0868	**0.0033**	0.1458	0.107	0.0891	0.0756
	$R^2 Score$	0.58	**0.96**	0.10	0.70	0.66	0.62
CMJH	MSE	0.023	**0.0042**	0.030	0.018	0.020	0.021
	MAE	0.1170	**0.0075**	0.1153	0.1131	0.1111	0.0846
	$R^2 Score$	0.59	**0.96**	0.65	0.61	0.63	0.61
SP10	MSE	0.011	**0.0034**	0.024	0.0094	0.012	0.0091
	MAE	0.0839	**0.0316**	0.1297	0.0692	0.0925	0.0743
	$R^2 Score$	0.72	**0.86**	0.28	0.80	0.68	0.64
SP20	MSE	0.039	**0.0021**	0.035	0.016	0.030	0.0085
	MAE	0.1564	**0.0596**	0.1475	0.0884	0.1286	0.0704
	$R^2 Score$	0.44	**0.97**	0.52	0.78	0.58	0.67
SR	MSE	0.019	**0.0020**	0.033	NA	0.025	0.048
	MAE	0.1178	**0.0440**	0.108	NA	0.1269	0.1054
	$R^2 Score$	0.64	**0.95**	0.49	NA	0.46	0.54
HAST	MSE	0.036	**0.0033**	NA	NA	NA	0.023
	MAE	0.1256	**0.0674**	NA	NA	NA	0.1584
	$R^2 Score$	0.11	**0.93**	NA	NA	NA	0.16

CMJF, as expected. It was followed by abdominal ST (R^2 score: 0.86, Δ: 10.29%), Biceps ST (R^2 score: 0.87, Δ: 8.82%) and body height (R^2 score: 0.87, Δ: 8.82%). Other measurements of the athletes did not have any effect on the prediction level of CMJF.

In the CMJH experiment, CMJF was calculated as the strongest factor on CMJH with a 61.90% decrement (R^2 score: 0.36) in the prediction level. Other important factors were HAST (R^2 score: 0.88, Δ: 7.93%) and age (R^2 score: 0.91, Δ: 4.76%). No other measured factors were influencing the CMJH.

In the SP10 experiment, only two skills (SP20 and suprailiac ST) changed the R^2 score of RBFNN (0.86) in training. The effects of SP20 and suprailiac ST on SP10 were calculated as 61.76% (R^2 score: 0.32) and 8.82% (R^2 score: 0.78), respectively. Other measurements of the athletes did not have any effect on the prediction level of SP10.

In the SP20 experiment, RBFNN was not able to make a prediction without considering the SP10 during the training. This showed a 100% decrease in the performance of RBFNN. The other factors measured on SP10 were calf ST (R^2 score: 0.88, Δ: 8.62%) and suprailiac ST (R^2 score: 0.90, Δ: 6.89%).

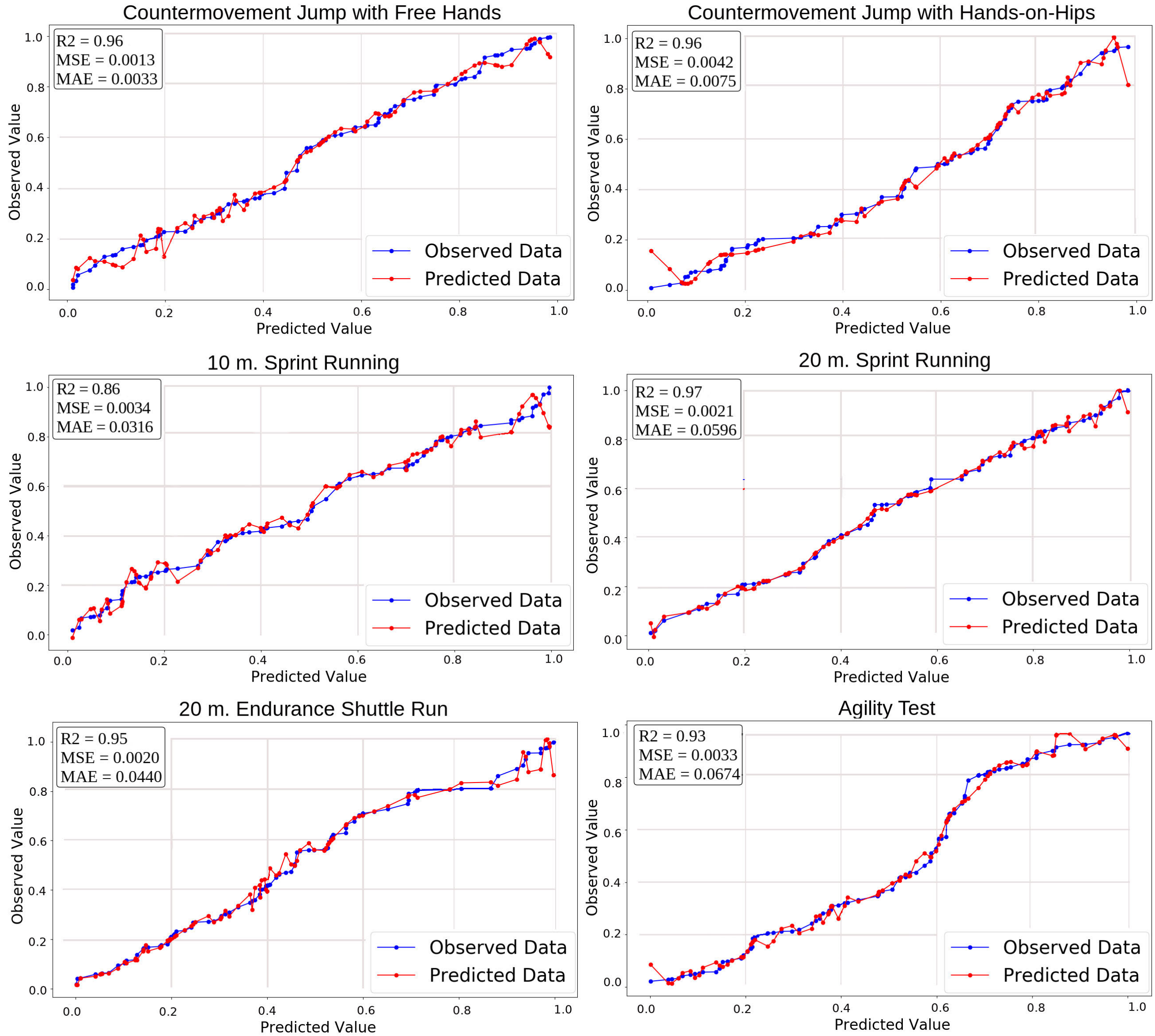

FIGURE 7. RBFNN predictions on observed data for all skills.

Other measurements of the athletes did not have any effect on the prediction level of SP20.

In the SR experiment, three attributes were measured as the factors that had an influence on SR. The age of the athletes was the strongest factor, and the R^2 score of RBFNN for SR (0.95) decreased to 0.55 (Δ: 41.30%). It was followed by midaxillary ST (R^2 score: 0.82, Δ: 13.04%) and chest ST (R^2 score:0.86, Δ: 8.69%). There were no other measurements, influencing the SR.

In the HAST experiment, four strong factors were calculated. The RBFNN could not perform any prediction for HAST without CMJF, which shows the 100% change in the performance. Suprailiac ST, SR, and chest ST had significant influences on the prediction level of the RBFNN with rates of 93.75% (R^2 score: 0.05), 91.66% (R^2 score: 0.07) and 58.33% (R^2 score: 0.38), respectively. Other measurements of the athletes did not have any effect on the prediction level of HAST.

Table 3 shows the results obtained from the analysis of factors that affect prediction levels in decreasing order, and Figure 8 presents the visualized results as a heatmap of the factors influencing the considered skills.

IV. DISCUSSIONS

We used machine learning models to predict six physical exercise test results by applying 23 parameters, including age, anthropometric measurements, and physical tests to the models.

Different regression evaluation metrics are used to measure the different characteristics of the results produced by the models. *MSE* is highly sensitive to the outliers in the data by squaring the error between the predicted and observed data;

TABLE 3. Athletes performance factors that affect prediction results of RBFNN.

	CMJF		CMJH		SP10	
No.	*Factor*	Δ	*Factor*	Δ	*Factor*	Δ
1	CMJH	66.66%	CMJF	61.90%	SP20	61.76%
2	Abdominal ST	10.29%	HAST	7.93%	Suprailiac ST	8.82%
3	Biceps ST	8.82%	Age (years)	4.76%	-	-
4	Body Height	8.82%	-	-	-	-
	SP20		**SR**		**HAST**	
No.	*Factor*	Δ	*Factor*	Δ	*Factor*	Δ
1	SP10	No prediction (100%)	Age	41.30%	CMJF	No prediction (100%)
2	Calf ST	8.62%	Midaxillary ST	13.04%	Suprailiac ST	93.75%
3	Suprailiac ST	6.89%	Chest ST	8.69%	SR	91.66%
4	-	-	-	-	Chest ST	58.33%

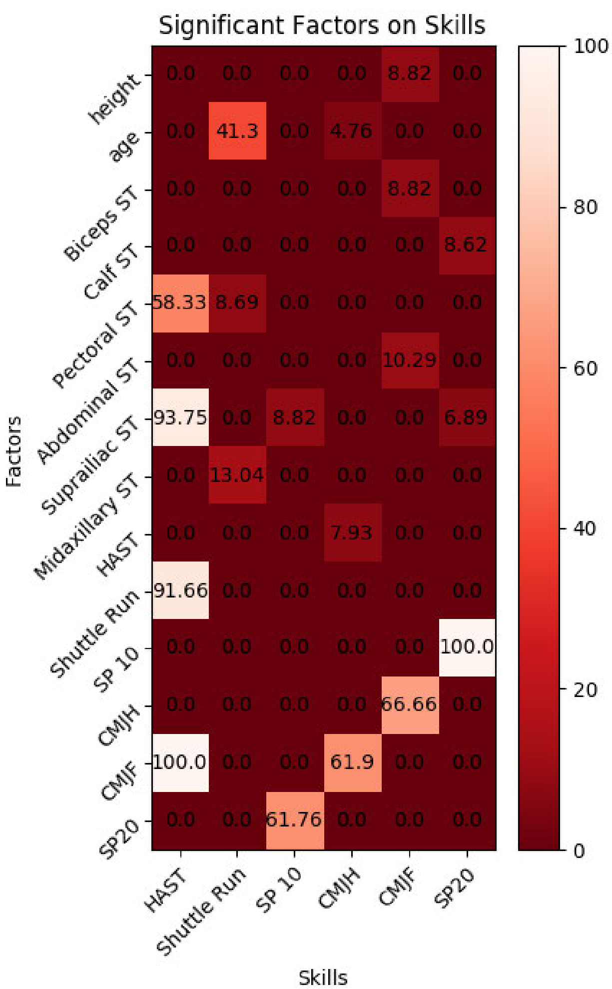

FIGURE 8. Visualization of factors on skills.

however, MAE is not sensitive to the outliers while it only considers the absolute difference of predicted and observed data. R^2 score is a measure of how well the models' regression line fits the data.

When the *MSE* results were considered, LR and deep LSTM models followed the RBFNN in the experiments that linear relations could be created. Although deep LSTM produced more stable results in all experiments, LR achieved better performance in error minimization. But the nonlinear relation between the attribute and the skills in the SR and HAST experiments caused LR not to make predictions. On the other hand, the neural network model BP could not minimize the *MSE* as well as other models in any of the experiments. SVR and DT, which are other nonneural models considered in this study, produced close *MSE* results to each other in all experiments except HAST, where the SVR and DT were not able to make predictions on the test data.

In MAE results, the level of achievement for all models is similar to the *MSE* results, and deep LSTM and LR followed RBFNN. Similarly, the BP, SVR, and DT produced results as at the same level as *MSE* results.

When R^2 scores were analyzed, fluctuations were observed between the experiments. RBFNN produced the highest R^2 scores for all experiments. Even the DT achieved similar *MAE* and *MSE* results in all experiments, it produced the lowest R^2 scores in CMJF and SP10 experiments. This was the reason for the researchers to consider more than one evaluation metric in their studies. Even the convergence of SVR was successful in five experiments, it could not produce optimal results in any of the experiments. It was also observed that nonneural models SVR and DT produced close R^2 scores in CMJH, SP20, and SR experiments. In addition to this, neural network models deep LSTM and BP, produced stable results in four of the experiments except HAST and SR, in which all models had difficulties in producing sufficient results. LR followed the RBFNN in three experiments when the R^2 scores considered; however, it could not produce the optimal results in the experiments.

When we compared the models by considering all experiments, the general neural network models (BP, RBFNN, and deep LSTM) achieved more stable prediction results than the nonneural network models (SVR, LR, and DT). Although the prediction rates of BP and deep LSTM were not as high as those of the RBFNN, the rates showed that neural network models could be more effective solutions for prediction problems, especially in datasets with nonlinear relationships. The characteristics of the dataset and the relationship and correlation between the attributes caused inefficient convergence of data, and the obtained prediction results either fluctuated or were unsuccessful for the non-neural network models. The *MSE* and *MAE* results of deep LSTM were at a level that can be considered as a successful, but lower R2 scores indicated that overfitting occurred in deep LSTM. If training can be performed with more data, overfitting can be eliminated, and more efficient convergence can be provided. In all experiments, the radial basis function neural network (RBFNN) produced the best results for predicting the performance of female athletes in terms of accuracy and consistency. The use of radial-basis functions in the RBFNN hidden layer minimizes the parameters of the neural network and provides statistical data for the next layer. This leads to effective error minimization and efficient convergence.

Linear relationships were only observed for the CMJF, CMJH, SP10, and SP20 in which the parameters are markers of the same physical characteristics (explosive power and acceleration). However, the RBFNN managed to produce prediction results for all exercise tests with much higher prediction rates than the other models.

The variety of ML models provides an advantage for researchers to obtain superior results by performing comparative studies on particular applications. Therefore, most of the studies consist of comparative evaluations of the considered models on the data used for a particular problem. Because of the data dependency of ML models, the one model that produces optimum results in a specific dataset might not produce sufficient results in another dataset. Therefore, each study and result should be analyzed by using the considered dataset, and only a general deduction can be made by considering recent and similar applications. Table 4 summarizes the recent studies and the obtained results in sports sciences for both classification and prediction applications.

In the study of Hore and Bhattacharya [17], SVM outperformed the naive Bayes, random forest and multilayer perceptron models by 85.65% in terms of classification accuracy for the sustainability model in NBA players in the USA, and in the study of Anik *et al.* [23], SVMs achieved higher classification accuracy than logistic regression (91.50%). Musa *et al.* [19], [20] performed two different studies for archery, and comparisons included the ANN and k-NN in both studies. The ANN and k-NN outperformed each other in various studies. Four of the five classification studies on sports sciences, which are summarized in Table 4, had comparative studies with different ML models, and the results obtained in these studies demonstrate the efficiency of k-NN, ANN, and SVMs in classification tasks, particularly in sports sciences.

In sports sciences, prediction tasks were considered more limited than classification applications. Jesus *et al.* [21] implemented and compared a linear model and ANN for swimming start performance, and the ANN outperformed the linear model. The mean absolute error was used as an evaluation criterion, and it was concluded that the ANN was superior for minimizing error. The most similar study to the present study, which used countermovement jump experiments, was performed by Zhou *et al.* [25] to predict the heights of countermovement jumps with free hands in football players. The comparison was performed among linear regression, decision tree and random forest models. Evaluation was performed by the R^2 score, and the correlation was measured as 0.886, while the R^2 score of the superior linear regression model was 0.689. Even if the different data were created using different sport branches, sexes, and physical properties, similar results were obtained via linear regression with the same exercise protocol. The R^2 score of the CMJF was 0.70 in this study, and 0.689 was achieved by Zhou *et al.* [25]. However, the RBFNN achieved an R^2 score of 0.96 in the same experiment. It is common knowledge that the dataset has a huge impact on the efficiency of the ML model. The characteristics of the dataset can increase or decrease the scores of the obtained results.

In sports sciences, studies that include neural networks have generally been limited to backpropagation, and the use of deep LSTM and RBFNNs has not been considered. The results obtained in this research showed that the RBFNN provided superior results than the other models within this research, and this may encourage consideration of different types of neural networks with other ML models for other prediction studies in handball or other sports.

When we analyze the factors that affected the predictions of the RBFNN as our primary machine learning model, according to the results, there was no common parameter for all tests that affected the prediction ability of the model. For this reason, each exercise test was analyzed separately.

The CMJH was the most important factor for CMJF prediction (66.66%). The other factors that affected the model's prediction were abdominal ST, biceps ST and body height, with much lower values (10.29%, 8.82%, and 8.82%, respectively). Similarly, the CMJF was the most important factor for CMJH prediction (61.90%) as expected, and the following factors had significantly lower values (agility (7.93%) and age (4.76%)). A linear relationship was also shown between the CMJF and CMJH by the LR model. This was expected since the two tests are very similar in terms of biomechanics and physiology. A countermovement jump was designed to determine the explosive lower body power of an athlete [40]. It may be performed with (CMJF) or without arm swing (CMJH). Although it was shown that arm swing increased jumping performance, both tests are used for indirect measurement of lower limb power [41].

Similar results were observed for the SP10 and SP20, which are sprint runs. The SP10 was affected by the SP20 with a value of 61.76%, and the RBFNN was unable to create a prediction for the SP20 without the SP10 data. A linear relation between the SP10 and SP20 was also observed in the LR model. This is not surprising because they are both used for measuring an athlete's acceleration and show linear velocity capability.

Our SR prediction results were affected by age (41.30%), midaxillary ST (13.04%), and chest ST (8.69%). The 20-meter shuttle run test (SR) is the most commonly used test

TABLE 4. Summary of recent researches on sports sciences and machine learning.

Research	Year	Branch/ Performance	Task [a]	Methods	Optimal method	Final Evaluation Metric	Optimum Result
Mezyk and Unold [15]	2011	Swimming	C	• Fuzzy Logic	-	Accuracy	68.66%
Zhou et al. [25]	2017	Countermovement jump heights	P	• Linear Reg. • Random Forest • Decision Tree	Linear Reg.	R^2 Score	for corr.: 0.886 model eval.: 0.689
Hore et al. [17]	2018	Basketball	C	• Naive Bayes • Random Forest • MLP • SVM	SVM	Accuracy	85.65%
de Jesus et al. [21]	2018	Swimming	P	• Linear Model • ANN	ANN	MAE	minimized error
Anik et al. [23]	2018	Cricket	C	• Logistic Regres. • SVM	SVM	Accuracy	91.5%
Musa et al. [19]	2019	Archery	C	• 6 types of k-NN • ANN	weighted k-NN	Accuracy	82.50%
Musa et al. [20]	2019	Archery	C	• k-NN • ANN	ANN	Accuracy	92.00%
This Study	2020	Six Performances in Handball	P	• ANN • RBFNN • DT • Linear Reg. • SVR • dLSTM	RBFNN	R^2 Score	0.86 - 0.97

[a]C: Classification, P: Prediction

to measure aerobic power [46]. It is well-known that aerobic power is directly related to age and body composition as well as genetics, sex, and training [42], which is consistent with our findings.

We used the handball agility specific test (HAST) to determine the agility levels of our participants. Agility was described by Sheppard and Young as' a rapid whole-body movement with change of velocity or direction in response to a stimulus' [43]. Since it is a complex response to a stimulus, it is affected by many cognitive, physical, and technical factors [40], [43], [44]. Our results showed that many factors strongly influenced HAST. It is not possible to make predictions without the CMFJ parameter as a marker of explosive leg power [45], which was shown to be a very important factor for agility [40]. Suprailiac ST, SR, and Chest ST were the other factors that affected HAST prediction with strong values (93.75%, 91.66%, and 58.33%, respectively), supporting the multifactorial structure of agility.

V. CONCLUSION

Analysis of different athletic abilities and performances is crucial for predicting actual performance in the field. Athletic performance is affected by many factors in different sports, and it is not easy to estimate which factors are most important and decisive. These factors largely do not show any linear relation with actual performance, and performance is a complex composition of many factors. Determination of these factors can help coaches clearly see the strengths and weaknesses of their athletes and establish their training programs according to the personal needs of the athletes. Machine learning models as artificial intelligence techniques are probably the most valuable way of performing predictions for challenging tasks.

Our results showed that it is possible to establish nonlinear relationships for different physical and exercise parameters in women handball players with a machine learning model, namely, a radial basis function neural network.

This is one of the first studies using machine learning in the field of athletics and particularly for handball players. The results are encouraging for future studies, and more studies are needed for specific types of athletic performance with a larger number of participants and parameters and possibly with other artificial intelligence models.

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