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Using Machine Learning Algorithms for Jumping Distance Prediction of Male Long Jumpers

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Abstract
The long jump is defined as an athletic event, and it has also been a standard event in modern Olympic Games. The purpose of the athletes is to make the distance as far as possible from a jumping point. The main purpose of this study was to determine the most successful machine learning algorithm in the prediction of the long jump distance of male athletes. In this paper, we used age and velocity variables for predicting the long jump performance of athletes. During the research, 328 valid jumps belonging to 73 Turkish male athletes were used as data. In determining the most successful algorithm, mean absolute error (MAE), root mean square error (RMSE), Mean Squared Error (MSE), R^2 score, Explained Variance Score (EVS), and Mean Squared Logarithmic Error (MSLE) values were taken into consideration. The outcomes of the analysis showed that long jump performance can be determined by chosen independent variables. The 5-fold cross-validation technique was used for the performance evaluation of the models. As a result of the experimental tests, the Gradient Boosting Regression Trees (GBRT) algorithm reached the best result with an MSE value of 0.0865. In this study, it was concluded that the machine learning approach suggested can be used by trainers to determine the long jump performance of male athletes.

Keywords: Long jump performance, machine learning, run-up velocity

1. Introduction

In the long jump, the goal is to gain speed on the running track and to jump as far from the board as possible. Besides the many parameters, the horizontal velocity, which has the highest biomechanical effect on flight distance, is very essential in the long jump (Hay, Miller, & Canterna, 1986; Linthorne, 2008). Some high-level long jumpers, such as Carl Lewis and Marion Jones, are also known to be high-level sprinters (Derse, Hansen, Tim, & Stolley, 2012). The fastest sprinters are not the best long jump athletes; however, it can be said the best long jumpers are the fastest ones. The long jump biomechanical analysis report of the 2009 IAAF World Athletics Championships confirms this; The athletes who ranked first had higher run-up velocities than others (Hommel, 2009). It was seen that the athletes who have the top three of the world rankings had 11 m/s of horizontal velocity (Fukasiro and Wakavama, 1992). As seen, run-up velocity is the most significant determinant of long jump performance (Açıkada, Arıtan, & Yazıcıoğlu, 1993; Bridgett, Galloway, & Linthorne, 2002; Bridgett and Linthorne, 2006; Hay, 1993; Hay, et al., 1986; Lees, Graham-Smith, & Fowler, 1994) It has been determined that there is a powerful relationship of 0.96 between the horizontal velocity and jump distance (Bridgett and Linthorne, 2006). Similarly, there are some studies indicating the relationship between velocity and jump distance (Bridgett, et al., 2002; Hay, 1993; Hay, et al., 1986; Lees, et al., 1994; Mishra and Rathore, 2016; Moura, Moura, & Borin, 2005, Rahim, et al., 2020; Takahashi & Wakahara, 2019). When the run-up velocity is artificially increased, a high increase in the jumping distance is observed (Schulek, 2002). According to the calculations, an increase of 0.1 m/s in velocity provides a rise in the jump distance by 6 to 12.8 cm (Bridgett and Linthorne, 2006; Hay, 1986).

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Studies focused on building a model to predict jumping distance related to run up velocity often used linear or nonlinear equations (Fukasiro and Wakavama, 1992; Hay and Miller, 1985; Lees, et al., 1994; Mikhailov, Yakunin, & Aleshinsky, 1981; Tiupa, Aleshinsky, Primakov, & Pereverzev, 1982). Most of these models were developed on a limited number of top athletes so models could predict non-acceptable jumping distance for extrapolated data. For instance, the nonlinear model of Mikhailov et al. (Mikhailov, et al., 1981) predicted a jumping distance of 44.25m for 10m/s run-up velocity. Some of these models had high accuracy estimations for low run-up velocities while others had better accuracy for high run-up velocities. Bayraktar and Çilli investigated a linear model, using 328 valid trials of 73 athletes during official competitions, which had better estimations for both lower and higher values (Bayraktar and Çilli, 2018).

The results of the studies showed that more sensitive and reliable models were needed. Linear or non-linear models did not have sufficient estimations for the wide range of velocity values. Recently, however, more advanced non-linear systems based on artificial intelligence have been used for modeling processes instead of linear approaches. Ofoghi et al. used machine learning techniques to develop approaches that predict performance models at the Track Cycling Omnium championships (Ofoghi, Zeleznikow, MacMahon, & Dwyer, 2010). In 2017, machine learning techniques were used to measure the hitting loads in tennis (Whiteside, Cant, Connolly, & Reid, 2017). As of 2018, there have been studies to estimate the performances of athletes. In a study to estimate biathlon shooting performances with the help of machine learning techniques, the results of the 5th season were tried to be accurately determined using the data of the previous 4 seasons (Maier, Meister, Trösch, & Wehrlin, 2018). The predicted accuracy rate of the study remained at 62%. In 2019, a classification approach was presented to predict the future success of potential young archers (Musa et al., 2019). As the studies indicated, it was clear that computers and especially machine learning (artificial intelligence) techniques could be used at many points that require experience from the choice of the athletes to the training load and the estimation of their degrees. Today, it is seen that ML techniques are used in many areas of sports, from predicting results in team sports (Bunker and Susnjak, 2022), to athlete health and injury prevention (Eetvelde et al., 2021). Despite the popularity of ML techniques in sports sciences recently, any study has been found in which ML techniques are used for prediction and modeling in the field of the long jump. In this study, we used different machine learning algorithms for estimating the jumping distance of male long jumpers. Thus, besides introducing ML techniques to the field of long jump, it has been tried to show that successful results can be obtained as an alternative to the techniques used in the past and based only on run-up velocity. In addition, detailed analyses were made on which ML approach could yield more successful results, and information on the parameters used was given. After determining the most successful model, we developed a web application that trainers could use.

This paper is organized as follows. Section 2 presents the research methodology, in which the data, analysis methods, and evaluation techniques are explained. Section 3 provides a comparative analysis of models. In Section 4, the results are discussed and explained. The paper is concluded in Section 5.

2. Material and Methods

2.1. Participants

Data used in this study consisted of 328 valid trials of 73 Turkish male athletes and were also used in the study presented by Bayraktar and Çilli (Bayraktar and Çilli, 2018). The average age of these long jumpers was 18.7 (±2.8) years old. All data were gathered from 11 competitions which were in the Turkish Athletic Federation's official calendar. Data collection was begun after the permission of the Turkish Athletic Federation and the approval of the Sakarya University Ethics Committee.

2.2. Research Design

The photocells were placed at 1, 6, and 11 meters behind the takeoff board to determine athletes' running times. For each jump, velocities V1, V2 and Vloss were calculated for the sections 11m-6m, the 6m-1m, and the difference between V2 and V1, respectively. In addition, official jump distances were recorded.

2.3. Dataset

The information about the obtained data from 328 valid trials is given in Table 1. The average age of the athletes, whose youngest is 14 years old and the oldest 28 years old, is 18.7. The average jumping distance of all athletes is 6.30 meters. The V1 and V2 averages of the athletes are 8.88 and 8.92 m/s, respectively.

Table 1. Mean and standard deviation values of the variables for the samples.

Variables	n	Mean (SD)	Min	Max
Age(year)		18.7 (2.80)	14.4	28.5
Jump Distance		6.30 (0.71)	4.53	7.74
V1 (m/s)	328	8.88 (0.71)	7.08	10.89
V2 (m/s)		8.92 (0.54)	7.52	10.20
Vloss (%)		0.71 (5.61)	-11.66	17.82

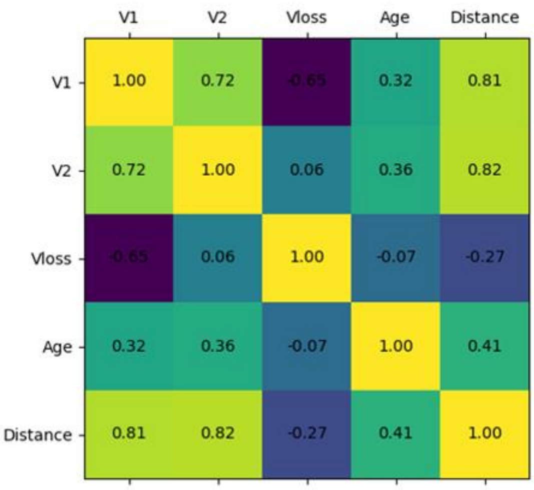

Figure 1. Calculated correlation values between jumping distance and variables.

As shown in Figure 1, correlation statistics were calculated between jumping distance and variables. It was found that the run-up velocity variables V1 and V2 had positive and strong relationships with jumping distance. The correlation between age and jumping distance was a positive and moderate relationship ($r=0.41$, $p>0.05$). The correlation between velocity losses and jumping distance was a negative and weak relationship ($r=-0.27$, $p>0.05$).

2.4. Machine Learning Methods

In this paper, five popular machine learning techniques were used: Artificial Neural Networks, Ridge Regression, Decision Trees, K-Nearest Neighbors Regression, Random Forest, and Gradient Boosting Regression Trees. These modeling techniques were briefly discussed below. In addition, for hyperparameter optimization, the Grid Search technique was used to find the most suitable one by trying different parameters. The parameters evaluated during the training phase was given in Table 2.

Table 2. Evaluated parameters of each machine learning methods

Model	Parameter	Start	Finish	Increment
ANN	Hidden Layer 1 Neuron	5	50	5
	Hidden Layer 2 Neuron	5	50	5
Ridge	Alpha	0.1	3	0.1
KNN	Neighbors	1	20	1
Gradient Boosting	Estimator	100	1000	100
Random Forest	Estimator	100	1000	100

Artificial neural networks (ANN) are biologically inspired mathematical techniques that can model complex nonlinear functions (Haykin, 2009). We used multilayer perceptron (MLP) Neural Network architecture with a backpropagation type supervised-learning algorithm. MLP was used to generate regression-type estimation models for numerical variables (Hornik, Stinchcombe, & White, 1990).

ANN architecture used in the study was given in Figure 2. The ANN had one input layer, two hidden layers, and one output layer. The input layer was used to receive the input data and the amount of the input layer neurons was adjusted by the type and number of input variables in the dataset. An output layer was used for giving a probability vector for predictions. The hidden layers were used for representing the input vector in a more abstract form. To find the optimum number of neurons for each hidden layer we tested different numbers of neurons between 5 and 50 through an iterative experimentation process. According to the test results seen in Table 3, the most successful RMSE score was obtained when 45 neurons were used in hidden layers 1 and 2. Rectified Linear Unit (ReLU) activation function was used for the hidden layers and the linear activation function was used for the output layer. Mean square error, which is the most commonly used regression loss function, was selected as the loss function. Adam optimizer was used in backpropagation and the learning rate was selected as 0.001.

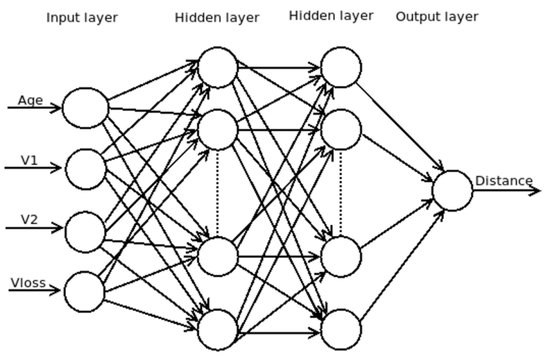

Figure 2. Graphical representation of the ANN architecture developed for the research.

Ridge regression (RR), is a technique used to calculate the approximate result of equations without a unique solution. RR adds a bias to the conventional regression calculation and reduces standard errors. In ridge regression, the alpha value is used for the regularization and it is selected as 1.9 in our model (Figure 3).

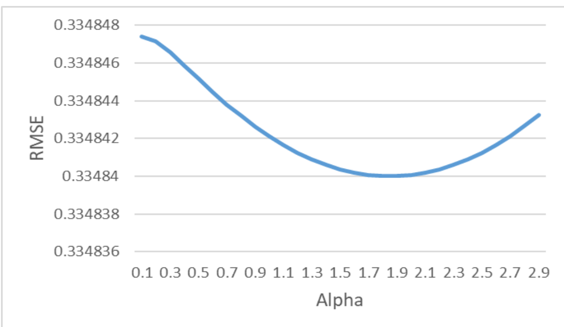

Figure 3. Alpha value vs. root mean squared error for ridge regression.

The *k-nearest neighbors (KNN)* algorithm is another machine learning method that can be easily used to calculate regression problems. In order to increase the efficiency of the KNN model, we determined the optimal value of the neighbor parameter used in the model. In this research k value was selected as 12 and Minkowski distance was selected as the similarity measure (Figure 4).

Table 3. RMSE values for different neuron numbers of first and second hidden layers

Layer1/Layer2	5	10	15	20	25	30	35	40	45	50
5	0.3296	0.3350	0.3289	0.3431	0.3466	0.3412	0.3390	0.3338	0.3427	0.3314
10	0.3264	0.3286	0.3346	0.3235	0.3278	0.3360	0.3328	0.3374	0.3429	0.3406
15	0.4064	0.3166	0.3288	0.3216	0.3219	0.3304	0.3249	0.3359	0.3406	0.3279
20	0.7172	0.3372	0.3272	0.3449	0.3249	0.3297	0.3185	0.3233	0.3287	0.3245
25	0.3317	0.3222	0.3197	0.3410	0.3208	0.3441	0.3354	0.3277	0.3300	0.3385
30	0.3327	0.3149	0.3330	0.3181	0.3216	0.3304	0.3332	0.3319	0.3252	0.3361
35	0.3329	0.3332	0.3217	0.3259	0.3261	0.3255	0.3252	0.3232	0.3292	0.3312
40	0.3188	0.3385	0.3357	0.3271	0.3359	0.3331	0.3426	0.3284	0.3305	0.3255
45	0.3148	0.3333	0.3373	0.3201	0.3336	0.3272	0.3211	0.3239	**0.3096**	0.3251
50	0.3225	0.3161	0.3241	0.3128	0.3195	0.3194	0.3230	0.3174	0.3268	0.3142

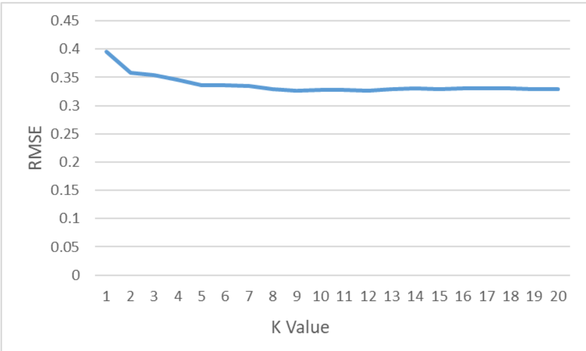

Figure 4. Number of neighbors vs. root mean squared error for KNN.

Decision Trees (DT) can identify different patterns by using dependent and various independent variables as an alternative to regression models (Cox, 2002). The decision tree approach generally establishes heuristic models that make more accurate predictions. The first and last nodes of the decision tree are called root and end nodes, while intermediate nodes are called leaf nodes. The variables in the nodes are checked with the training data set. Starting from the root (the top node), the decision tree algorithm creates the tree from the first node to the end nodes by determining which variable to be tested.

Random Forest algorithm is a very popular and highly sensitive learning algorithm for classification and regression tasks based on decision trees. A random forest consists of a combination of trees created using a random vector that is sampled independently from each input vector (Breiman, 2001). The Random Forest algorithm solves the over-fitting problems of decision trees. Figure 5 shows the test results for parameters of Random Forest algorithm.

Gradient Boosting Regression Trees (GBRT) enables the optimization of arbitrary differentiable loss functions by creating an additive forward stage-wise model. A regression tree fits on the adverse gradient of the specified loss function at each level. It is an accurate and effective model that can be used for the problems of classification and regression. The number of the boosting stages is determined by an iterative experimentation process. Gradient boosting is relatively robust to over-fit, so a big amount generally leads to better performance (in this study we used the 100 boosting stage). Figure 6 shows the test results for parameter selection.

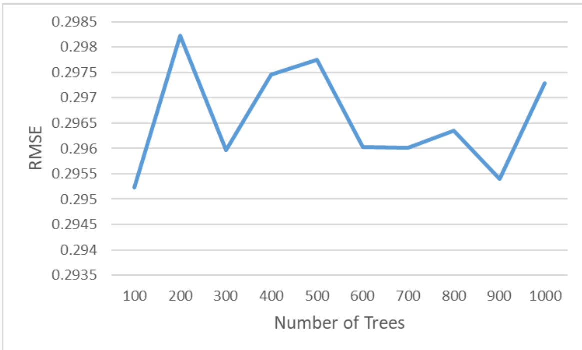

Figure 5. Number of trees vs. root mean squared error for random forest.

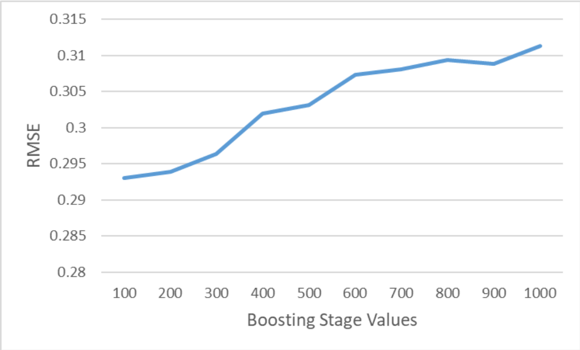

Figure 6. Number of the boosting stages vs. root mean squared error for GBRT.

3. Results

In the experiments, the performance of the methods was evaluated using the 5-cross validation approach. 80% of the data was used for training and 20% for testing in each fold and the experiments were repeated for each test group. To evaluate the prediction successes of algorithms, six error measurement techniques were used. They are the most popular metrics for the accurate evaluation of continuous variables.

Mean Absolute Error (MAE), without considering direction, evaluates the mean errors in the predictions set. It is the mean of the absolute difference between the predicted values and observed values. Mathematically, it is calculated using Eq. 1.

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \quad (1)$$

Root mean squared error (RMSE) measures the average error as quadratic. RMSE is the square root of the average of squared differences between predicted values and observed values. It is calculated using Eq. 2.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2} \quad (2)$$

In addition, the results of the Mean Squared Error (MSE), R^2 score, Explained Variance Score (EVS), and Mean Squared Logarithmic Error (MSLE) metrics used in different ML studies are also included.

In this part, the performances of the proposed machine learning algorithms are evaluated. We compared previously developed linear and nonlinear models as well as machine learning techniques such as artificial neural networks, ridge regression, decision trees, K-nearest neighbors regression, random forest, and gradient boosting regression trees. The prediction results of the Nonlinear-1 model (Mikhailov, et al., 1981) are quite different from the real values as mentioned earlier. The estimations of the Nonlinear-2 model (Tiupa, et al., 1982) are slightly behind the results of other estimation algorithms. Although the prediction results of the Linear (Bayraktar and Çilli, 2018) model are better than the previous non-linear models, its success is below the machine learning techniques. The results showed that the GBRT had the lowest error for all used metrics (Table 4).

Table 4. Performance comparisons of machine learning algorithms and other models for distance prediction of all 5-folds average.

Model	MSE	RMSE	MAE	EVS	MSLE	R^2	Time (sec.)
Linear	0.1225	0.3489	0.2732	0.7606	0.0025	0.7546	-
Non-Linear-1	902.08	30.03	29.82	-24.54	2.6422	-1818	-
Non-Linear-2	0.1512	0.3861	0.2934	0.7570	0.0030	0.6975	-
ANN	0.0964	0.3096	0.2365	0.8110	0.0020	0.8061	2.885
Ridge	0.1127	0.3348	0.2643	0.7787	0.0023	0.7726	**0.035**
KNN	0.1082	0.3270	0.2520	0.7905	0.0023	0.7837	0.070
Decision Tree	0.1561	0.3907	0.2963	0.6823	0.0032	0.6736	0.049
Random Forest	0.0874	0.2952	0.2236	0.8287	0.0018	0.8235	0.789
Graident Boosting	**0.0865**	**0.2930**	**0.2198**	**0.8323**	**0.0018**	**0.8238**	0.280

The results of the GBRT algorithm for each fold were shown in detail in Table 5.

Table 5. Results of GBRT algorithm for each fold.

FOLD	MSE	RMSE	MAE	EVS	MSLE	R^2
1	0.09297	0.30491	0.23667	0.84040	0.00189	0.82985
2	0.06300	0.25099	0.19039	0.89252	0.00128	0.88677
3	0.10551	0.32482	0.22731	0.81141	0.00222	0.79088
4	0.09153	0.30254	0.24186	0.76458	0.00193	0.76055
5	0.07937	0.28172	0.20268	0.85237	0.00170	0.85101

The closest and farthest predictions of each method to the real data were given in Table 6. While the closest estimate was made with GBRT, the farthest estimate was made with the Nonlinear-1 method (Mikhailov, et al., 1981).

Table 6. Maximum and minimum difference between actual and predicted data

Algorithm	Max.	Min.
ANN	1.0550336	0.0020013
Ridge	0.9385549	0.0016124
KNN	1.4708333	0.0025000
Decision Tree	1.3000000	0.0000000
Random Forest	0.9080000	0.0009000
Graident Boosting	1.1547455	0.0000923
Linear	1.0223000	0.0001300
Nonlinear-1	39.3241981	20.4664035
Nonlinear-2	1.1759100	0.0028119

The results of the proposed models were compared to the real data in Figure 7. Measured jumping distances and predicted values were shown separately for each of the linear and machine learning methods. The red color indicated the measured distance, while the gray color (dashed line) indicated the results of the prediction methods. As can be seen in the graphs of machine learning methods, the similarity of red and gray lines was higher than the linear method. In addition, it was seen that the similarity of the predictions made with the GBRT algorithm to the real values was significantly more.

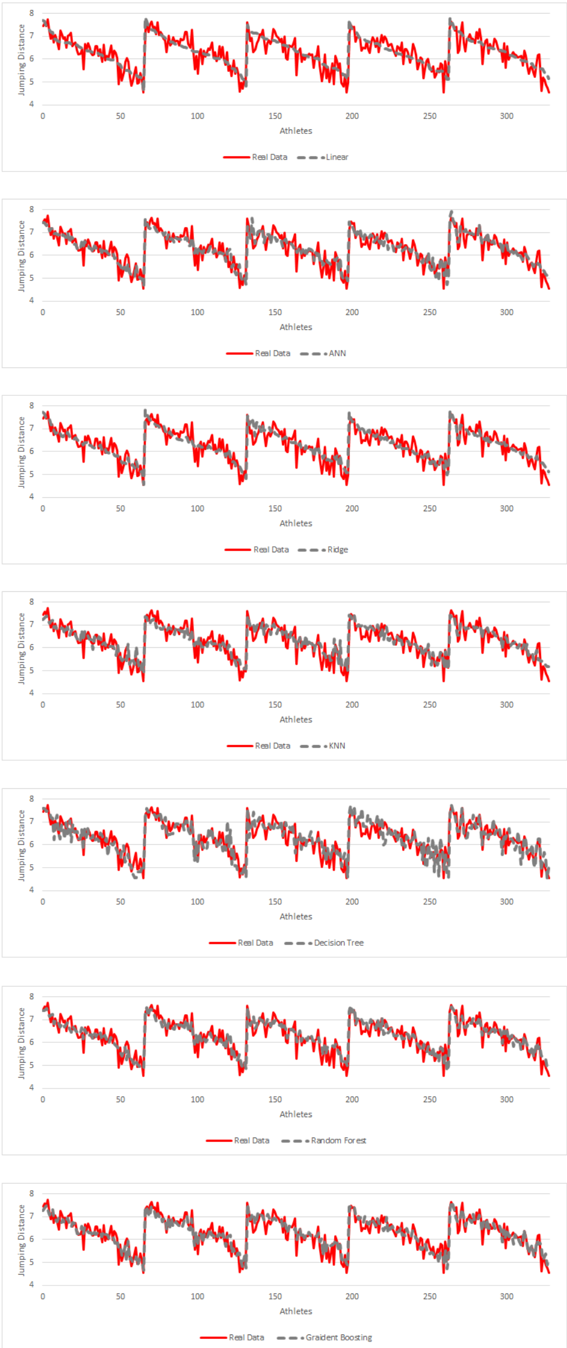

Figure 7. Comparing the predictions to the observed data.

Figure 8 shows the differences between the observed distances and predicted values for the GBRT method (purple color) and the Linear model (dashed line). While plotting the graph, the absolute differences between the estimated results and the actual values for both methods were ordered from largest to smallest. Therefore, predictions which were close to zero were more successful. It is obvious that the predictions yielded by the GBRT method are more successful than the linear method.

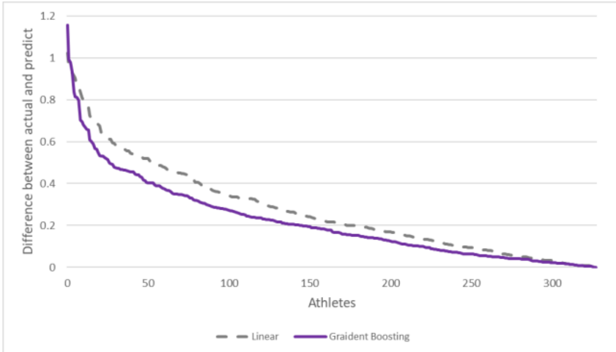

Figure 8. Difference between predicted and observed jump distances for Linear model and GBRT algorithm.

4. Discussion

The results of the study showed that besides the run-up velocity values such as V1 (0.81) and V2 (0.82), the age (0.41) parameter also had an effect on long jump distance. In the literature, the velocity values in the last 10 meters were utilized by most researchers, and models that could be expressed with a first-order or quadratic equation were developed. (Bayraktar and Çilli, 2018; Mikhailov, et al., 1981; Tiupa, et al., 1982).

In previous studies, a model was developed based on the data and the accuracy of the model was tried to be tested with the same data. However, in this study, 5-fold cross validation technique was applied and 80% of data were used for training and 20% of data were used for testing in each fold.

In many studies, it was stated that increasing the average speed would have a direct positive effect on jump distance (Bridgett, et al., 2002; Hay, 1993; Hay, et al., 1986; Lees, et al., 1994; Rahim, et al., 2020; Takahashi & Wakahara, 2019). There were also studies expressing the threshold velocity required for an athlete to jump 8 meters (Linthorne, 2008; Moura, et al., 2005). They argued that the horizontal velocity should be 10.5 m/s or 10.6 m/s. The common feature of all these studies was that the distance increases as the run-up velocity increases. Furthermore, these models did not contain any statement that the age of the athletes also had an effect on distance.

The fact that an action performed by a very complex organism, such as a human being, cannot be explained by a single phenomenon, is valid even in sports branches that are completely individual. For this reason, many physical and psychological researches are carried out in the literature even in individual branches. It is also a well-known fact that physical and psychological conditions are important factors that may affect the outcome of the competition.

Nowadays, it is not realistic to explain these complex cause-effect relationships with a simple mathematical model. Instead, it is clear that the structure of artificial intelligence, which can easily establish complex relationships and solve complex models, should be utilized in the estimation of results.

It was seen that the machine learning method proposed in this study produced consistent results when compared with the accurate results of linear models. And also proposed model generated much lower errors than the error rates of the linear model.

In addition a web application were developed with the obtained results of this study using the Gradient Boosting Regression Trees algorithm (Figure 9). Trainers may use this application for athletes. When they use the velocities for the 11m-6m section (V1), the 6m-1m section (V2), and age as the input parameters, the program will produce an output (predicted jumping distance) for them. The web link of the used models and dataset is: https://github.com/mrtucar/LongJumpEstimation

5. Conclusions

In this study, a new method for the jumping distance prediction of male long jumpers was proposed based on a machine learning algorithm. To achieve the highest efficiency, various regression algorithms were applied. After the most successful model was determined, a web application was developed that trainers can use.

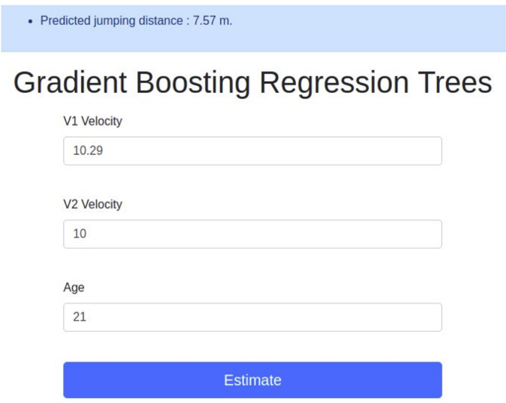

Figure 9. Developed web application.

It will be easier to calculate the “technical efficiency index” (TEI) (Bayraktar and Çilli, 2018) using the proposed method. With the help of the score calculated as TEI = 100 x Measured Distance / Estimated Distance, trainers will be able to evaluate the status of their athletes according to their jumps. Thus, athletes with a score of less than 100 points, will need to increase their technical skills. The trainers will be able to obtain the TEI values with the help of the proposed method for developing the exercises that will emphasize the technical skills of the athletes.

Considering that records and grades are developed with only a few centimeters today, it is clear that every step taken to improve the athlete's technical skills is valuable. Artificial intelligence applications, which have started to enter all areas of life with developing technology, will help coaches in many athletic events in the near future.

Fuller et al. stated that using ML methods in studies requiring physical activity such as sports branches has not reached a sufficient level yet (Fuller et al., 2022). They also stated that the increase in the number of studies on the use of ML methods in sports fields by using large and open datasets can contribute to the field. Therefore, we consider our study to be a valuable contribution in terms of utilizing and comparing machine learning algorithms that are used for the first time to estimate long jump distance. Furthermore, live predictions of the jumping distance of individual jumps could be attractive for broadcasting purposes.

It is considered that the estimation results of the artificial intelligence model will increase with the addition of body structure information and detailed information of training.

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