Clinical and Experimental Health Sciences

Plantar Pressure Topography Based Sports Branch Prediction System Modeling in 7-11 Years Old Athletes

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ABSTRACT

Objective: The sole of foot plays a crucial role in sports movements, as it applies pressure to the ground and transfers loads. The foot pressing types vary depending on the sport played by the athlete. The aim of this study is to develop a model that can predict sports branches from the plantar pressure types of athletes.

Methods: A total of 80 athletes, 54 athletics and 26 combat athletes, between the ages of 7-11 were included in the study where static pedobarographic measurements of the participants were collected. First we applied conventional statistical analysis on the featured obtained from the measurements of the data using Fisher Freeman Halton Exact test. Then, we implemented sports branch prediction based on the data obtained from these measurements using advanced machine learning and deep learning techniques.

Results: There was no statistically significant difference between the plantar compression types of the participants according to the branches ($p > .05$). In the machine learning classification based on foot plantar compression, the best success was found to be 56.9% with Linear Support Vector Machine. When the branch prediction successes made with deep learning were examined, it was found that the average branch prediction was 82.58±7.62% in the foot with pes planus, 87.84±17.56% in the normal foot, and 85.95±21.19% in the foot with pes cavus.

Conclusion: In the study, it was determined that the success of branch prediction made with machine learning techniques was low, and the success of deep learning was high. With the development of the method used in this study in future studies, an idea can be obtained about which branch of the foot plantar pressure type is more prone to and innovations can be brought to the branch selection methods.

Keywords: Deep learning, machine learning, foot, plantar pressure, sports

1. INTRODUCTION

The foot, which has a complex structure consisting of many bones, synovial joints and ligaments, has the task of carrying the body weight and pushing the body forward by acting as a lever arm during movement (1, 2). The medial, lateral and transverse arches of the foot ensure load transfer and create a static and dynamic order (3). Pes planus and pes cavus, which result from changes in height in the medial longitudinal arch due to muscular imbalances and changes in Body Mass Index, can be cited as the major examples of the disruption of this order (3-5). While pes cavus is defined as the elevation of the medial arch of the foot above normal, pes planus is defined as flattening of the medial arch of the foot, i.e., a decrease in the normal height of the medial arch of the foot (3).

The pressure exerted by the foot on the ground plays a crucial role in the transmission of force during movements such as running, walking and jumping. For this reason, the sole of the foot has important functions in athletic movements. Pressure changes in the foot in pes planus and pes cavus can lead to various musculoskeletal problems (6-9). Therefore, there has long been great interest in the literature in the study of plantar pressure and the detection of these pressure problems (10-13). Plantar pressure measurements are used to assess plantar pressure and some indices are used to determine the individual foot pressure types (14, 15).

Machine learning and deep learning methods can also be used to evaluate foot pressure types for various purposes. In a study that aimed to determine the severity of Parkinson's disease based on the plantar pressure of individuals, four supervised machine learning algorithms were used, namely decision tree (DT), support vector machine (SVM), ensemble classifier (EC), and Bayes classifier (BC) (16). In the study by Chae et al (17), a deep learning model based on artificial intelligence was developed

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to classify foot deformities as concave, normal and flat feet. As you can see, these studies focused on determining foot types, estimating the severity of the condition based on plantar pressure, and determining the foot problem caused by the condition.

Studies in the literature investigating the relationship between type of branch and type of foot pressure have shown that the type of foot pressure varies depending on the type of sport branch. However, these studies were limited to statistical methods (18, 19). When examining other literature studies that evaluate foot type using artificial intelligence methods, there are studies based on estimating the population of people who run with or without shoes or studies that use deep learning models that can make predictions about foot injuries (20, 21). Again, studies have been conducted in the literature to differentiate foot images (22). However, no study was found that made predictions about sports branches based on foot type. The main objective of this study is to develop artificial intelligence algorithms that can predict sports branches of athletes based on foot type. Machine learning and deep learning methods, i.e. artificial intelligence methods, were used for the study. In addition, the development of these algorithms may lead to the creation of new test criteria for talent selection in the future.

2. METHODS

2.1. Participant

The sample of the study consists of child athletes of both genders, aged 7-11, registered in athletics and combat sports branches (karate, taekwondo, and judo) registered at the sports center in Üsküdar district of Istanbul. The criteria for inclusion in the study included participating in athletics or combat branches for at least one year, being an athlete registered in the sports centers of Üsküdar district of Istanbul, training at least 2 days a week, and participating in the study voluntarily. Exclusion criteria for the study included having any neurological or musculoskeletal system disorders. According to the G-Power analysis, a total of 80 athletes from 54 athletics and 26 combat sports were included in the study within the framework of a 95% confidence interval and 5% margin of error. The mean age of the participants was 9.88±1.38; the mean age of starting sports was 6.55±2.01; the duration of the branch (months) was 27.51±12.83. Demographic information based on the sports branches is given in Table 1.

Table 1. *Other demographic information of the participants by sport branch*

Branches	Variables	N	Min	Max.	Mean	Sd.
Athletics sport	Age	54	7	11	9.815	1.36
	Sport starting age	54	3	10	6.444	2.03
	Duration of sports month	54	12	60	27.111	12.19
Combat sportsThis	Age	26	7	11	10.000	1.44
	Sport starting age	26	4	10	6.769	1.99
	Duration of sports month	26	12	61	28.346	14.27

N.: Number; Min.: Minimum; Max.: Maksimum; Sd.: Standart Deviation

2.2. Procedure

Static pedobarographic measurements were carried out on the participants as part of the study. The devices were positioned before the measurement. The participants, accompanied by their parents, were invited to the measurement area and informed about the study. The participants and their parents completed the informed consent form and the participants were voluntarily enrolled in the study. Participants who had completed the participant information form were taken to the measurement area in turn. The study was approved by the Ethics Committee of Marmara University Institute of Health Sciences with the approval date and number T7.01.2022-03.

2.3. Data Collection Tools

The pedobarographic measurement was performed with the GHF550 Foot Checker device. The device enables a weight measurement between 16-150 kg. The device, which consists of a matrix sensor system, has a sensor area of 480mm x 480mm, dimensions of 590mm x 525mm x 55mm, and input and output pads can be added without sensors. There are 2304 sensors in the device and each sensor has a frequency of up to 60 Hertz.

Static pedobarographic measurements were taken with the Pedabarograph while participants were facing a fixed point in front of them, feet open at shoulder level, arms relaxed on both sides and in an upright position. The measurements were taken with bare feet. The purpose of this measurement is to reveal the pressure distribution and foot deformities of the subjects while they are pressing on the floor in a static position.

2.4. Data Preparation

Calculation Chippaux Smirak Index

Many indices are used to detect pressure problems in static sole analysis. One such index is the Chippaux-Smirak Index (CSI), an index commonly used in screening for pes planus and claimed to have better predictive capacity (23, 24). In this study, the CSI index was used to classify the participants' feet as pes planus, pes cavus and normal foot. The index is calculated by dividing the narrowest width of the mid-arch area of the foot (a) by the maximum width of the metatarsal region (b) (Figure 1). The lengths of regions a and b were determined by measuring the length using the Analysis System application. This data was then transferred to Excel and the CSI values were determined using the b/a equation. If the CSI≤0.299, it was classified as a pes cavus foot, if 0.3≤CSI≤0.399, it was classified as a normal foot, and if CSI≥0.4, it was classified as a pes planus foot (25). Additionally, Information on the foot classes obtained is given in Table 2.

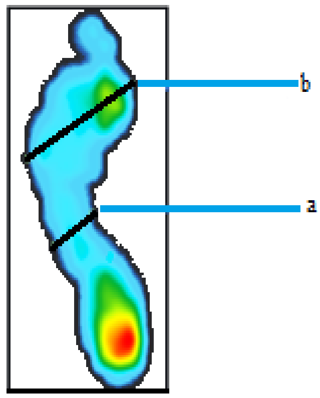

Figure 1. *The a and b length regions used in Chippaux Smirak Indeks*

Table 2. *Information on the foot images obtained*

Branches	Foot type	Right foot	Left foot	Number (N) of foot images raw data	Number (N) of foot images after data augmentation
Atletics sports	Pes cavus	43	42	85	12240
	Normal	6	6	12	1728
	Pes planus	5	6	11	1634
Combat sport	Pes cavus	17	17	34	4896
	Normal	7	7	21	2016
	Pes planus	2	2	6	576

Preprocessing for Image Data with Data Augmentation for Deep Learning Classification

The data augmentation method is a technique that increases the amount of data. The Convolutional Neural Network (CNN) is a deep learning method and a commonly used technique for image classification. Even though deep learning techniques are very successful, the imbalance of the dataset or the lack of sufficient training data can cause some difficulties (26). To overcome such problems, the data is augmented and synthesized by methods such as cropping, zooming in and out, flipping, shifting, and changing the color (27, 28). This increases the size and quality of the training datasets (29). In this study, data augmentation methods were applied to the dataset to improve the result of the deep learning method for foot type classification. MATLAB2021b software was used to process foot image data, standardize it, and apply data augmentation methods. MATLAB is a programming tool used to analyze data and to develop and create models (30).

First, the foot plantar pressure images obtained from the pedobarography device were processed with MATLAB software and converted into two images, the image of the right foot and the image of the left foot, and the texts such as participant number, date, etc. on the image were deleted with a different code.

In the next phase of the study, rotation, vertical flipping, color, and Gaussian filtering were used as data augmentation techniques. Random deleting and random cropping were not favored to avoid data loss. By writing code for each data augmentation method used in the study, the codes were run in MATLAB software and the data size was increased. Rotation involved rotating the images 45, 90, 135, 180, 225, 270, and 315 degrees. Each data augmentation method was applied to the raw data and the data obtained from the previous data augmentation step. Thus, 144 foot images were obtained from one foot image. A total of 15,552 foot images were obtained for athletics sport (N=54) and 7488 foot images were obtained for combat sports (N=26). The image examples obtained through the data augmentation are shown in Figure 2.

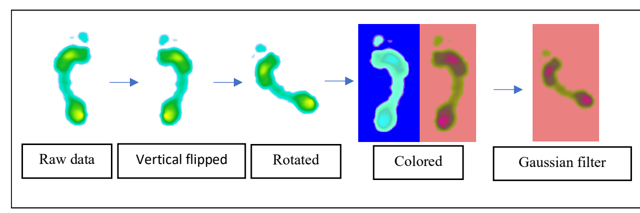

Figure 2. *Schematic representation of the images obtained by data augmentation*

The images of the plantar pressure are divided into three folders: pes cavus, normal and pes planus, according to the type of footprint, which is derived from the Chippaux-Smirak Index. The data numbers in the foot pressure type classes are given in Table 2. The data obtained were used for branch prediction using the deep learning technique.

2.5. Data Analysis and Classification

Foot Type Classification with Machine Learning Technique

In the preparatory phase, the foot data obtained from the pedobarography device was processed with the MATLAB program. The values of the pressure falling on each sensor were included in the foot data and the color distribution indicated the foot pressure density. Using the code created in MATLAB, the toes were removed from the data. The forefoot, midfoot and hindfoot areas were then determined separately for the left and right feet (Figure 3). The top, bottom, right and left edges of each foot were determined with the code and the total area of the foot was calculated in MATLAB and the foot was divided into three parts. As a result, the data was converted into 6 features. The features obtained were the right forefoot, right midfoot, right hindfoot, left forefoot, left midfoot and left hindfoot pressure amounts.

The dataset, which consists of six features (right forefoot, right midfoot, right hindfoot, left forefoot, left midfoot and left hindfoot pressure) and 2 classes (athletics and combat branches), was subjected to classification using all possible kernels of the Support Vector Machine (All SVM) in Matlab Machine Learning Toolbox. Linear, quadratic, cubic, fine Gaussian, medium Gaussian and coarse Gaussian classifiers of SVM were used.

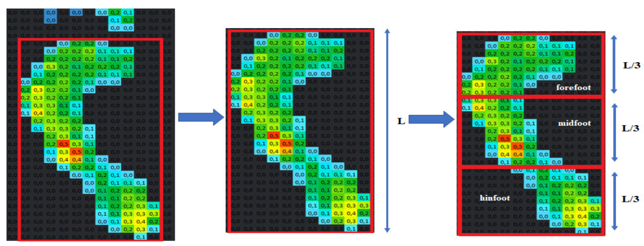

Figure 3. *Determination of fore, mid and hind foot regions separately in MATLAB*

Foot Type Classification with Deep Learning Technique

Deep learning is based on representation learning, in which several features of the data are used. In representation learning, the data is used for pixel density vectors, edge sets, etc., which are learned, and algorithms are used to extract data features (31). Since classification with machine learning could not achieve high classification success, the plantar pressure images were processed with deep learning techniques for branch prediction. The Convolutional Neural Network (CNN) method, one of the deep learning techniques, was used in the study. CNN is a widely used deep learning technique for image data classification (32). This method was used to classify the participants' foot images.

The foot images of the participants according to their branches were divided into the classes pes planus, normal, pes cavus foot folder according to CSI. The number of images present in the foot pressure type folders of each branch is shown in Table 2. The data in the obtained folders were classified using the deep learning method. A separate deep learning algorithm was created for each foot folder.

Figure 4 shows the deep learning algorithm for the normal foot, Figure 5 for pes planus, and Figure 6 for pes cavus. To create learning models, the entire dataset used is divided into 80% for training and 20% for testing. The summary of the algorithms created for each plantar compression type can be found in Tables 3, 4 and 5.

Table 3. *Summary of the proposed model for normal foot*

Layer (type)	Output Shape	Parametres
Convolution 1	(None, 256, 256, 16)	448
Max Pooling 1	(None, 128, 128, 16)	0
Dropout 1	(None, 128, 128, 16)	0
Convolution 2	(None, 128, 128, 16)	2320
Max Pooling 2	(None, 64, 64, 16)	0
Dropout 2	(None, 64, 64, 16)	0
Convolution 3	(None, 64, 64, 32)	4640
Max Pooling 3	(None, 32, 32, 32)	0
Dropout 3	(None, 32, 32, 32)	0
Convolution 4	(None, 32, 32, 32)	25632
Max Pooling 4	(None, 16, 16, 32)	0
Dropout 4	(None, 16, 16, 32)	0
Convolution 5	(None, 16, 16, 64)	18496
Flatten	(None, 16384)	0
Dense 1	(None, 128)	2097280
Dense 2	(None, 2)	258

Table 4. *Summary of the proposed model for pes planus*

Layer (type)	Output Shape	Parametres
Convolution 1	(None, 256, 256, 16)	1216
Max Pooling 1	(None, 128, 128, 16)	0
Dropout 1	(None, 128, 128, 16)	0
Convolution 2	(None, 128, 128, 16)	2320
Max Pooling 2	(None, 64, 64, 16)	0
Dropout 2	(None, 64, 64, 16)	0
Convolution 3	(None, 64, 64, 32)	12832
Max Pooling 3	(None, 32, 32, 32)	0
Dropout 3	(None, 32, 32, 32)	0
Convolution 4	(None, 32, 32, 32)	9248
Max Pooling 4	(None, 16, 16, 32)	0
Dropout 4	(None, 16, 16, 32)	0
Convolution 5	(None, 16, 16, 32)	25632
Max Pooling 5	(None, 8, 8, 32)	0
Dropout 5	(None, 8, 8, 32)	0
Convolution 6	(None, 8, 8, 32)	9248
Flatten	(None, 2048)	0
Dense 1	(None, 128)	262272
Dense 2	(None, 2)	258

Table 5. *Summary of the proposed model for pes cavus*

Layer (type)	Output Shape	Parametres
Convolution 1	(None, 254, 254, 16)	448
Max Pooling 1	(None, 127, 127, 16)	0
Dropout 1	(None, 127, 127, 16)	0
Convolution 2	(None, 123, 123, 16)	6416
Max Pooling 2	(None, 61, 61, 16)	0
Dropout 2	(None, 61, 61, 16)	0
Convolution 3	(None, 57, 57, 32)	12832
Flatten	(None, 103968)	0
Dropout 3	(None, 103968)	0
Dense 1	(None, 128)	13308032
Dropout 4	(None, 128)	0
Dense 2	(None, 2)	258

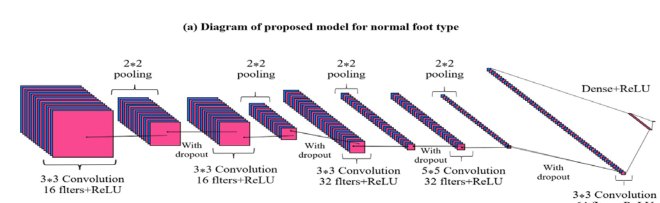

Figure 4. *Diagram of the proposed network model for normal foot type*

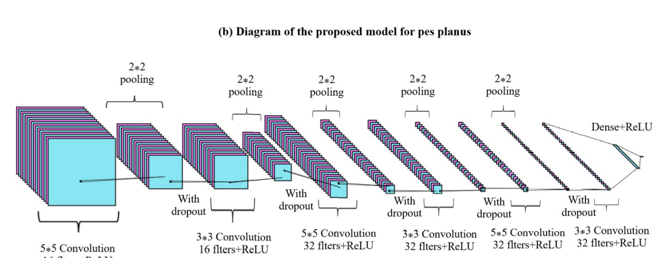

Figure 5. *Diagram of the proposed network model for pes planus*

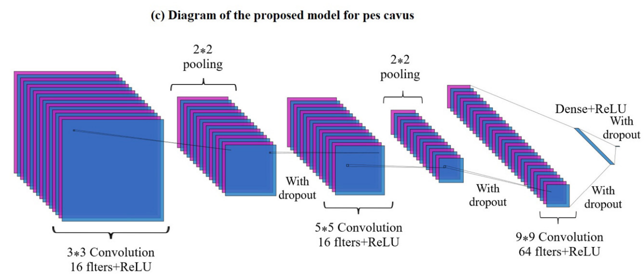

Figure 6*. Diagram of the proposed network model for pes cavus*

2.6. Statistical Analysis

The analyses were carried out using the Statistical Package for the Social Sciences (SPSS) 26.0. The significance value was set at $p < .05$. Descriptive statistics such as minimum, maximum, mean value, standard deviation and Fisher Freeman Halton Exact Test were used to analyse the data.

In data analysis, in order to determine whether there was a difference between foot pressure types according to branch, a 2x3 cell chi-square test had to be used, since both of our variables consist of categorical data, branch (athletics, combat) and foot pressure type (pes cavus, pes planus, normal). Additionally, the expected number of cells with values less than 5 exceeded 20%. For this reason, the Fisher Freeman Halton Exact test was used in data analysis. The analysis was done separately for the right and left foot.

3. RESULTS

3.1. Examining the Difference between Foot Classes According to CSI Based on Branch

The participants' foot types were classified according to CSI as pes planus, pes cavus and normal foot. When analyzing the obtained data with Fisher Freeman Halton Exact, no significant difference was found between the types of foot pressure according to the branch (for the left foot: $X^2=3.127$, $p > .05$; for the right foot: $X^2=3.153$, $p > .05$). On this basis, we decided to investigate whether the athletes' branch predictions could be made using artificial intelligence methods. In the second and third steps, we predicted the participants' branching based on their foot types using machine learning and deep learning techniques.

3.2. Machine Learning Classification

Machine learning classification was performed on the basis of branch prediction based on foot plantar pressure. The accuracy data of the test data obtained with each method is shown in Figure 7. The best classification success was found to be 56.9% with Linear SVM. From this we can conclude that this classification success is not very good, as it can be assumed that the discrimination rate of two random groups is perhaps 50%. For this reason, we decided to apply the classification method using deep learning techniques.

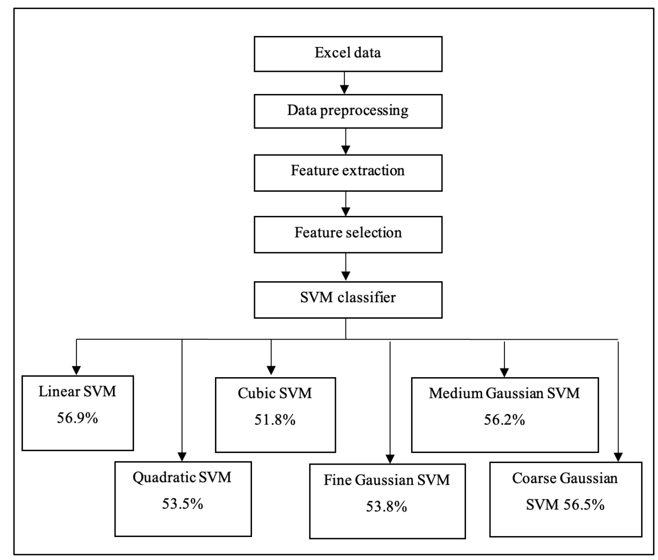

Figure 7. *Machine Learning Classification Method and Accuracy Result of Test Data (SVM: support vector machine)*

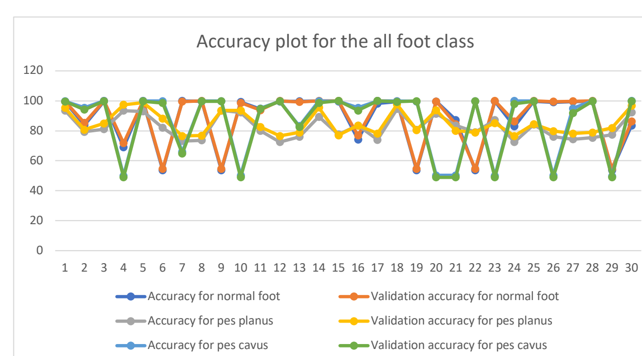

Figure 8. *Accuracy plot for the all foot class*

3.3. Deep Learning Classification

In this study, the CNN method, one of the deep learning techniques, was used because the data to be used for classification are images. When processing the data in the algorithms, 80% of the total data was used as test data and 20% as training data. Each classification was repeated 30 times. The graphs of the percentages of success obtained are given in Figures 8 for each class. When the average success rates of the algorithms were examined, it was found that the average branch prediction was 82.58%±7.62% for the pes planus foot, 87.84±17.56% for the normal foot, and 85.95±21.19 for the pes cavus foot (Table 6).

Tablo 6. Deep learning accuracy ratio descriptive statistic values

Foot type	Accuracy ratio	N	Min.	Max.	Mean	Sd.
Pes planus	Accuracy	30	72.51	94.62	82.58	7.62
	Validation accuracy	30	76.62	98.84	85.06	7.76
Normal	Accuracy	30	53.67	99.93	87.84	17.56
	Validation accuracy	30	54.55	100.00	88.44	17.15
Pes cavus	Accuracy	30	48.82	100	85.95	21.19
	Validation accuracy	30	48.82	100	85.22	21.52

N.: Number; Min.: Minimum; Max.: Maksimum; Sd.: Standart Deviation

4. DISCUSSION

The aim of the study was to determine if there exists a statistical difference between branches in terms of foot type and to use artificial intelligence methods to make predictions about the branch based on the foot pressing types of athletes. The lack of a similar study in the literature accounts for the originality of the study. In addition, it was determined which method is more successful in predicting branches.

Artificial intelligence (AI) technology has become a very active technology in recent years and is used in many fields such as education, and health (33, 34). Machine learning and deep learning methods, which are fields of artificial intelligence, are among the methods whose effectiveness has been demonstrated for such research (35). Recently, these methods have been used in sports science-based studies to predict the performance of athletes and to detect sports injuries, etc. was used for the purpose (36, 37). In this study, branch prediction was generated from the footstep pictures of the athletes by using support vector machine method from machine learning techniques and convolutional neural network methods from deep learning techniques.

Athletes can have different foot types depending on the sport. Klingele et al. (38) found in their study that endurance runners have an increased risk of flat feet. Ślężyński and Dębska (39) explained in their study that elite wrestlers have the highest level of medial longitudinal arch and that pes planus rarely or only slightly occurs in these athletes. In the study by Ramos-Álvarez et al (18), the incidence of pes planus was found to be highest in taekwondo players and lowest in track and field athletes. Lessby et al (19) found that susceptibility to pes cavus was higher in powerlifters, swimmers and field athletes than in pes planus. In another study conducted on sedentary women and female athletes, the pes cavus foot type was found to be most common in both groups (40). In this study, there are two branches, namely athletics and combat (karate, judo, taekwondo). As you can see, the literature argues that there is a difference in foot type depending on the sports branch. When examining the statistical analyzes of the study, no significant difference was found between the foot types of the two branches. The reason for this difference not occurring could be the inclusion of three different sports branches within the combat sports branch. This fact is a limitation of the study and it is recommended that combat sports be examined separately in similar studies conducted in the future. In addition, the inbalance number of participants in athletics (N=54) and combat (N=26) branches included in the study may have resulted in the difference not occurring. It is recommended to select an equal number of athletes from the branch in future studies.

In the study, a branch classification was performed based on the Support Vector Machine Classifier, one of the machine learning techniques, and the plantar pressure images. In this study, the success rate of SVM classification based on six features from the participants' footprints was about 50%. The success of branch prediction with machine learning was found to be low.

In traditional machine learning, engineers or data scientists typically compute features from the raw data before feeding them into the algorithms. And these features become a representation of the input data that make it easier for the algorithms to learn patterns. On the other hand, deep learning algorithms can automatically learn feature representations from the raw data which is useful in eliminating the need for manual feature engineering. Deep learning performs representational learning-based learning by learning multiple features of data. In representation learning, features such as pixel density vectors, edge sets, etc. of the data are learned and algorithms are used to extract data features (31, 41, 42). In addition, with deep learning, low-dimensional features of the data are extracted and converted into high-dimensional features (32). Thus, a model with high classification success can be produced by performing a more detailed data analysis in deep learning. The superiority of deep learning over traditional machine learning methods depends on the specific task, dataset characteristics, and available computational resources. Deep learning is particularly popular in recent years because people learn that we can automate the process of feature construction rather than have human labor to work on that as in traditional machine learning. Also, given the progress of modern technology, which has much more complicated structure and large dataset, the deep learning method can take advantage of that and a better and better performance in many different applications such as image recognition, computer games and so on.

Studies have shown that deep learning has better classification success than the machine learning method in large-scale data (43, 44). However, it is known that obtaining large datasets is quite difficult (32, 45). Obtaining datasets used especially for medical diagnoses is costly, labor-intensive and can be difficult due to patient protection reasons, etc. In such cases, the data augmentation method can be used (28, 46-49). To increase the classification success with deep learning, this study preprocessed the data and augmented the foot images showing the plantar pressure distributions using the data augmentation method. Random deletions and random clipping are not favored to avoid data loss. The success of deep learning has been enhanced by increasing the amount of data based on the preferred methods. Increasing the number of datasets using these methods is the strength of the study. In the results obtained with CNN, the average success of branch prediction from images of pes planus feet is 82.58%±7.62%, the average success of branch prediction from images of normal feet is 87.84±17.56%, and the average success of branch prediction from images of pes cavus feet is 85.95±21.19%. It should be noted that, logically, there is a 50% probability of guessing which of the two branches the athlete belongs to. However, the predictions made with deep learning methods show accuracy rates of over 80%. These high estimates show that the deep learning models developed provide sound and reliable results.

The use of an inbalance dataset in the study constitutes the limitations of the study. It is recommended to use a balanced dataset in similar studies using the machine learning method in the future. The strength of the study is that it is a first in the literature and that the data augmentation method is used to increase the success of deep learning. In addition, creating sports branch predictions based on each foot type (pes planus, pes cavus, normal foot) increases the level of detail of the study and represents one of the strengths of the study. These results lay the foundation for the development of technological products to be produced in the future for talent selection methods.

5. CONCLUSION

Studies show that there is a correlation between the type of athlete's foot and the type of sport. Starting from this point, we tried to predict the type of sport the participants would play step by step based on their foot type. The statistical results showed that athletes from two different branches had similar foot types. The machine learning technique was not sufficient to predict the sports based on foot type. In contrast, the deep learning models developed for branch prediction based on foot type showed high success rates in the study. We have developed deep learning models for predicting sports branches, and these methods can give an idea of which sports people are more likely to play based on their foot types. Using these deep learning models, future studies can ensure that athletes choose their sports branch based on their foot type as part of talent selection.

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Author Contributions:
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Design of the study: SAK, ADD, MÜ
Acquisition of data for the study: SAK, MÜ
Analysis of data for the study: SAK, ADD
Interpretation of data for the study: SAK, ADD
Drafting the manuscript: SAK, MÜ, ADD
Revising it critically for important intellectual content: ADD, SAK, MÜ
Final approval of the version to be published: ADD, SAK, MÜ

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