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Araştırma Makalesi / Research Article

Comparison of Artificial Neural Networks with other Machine Learning Methods in Foot Movement Classification

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Abstract

Modern prostheses can be controlled by using gait analysis data from Inertial Measurement Units compared to traditional prostheses. This article aims to classify foot movements for the robotic ankle system in lower limb prostheses to recognize motion intent and adapt to abnormal walking conditions. The statistical features are extracted from IMU data from 11 volunteers aged 20-34 and then the features are classified using machine learning. In this study, the classification accuracies of Naïve Bayes Classifier, Linear Discriminant Analysis, K-Nearest Neighbour Classifier and Support Vector Machines and Artificial Neural Networks in classifying foot movements are examined separately for the raw data and the processed data such as Euler angles and quaternions which estimate with Madwick Filter. Gait analysis data were obtained by using the Inemo inertial module LSM9DS1 work on an NRF52 including 9 DOF, triaxial gyroscope, triaxial accelerometer, and triaxial magnetometer in the Biomechanics Laboratory of the Department of Mechanical Engineering, Middle East Technical University from eleven subjects and achieved an highest classification accuracy rate of 90.9% on test data, 97.3% for training data.

Keywords: K-Nearest Neighbor, Support Vector Machines, Accelerometers, Gyroscope.

Ayak Hareketleri Sınıflandırmasında Yapay Sinir Ağlarının diğer Makine Öğrenme Yöntemleri ile Karşılaştırılması

Öz

Modern protezler, geleneksel protezlere kıyasla Atalet Ölçüm Birimlerinden (IMU'lar) alınan yürüyüş analizi verileri kullanılarak kontrol edilebilir. Bu makale, hareket niyetini tanımak ve anormal yürüme koşullarına uyum sağlamak için alt ekstremite protezlerinde robotik ayak bileği sistemi için ayak hareketlerini sınıflandırmayı amaçlamaktadır. 20-34 yaşları arasındaki 11 gönüllüden toplanan IMU verilerinden istatistiksel özellikler çıkarılmış ve daha sonra öznitelikler makine öğrenmesi kullanılarak sınıflandırılmıştır. Bu çalışmada, Naive Bayes Sınıflandırıcısı, Doğrusal Ayırım Analizi, K-En Yakın Komşu Sınıflandırıcısı ve Destek Vektör Makineleri ve Yapay Sinir Ağları ayak hareketlerini sınıflandırmadaki sınıflandırma doğrulukları ham veriler için ve Madwick Filtresi ile tahmin edilen Euler açıları ve kuaterniyonlar gibi işlenmiş veriler için ayrı ayrı incelenmiştir. Yürüyüş analizi verileri, Orta Doğu Teknik Üniversitesi Makine Mühendisliği Bölümü Biyomekanik Laboratuvarı'nda on bir denekten üç eksenli jiroskop, üç eksenli ivmeölçer ve üç eksenli manyetometre içeren 9 serbestlik dereceli bir NRF52 üzerinde Inemo atalet modülü LSM9DS1 çalışması kullanılarak alındı ve test verilerinde % 90.90, eğitim verilerinde %97.3 en yüksek sınıflandırma doğruluk oranı elde edildi.

Anahtar Kelimeler: K-En Yakın Komşu, Destek Vektör Makineleri, İvmeölçer, Jiroskop.

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1. Introduction

Amputation is a surgical operation that causes the loss of function and is cut off from the limb that cannot be fed due to trauma, tumor, infection, vascular diseases, etc (Hoile, 1996). An article published in 2019 shows that at least 7000 diabetic patients in the UK have undergone lower limb amputation (Kerr et al.). The purpose of a prosthesis is to create a device that will not feel the lack of the missing limb. One of the most important tools used in prosthetic foot design and actuator selection in clinical gait analysis data obtained from the analysis of human movement.

Robot movements are determined by researchers by mimicking human movements. For this purpose, human movements are collected, learned, and transferred to the robot with motion capture systems (Pollard et al., 2002; Miura et al., 2011). If we consider the prosthetic foot as a robot, human foot movements are also used to determine the movements of the prosthetic foot. Traditionally, gait analysis is carried out with optical devices which are motion capture systems, but complex systems including cameras, markers, infrared light have a disadvantage such as requiring both a laboratory environment and limited field of view. Instead, IMUs with lower cost and easily used devices may be preferred. Wireless sensors are worn by the body ensure long-term monitoring of the patient so that data can be obtained anytime and anywhere, without limiting the movement of the person (Hacker et al., 2014). Amputees need prostheses to gain the ability to walk properly. Since current passive prostheses cannot adapt to complex environments, prostheses with features such as perception of walking environment, user intention estimation, user activity detection are preferred. The IMUs have high accuracy in detecting user activity. IMU signals are a good option for use in machine learning approach as they provide rich signal information in terms of walking angular velocity and acceleration.

Parkka et al. obtained data to create a large and realistic data library of 16 volunteers using only the accelerometer. Using these data, they successfully classified daily activities such as sitting, standing, walking, and lying, using the custom decision tree, automatically generated decision tree, and the artificial neural network after feature extraction and 12-fold cross-validation. The highest overall classification accuracy of 86 % was obtained for the automatically generated decision tree. (Parkka et al., 2006).

In the study published in 2014, gait experiments were carried out by a 40-year-old transfemoral amputated male subject by attaching the upper leg, the lower leg, and foot with 6 IMUs at a measurement rate of 60 Hz (Seel et al., 2014).

In the study given in (Haoyu et al., 2019), an adaptive and on-line classification method was proposed to detect four lower extremity activities such as walking, running, stair ascent, stair descent with IMU signals. In this experiment, 10 healthy subjects (3 female, 7 male) were used regardless of the user's gender, height, and activity speed, and classification accuracy of up to 99.2 % was obtained.

In another study (San-Segundo et al., 2016), Segundo et al. proposed a human activity recognition and segmentation (HARS) system using publicly available data set by collecting smartphones inertial signals from 30 volunteers to recognize 6 activities such as walking, sitting, standing, lying, stairs up, and stairs down. The error rate has been reduced so that the segmentation error rate is less than 0.5%.

In (Fullerton et al., 2017), it was aimed to detect daily activity by using unfiltered data collected from 10 participants with the help of 9 body-worn accelerometer sensors. KNN classifier with mean and standard deviation features was used and recognition accuracy of 97.6 % was obtained. In the study in (Gao et al., 2020), a geometry-based locomotion mode recognition system was proposed.

The performance of the proposed system was tested on three healthy (3 males, 25-30 years) and three unilateral transtibial amputees (1 female, 2 males, 21-42 years) for 5 locomotion mode. Experimental results showed that the average accuracy rate for 6 subjects was 98.5 %. By combining the basic classifier AdaBoost algorithm with graphic models such as the Hidden Markov model and Conditional Random Field, Wen and Wang (Wen and Wang, 2016) proposed a method that can automatically select the most discriminating features and improve efficiency recognition accuracy during the adaptation process without human intervention.

A human activity recognition study was performed by creating an unbalanced data set from the data with inertial sensors obtained by Wu et al. (Wu et al., 2016). In this study, a mixed-kernel based weighted extreme learning machine was proposed to find a solution to class imbalance, and successful results were obtained.

Khera et al. (Khera et al.,2020) classified plantarflexion, dorsiflexion, inversion and eversion movements using EMG signals in 2020. They used Support Vector Machines (SVM), Neural Networks (NN) and Logistic Regression as algorithms. The highest classification accuracy was obtained with the SVM algorithm.

Chaobankoh et al. classified Dorsiflexion, Neutral position and Plantarflexion movements using EMG signals in 2022. For this, they preferred the 2D-CNN network. While the algorithm showed high success in training, it achieved average success in testing (Chaobankoh et al., 2022).

In our previous study, a dynamic model of the ankle-foot system, which have sufficient degrees of freedom and range of motion to adapt to human anatomy, has been created. The purpose of prosthesis studies is to prevent the absence of the missing limb. We can achieve this by using a variety of control methods that will allow to minimize the difference between input and output signals. Measuring instruments such as force, pressure, electromyography (EMG), IMU sensors are used to obtain input signals for controllers (Aydin Fandakli et al. 2018).

It is aimed to shorten the rehabilitation period of amputees and increase their performance in daily work by developing an active ankle-foot prosthesis that can effectively detect human gait in a way that prevent gait asymmetry and damage to the healthy leg. The study will contribute to orthotic/ prosthesis specialists to determine personalized treatments for patients, and to the robotic scientists to develop two-legged robot that imitates human motion. If sensing walking environments and predicting user intent can be performed, prosthetics would help amputees adapt to complex environments more easily. In this study, it was aimed to develop a prosthesis that can be controlled by gait analysis by classifying foot movements. After this stage, it will be passed to the stage where clinical practice studies for amputees will begin. Thus, prosthetic foot control will be provided by using healthy foot data for amputees.

2. Materials and Methods

In this study, the raw data obtained from IMUs from the foot and lower leg of 11 volunteers were classified extracting features with Linear Discriminant Analysis (LDA), Gaussian Naïve Bayes, Linear-Support Vector Machine (L-SVM), Quadratic SVM (Q-SVM), Fine-k-Nearest Neighbor (F-KNN), Weighted-KNN (W-KNN) and Artificial Neural Networks (ANN).

Gait analysis data were obtained by using the Inemo inertial module LSM9DS1 work on an NRF52 including 9 DOF, triaxial gyroscope, triaxial accelerometer, and triaxial magnetometer in the Biomechanics Laboratory of the Department of Mechanical Engineering, Middle East Technical University. In Figure 1, a schematic representation of LSM9DS1 is given in (URL-1, 2021). As shown in Figure 2, data are collected from the lower leg and foot with four IMU sensors. Before starting the experiment, if it is to be measured for the first time during the day, it is necessary to synchronize the IMUs first. IMUs must have the same or very close values. Otherwise, it will sync again. This process continues until values close to each other are obtained and then the recording is started.

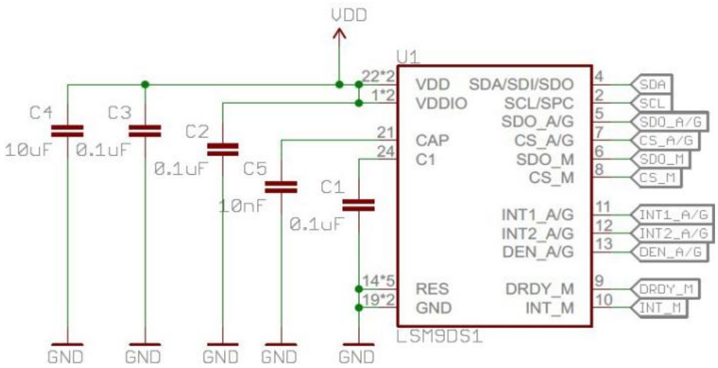

Figure 1. Schematic representation of LSM9DS1

Figure 2. Fitting the sensors to subjects

IMUs can be used to find the three-dimensional orientation of an object. We can calculate Euler angles (φ, roll: rotation around x-axis; θ, pitch: rotation around y axis; ψ, yaw: rotation around z axis) using the data obtained from the IMU, and this is the easiest way to show this orientation. With gyro, only angular velocities are calculated. With the accelerometer, pitch and roll angle can be calculated, but it contains noises that prevent to obtain accurate information. The magnetometer sensor is also used to calculate angles in the yaw axis. Because it can detect fluctuations in the Earth's magnetic field, its motion is combined with sensor fusion with accelerometer and gyroscope data to determine absolute direction and orientation. To explain the three-dimensional orientation of the Euler angles, the quaternions method, which assure transition from inertial frame to the body frame of the sensor and is a vector with 4 variables, can be used instead of 3 angles. Filters are used to prevent shifting angles, which calculates angular velocity even in a fixed object. In our study, the Madwick filter was used to calculate Euler angles and quaternions. As shown in Equation (1), quaternions contain four coefficients consisting of one scalar q0, 3 vectors q1, q2 and q3. The scalar part determines the amount of rotation of the vector part (Craig, 2005; Bernal-Polo and Martínez-Barberá, 2019). When rotated by the θ angle, the quaternion coefficient is expressed as in Equation (2). In this study, quaternions and Euler angles are estimated from the raw data from the sensor with Madwick filter as seen in Equation (3), (4) and (5) (Madwick, 2010).

$$q = q_0 + iq_1 + jq_2 + kq_3 \tag{1}$$

$$q(\theta, v) = \cos(\frac{\theta}{2}) + iv_1 \sin(\frac{\theta}{2}) + jv_2 \sin(\frac{\theta}{2}) + kv_3 \sin(\frac{\theta}{2}) \tag{2}$$

$$\varphi = a\tan 2(2(q_2 q_3 - q_0 q_1), 2q_0^{\,2} - 1 + 2q_3^{\,2}) \tag{3}$$

$$\theta = -\arctan\left(\frac{2(q_1 q_3 + q_0 q_2)}{\sqrt{1-(2q_1 q_3 + 2q_0 q_2)^2}}\right) \tag{4}$$

$$\psi = a\tan 2(2(q_1 q_2 - q_0 q_3), 2q_0^{\,2} - 1 + 2q_1^{\,2}) \tag{5}$$

The general structure of the study consists of Data Acquisition, Filtering, Feature Extraction, Size Reduction, Classification, and Control Signal Generation stages as given in Figure 3.

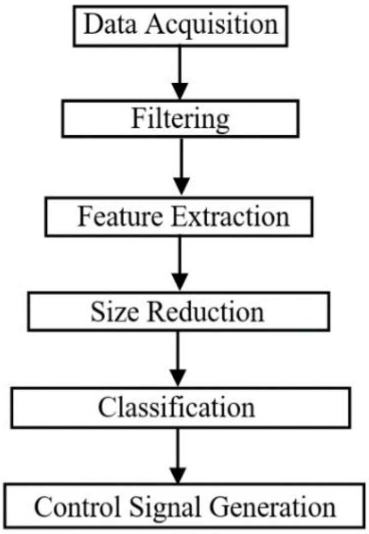

Figure 3. The general structure of prosthetic foot reference signal production

2.1. Data Set Description

The movements of eleven healthy subjects (8 Male, 3 Female, aged 20-34 years) were measured each subject completed fifty trials on a force plate at a self-selected speed. The data obtained using four inertial sensors which are connected to the right and left shank (lower side leg) and others are connected to the right and left metatarsal (foot) and they were transferred to PC via USB-6212 Multifunction I/O Device from National Instruments were analyzed off-line using MATLAB environment. The raw data was sampled at 100 Hz.

In this study, only the data collected by the inertial sensor in the right metatarsal, and right shank were used. Whereas gyroscope measures angular velocity in degrees per second, accelerometer measures acceleration and magnetometer measure the power and direction of magnetic field data were collected, force data were obtained from the BERTEC drill force platform simultaneously.

However, the force plate data are outside the scope of this study and will be used separately in another study. Foot movements to be classified are given in Figure 4.

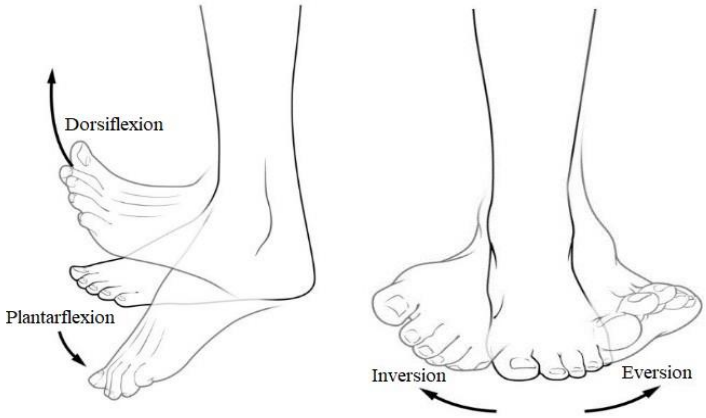

Figure 4. Foot movements

Eleven healthy volunteers signed an informed consent form after the ethics committee report was issued for the measurements. Ethics Committee Approval document numbered 24237859-595 was received by Karadeniz Technical University, Faculty of Medicine, Scientific Research Ethics Committee Chairmanship. Data from eleven healthy subjects regardless of the user's gender, height, and activity rate were processed firstly as raw. Before starting the experiment, if it is to be measured for the first time during the day, it is necessary to synchronize the IMUs first. IMUs must have the same or very close values. Otherwise, it will sync again. This process continues until values close to each other are obtained and then the recording is started.

Before the experiments in this study, reliability tests were conducted with 3 different people. Gait analysis data were collected, except for foot movements. 11 volunteers were allowed to do each foot movement 50 times. Apart from this, these 11 volunteers were asked to walk 10 times within certain limits and their data were collected and tested.

2.2. Feature Extraction

The first step to use the data from the sensor in classification is the feature extraction phase. With the feature extraction process, the size of the input dataset is reduced to lower-dimensional features containing important information of the original data (Aydin Fandakli et al. 2017). The selected features are those obtained by trial-and-error method to achieve the highest classification accuracy.

Firstly, the raw data obtained from the sensors for foot and lower leg was inserted into classifiers after statistical features such as mean, standard deviation, skewness, kurtosis, covariance, sum were extracted.

Data are handled in 9 dimensions as 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometers. In the first experiment, a 1x9 dimensional feature vector for each movement was obtained calculating the mean of each feature in the 3790x9 dimensional feature matrix. The feature vectors obtained by 4 different movements taken from 11 people were combined to create a 44x9 dimensional feature matrix, and the feature matrix for training and testing was divided into two, and 22x9 dimensional matrices for training and testing were obtained.

The statistical features used in the study are given in Equation (6), (7), (8), (9), (10), (11) and (12).

$$X = \sum_{i=}^{n} (x_1 + x_2 + \ldots + x_n) \tag{6}$$

X is sum of the data, $x_1, x_2 \ldots x_n$ are the samples, n is the number of samples.

$$\bar{X} = \frac{X}{n} \tag{7}$$

$\bar{X}$ is obtained by dividing the sum of the data by the number of samples.

$$SD = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{X})^2}{n}} \tag{8}$$

Standard deviation, indicated by SD, refers to how far data deviates from the mean. Skewness, S refers to the measurement of the asymmetry of the data distribution. Kurtosis, k measures the distribution of the signal according to the Gauss distribution.

$$S = \frac{\frac{1}{n} \sum_{i=1}^{n} \left(x_i - \bar{X} \right)^3}{\left(\sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(x_i - \bar{X} \right)^2} \right)^3} \tag{9}$$

$$k = \frac{n\sum_{i=1}^{n}\left(x_i - \bar{X}\right)^4}{\left(\sqrt{\sum_{i=1}^{n}\left(x_i - \bar{X}\right)^2}\right)^2} \tag{10}$$

$$\operatorname{cov}(x, y) = \frac{\sum_{i=1}^{n}\left(x_i - \bar{X}\right)\left(y_i - \bar{Y}\right)}{n-1} \tag{11}$$

Covariance, cov(x,y) is used to measure the directional relationship between x and y variables.

$$\|x\|_2 = \left(\sum_{1}^{n}|x_i|^2\right)^{1/2} = \sqrt{x_1^2 + x_2^2 + \ldots + x_n^2} \tag{12}$$

Norm, $\|X\|_2$ is the calculation of the length or magnitude of the vectors.

2.3. Classification

The classification process was carried out to detect all four-foot movements with 7 classifiers such as Naïve Bayes, LDA, KNN, and SVM and ANN. Different KNN and SVM algorithms have been used to increase the classifier diversity. Fine KNN is an algorithm that makes detailed separation by setting the number of neighbors to 1, while weighted KNN is an algorithm that uses distance weighting. The difference between SVMs is that the kernel function is linear or quadratic.

2.3.1 Linear Discriminant Analysis

This algorithm, which separates the different classes with a strict line, that is, trying to maximize the distribution among different classes, and minimize the distribution within the class, is an approach developed by Fisher (Welling, 2005; Tharwat et al. 2017). It is frequently used in fields such as statistics, machine learning, model recognition, and artificial learning, data mining, biometric, information access. The LDA, which aims to transform the original data matrix into a lower-dimensional matrix, is used as a classifier in this study, although it is mostly used in size reduction, which is a preprocessing (McLachlan, 2004). Fisher's linear discriminant analysis maximizes Equation (15) for the purposes.

There, S_{w} gives the within classes scatter matrix, S_B refers to the scatter matrix between classes as given in Equation (16) and (17), respectively (Fisher, 1936).

$$J(\mathrm{w}) = \frac{\mathrm{w}^T S_B w}{\mathrm{w}^T S_W w} \tag{15}$$

$$S_W = \sum_{j=1}^{C} \sum_{i:c_i=j} (x_i - \mu_j)(x_i - \mu_j)^T \tag{16}$$

$$S_B = \sum_{c=1}^{C} n_c (\mu_c - \mu)(\mu_c - \mu)^T \tag{17}$$

x and w represent the input vector and the projection vector, respectively. $J(w)$ is the expression that shows the maximum class separability. μ and μ_c gives the mean and global mean, respectively. T is threshold value, n_c is the number of cases in class c.

2.3.2 Naïve Bayes Classifier

Based on the Bayes theorem given in Equation (18), the Naïve Bayes classifier has a simple but powerful probabilistic algorithm that can be used even in unbalanced datasets (Han et al. 2011; Friedman et al.,1997).

$$P(A/\mathrm{B}) = \frac{P(B/A)P(A)}{P(B)} \tag{18}$$

Here, $P(A/B)$ expresses the probability that event A occurs when event B occurs,
$P(A)$ refers to the probability of occurrence of event A.
$P(B/A)$ expresses the probability that B occurs when event A occurs,
$P(B)$ refers to the probability of occurrence of event B.

This approach, put forward by the English mathematician Thomas Bayes, is widely used due to its high efficiency and good classification accuracy. Naïve Bayes classifier performs the classification according to the highest probability value by calculating the probability of each state of an element (Bhargaviand and Jyothi, 2009).

2.3.3 K-Nearest Neighbor Classifier

The nonparametric KNN algorithm, determined by taking advantage of the fact that similar things are close together, is simple and easy to implement, high estimation power, low calculation time, and easy to interpret the output. When estimation is made with this algorithm, which is included in the lazy learning algorithm, the neighborhood of the whole data set is considered. K indicates how many the nearest elements to look at, in neighborhood research. The distance between the K element and the test value must be calculated. Besides, the most common use of Euclidean Distance in the distance calculation, Manhattan, Minkowski and Hamming distance are also used in Equation (19), (20), (21), (22), respectively (Gohari and Eydi, 2020). In equation, x is the training data, y is the test data and k is the number of neighbors.

$$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{19}$$

$$\sqrt{\sum_{i=1}^{k}\left|x_i - y_i\right|} \tag{20}$$

$$\sqrt[q]{\sum_{i=1}^{k}(\left|x_i - y_i\right|)^q} \tag{21}$$

$$D_H = \sum_{i=1}^{k}\left|x_i - y_i\right| \tag{22}$$

2.3.4 Support Vector Machines

The support vector machines have an algorithm that separates the two classes from each other by a plane in the most distant place to their elements. For this, the algorithm determines the hyperplanes that best separate the data as given in Equation (23) (Theodoridis and Koutroumbas, 2006). H_o represents the hyper plane, W is the weight vector, b is the constant number and X is attribute.

$$H_o : W^T X + b \tag{23}$$

2.3.5 Artificial Neural Networks

Inspired by the nervous system in the brain, Artificial Neural Networks (ANNs) contain neurons that transmit data to each other. As shown in the Figure 5, in a simple network with input layer, hidden layer and output layer, it is connected to each other from certain layers, revealing its difference from neurons in the brain.

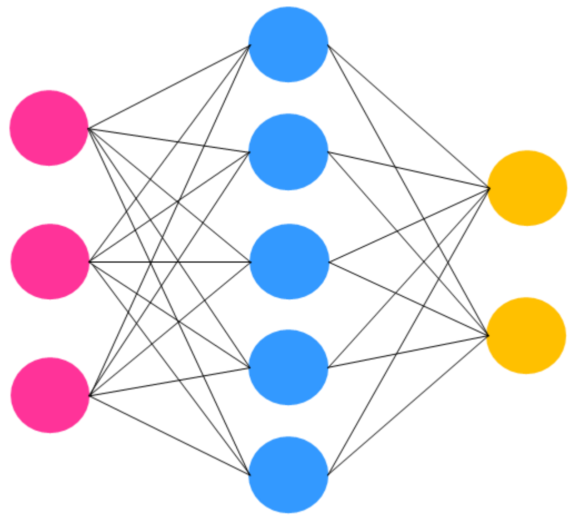

Figure 5. Neural Network Architecture

3. Results

Table 1 shows the sensor characteristics. Table 2 gives the characteristics of different KNN classifiers, Table 3 gives the characteristics of different neural network classifiers used in the study. Eleven volunteers healthy subject whose characteristics are given in Table 4 signed an informed consent form after the ethics committee report was issued for the measurements. Measurements were made on the force plate in the laboratory environment. Dorsiflexion and plantarflexion movements were taken while sitting on the chair, inversion and eversion movements were taken while standing. Performing the movements is based on the maximum degrees that the foot can reach.

K-fold cross-validation was performed and the average of five trials was used in all studies to obtain the classification accuracy given in Equation (24).

$$CA = \frac{TP + TN}{TP + TN + FP + FN} \tag{24}$$

Where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

Table 1. The sensor characteristics of the LSM9DS1

Parameter	Typ.	Unit
Linear acceleration measurement range	±2	g
	±4	
	±8	
	±16	
Magnetic measurement measurement range	±4	gauss
	±8	
	±12	
	±16	
Angular rate measurement range	±245	dps
	±500	
	±2000	

Table 2. Fine KNN and Weighted KNN characteristics

Model Type	Fine KNN	Weighted KNN
number of neighbors (K)	1	10
distance matrix	Euclidean	Euclidean
distance weight	equal	squared inverse

Table 3. Neural network characteristics used in the study

	Narrow Neural Network	Medium Neural Network	Wide Neural Network	Bilayered Neural Network	Trilayered Neural Network
Number of fully connected layers	1	1	1	2	3
First layer size	10	25	50, 100	10	10
Second layer size	-	-	-	10	10
Third layer size	-	-	-	-	10
Activation	ReLU	ReLU	ReLU	ReLU	ReLU
Iteration number	1000	1000	1000	1000	1000

Firstly, the mean of training and test data as a feature was then given to the classifiers using 5-fold cross-validation. The classification accuracies of four-foot movements obtained by averaging the 5 trial results are given as Classification Accuracy 1 (CA-1) in Table 5 and Table 6, respectively. Secondly, the sum as a feature was selected and classification accuracies are given as Classification Accuracy 2 (CA-2). When the mean, standard deviation, skewness, and kurtosis as features were chosen, the obtained results of the experiment are given as Classification Accuracy 3 (CA-3) and if the standard deviation, skewness, and covariance for features is chosen, the results show as Classification Accuracy 4 (CA-4) in the same table.

Table 4. The characteristics of the volunteer subject

Subject	Height(m)	Weight(kg)	Age(years)	Body Masss Index (BMI)
1- Male	1.78	90	20	24.8
2-Male	1.81	83	20	25.3
3-Male	1.80	86	20	26.5
4-Male	1.75	67	20	21.9
5-Female	1.72	60	26	20.3
6-Male	1.90	150	29	41.6
7-Female	1.64	68	30	25.3
8-Male	1.80	77	34	23.8
9-Male	1.80	68	31	21
10-Male	1.62	80	20	30.5
11-Female	1.65	55	31	20.2

Table 5. The classification accuracy (%) of the raw training data for foot

Classifier	Classification Accuracy				
	CA-1	CA-2	CA-3	CA-4	**Average**
Linear Discriminant Analysis	67.26	68.18	85.48	81.82	75.69
Gaussian Naïve Bayes	76.38	77.30	**97.30**	77.26	82.06
Linear SVM	88.18	**89.10**	91.82	81.82	**87.73**
Quadratic SVM	86.36	87.28	90	89.08	**88.18**
Fine KNN	80	86.38	89.10	80.92	84.1
Weighted KNN	82.76	86.40	80.92	80.02	82.53
Narrow Neural Network	87.38	86.38	88.20	84.54	86.63
Bilayered Neural Network	80.94	86.38	86.36	77.28	82.74

Table 6. The classification accuracy (%) of the raw test data for foot

Classifier	Classification Accuracy				
	CA-1	CA-2	CA-3	CA-4	**Average**
Linear Discriminant Analysis	64.54	66.34	80.90	80.92	73.18
Gaussian Naïve Bayes	60	63.62	84.58	77.28	71.37
Linear SVM	66.34	69.98	90	80.90	**76.80**
Quadratic SVM	66.36	69.98	86.36	87.26	**77.49**
Fine KNN	67.24	70.90	82.74	74.54	73.86
Weighted KNN	70	70	**90.90**	72.72	75.91
Narrow Neural Network	68.2	69.10	84.58	72.70	73.65
Bilayered Neural Network	**72.72**	69.08	85.46	75.46	75.68

Considering the tables, when the only feature is selected, the **L-SVM** for training data has the highest classification accuracy with an average of **89.10 %** and **Bilayered Neural Network** highest classification accuracy was achieved with an average **72.72 %** for test data.

If more than one feature is extracted, **W-KNN** gives the highest accuracy again for test data. When the average of the results of all the features is considered, it is seen that the highest results are obtained with the **SVM**.

Secondly, the raw data from the IMU sensor for the lower side leg are classified by the same classifiers used for foot after the features extraction process in the same order. The results obtained when using the mean as features are given as CA-1 in Tables 7 for training data, respectively.

Table 7. The classification accuracy (%) of the raw training data for lower leg

Classifier	Classification Accuracy				
	CA-1	CA-2	CA-3	CA-4	**Average**
Linear Discriminant Analysis	**90.94**	65.44	56.36	57.26	**67.50**
Gaussian Naïve Bayes	50.90	62.72	60.02	59.10	58.19
Linear SVM	67.26	59.08	59.08	68.16	63.40
Quadratic SVM	58.16	49.10	59.08	69.10	58.86
Fine KNN	50	47.30	39.10	60	49.10
Weighted KNN	52.72	49.10	35.46	51.80	47.27
Narrow Neural Network	59.96	59.08	46.38	62.72	57.04
Bilayered Neural Network	53.62	51.82	51.82	52.72	52.50

Considering all the tables, **LDA** provides the highest accuracy with an average **90.94 %** for CA-1 results, **67.50 %** for average results in the classification of the training data.

In the classification of foot movements, data from the sensors connected to the foot and lower leg were studied. Classification accuracy is higher than the lower leg, since the foot has more range of motion. This is also expected state.

As can be seen from Figure 6, the highest results with 97.3% were obtained for the CA-3 features. Therefore, in the next step, using these features to compare Naive Bayes, SVM, KNN and Artificial Neural Network, results were obtained again and recorded in Table 9 and comparison results of different neural networks are given in Table 8.

According to the results in the tables, the classification accuracy of the single-layer neural network is higher than that of the bilayered and trilayered neural networks. Also, as the size of the first layer increases, the accuracy of the results increases.

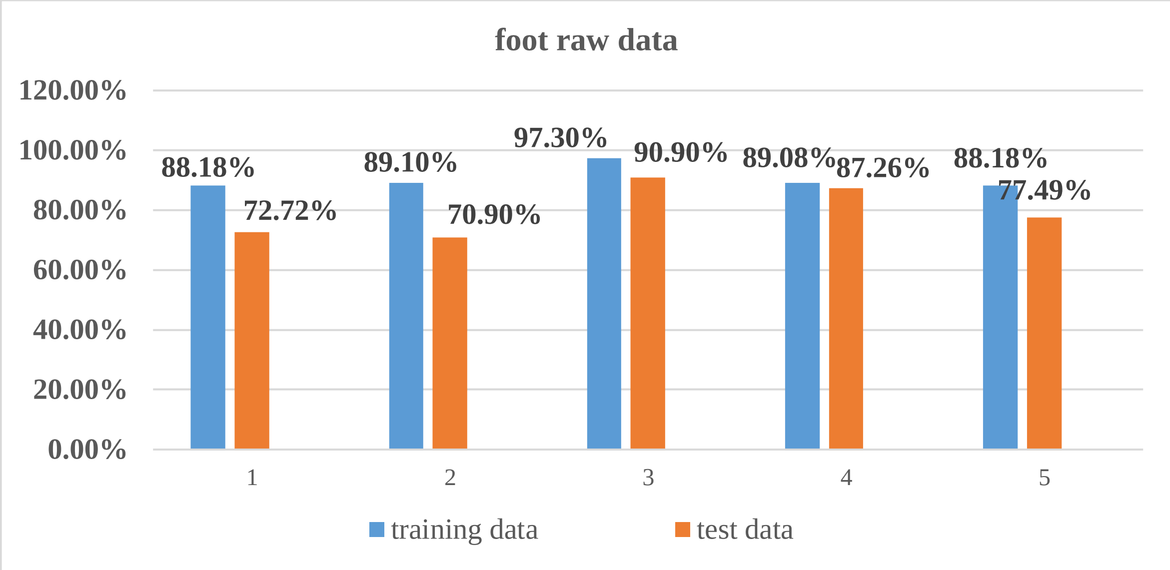

Figure 6. Classification accuracy (%) of the raw data for foot (1-mean; 2- sum; 3-mean, standard deviation, skewness, kurtosis; 4-standard deviation, skewness, covariance; 5- average of the features results)

Table 8. Comparison results of different neural networks

	5-trial average
Narrow neural network	88.18
Medium neural network	90.02
Wide neural network	**90.92**
Bilayered neural network	86.38
Trilayered neural network	79.10

Table 9. SVM, KNN and neural networks comparison results

	5-trial average
Gaussian Naïve Bayes	92.74
Linear SVM	90
Fine KNN	90.92
Wide Neural Network	**93.66**

4. Discussion

It is seen that for motion recognition, EMG signal were used in the most of studies in the literature. Because analyzing of EMG data is very complicated, we proposed to perform motion recognition in the lower extremity using only IMU data in this paper. The obtained results show the proposed method presents a classification with a high accuracy. To prove our recommendation, our comparison with other articles in the literature is presented in the Table 10. In this study (Maragliulo et al.,2019), 5 movements in the same plane were examined with the SVM algorithm, although it is in a single plane, it has lower classification accuracy. In the study cited in reference (Khera et al., 2020), the number of people is less, the SVM algorithm is preferred and the EMG signal is used.

Again, lower accuracy was achieved. In the study cited in reference (Hooda et al, 2021), the number of planes was increased, however lower accuracy was obtained. These prove that IMU is a more reliable method than EMG in motion recognition. Unlike other articles, this article is suggesting that high accuracy can be achieved with Artificial Neural Networks using only IMU in motion recognition.

There is very little research in the literature for ankle motion recognition from the lower extremity joints. Studies have generally been conducted using EMG signals. These studies were also limited, as the sEMG of the lower extremities was affected by body gravity and muscle tremors, resulting in very noisy data. IMU sensors, which is a simpler method, were preferred due to the difficulties in real-time implementation of assessments, difficulties in signal processing and insecurity in the accuracy of the obtained data based on Electromyography (EMG) and Electroencephalography (EEG).

Table 10. Comparison of our study with previous studies

	This article	(Maragliulo et. al, 2019)	(Khera et al., 2020)	(Hooda et al, 2021)
Sensors	IMU(4)	sEMG(2)	sEMG(2)	sEMG (6)
Motion types	4 movements (sagittal plane frontal plane)	5 movements (sagittal plane)	4 movements (sagittal plane frontal plane)	4 movements (sagittal plane frontal plane)
Classifier	ANN	SVM	SVM	SVM
Accuracy (%)	93.66	90.04	93.23	91.85
Subject	11 healthy	3 healthy	10 healthy	20 healthy 5 patients

5. Conclusion

Compared to the classification accuracy of foot and lower side leg, the foot was higher. When all studies were examined, it was observed that the ANN algorithm worked better in the classification of foot movements. This study also showed that human movements can be determined by classification. As a result of the foot movements classification study, a quality prosthesis that can be controlled by gait analysis will have been developed and will have reached a stage where it will be ready for clinical trial. At this stage, clinical practice studies for amputees will begin. Thus, the prosthetic foot will be controlled by using the healthy foot data of amputees. Data can be collected not only for foot but also for knee, upper knee and hip prostheses and their clinical application can be realized. This study is similar to the gait analysis classification using IMUs. The literature shows that gait classification can be made with a small number of people. The effect of this on the classification results by increasing the number of people or expanding the dataset will be examined in future studies.

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Authors' Contributions

All authors contributed equally to the study.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The author declares that this study complies with Research and Publication Ethics.

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