Comparison of Classification Algorithms for Detecting Patient Posture in Expandable Tumor Prostheses

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***Abstract*—Autonomous tumor prostheses are extended without the need of a clinic and of a medical supervision. It is necessary to make sure that the patient is not standing before extending these prostheses. This study aims to determine the posture of the patient for expandable tumor prostheses by employing oft-used three machine learning-based classification methods through comparing them all with each other. Patient posture is determined by using accelerometer and gyroscope data from inertial control unit placed in autonomous expandable tumor prosthesis. By using the created dataset, 48 features are extracted. Then, for optimization, with feature selection, the number of features is reduced to 10. The selected features are processed using the decision tree, the k-nearest neighborhood and support vector machine algorithms. These algorithms were compared with each other using machine learning performance parameters. Accuracy, recall, precision and F-score values are calculated and compared. Consequently, support vector machine is determined as the most successful technique. Then, the model is tested on the experimental setup developed within the scope of the study, and the posture is determined. It is found that with this system, in the presence of a load on the prosthesis, it can be accurately detected at a rate of 97.1% (the recall parameter).**

***Index Terms*—biomedical measurement, machine learning, prosthetics, supervised learning, support vector machines.**

I. Introduction

Bone cancer is a common type of cancer that often occurs during children's growth period. The most common site of bone cancer in the human body is the long bones of the lower limb, especially the distal part of the femoral bone. In cases that occur in the legs, the cancerous portion of the bone is usually surgically taken, including the growth plate, and a prosthesis is inserted instead. The child's healthy leg continues to grow but its prosthetic leg does not grow. This causes posture and gait disturbances as well as severe pain. Therefore, expandable tumor prostheses are used in pediatric patients. Surgical intervention is not required to perform an extension procedure after implantation in today's expandable tumor prostheses [1–6]. However, during the extension of these prostheses, the patient has to be in the clinical setting. The amount of elongation during the procedure is monitored using medical imaging techniques. The main problems here include increased physician workload, potential human errors that may occur during the measurement of the limb length, patient's exposure to radiation at every measurement, extension of relatively large sizes, and the fact that the patient often has to go to the clinic for measurements and lengthening. In order to eliminate these problems, the extension should be done autonomously to be clinically independent.

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During the extension of the existing prostheses, the physician ensures that the patient is in the supine position. This allows the patient's body weight not to be on the prosthesis, and the prosthesis can thus be extended by applying less force. It is necessary to determine whether the patient is in the supine position, because the extension procedure in autonomous prostheses will not be performed in the clinical environment and will not be physician's supervision.

Numerous nonlinear modeling approaches are available in the literature of health and medicine. Methods that successfully model nonlinear systems such as multivariate polynomial regression, artificial neural networks, Support Vector Machines (SVM), Bayesian filtering and fuzzy rule interpolation have been used in various studies [7-10].

Human activity recognition is an important research area with a wide range of applications. Today, activity recognition is used in many areas such as industrial automation, sports and entertainment, health applications, and rehabilitation. There are many studies on the activity recognition by microcontroller-based systems on wearable and portable structures. Most of these studies use SVM as a classification method [11–15].

Although there are a large number of studies available in the field of activity recognition, the number of studies on posture recognition is relatively low. The majority of these studies, though, rely exclusively on vision-based techniques, not on Inertial Measurement Unit (IMU) [16–22].

Huang J., Yu X., Wang Y., and Xiao X. have connected five IMUs to varying parts of the body of elderly individuals to determine their posture and location in the house [23]. Similarly, Gjoreski H., Luštrek M. and Gams M. have connected 4 accelerometers to the body of elderly individuals to determine their posture [24]. Allen F.R., Ambikairajah E., Lovell N.H. and Celler B.G. performed the same procedure with a single accelerometer fitted to the belt on the waist of an elderly person [25]. Sazonov E.S., Fulk G., Hill J., Schutz Y. and Browning R. determined whether the patient is standing or sitting of obesity patients with accelerometer and pressure sensors placed on the shoe [26]. All of these studies are aimed at fall detection of elderly people at home. Chen et al. used vision-based posture detection in the workplace of construction workers with IMU data placed on the worker's helmet for verification purposes [27]. Nevertheless, the literature presents virtually

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no study aimed at recognizing activity or posture in an implantable system.

In contrast to the literature, this study recognizes patient posture using the Attitude and Heading Reference System (AHRS) in the implantable prosthesis structure. Patient posture recognition is performed on the autonomous expandable tumor prosthesis previously developed by the authors in the scope of same project [28]. Detailed information about the project is available at http://ytubiomechatronics.com/portfolio-item/tumor-prost/. The contribution of this study to the literature is that, the posture of a patient for expandable tumor prostheses is recognized for the first time and while doing so, the study uses AHRS and machine learning. This study could contribute significantly to the development of autonomous tumor prostheses.

The study is organized as follows. Section 2 introduces the autonomous tumor prosthesis and experimental setup developed within the scope of the study. Section 3 presents how to achieve posture recognition. The steps of collecting and processing data are also mentioned in this section. Section 4 gives the results of the study in 3 subsections: training results, test results, and experimental results. Section 5 gives discusses of the findings of this study.

II. Tumor Prosthesis and Experimental Setup

The tumor prosthesis developed within the scope of the study is designed for use in the distal part of the femur bone. The internal control unit, which controls the internal components of the prosthesis, is placed in the artificial knee joint. This unit is developed based on the Atmega 2560 microcontroller. The internal control unit sensors inside the prosthetic knee joint measure the amount of elongation, temperature, internal battery charge level, and patient posture. It also wirelessly shares the information received from the sensors (internal temperature rise, reduced internal battery charge, etc.) with the external control unit.

The prosthesis communicates with the external units of the system wirelessly. XBee; wireless communication module employed in this study is capable of point-to-point communication using the IEEE 802.15.4 network protocol. With 128-bit encryption, it is only possible to exchange information between previously matched XBee modules. To test the success of the system, the experimental setup in Figure 1.a is used. This setup involves a skeleton model cut from the lumbar vertebrae, only using the lower extremity part. The skeleton model is combined with an artificial lower extremity model for easy application of the wearable units. Another property of this model is that the developed prosthesis is implanted in the distal part of the right femur bone of the skeletal model.

In the current study, a GY-953 AHRS module is inserted into the prosthesis to determine the posture status of the patient before the extension is performed. This module consists of a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer. The acceleration range can be adjusted between 2g and 16g, the angular velocity can be adjusted between 250 dps and 2000 dps, and the magnetic field density can be adjusted between 0.15μT and 0.6μT. Figure 1.b shows the posture recognition hardware structure in the developed system, the details of which are given in Section 3.

III. Posture Recognition

Machine learning uses programmed algorithms that acquire and analyze input data to evaluate output values within an acceptable range. As new data are added to these algorithms, they examine and optimize their operations to increase productivity and improve intelligence over time [29-31].

In studies on human posture recognition, firstly, a database is formed from AHRS data. The database is divided into two parts: training and testing. Following the feature extraction, classification is performed based on these features, an appropriate algorithm is selected, and the success is tested. Of particular importance are the steps of feature selection and classification algorithm selection, which can potentially affect the success of the system and the steps the researcher focuses on [32–35]. The increase in the size of the data, the number of features, the complexity of the calculations and the increase in the degree of the classification algorithm bring up the problems of storage space and processing time, particularly in microcontroller-based applications.

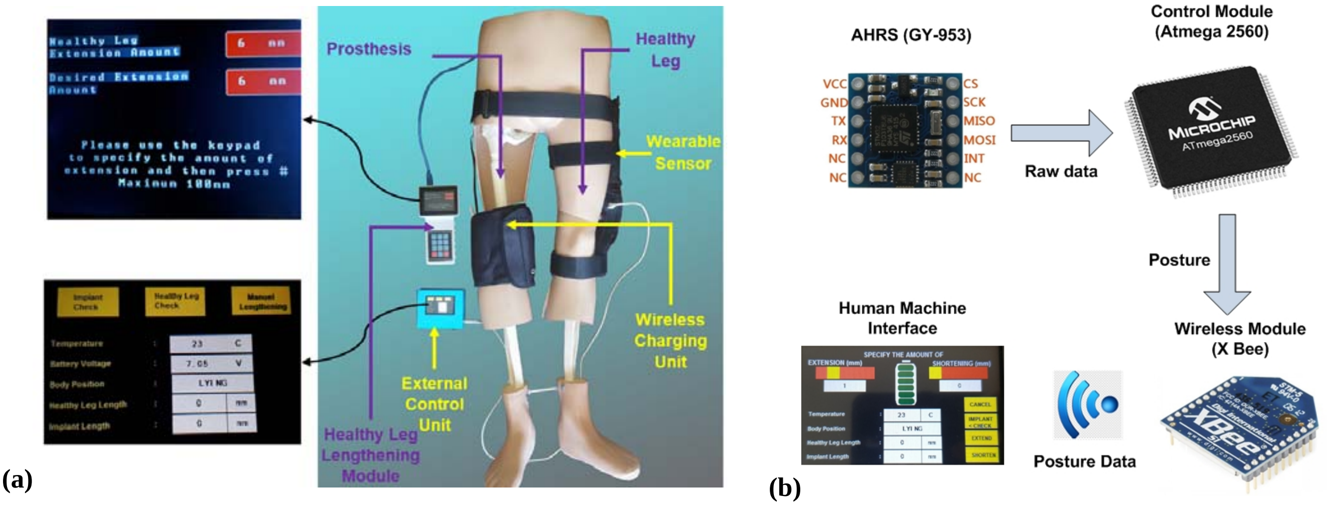

Figure 1. a) Experimental setup and user interface screen b) Posture recognition hardware structure

Therefore, studies on wearable, portable, or implantable systems should take into consideration not only the success in terms of classification but also memory usage, each of which should ideally be optimized.

Of the three sensors (accelerometer, gyroscope and magnetometer) in the AHRS structure, only the accelerometer and gyroscope are used in this study. The magnetometer is not included as it is not directly relevant in determining activity and posture. The ranges of the accelerometer and gyroscope sensors are set at ± 2g and ± 250dps, respectively. 3-axis sensor data is collected from experimental setup at a 100 Hz sampling frequency. Since the research is not directly conducted on a live subject and experiments are carried out on the experimental setup that manually brought into various postures by the researchers, the range and frequency values are defined in this way. Prosthesis load status information recorded for each data: 1 (patient standing, extra load on the prosthesis), 0 (patient is lying on his back, the prosthesis is ready to elongate). In fact, the patient's posture could be very diverse. However, what really matters is to accurately determine whether there is a load on the prosthesis or not. For this reason, all postures with a load on the prosthesis are evaluated as 1, and all postures without a load on the prosthesis are evaluated as 0. The purpose of feature extraction is to convert the original dataset into a dataset with a small number of variables containing the most distinctive information. This reduces the data size, removes unnecessary or irrelevant information, and turns the dataset into a more suitable form for later classifications. In order to increase the classification performance and achieve high classification speed, the bandwidth of the input data should be reduced and presented to the classifiers [36, 37]. Oft-used 8 features in activity recognition are extracted using raw data from the AHRS. The specified features are described in Table 1 and explained in detail below.

PCA: In the *Principal Component Analysis* (PCA) method, a new dataset is created by multiplying the feature vector created by the eigenvalues and eigenvectors from covariance matrix. Covariance matrix is the difference between the average of each component of the dataset and its eigenvectors. PCA is a method converting the dataset into another dataset with fewer variables. At this point, the new variables happen to be the linear components of the original variables. In other words, the method of converting a structure with a definite number of variables in correlation with each other into another structure with less variables having no correlation with each other is called PCA.

Mean: It is the result of summing all the components of the dataset and dividing the sum by the number of components, and is given by the following equation:

$$\overline{X} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

Median: It is the value separating the greater half from the lesser half of a data sample, a population or a probability distribution. For a dataset, it could be thought of as the "middle" value.

Energy: It is the result obtained by squaring each variable in the dataset and summing them, and is given by the following equation:

$$Energy = \sum_{i=1}^{n} x_i^2 \tag{2}$$

Variance (σ^2): It is dividing the multiplication of the squares of the difference between the arithmetic mean and each component to preceding number of components, and is given by the following equation:

$$\sigma^2 = \frac{\sum_{i=1}^{n} (x_i - \overline{X})^2}{n-1} \tag{3}$$

Standard Deviation (σ): It is the square root of the variance, and is given by the following equation:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \overline{X})^2}{n-1}} \tag{4}$$

Sum: It is the value obtained by summing the components in the dataset, and is given by the following equation:

$$Sum = \sum_{i=1}^{n} x_i \tag{5}$$

Band Power: It is the average of the sum of squares of the components in the dataset, and is given by the following equation:

$$BandPower = \frac{\sum_{i=1}^{n} x_i^2}{n} \tag{6}$$

Accuracy is the performance parameter which shows the success rate of classification where T_P stands for true positives, T_N stands for true negatives, F_P stands for false positives, and F_N stands for false negatives and is given by the following equation:

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{7}$$

One of the critical parameters in the posture recognition for our system is to accurately determine when there is a load on the prosthesis. This is met by the term **"recall"** in machine learning, and is calculated as in Equation 8.

$$Recall = \frac{T_P}{T_P + F_N} \tag{8}$$

TABLE I. FEATURES USED FOR CLASSIFICATION

Feature	Description
PCA coefficient	Principal Components Analysis coefficient of the signal
Mean	The average value of the signal
Median	The median signal value
Energy	Quadratic sum of the signal
Variance	The average of squares of the difference of the signal and the mean
Standard Deviation	The square root of the variance
Sum	The sum of the signal
Band Power	Average power value of the signal

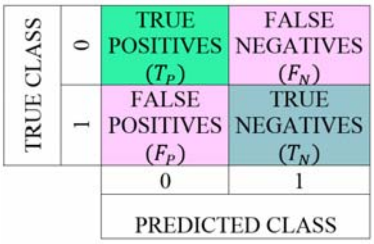

Figure 2. Confusion matrix

The secondary significant parameter is the **"precision"**, which reflects how true is the detection of the presence of a load on the prothesis. It is calculated as in Equation 9.

$$Precision = \frac{T_P}{T_P + F_P} \tag{9}$$

The **F-score,** obtained from the recall and precision parameters, which indicates the real success rate of the system, is given by Equation 10.

$$F = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{10}$$

Decision Tree (DT), k- Nearest Neighborhood (k-NN), and Support Vector Machines (SVM) are the most commonly used classification algorithms in the field of posture and activity classification. A DT is a decision support tool that uses a tree diagram or decision model and their possible outcomes, including the results of random events, resource costs, and benefits. It is a way to display an algorithm that contains only conditional control expressions. Tree-based learning algorithms are one of the best and most widely used methods of supervised learning. Tree-based methods provide predictive models with great accuracy, stability, and ease of interpretation. Unlike linear models, they match nonlinear relationships quite well. They are used in the solution of many classification and regression problems. In DTs, the evaluation starts from the root of the tree to estimate the class tag of a record. Root attribute values are compared to the attribute of the record. On the basis of comparison, it follows the branch corresponding to this value and skips to the next node. It continues to compare the attribute values of the record with other inner nodes of the tree until a leaf node with the predicted class value is reached. The modeled DT can be used to predict the target class or value. DTs have been applied to a wide range of classification problems [38-41].

The k-NN algorithm is one of the simplest and most widely used classification algorithms. k-NN is a non-parametric, lazy learning algorithm. Unlike eager learning, lazy learning does not have a training phase. It does not learn training data; instead, it "memorizes" the training dataset. When an estimate is desired, the closest neighbors in the whole dataset are searched. In the process of this algorithm, a k value is determined. The meaning of this k value is the number of the elements to be looked up. When a value comes, the distance between the incoming value is calculated by taking the nearest k element. Euclidean function is often used in distance calculation. As an alternative to the Euclidean function, Manhattan, Minkowski and Hamming functions could also be used. After the distance is calculated, it is sorted and the incoming value is assigned to the appropriate class. The k-NN algorithm has been used by many researchers for posture and activity recognition [42-45].

SVM is a popular method of machine learning based on finding hyperplanes that determine the maximum margin among the models of each class and the most suitable margin among the classes. In addition, by using the so-called basic functions, they could project data from one original feature area to another large area. In this way, a linear separation in the new field becomes equivalent to a nonlinear classification in the original field. An optimization technique is used to find hyperplanes of optimal separators that perform the necessary classifications. Typically, three types of kernels are used for optimum SVM: linear, polynomial, and radial basic function (RBF) kernel. Generally, the linear kernel is suitable for linearly separable datasets, while polynomial and RBF kernels are suitable for datasets that cannot be separated linearly [37]. The SVM algorithm has been used by many researchers [46-49]

In this study, the data is divided into two parts for 80% training and 20% testing. The cross validation is selected as 10 folds and the number of neighborhoods in k-NN is selected as 10.

The results obtained under the specified conditions are described in detail in the next section.

IV. RESULTS

In data classification applications, a feature selection process is generally performed. Feature selection has many potential benefits, such as simplifying data visualization and understanding, reducing measurement and storage requirements, reducing training and usage times, reducing the size of the data, and improving recognition performance [50].

In this study, F-score for feature selection strategy is used [51], the performance parameters are analyzed, and 48 features acquired from the AHRS raw data are grouped as relevant, irrelevant, and redundant (Table 2). First, the F-score value of each feature is calculated. Then, the classification success of the system is measured by trying various threshold values. As a result of this process, the optimum threshold value is determined to be 0.7. Features with an F-score below threshold are determined as irrelevant and features with an F-score greater than 0.7 are relevant. One of the relevant features, which gives the same classification result for each raw of train data, is marked as redundant. Only one of the relevant features found is derived from the data of the gyroscope sensor. Five of the other nine features belong to the z axis of the accelerometer. Considering the functions of these sensors, an axis of the accelerometer is already expected to be more effective in determining the supine position of the patient. It is found that 3 features in z axis and 2 features in x axis belonging to the accelerometer contribute greatly to the classification. However, it is noticed that they are met by other features and are thus excluded from the classification by being marked as redundant. Thus, the 10 relevant features are determined and the classification is made. In the classification, DT, k-NN and SVM methods are tried separately.

TABLE II. INDIVIDUAL PERFORMANCE PARAMETERS OF FEATURES FOR FEATURE SELECTION

Feature	Sensor	Axis	T_P	T_N	F_P	F_N	Accuracy	Recall	Precision	F-score	Effect
PCA coefficient	ACC	X	25	10	6	9	0.700	0.735	0.806	0.769	Relevant
		Y	24	3	13	10	0.540	0.706	0.649	0.676	Irrelevant
		Z	32	14	2	2	0.920	0.941	0.941	0.941	Relevant
	GYR	X	21	7	9	13	0.560	0.618	0.700	0.656	Irrelevant
		Y	14	16	0	20	0.600	0.412	1.000	0.583	Irrelevant
		Z	22	3	13	12	0.500	0.647	0.629	0.638	Irrelevant
Energy	ACC	X	20	3	13	14	0.460	0.588	0.606	0.597	Irrelevant
		Y	19	4	12	15	0.460	0.559	0.613	0.585	Irrelevant
		Z	26	10	6	8	0.720	0.765	0.813	0.788	Relevant
	GYR	X	23	6	10	11	0.580	0.676	0.697	0.687	Irrelevant
		Y	22	7	9	12	0.580	0.647	0.710	0.677	Irrelevant
		Z	23	5	11	11	0.560	0.676	0.676	0.676	Irrelevant
Median	ACC	X	27	11	5	7	0.760	0.794	0.844	0.818	Relevant
		Y	24	3	13	10	0.540	0.706	0.649	0.676	Irrelevant
		Z	32	14	2	2	0.920	0.941	0.941	0.941	Redundant
	GYR	X	21	7	9	13	0.560	0.618	0.700	0.656	Irrelevant
		Y	21	7	9	13	0.560	0.618	0.700	0.656	Irrelevant
		Z	19	7	9	15	0.520	0.559	0.679	0.613	Irrelevant
Sum	ACC	X	25	10	6	9	0.700	0.735	0.806	0.769	Redundant
		Y	24	3	13	10	0.540	0.706	0.649	0.676	Irrelevant
		Z	32	14	2	2	0.920	0.941	0.941	0.941	Redundant
	GYR	X	23	7	9	11	0.600	0.676	0.719	0.697	Irrelevant
		Y	15	14	2	19	0.580	0.441	0.882	0.588	Irrelevant
		Z	20	7	9	14	0.540	0.588	0.690	0.635	Irrelevant
Var	ACC	X	33	1	15	1	0.680	0.971	0.688	0.805	Relevant
		Y	33	0	16	1	0.660	0.971	0.673	0.795	Relevant
		Z	15	7	9	19	0.440	0.441	0.625	0.517	Irrelevant
	GYR	X	22	8	8	12	0.600	0.647	0.733	0.688	Irrelevant
		Y	22	7	9	12	0.580	0.647	0.710	0.677	Irrelevant
		Z	21	5	11	13	0.520	0.618	0.656	0.636	Irrelevant
Mean	ACC	X	25	10	6	9	0.700	0.735	0.806	0.769	Redundant
		Y	24	3	13	10	0.540	0.706	0.649	0.676	Irrelevant
		Z	32	14	2	2	0.920	0.941	0.941	0.941	Redundant
	GYR	X	23	7	9	11	0.600	0.676	0.719	0.697	Irrelevant
		Y	15	14	2	19	0.580	0.441	0.882	0.588	Irrelevant
		Z	20	7	9	14	0.540	0.588	0.690	0.635	Irrelevant
Std. Dev.	ACC	X	31	1	15	3	0.640	0.912	0.674	0.775	Relevant
		Y	34	0	16	0	0.680	1.000	0.680	0.810	Irrelevant
		Z	26	3	13	8	0.580	0.765	0.667	0.712	Relevant
	GYR	X	23	8	8	11	0.620	0.676	0.742	0.708	Relevant
		Y	17	11	5	17	0.560	0.500	0.773	0.607	Irrelevant
		Z	20	5	11	14	0.500	0.588	0.645	0.615	Irrelevant
Band Power	ACC	X	20	3	13	14	0.460	0.588	0.606	0.597	Irrelevant
		Y	19	4	12	15	0.460	0.559	0.613	0.585	Irrelevant
		Z	26	10	6	8	0.720	0.765	0.813	0.788	Relevant
	GYR	X	23	6	10	11	0.580	0.676	0.697	0.687	Irrelevant
		Y	22	7	9	12	0.580	0.647	0.710	0.677	Irrelevant
		Z	23	5	11	11	0.560	0.676	0.676	0.676	Irrelevant

A. Training Results

The new feature dataset is created using 10 relevant features, and then is processed on MATLAB Classification Learner Toolbox. Using 80% of raw data for training, classification is performed with DT, SVM and k-NN methods. The classification performance of DT remained low compared to other methods. The most successful method for classification is the SVM with an 89.5% accuracy with an F-score of 92.6%. Similarly, the accuracy and F-score values of the k-NN algorithm are high. However, both parameters appear to be more successful in SVM. Training results of the DT algorithm have been well below the SVM and k-NN algorithms. Especially the recall value being 88.5% is an indication that the DT algorithm will not be suitable for this application. Details of the training results are given in Figure 3. It is seen that positive results are obtained from the approach that solves the memory problem for computer-independent systems and thus increases the speed of classification process by decreasing the number of features. In this study, although the number of features has been reduced from 48 to 10, the performance is almost never decreased. It is concluded that the accuracies of various classification algorithms have quite different results in solving this problem.

B. Test Results

The part of the feature dataset reserved for testing is processed in MATLAB Classification Learner Toolbox as in training data. The 20% portion of the raw data, which was previously not used for training, is tested on DT, SVM and k-NN models. The purpose of the test is to determine whether the models created with a limited amount of data show a performance comparable to the training when they meet a new set of data. The parameters found in the test result are given in Figure 4. The test results show that success is slightly lower than the training results. Again, SVM stands out as the most successful classifier. The accuracy parameter, which shows the overall success of the classification, indicates that 83.3% of the samples are saved to the correct class using SVM. All of the other parameters come out to match the training results. At this point, it is understood that the classifier does not have a problem like over-learning.

C. Experimental Results

As a result of the operations performed in the simulation environment, it is concluded that for this study, SVM is a better classification tool than the other methods. The SVM model is converted to C code and experimentally applied to the internal control unit processor of the tumor prosthesis. In order to test the efficiency and precision of the applied classification model, experiments have been done on the experimental setup. Experimental setup is manually moved into various posture states, 200 times in total. During the experiments, the experimental setup is positioned as follows; lying on its back, lying on its face, lying on its right side, lying on its left side, and standing, in different speeds and combinations. The classes estimated by using the data of the AHRS (3 axis accelerometer and 3 axis gyroscope data) are transferred to the computer wirelessly (Figure 5). The received data is: 1 (patient standing, extra load on the prosthesis), 0 (patient lying, prosthesis is ready to extend). The output values are compared to the actual values that are recorded manually and T_P, T_N, F_P and F_N values are determined. In Figure 6, these values are given on the confusion matrix. Accuracy, recall, precision, and F-score values are calculated using these values. The general accuracy of the classification is calculated as 88%. However, a crucial purpose of this study is to be able to accurately detect the presence a load on the prosthesis and thus not to initiate the extension process. This success is measured by the recall value, which, according to the experimental results, is determined as 97.1%. Despite the fact that the prosthesis does not actually have a load on it, the conditions determined by the classifier as a load are considered as false alarms. Precision value is the rate that indicates how low false alarms are. In this classification, it is 86.8%. This means that although the prosthesis does not have a load on it, system recognizes one and thus, does not initiate the extension procedure. This failure could be seen in 13.2% of the trials and could be taken as reasonable. The F-score value, which indicates the overall performance of the classification, is determined as 91.7%. The results of the reexamination of the data collected this way are given in Figure 7. The classification success of the study overlaps with other studies in the literature that perform 2-state posture analysis [22].

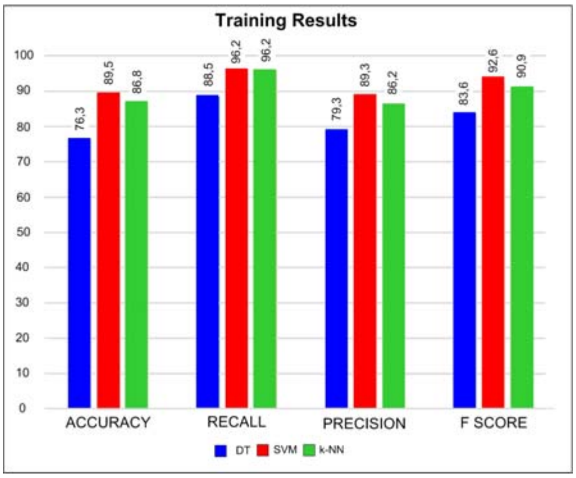

Figure 3. Performance indicators of training results

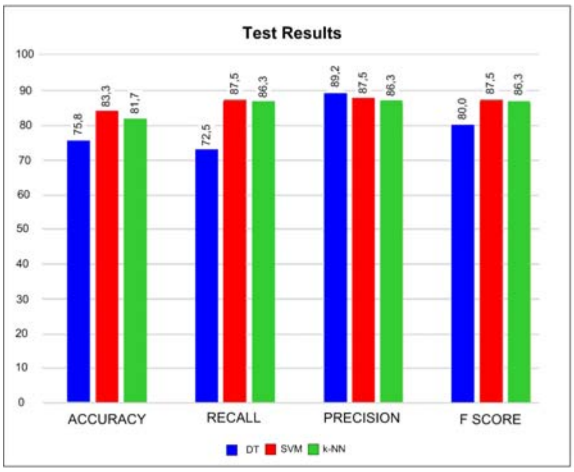

Figure 4. Performance indicators of test results

Figure 5. Experimental data collection process

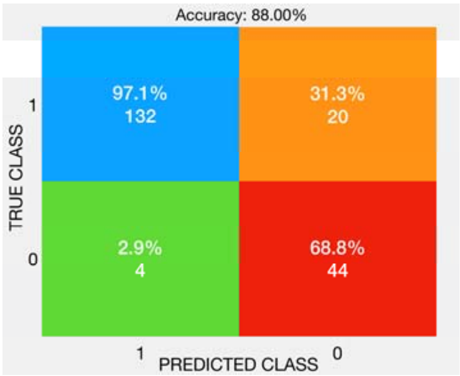

Figure 6. Confusion matrix of experimental classification results

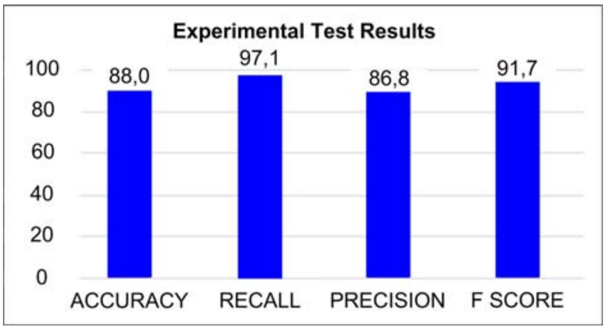

Figure 7. Performance indicators of experimental SVM

V. Conclusion

This study aims to determine whether there is a load on the prosthesis before extending autonomous tumor prosthesis. For this determination, the posture status of the patient using the prosthesis is recognized. The 3-axis data obtained from the accelerometer and gyroscope sensors used in the prosthesis structure are processed by machine learning, and the classification is made and the posture status is estimated. The experimental setup with the prosthesis developed within the scope of the study is positioned in various posture states and the sensor data is transferred to the computer wirelessly. Then, the dataset is created. 8 features are created for the sensor axis outputs (6 axis) that constitute each column of the dataset, so that a total of 48 features are obtained. Classification process is done by using these features one by one and classification performances of each feature are calculated. 10 of the features, which made the most positive contribution to the classification, are selected based on the F-score values. Using these features, classification has been tried with SVM, DT and k-NN algorithms and the most successful classification is achieved with SVM. The created model is loaded on the microprocessor of the prosthesis. After applied experiments, it is observed that the system successfully classified the posture.

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