Multipurpose wearable sensor-based platform for weight training

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Abstract

In recent years, there has been a growing interest in automated tracking and detection of sports activities. Researchers have shown that tracking and monitoring the workout activities aids in keeping the individuals' motivation by providing feedback and information about their progress and achievement throughout their exercise program. In this regard, wearable devices are great tools for monitoring the exercise without imposing any additional limitation on users' performance. This study presents a novel multipurpose wearable device for automatic weight detection, activity type recognition and count repetition in sports activities such as weight training using various classification technique. The autonomous weight detection and activity recognition device would maximize workout efficiency and prevent overreaching and overtraining. The device monitors weights and activities by using an Inertial Measurement Unit (IMU), an accelerometer and three force sensors mounted in the glove and classifies them by utilizing developed machine learning models. For weight detection, different classifiers including Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Multi-layer Perceptron Neural Networks (MLP) were investigated. For activity recognition, we utilized K Nearest Neighbor (KNN), Decision Tree (DT), Random Forest (RF), and SVM models. Experimental results indicate that SVM classifier can achieve the highest accuracy for weight detection application and RF can outperform other classifiers for activity recognition application. The results reveal that the suggested wearable device can provide in-situ accurate information regarding the lifted weight and activity type with minimum physical intervention.

Keywords: Sport wearable; Force sensor; Inertial measurement unit; Machine learning; Support vector machine; Random forest; Neural networks

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Chapter 1.

Introduction

1.1 Background

Weight training has received increasing attention in recent years and has been among the top ten activities in fitness trends worldwide surveys since 2007 [1] due to the massive benefits providing for human health including movement control, functional independence, cognitive abilities, body fat and blood pressure reduction, increasing the cross-sectional areas of muscle and connective tissues [2]–[4], prevention and management of type 2 diabetes [5], and emotional well-being [6].

The popularity of weight training in fitness trends has caused a great market shift in wearable devices due to their different sensing capabilities in providing end-user with many applications in activity monitoring. The reason for the huge interest to monitor weight training activities using wearables underlies the growing need in improving and individualizing the design of training and exercise programs to maximize the performance progress and efficiency and avoid overtraining and overreaching [7], [8]. Besides, studies have shown that visualization of personal data during workout can bring motivation and adherence to help users to improve workout plans and consequently the state of their health [9], [10].

There exist different types of wearable and smart devices with various applications and capabilities in sport applications. Wearables can be categorized into embedded equipment, smart textiles and body worn devices. Among these types of sport wearables, body worn devices are the most popular ones (e.g., fitness trackers, smart watches, smart gloves). The goal of these different approaches in wearable technology for sport purposes is enabling the users having the best possible way of monitoring their performances without hindering any movement. This is dependent on the design factors like type of the sensor and its placement on a body [11]. The application of the wearable defines what sensor is required to be utilized in the system. Due to the various working principles of sensors, sensors position on body is contingent to the assessment of finding the body part which can provide the highest number of accurate data for an application. The mostly used sensors in sport wearables are accelerometers, gyroscopes, magnetometers, pressure sensors, heart rate sensors and pedometers. The working principles, varieties and deployment of these sensors are discussed below.

1.1.1 Accelerometers

Accelerometers have been widely accepted as useful and practical sensors for wearable devices to measure and assess physical activity. Piezoresistive, piezoelectric and differential capacitive accelerometers are the most common types of accelerometers that have been used in wearables. An accelerometer works based on a mechanical sensing element which produces an output voltage proportional to the acceleration. Any change on mechanical element causes a change in an output voltage and measuring the voltage is proportional to the value of acceleration.

Small size, low cost, availability, and sensitivity of the accelerometers have made them a prominent choice in sport wearables. One of the areas that accelerometer has been universally used at, is activity classification and posture correction. The recorded longitudinal data is suitable for identifying activity patterns and in some studies posture patterns [12]–[16]. Another area of accelerometer employment in sport wearables is energy expenditure determination. Studies have shown that the magnitude of acceleration has some relations with the intensity of measured activities which can be used to estimate energy expenditure [17].

1.1.2 Gyroscopes

Gyroscope is another common sensor used in wearable technologies. They measure angular velocity and acceleration. These sensors are listed as Ring laser gyroscope, Fiber-optic gyroscope, Fluid gyroscope, and Vibration gyroscope. MEMS (micro electromechanical sensor) gyroscope sensor are the poplar ones in wearable which deploys vibration gyroscope in its system. Their working principle is based on a combination of mechanical oscillation and Coriolis force. The Coriolis force is the inertial force that acts in a direction perpendicular to the rotation axis. The movement produces a potential difference that is converted into very low-current electrical signals. Gyroscopes mostly are combined with acceleration sensors in inertial measurement unit sensors (IMU) to gather the orientation data in a wearable system [18], [19].

1.1.3 Magnetometers

Magnetometers, as the name suggests, measures the strength and direction of the magnetic field. This sensor is fused with accelerometer and gyroscope in IMU sensors to complement them in finding the orientation and heading of a system [20].

1.1.4 Pedometers

Pedometers are the simplest sensors in wearable systems which are used to count steps. There are two types of pedometers: mechanical and electrical. Modern pedometers are partly electronic. There is a metal pendulum inside a pedometer wired into an electronic counting circuit by a spring. There is no flow through the circuit while the system is at rest. By taking a step, the pendulum swings across and touches a metal contact, completing the circuit and allowing current to flow. The current flow activates the circuit and adds one to step count. After taking a step, the spring in the system helps the pendulum swing back again and makes the circuit open, effectively putting the pedometer at rest. The number of steps during motion will be converted to walking distance in miles or kilometers.

1.1.5 Heart Rate Sensors

There are two primary types of heart rate sensors in sport wearable, electrocardiography (ECG) and photoplethysmography (PPG). ECG sensors are mostly used in chest straps. They include electrodes to monitor and measure tiny electrical activities of heart when it contracts. The sensor data is then sent to be analyzed and used to calculate heart rate. PPG devices are mostly used in wristbands. They contain photodiode (a light-sensitive sensor) and some numbers of LEDs. LEDs send light into body tissue and the system records the absorbed light by tissue and reflected light to the photodiode. The amount of absorbed light is used for measuring a blood flow and further hear rate. Heart rate measurement is used to determine the energy expenditure in wearables [21], [22].

1.1.6 Pressure Sensors

The study over the application of pressure sensors in wearables is one of the indispensable topics in this industry since these sensors are flexible, lightweight, affordable, and sensitive enough that make them suitable for wearable devices. There exist a wide range of force and pressure sensors with different characteristics. Many variables involve in categorizing all types of pressure and force sensors. The most general and common kinds of them are piezoelectric sensors, piezoresistive sensors, capacitive sensors, and barometric MEMS. A piezoelectric pressure sensor is a device that uses the piezoelectric effect, which causes internal polarization in the piezoelectric material of the sensor under pressure. The generated polarization produces electrical charge on the crystal of the material proportional to the applied force. These devices are applicable for dynamic applications since their sensitivity are extremely high. This characteristic of the sensor has made it practical in heart rate monitoring wearables[23]. The working principle of piezoresistive sensors are based on piezoresistive effect which can cause a change in the electrical resistivity of a semiconductor or metal when mechanical strain is applied. The simplicity and robustness of piezoresistive sensor have made them very promising in different sport wearables applications such as activity recognition [24], [25]. Capacitive pressure sensors work by measuring the changes in the material capacitance when a force is applied. They are more accurate than piezoresistive sensors however, their sensor conditioning circuit is quite complex. They are extensively employed in gesture recognition application of wearables[26]. Barometric MEMS are practical in measuring a change in air pressure or inside a liquid when hydrostatic pressure differs. Their application is usually when a user goes through a different elevation during their activities. There are some other types of force sensors which are based on magnetic fields or lights. They mainly work by measuring the displacement that the applied force generates on an elastomeric component of the device. They are custom-made and just for scientific purposes and literatures [27].

1.2 Motivation and Research Objectives

Keeping up with the regular training and expanding the practice routine are the two main challenges in the sport of weight training. It has been seen that the majority of individuals do not hold the suggested level of activity due to the lack of motivation after certain amount of time starting the exercise. Researchers have proven that automatic exercise tracking can significantly improve the individual’s motivation in maintaining their activity program [28], [29]. Beside activity tracking, it is also critical to have control over the carried weights in the feedback system during the workout. The free weights carried by a user during weight training exercises exerts certain forces on their palm, which can affect the musculature near the elbow down to the fingertips. The imposed pressure can cause a variety of injuries when the weight is beyond user fitness level. As of these issues there is an essential need in developing a wearable platform to recognize the type of activity, holding weight and number of repetitions automatically.

Among all the introduced sensors, inertial measurement units (IMU) and force sensors have been utilized in several research studies to produce data for developing classifiers to track and monitor human activities. In this respect, many studies have focused on recognizing daily activities such as walking, sleeping, standing, and cycling. Unfortunately, weight training, which has great health benefits, is mostly excluded in products and studies due to the large dataset availability requirement. Since there are relatively smaller number of people doing weight training, in comparison with activities such as walking and running. There have been handful number of studies aiming weight training activity recognition. In one of these studies conducted by Shen C et.al [30], the authors explored different machine learning methods using smartwatch sensor data attached to participants' arms for collecting 15 types of exercises data to detect both cardio and weightlifting workouts from non-workout activities and counting repetition. They utilized a two-stage classifier which automatically segments user’s activities, distinguishes workout activity from non-workout activity, and ultimately detects the type of workout. They also used the naive peak detection algorithm to count repetitions. The average of 90 percent precision and recall for classification problem and average error of 1.12 reps out of an average of 9.65 for repetition counting algorithm are reported in this study. In another study conducted by Qi et al. [31] the authors utilized two accelerometers on wrist and chest and an ECG electrode on the chest to gather data during three types of activities including aerobics, static postures and ten types of typical free weight movements. The framework is divided into two layers based on the free weight (anything you can hold in hands and work against gravity such as dumbbells) and non-free weight (exercise machines) boundary. In this study, a type of binary SVM, called OC-SVM, is applied in the first layer to separate free weight and non-free weight activities, whereas in the second layer, a Neural Network and Hidden Markov Model is adopted to classify the non-free-weight and free-weight activities, respectively. Their proposed system reached an accuracy of 90 percent in predicting the type of the performed activity. In the study conducted by Akpa A et al [32], a glove prototype has been developed with deployment of 16 force-sensitive resistor (FSR) sensors on the palm to classify ten types of gym activities and count repetitions. They developed decision tree, random forest, SVM and KNN models for the classification study and assessed their performances to find the most accurate model. Their developed model demonstrated an average accuracy of 82% for activity tracking model. An average counting error of 9.85% with a standard deviation of 1.38 with peak detection and elimination algorithm for count repetitions was observed. Some commercial products have appeared in the market for mobile health devices such as the "Apple HealthKit" and "Fitbit", which exploit both wearable devices and smartphones. However, users require to start and stop activities manually since they are not able to segment and identify activities automatically. There are some other commercial products like ''Strenx" by GymWatch, ''PushBand" by PUSH, and ''Wristband 2" by Atlas that provide feedback about used free weights, however they require users to manually enter the weight they pick up. Entering weights manually is inconvenient and forgetting to change the weight for each exercise can lead to inaccurate feedback. There exists a wide range of force transducers to extract information about force in different wearable devices applications. Most of the sensors found in literature belong to a sensor group which employs resistive polymer-thick-film (RPTF) technology such as force sensing resistors (FSR), Flexiforce® sensors, and other customized RPTF sensor arrays and matrixes [33]. As an instant, in [34] an arm brace with 8 FSR sensors was developed with the intention of developing a wearable which can model gripping force between zero to 20 N and identifies physiological changes that happens when weak muscular contractions take place. They achieved average RMSE of 5.48 N with a deviation of 2.17 N. [35] introduced a new methodology using FSR sensors for controlling robotic prosthesis in practical settings such as Cybathlon competition. The accuracy improvement technique was based on dividing the 11 different force grips according to their opposed thumb and non-opposed thumb direction. The final precision was reported as 89 percent. [36] was dedicated to assessing the lower limb movement such as thigh or ankle for gait detection using FSR technology. They were able to predict different walking modes and gait events from the thigh with high accuracy. FSR sensors are also utilized in the study of automatic detection of dumbbell weights. In [37] a wristband consisted of piezoresistive sensors and an IMU sensor has been utilized to develop a machine learning model for detection of three dumbbell weights 0.2lb,3lb and 8lb . Participants were recruited and asked to perform bicep curl and hammer curl activities and their data were collected while performing those activities. LDA classifier was developed to detect these dumbbells weight while performing those activities. The model reached an averaged validation accuracy of 88%.

Although there have been studies in the field of activity recognition and weight detection, there is a significant lack of capability of simultaneous recognition of weight and activity during the exercise by a single smart device. Performing multiple analysis on a single glove reduces any arising discomforts from using multiple wearable devices and brings wider range of information for the user throughout the exercise without hindering activities. In this study we developed a multitask wearable device which is capable in identifying nine common weight training activity types, counting the repetition of each activity, and detecting the weight lifted by the user in an automatic manner. The proposed system can detect the weight in any common orientation the weight held by the user instantly. The activity recognition model can recognize nine different most common practices including machine based, upper body and leg exercises by using only a single IMU embedded in the wrist of the glove with high accuracy, precision, and recall. The proposed platform consisted of three integrated Flexiforce sensors, accelerometer and IMU mounted on a glove for taking the signal measures during the exercise. To prepare the signal data for the machine learning module, the microcontroller unit (MCU) is employed for reading and sampling the sensors data and communicating to the mobile app for storing them. The most mainstream machine learning models are trained for the two under investigated objectives and their performances are assessed by the evaluation metrics to obtain the most practical models for the designated applications. The steps that were taken in this thesis to reach to the goal of the study are listed as the four objectives in the following:

Objective 1: Design and development of a multifunctional wearable sensor platform using the integration of pressure sensors, an accelerometer and an IMU into a glove to create a sensory system.

Objective 2: Investigation and evaluation of the performances of different machine learning models for automatic weight tracking in sport settings

Objective 3: Investigation and evaluation of the performances of different machine learning models in autonomous recognition of common strength training activities.

Objective 4: Proposing a method to count the repetition of the recognized activity to utilize in the developed glove.

1.3 Thesis Outline

The body of this thesis is organized as the following chapters:

Chapter 2. In this chapter literature review is conducted on advantages and shortcomings of the studies over sensory systems. The methods and machine learning models employment for human activity recognition, counting activity repetition, and force monitoring in wearables have been comprehensively studied and their potentials usage for our study has been explored.

Chapter 3. This chapter describes the design and development of a smart multipurpose wearable device for monitoring force and motion at gym using piezoresistive sensors, an accelerometer and an IMU. Further, three common machine learning models have been investigated with the purpose of instant weight detection by collecting force sensors data from participants while performing designated activities. The models' performances have been evaluated to find the most feasible classifier for the objective of the study.

Chapter 4. In this chapter, Euler angles data from twelve participants right wrists during performing of nine common activities are exploited for training an accurate and reliable machine learning model for activity recognition study. Different models are compared, and the best model is introduced. Methods such as data segmentation, feature extraction, model training and model assessment are explained in this chapter and the results are discussed. An algorithm for counting sports repetitions has been investigated and its performance has been assessed.

Chapter 5. This chapter concludes the thesis by discussing how the objectives of the thesis were achieved.

Chapter 2.

Background

1.4 Activity Tracking in Wearables

Activity tracking and recognition is necessary, e.g., in creating context-aware conditions and physical therapies. Assessing physical activities intensity and types provides better understanding of an individual's behaviors and habits and expediting lifestyle change process. Physical inactivity can be a great risk factor in cardiovascular disorders, high blood pressure, diabetes, anxiety and depression and musculoskeletal disorders. In the case of senior people, activity tracking can act as a life changing device by detection of long-time inactivity periods or fall events [38]. Early detection of fall events can prevent enfeeblement and fatal outcomes caused by inactivity due to the inability of recovery after the fall. Therefore, sensitive activity recognition systems are required for detecting these critical times and events [39].

In recent years great attention has been devoted to human activity recognition (HAR) research due to the benefits it provides in different fields such as the ones mentioned earlier. Wearable IMU sensors have been the pioneer sensors in this field since they are very power efficient, non-intrusive, cheap, and compact and they can easily be mounted on different parts of a body to measure a wide range of motions during physical activity. IMUs can be exploited to extract diverse types of variables such as triaxial acceleration, triaxial angular velocity, magnetic field measurements and orientation and position of a body. Different combinations of these sensors' variables have been investigated in HAR research. These variables have been collected from many parts of an individual body like head, arm, wrist, waist, hip, knee, and ankle. In some studies, multiple sensors have been mounted on different parts and combinations of their data have been assessed to check if the overall accuracy of the model enhances in this case. In this chapter these literatures will be reviewed.

1.4.1 Process of Human Activity Recognition

Study of human activity recognition has a great similarity with pattern recognition problems which corresponds to specific stages starting from data collection and ending with classification model. This process requires a set of steps of transformations of the sensors raw data to create practical human activities classification models. The HAR methodologies with wearable IMU can be categorized into two groups of approaches. One approach focuses on shallow machine learning algorithms (e.g., SVM, KNN, decision tree, random forest). [40] While the other approach focuses on the use of deep learning algorithms (e.g., CNN, RNN, RBM, SAE, DFN, and DBM). [41] The main difference between them is based one the way how feature extraction is being carried out. In conventional approach (shallow algorithms), feature extraction and selection are made manually, while in the deep learning approach, feature selection is made by the algorithm itself [42]. Figures 1 and 2 show the steps followed in both approaches. [43] From the figures, it can be seen that the conventional approach has two extra steps segmentation and features. We will be focusing on the conventional approach in this thesis since for performing deep learning algorithms a huge amount of data is required and lack of enough data can lead to model overfitting. Therefore, for the amount of data we were able to gather we concluded conventional models outperform deep learning models.

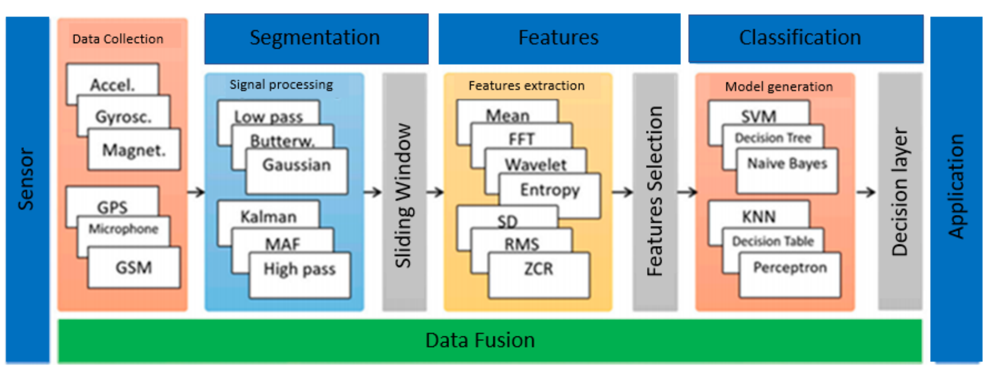

Figure 2-1. Steps in conventional machine learning models

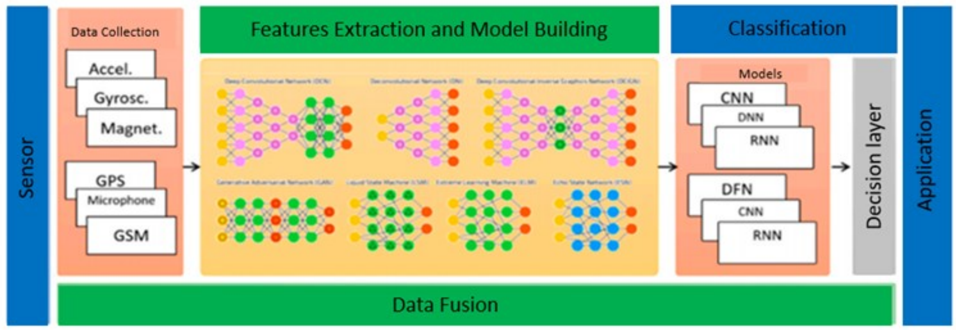

Figure 2-2. Steps in deep learning models

1.4.2 Data Collection

HAR data collection process involves with gathering data in the form of time series. Accelerometer, gyroscope and orientation data for example can be shown with sets of vectors like $Acci$={ax_i, ay_i, az_i}, $Gyro$={gx_i, gy_i, gz_i}, $Euler\ angles$={ x_i, y_i, z_i} where x, y and z represent axes and i={$1,2,3, \ldots n$} represent number of data samples.

Generating HAR classification models, considering elements such as time, frequency rate, sensor placement and type of data is unavoidable. Studies have performed data collection in a wide range of sensor frequency rate. Selecting a right frequency rate plays an important role in producing an efficient classification model since proper frequency rate provides more relevant and better information about the human activities. Studies have employed frequencies among $1Hz$ to $200\ Hz$ for the IMUs [44]– [49].

Another important factor with great impact on classification model accuracy and data quality is a sensor placement on a body because signal patterns are quite different on each body part and some parts can deliver higher quality information about activities. Research has been done on hip, ankle, chest and waist [44], [50]– [55] and although some of them have gained great accuracy since these measurement sites are less compliant, they are not practical solution for real world application. Due to the wide availability of wristbands, smartwatches, and armbands because of their user-friendliness and comfortability they seem feasible solutions for real world applications[56]. In a few next following sections, these studies will be reviewed.

Finally, the types of data used in data collection is another factor to take care of. Studies have used combinations of data to generate classification models including acceleration and gyros, IMUs data along with heart rate sensors [57], [58] IMUs along with ECGs (electrocardiogram) [59], IMUs with EMG (electromyography) [60]. Some studies used just one type of sensor like IMUs in order to provide more comfort for the users and to create a more realistic situation in their studies.

1.4.3 Segmentation

The first step for performing segmentation is data preprocessing. Preprocessing of raw data is required to minimize the noise effects due to changes in the users' behavior, movement, and environmental conditions like malfunctioning of gym equipment. The most common noise elimination method are lowpass filters, moving average filter, and Kalman filter [61]– [63].

The reason for doing segmentation is to divide data into segments that share the same characteristics, known as time windows or sliding windows. Sliding window-based segmentation is often used to separate sensor signal data into meaningful subsequences over time. This process is a prerequisite of the feature extraction process. Each segment is analyzed over its time interval. Time intervals or sliding windows can be fixed or variable size. This size should be set in a way that can contain sufficient characteristics to allow the recognition of a human activity at a given moment. The sample size of the variable length windows can be achieved based on changes in the signal mean and variance while the main element in defining the window size is the frequency rate of the data for the fixed size window. Different frequency rates have led to achieve different window sizes in studies [64]–[66]

Segments may be overlapping or non-overlapping windows. Overlapping means segments from the previous window intersect the samples from the next window. For example, window with 50 percent overlap contains half of the information of the previous window. However, in non-overlapping segments, there is no intersection between each data subgroup and segments.

1.4.4 Features

Feature is referred to the useful information each data segment provides. Features are quantitative measures that are extracted through the feature extraction process. They can be obtained from domains including time and frequency domains.

Features extracted from time domain employs mathematical functions to gain statistical information from the signals however, featured extracted from the frequency domain employs mathematical functions to capture repetitive patterns of signals and information regarding the natural periodicity of the activities. Common features from the two domains have been listed below.

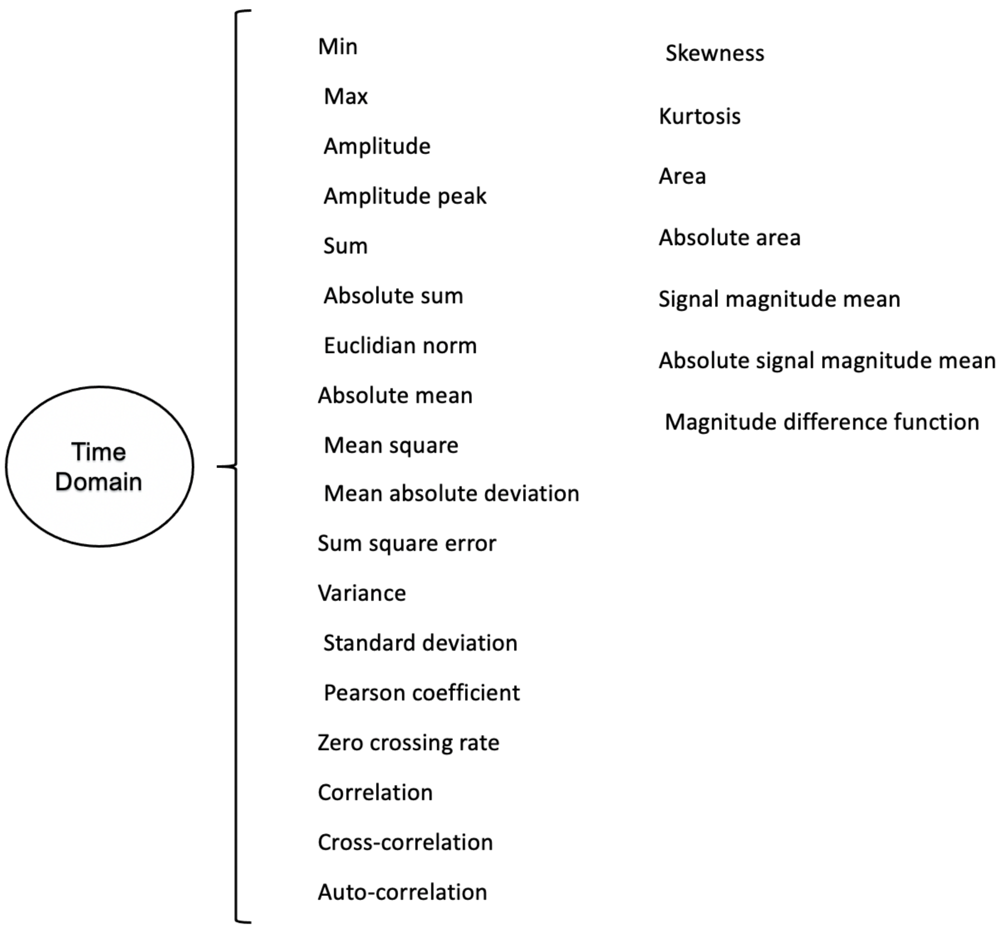

Figure 2-3. Statistical features in Time-domain

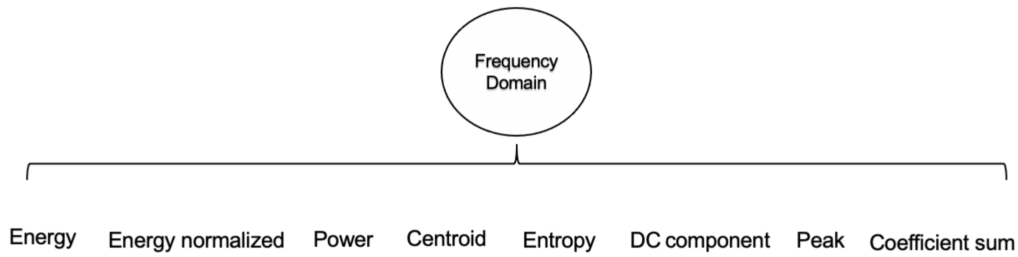

Figure 2-4. statistical features in Frequency-domain

Feature extraction from time domain is more common than feature extraction from frequency domain since extracting features from frequency domain requires some computations such as fast Fourier transformation or Wavelet transformation which cause the system to spend more time to extract a feature from a signal comparing with extracting features from time domain.

Sometimes in HAR research, dimensionality reduction is required. Dimensionality refers to the number of features extracted in feature extraction process, where each feature shows a dimension. Having a huge number of features manifests two issues. The first problem involves with the data processing cost and computation time to extract features and the second with the accuracy of the classification models. High dimensionality can create overfitted classification model [67]. In this regard, the data dimensionality reduction process must be performed to remove irrelevant features and select features which can improve the accuracy of classification models. There are two methods for data dimensionality reduction. First, deals with data after feature extraction is done while the second method deals with data while feature extraction is being performed.

Methods that are applied to features after extraction are called feature selection techniques. In general, feature selection can be categorized into three groups: filter methods, wrapper methods and hybrid methods [68]. These methods work by calculating linear or nonlinear correlation among features and discard features with high correlation from dataset. Selection of the right methods depends on the types of inputs and outputs data in the classification model. For example, in HAR context since input is numerical and output is categorical filter methods are used widely. In this study [30], two filter methods univariate statistical test and the tree-based feature ranking have been employed to select the best features. These methods rank a set of selected features according to the estimated weights of each feature obtained from a special statistical measurement. Methods that work during feature extraction process, utilize combinations of features, and compress them to reduce the dimensionality of data. The most used techniques in the application of HAR are Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Kernel Discriminant Analysis (KDA). These methods usually are used in larger dimension of data[43].

1.4.5 Classification

In this section, the most common classification techniques will be introduced and discussed.

1.4.5.1 KNN

KNN which stands for k nearest neighbors is the most basic algorithm in classification problems. In this model, learning phase is not required but considerable amount of storage is necessary to store the whole dataset. This algorithm classifies new observation based on similarity of the features of new data and the whole dataset. Euclidian distance between the new data and training set is determined in this algorithm to measure the similarity. This new observation is assigned to a class through a majority vote of its k nearest neighbors. In this study [69] KNN algorithm achieved a mean of 88.9 true positive rate and it outperformed LDA and QDA algorithms in recognition of 30 different gym activities using two IMU sensors mounted on left wrist and torso. Although KNN has done a great job in this study, it had poor results in [57]. It achieved 77 percent accuracy in recognition of 7 strength activities using two sensors one smartwatch and one heart rate sensor. SVM and DNN outperformed this classifier.

1.4.5.2 Support Vector Machine

Support Vector Machines (SVMs) is a well-known machine learning model that is generated from statistical learning theory. This model working principal is based on minimizing a cost function while maximizing the margin between model hyperplanes that separate data classes. Basically, SVMs are linear classifiers and used for binary classification problems. Using kernel functions to map the data space to high dimension feature space is a common practice for using SVM model in non-linear classification. Furthermore, for multiclass classification problem pairwise classification is being used, however this can make the process time consuming in applications requiring large amount of data.

SVM model has been used widely in the application of HAR in both sedentary activities and gym activities. In [31], SVM was used in a two layers recognition framework for distinguishing free weight from non-free weight activities in the first layer and detection of the types of activities in the second layer. This study has employed two accelerometer sensors on wrist and chest and ECGs to monitor heart rate. SVM has been used in the first layer and has achieved the accuracy of 85%. In another study [70], SVM model has achieved 99% accuracy in recognition of six physical activities using motion sensor on chest in Leave-one-subject-out cross-validation while 86% accuracy when using Leave-other-subjects-out cross-validation. This shows SVM model can reach high accuracy when using in HAR application.

1.4.5.3 Decision Tree

Decision Tree is another extensively used machine learning method in HAR studies [71]– [73]. This model has been used widely in recognition of sedentary activities like walking, cycling, seating, and standing. Although the performance of this model has been never as poor as KNN model, they have a limitation to reach better performance without overfitting. This problem lies in the size of a tree when is being trained. The deeper the tree, the higher probability of the model to overfit. This drawback of this model has been led to emerging of a new type of model called Random Forest (RF) which is an ensemble model of decision tree.

1.4.5.4 Random Forest

Random Forest is made of a combination of Decision trees. Random Forest uses a method called bagging to solve the overfitting problem of decision trees. This method selects random subsets of features with replacement each time and train a Decision Tree model using that subset and afterward the prediction is made based on a majority vote of Decision Tree models results. This makes this model very powerful among traditional models. This model has achieved great results in the context of HAR. In a study that Mircosoft has performed using arm band motion sensor accelerometer and gyroscope data called RecoFit [74], they achieved accuracies of 99%, 98%, and 96% of recognition of 4, 7, and 13 exercises, respectively, and exercises repetition counting accuracy of 93%. Despite the great results they have reached, this model uses window size of 5 seconds in segmentation which is quiet long time for real life experiences. In [75], four sensor's orientation data from armband, glove, chest strap and one mounted on a dumbbell was gathered and random forest model was applied for recognition of Unilateral Dumbbell Biceps Curl in five different fashions. This model gained 98.2% performance accuracy after applying 10-fold cross validation. Random Forest has obtained great accuracy even in sedentary activities with accelerometer, gyroscope, heart rate sensor and pedometer data using one smart watch. This model outperformed SVM, KNN and Decision Tree with 99% accuracy [76]. The great performance of RF model in these studies have made this model countable and promising in HAR context and especially in gym exercises recognition.

1.5 Force Tracking in Wearables

Beside wearable IMU approach, force sensors have obtained ever-increasing attention in wearable studies. Most studies in the context of force tracking have focused on an approach called force myography (FMG) which is a non-invasive procedure that investigates musculotendinous complex (MC) stiffness changes happen during muscle expansion and contraction and interprets the position or movement of a corresponding limb. The study of a position or movement of a limb can be used in physical activity monitoring. By placing force transducer on a targeted MC, changes in stiffness can be monitored. The targeted MC can be identified by squeezing our hands and using our fingers to feel the stiffness of extensor muscles. Then, the fingers can be replaced with force transducers [77]. Great results obtained from FMG studies have provided an opportunity for utilizing these popular forces transducers in other force tracking studies which measure applied direct forces rather than measuring a specific limb movement caused by applied force. Both types of research will be reviewed in the following.

There exists a wide range of force transducers in FMG research. Most of the sensors found in literature belong to a sensor group which employs resistive polymer-thick-film (RPTF) technology such as force sensing resistors (FSR), Flexiforce® sensors, and other customized RPTF sensor arrays and matrixes. Rest of the studies have utilized other types which are pneumatic, capacitive-optical fiber, piezoelectric-, and textile-based sensors.

The majority of FMG research have focused on the detection of upper limb movements to predict hand gestures. In these studies, an array of FMG sensors around forearm or wrist muscles have been placed and the sensor signals during performing variety of hand gestures have been gathered. In the study of [78] recognition of three sets of 48 gestures including 16 grasping tasks, 16 sign language hand gestures and 16 hand and fingers movement were investigated using an array of 16 FMG sensors on either the forearm or the wrist. The study achieved 96.7% and 89.4% in cross-validation and cross-trial accuracies. Although great results have been obtained from gesture recognition studies, there existed an ambiguity in the optimal sensor location and the number of sensors for the application. In [79] this problem has been investigated. The results represented that the high accuracy gained by a large spatial coverage of FMG sensors can be approximated by lower spatial coverage by placing sensors on an optimal location. These great results in application of human computer interaction drew researchers' attention to explore this method in rehabilitation application by making a wearable that can be useful for motor function improvement after injury. In [80] an arm brace with 8 FSR sensors were developed with the intention of developing a wearable which can model gripping force between zero to $20\,N$ and identifies physiological changes that happens when weak muscular contractions take place. They achieved average RMSE of $5.48\,N$ with a deviation of $2.17\,N$. In other studies, in rehabilitation application the deployment of FMG sensors in prosthetic were explored. [35] introduced a new FMG methodology for controlling robotic prosthesis in practical settings such as Cybathlon competition. The accuracy improvement technique was based on dividing the 11 different force grips according to their opposed thumb and non-opposed thumb direction. The final precision was reported as 89 percent. Other studies of FMG methodology were dedicated to assessing the lower limb movement such as thigh or ankle for gait detection. [36] were able to predict different walking modes and gait events from the thigh with high accuracy.

Great results obtained from FMG sensors made these sensors practical in other studies for force tracking and analysis. In one of the studies carried out by Komi et al [25]. Three types of thin, flexible force sensor were examined for grip force measurement during a golf shot under different loading conditions. The comparison of three sensors revealed that the Flexiforce sensor showed a durable and repeatability capability in golf grip force measurement application. In [81], force sensors are used for creating a backpack with pressure sensors which can measure and predict forces that are applied on shoulders and back to avoid excessive forces and their corresponding injuries. They encountered repeatability issue for long-time measurement. In [24], they built a smart glove consisted of sixteen Flexiforce sensors on hand palm. Their purpose was to detect 10 common fitness activities by reading pressure distribution on a palm. They were able to gain 88.90% of the F score for overall activity recognition and average counting error of 9.85%, with a standard deviation of 1.38 for repetition count system. Other types of studies that have employed FMG sensors in direct force measurement include gait cycle detection and gait assessment based on insole foot pressure measurement [82].

1.5.1 Force Sensors Processing

The processing technique in force sensor wearables is the same as the technique use in IMU wearables. It consists of the data collection, segmentation, feature extraction, feature selection and machine learning model development. Classification method in machine learning is used for discrete states predictions and regression method in machine learning is used for continuous hand movement detection.

1.5.1.1 Classification

Linear discriminant analysis (LDA), support vector machine (SVM) are the two most common classification models used in force sensing application. LDA classifies a new observation data by estimating the probability of the data belonging to a class. The class with the highest probability will be chosen as the output of the observation. The probability is calculated based on Bayes Theorem. In short, Bayes Theorem can determine the probability of given input (x) belonging to output class (k) using the probability of each class and the data belonging to that class. The popularity of LDA is generating from its straightforwardness and efficiency that makes it practical for utilization in real time control applications. Also, some publications concluded that LDA had remarkable or comparable performance when it’s compared with more complicated machine learning models. In [83] for example, LDA reached 5% higher accuracy than ANN in prediction of six hand gestures. In these studies, [35], [84], [85], it is approved that LDA and SVM can have a comparable performance in prosthesis control applications. Another common model in this application is SVM which is often represented higher performance comparing to other models [35], [84], [85], [86]. Despite the high accuracy of this model, fine-tuning the model can exceed the computation costs. There are some other types of classifiers in this application which have been used based on application constraints [87], [88].

1.5.1.2 Regression

Support vector regression (SVR), linear regression (LR) and artificial general regression neural network (GRNN), are the most used regression technique. Principal working of SVR is the same as the principal of SVM but in regression domain. The supported vector is identified from input data and then the model can be created. The utilization of this technique is mostly in prediction of exerted force by fingers [89], [90] .This method has also been used in prediction of fingers dynamic movements [91], [92].

LR is a simplest regression method which is learned based on the least square error. This method associates with continuous inputs and outputs. This method has been employed in prediction of different fingers movement and grip force [34], [93].

GRNN is the third most popular model used in this domain. This model consists of three layers, which are called input, hidden, and output layers. Adjacent layers are connected to each other with a certain number of nodes that are located on each layer. The corresponded weight for each node requires to be trained iteratively using optimization technique called gradient decent. This study [92] has exploited GRNN to predict wrist toque based on force sensor signals and they achieved high accuracy. [91] has utilized this method to predict continuous fingers movement with the aim of gesture prediction.

1.6 Conclusion

The previous works in gym activities recognition have mostly combined multiple types of wearable sensors to achieve high accuracy. Although great performances of machine learning models have been achieved, utilization of multiple wearable sensors is not the best practical solution in real life situation. This method can interfere with users' comfortability and restrain users' movement. In this study, the performance of a single wrist worn IMU wearable integrated in a glove in detection of common gym exercises have been assessed to find an optimal way of wearable sensor utilization in real life scenario.

Previous works in force tracking have been mostly dedicated to rehabilitation application. Although great achievements have been obtained in these studies, there is very limited studies focusing on the application of wearable force sensors in preventing injuries due to lifting excessive forces during different sport activities. In this research, we investigated the application of one of the most common force sensors in detection of lifted forces during gym activities with the aim of preventing injuries in sports and increasing effectiveness.

Chapter 3.

Evaluation of a Force tracking method in strength training

1.7 Introduction

This chapter is toward the first and second objectives of the thesis. In following, the design steps and development process of a smart glove device to meet the objectives of this study are explained. Then, the applications of three machine learning models for weight detection are investigated. The performance of these algorithms in a study with 6 participants performing movements which could provide necessary information for all the common hand orientations when holding dumbbells in real application scenarios are evaluated. After performance assessment of the models, the most practical model has been selected. In section 2, we start with describing the methodology and the system used in this study including the design and development of the glove, data collection experiments, data processing and classifiers development. In section 3, results of the evaluation of the classifiers performances are represented and discussed. Conclusion of the study is expressed in the section 4.

1.8 Methodology and System Description

1.8.1 Smart Glove Platform

The simplicity, low price, and comfortability of force sensitive resistor (FSR) sensors make them favorable for grip force measurement, pressure distribution and weight detection in wearable devices. The proposed glove consists of three Flexiforce A401 FSR model sensors which are located on the palm, ring and middle fingers' fingertips based on experiment. Each sensor has an active sensing area of 2.5cm diameter, with 0.203 mm thickness and can sense forces up to 111 N. The applied force to the sensors results in the variation of the electrical resistive values, this variation generates voltages which are corresponded to the applied force. These voltages values are not constant in all the orientations since the sensor's surfaces are not able to sense the surface of the weight fully in some orientations. Therefore, ADXL335 accelerometer was utilized in the system to measure hand orientations along with the force sensors data. An IMU (MPU 6050) unit which is a low power, low cost and high-performance motion tracking device was also placed in the glove's wrist to measure wrist Euler angles' data for activity recognition purpose. The data sampling and communication process was performed through Arduino Nano. Adafruit Bluefruit LE module was employed to transfer sensors data to BlufruitConnect mobile application developed by Adafruit. The Arduino board was powered up by a rechargeable 400 mA/h Li-Po battery. The proposed system is depicted in:

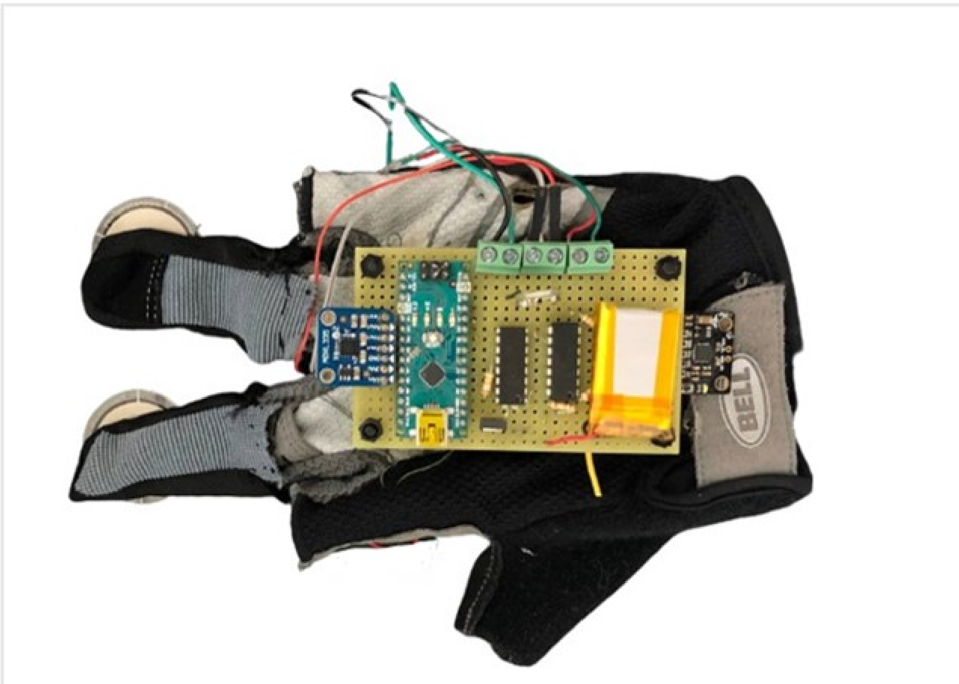

Figure 3-1. **Smart glove with all the mounted electronic components**

1.8.2 Circuit Design and Signal Conditioning

The FlexiForce QuickStart Board, which is an interface between FlexiForce sensor and data acquisition system, is an analog signal conditioning circuit that amplifies the sensor output according to the two variables R_f and V_{Ref} shown in Eq. 1. The output voltage is given by Eq. 1:

$$V_{out} = -V_{Ref} * (\frac{R_f}{R_s}) \qquad \text{Eq. 1}$$

We designed the output voltage to be in the range of zero to five volts. Based on the manufacturer charts, this voltage range can provide the sensor capability of measuring up to $25Ib$ force range. The force range can be set by defining different variables including voltage reference and resistor reference. Sensor resistance (RS) decreases to $30K\Omega$ at the maximum load therefore, to get the maximum voltage, which is $5volt$ in this application, we require to find out optimal value for the reference voltage. Then, we determined the required reference resistor from the formula and obtained $40K\Omega$ value.

1.8.3 Sensor Fabrication

Placing the pressure sensor directly on the glove palm can flex the sensor and create certain problems in terms of sensor's functionality. In the long term, this flexion will lead to sensor failure. To prevent these problems, a silicone rubber substrate built out of ECOFLEX 00-30 was designed and Finite Element Method (FEM) was employed for finding the practical size of it. The pressure sensor was then embedded inside the substrate at its bottom. The design contains an upper rectangular part and a lower base cylindrical part as demonstrated in Figure 3-2. The substrate would allow forces to be distributed uniformly on the sensitive area on the sensor. When a dumbbell is placed on the rectangular part, force will be transformed through cylindrical base to the active sensor area(Figure 3-3-C). To meet the two major critical design factors for the substrate, comfort, and elasticity, ECOFLEX 00-30 was utilized due to its hyper-elastic characteristics and widespread utilization in biomedical applications [94]. According to [95], inserting a tiny disc at the bottom of the proposed sensor in body and device interface can increase the accuracy of the sensor because the contact surface area will be increased. Thus, a tiny robber disc with the same diameter as the sensor sensitive area was put below the sensor to increase its accuracy.

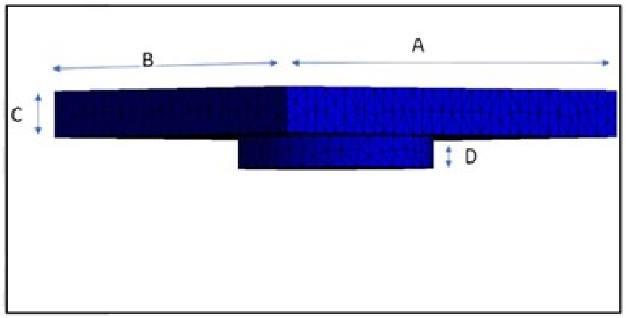

Figure 3-2. Silicon rubber substrate

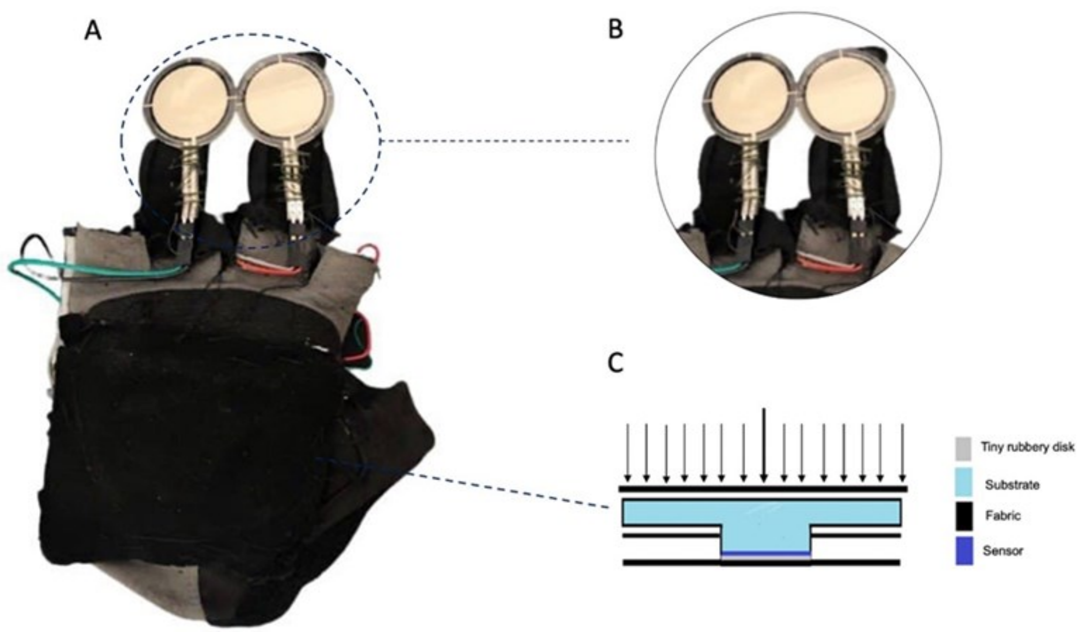

Figure 3-3. A) Glove prototype. B) Flexiforce force sensors. C) Layers of prototype in the glove, which are shown with the colors as gray tiny rubbery disk, light blue as substrate, black as fabric and dark blue as sensor

To determine the optimal size of the substrate under the maximum applied force ($10\ lb$ in this application) we performed Finite Element Analysis (FEA) in ANSYS 2021

R1. We used ECOFLEX 00-30 silicon rubber and obtained its mechanical characteristics from [96].To find out the practical size of our Silicon rubber substrate we required to solve an equation which related strain and stress of the hypeelastic material. In These types of materials there is no direct relationship between stress and strain, hence they do not follow Hook's law which explains the direct relationship between stress and strain. Hyperelatic materials behaviors can be explained with different mechanical term called strain energy density function as represented in Eq. 2.

$$S_{ij} = \frac{\partial W}{\partial E_{ij}} \qquad \text{Eq. 2}$$

In Eq. 2, S_{ij} represents components of the second Piola-Krichhoff stress tensor. where W is strain energy function per unit undeformed volume and E_{ij} represents the components of the Lagrangian strain tensor. The general strain energy function for an hyperelastic isotropic material is defined as Eq. 3.

$$w(I_1, I_2, I_3) = \sum_{m+n+k=1}^{\infty} C_{mnk}((I_1 - 3)^m \, (I_2 - 3)^n (I_3 - 1)^k \qquad \text{Eq. 3}$$

where I_i is called strain invariants and can be determined from Eq. 4 to Eq. 6.

$$I_1 = {\lambda_1}^2 + {\lambda_2}^2 + {\lambda_3}^2 \qquad \text{Eq. 4}$$

$$I_2 = {\lambda_1}^2{\lambda_2}^2 + {\lambda_2}^2{\lambda_3}^2 + {\lambda_3}^2{\lambda_1}^2 \qquad \text{Eq. 5}$$

$$I_3 = {\lambda_1}^2{\lambda_2}^2{\lambda_3}^2 \qquad \text{Eq. 6}$$

where λ in above equations is stretch ratio and is defined as Eq. 7.

$$\lambda = \frac{L}{L_0} \quad \text{Eq. 7}$$

where L represents a length of the material under load and L_0 illustrates initial length of it. There exist divers hyperplastic strain energy density models that can be used in different applications represented in Figure 3-4.

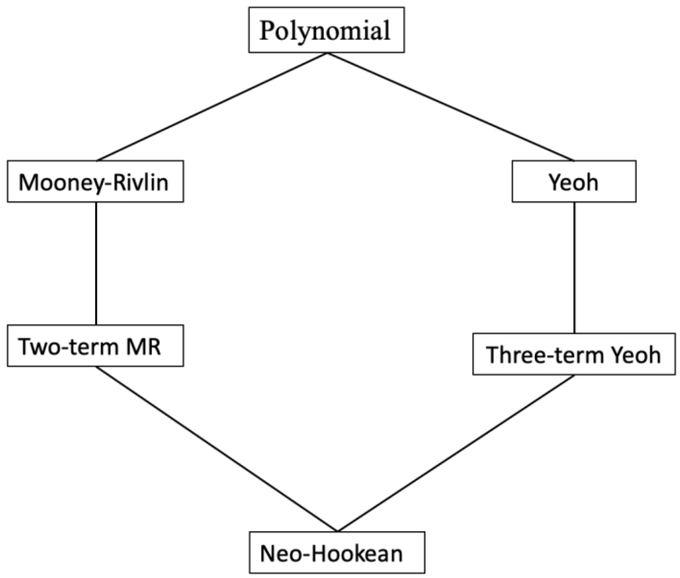

Figure 3-4. Types of hyperplastic strain energy density models

Selection of the hyperplastic model depends on conditions such as type of elastomer, loading conditions and material test data availability. Generally, a model which can provide closest stress-strain curve fit to test data is considered as a best model for a specific application. To meet the mentioned criteria, the Yeoh 3rd order solid model Eq. 3 was fitted to the test data to determine the model parameters Figure 3-5. Next, the 3D model of substrate under maximum force was investigated in ANSYS 2021 R1.

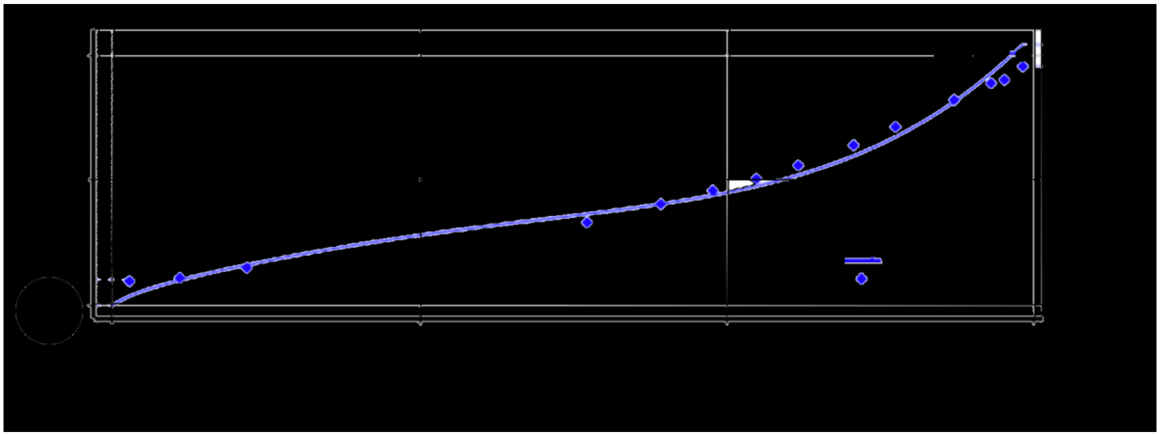

Figure 3-5. Yeoh 3rd order model fitted to the experimental uniaxial data of ECOFLEX 00-30.

The density function of this model is shown as Eq. 8.

$$W = \sum_{i=1}^{N} C_{i0}(\bar{I}_1 - 3)^i + \sum_{k=1}^{N} C_{k1}\,(J-1)^{2k} \qquad \text{Eq. 8}$$

In this equation, term W stands for strain energy, N is the order of the model, which is 3 here, C_{i0} and C_{k1} are material constants that are obtained from test data, $\bar{I}_1$ is the first invariant of Cauchy-Green strain tensor and J is the volume ratio which is equal to one for incompressible materials. After performing finite element method (FEM) on the substrate, model parameters are obtained as Table 3-1.

Table 3-1. Optimal parameters of the substrate.

Parameters	*Value*
A	6 cm
B	4.3 cm
C	0.6 cm
D	0.4 cm

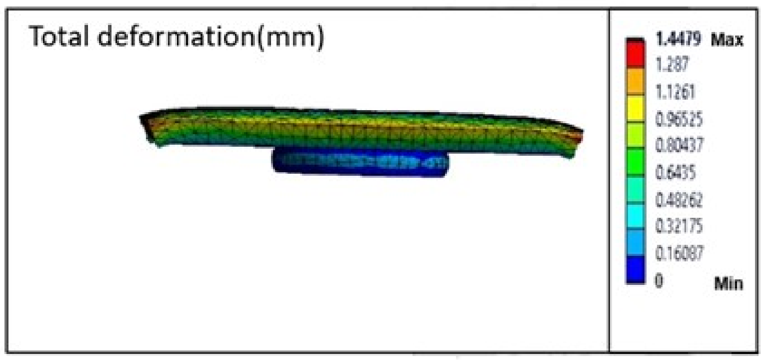

Figure 3-6. Total displacement(deformation) under maximum force ($10Ib$ based on the weight of the heaviest dumbbell)

After calculating the optimal size of the substrate by utilizing FEM, we produced the elastomeric parts by casting uncured ECOFLEX 0030 silicone rubber into 3D printed mold and placing the sensor at the aforementioned place after the sensor was cured under ambient conditions for approximately 4 hours. Then the sensor was sandwiched between the substrate and the produced rubber disc and placed into the glove palm.

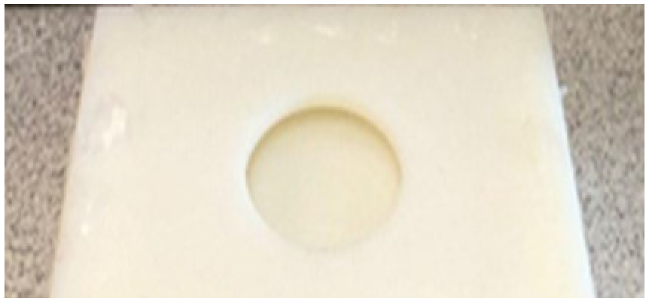

Figure 3-7. 3D printed mold.

1.8.4 Experiments

Two separate experiments were designed to collect force sensors and orientation data to analyze the proposed system's capability of recording and classifying dumbbell weights. One hour and a half workout session experiment was designed and ran for the weight detection objective. Six healthy participants for weight detection study (two men and four women) in a range of 20-35 years old were recruited to perform the designated activities. Activities for weight detection were selected in a manner that could cover most of the possible hand orientations that one may hold a dumbbell with to detect a weight instantly after holding it (Figure 3-8). In both experiments, activities with minimum possible of injuries are prioritized.

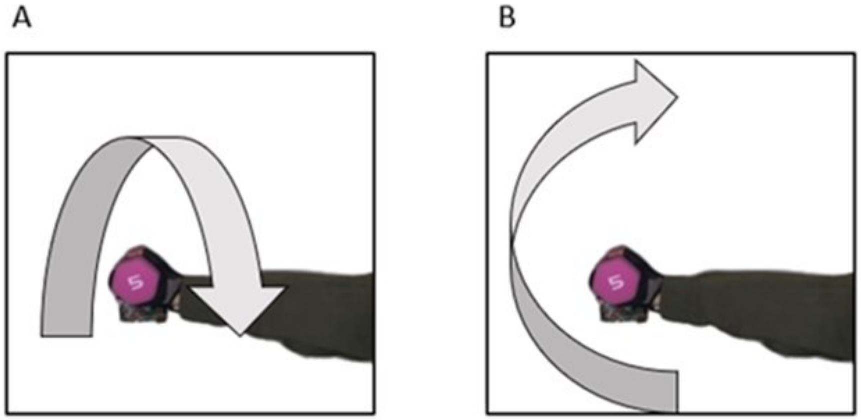

Figure 3-8. A) Rotating hand while roll angle is changing from 0 to 180. B) Rotating hand while pitch angle is changing from 0 to 180

Before starting any experiments, participants were asked to provide the informed consent form. Next, the two activities for weight detection were introduced to each group of the participants. The weight detection activities involved holding different dumbbells and rotating the hand in a way that roll and pitch angles varied from 0° to 180°. Three dumbbell weights were selected for the weight detection study, $2Ib, 5Ib$ and $8Ib$. By considering the capability of all the participants who were not experts in weight training exercises $8Ib$ was selected as the heaviest dumbbell. All the activities were asked to be performed for three sets of fifteen repetitions. Hand Euler angles along with force sensors data for weight prediction were gathered with sampling rate of $100Hz$ through the mobile app. The data were then sent to the researcher's computer after the experiment session was done. As this was the first prototype that we developed for this application, only a glove for right-hand is developed, therefore all of the data are corresponded to the right-hand orientations.

1.8.5 Data Preprocessing and Feature Extraction

In the study of weight detection, the aim is finding the associated force sensors value with hand orientation. In this regard, the following steps were taken. Once the sensors' signals were collected, the moving average filter (Eq. 9) was applied to the data to smooth the signals and eliminate noises. In Eq. 9, k is half of the number of data points, x_i is the data point i, t is time, and y_t is the filtered data. Moving average with a window size of 50 points was obtained empirically. The magnitudes of force signals associated with each hand orientation were then identified and stored in a data frame (see Figure 3-9). The mean value of all the three force sensors were computed and added to the data frame to contain more features for the machine learning models development. Eventually, a data frame consisted of the magnitude of the three sensors, their mean value and their corresponding pitch and roll angles were fed into the models.

$$y_t = (2k+1)^{-1} \sum_{i=t-k}^{t+k} x_i \qquad \textit{Eq. 9}$$

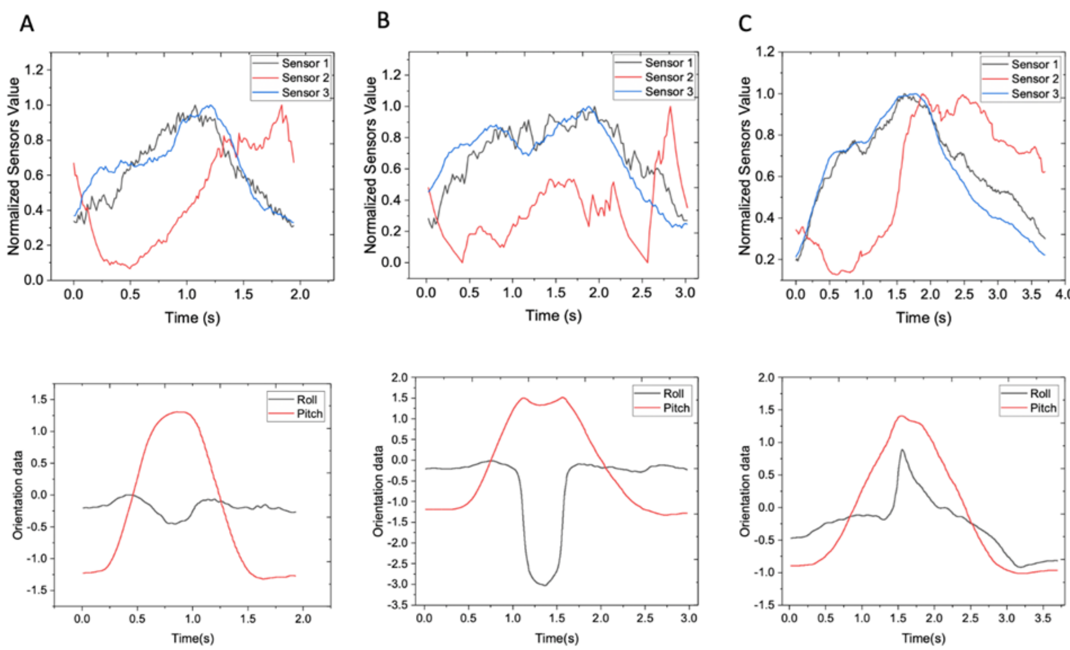

Figure 3-9. **An example of one repetition of three force sensors with their corresponding pitch and roll angles during the second data collection step. A) Force sensor and orientation signals for 2lb weight. B) Force sensor and orientation signals for 5lb weight. C) Force sensor and orientation signals for 8lb weight.**

1.8.6 Classification

Three mainstream classification algorithms, Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) and Multilayer Perceptron Neural Network (MLP) that have been widely used in the application of force studies analysis were trained to classify the dumbbell's weights. LDA classifier was developed by using Sklearn package in Python. This classifier seeks a linear combination of inputs to characterize different classes based on different distributions and form a decision boundary between them. SVM classifier and MLP were also developed with the Sklearn package in Python. SVM algorithm works by defining optimal hyperplanes called decision boundaries among classes of features to make them separable so that any future observations could be identified, which classes they fall into. SVM method uses Kernel tricks to create decision boundaries among classes. In this study, Radial Basis Gaussian (RBF) kernel function was chosen to develop a SVM model. The internal parameters of the SVM, (i.e., C and Gamma) were optimized by performing grid search. Due to the superiority of artificial neural networks in modeling the extremely complex functions and data relationships, the MLP consisted of one hidden layer comprising 100 neurons were designed with the Relu activation function and gradient decent solver for this study. 70 percent of the data were used for training and 30 percent of them were utilized as the test set. A 10-fold cross validation method was used in which data was split into 90 percent for training set and 10 percent as the validation set. 10-fold cross validation method was applied to avoid overfitting and to assess the performance of the developed machine learning on new subsets of data. The accuracy of the model was then determined out of the average of accuracies of the 10-fold cross validated models. Other evaluation metrics such as precision, recall and f-score were also determined to find the most practical classifier in this application.

1.8.6.1 LDA

LDA is the simplest machine learning model in the classification problems. In multiclass classification problems, this model assumes that the data are drawn from a multivariate Gaussian distribution $N(\mu_k, \Sigma)$, where μ_k is the average of the k_{th} class and Σ is the common covariance to all the classes. This algorithm incorporates these values into the likelihood function (Eq. 10) to characterize and separate observations linearly

(Figure 3-10. LDA classifier). To classify new data, the model computes the likelihood and then it assigns them to the class with maximum likelihood score.

$$\hat{\delta}_k(x) = x^T \Sigma^{-1} \hat{\mu}_k - \frac{1}{2} \hat{\mu}_k{}^T \Sigma^{-1} - \hat{\mu}_k + \log(\hat{\pi}_k)$$ *Eq. 10*

In Eq. 10, $\hat{\delta}_k(x)$ is called likelihood or discriminant score that defines if the input x will fall in the k_{th} class. $\hat{\pi}_k$ is the prior probability that expresses if an observation belongs to the k_{th} class and it is obtained from the training data.

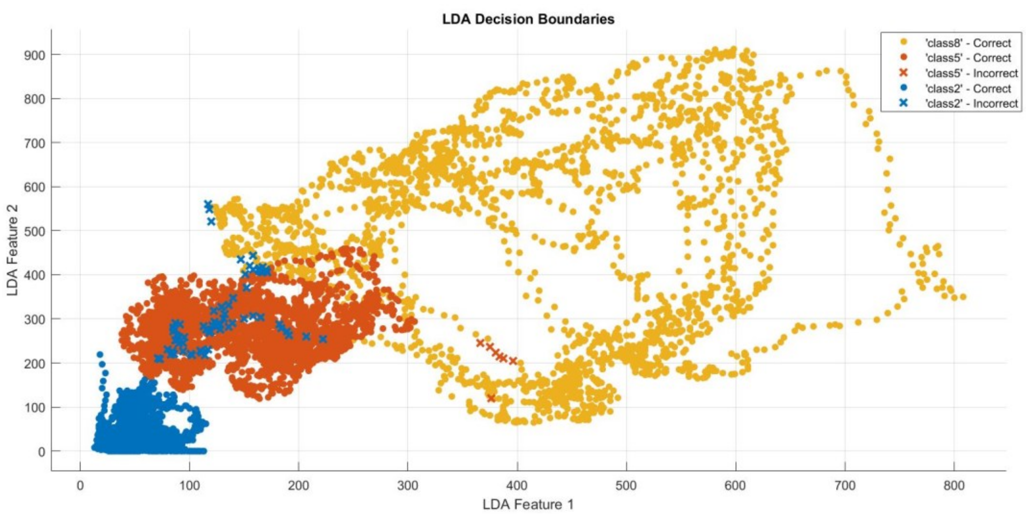

Figure 3-10. LDA classifier

1.8.6.2 SVM

Support Vector Machine (SVM) is one of the most feasible machine learning models in the application of pattern recognition. SVM algorithm works by defining optimal hyperplanes called decision boundaries among classes of features to make them separable so that any future observations could be identified, which classes they fall into. SVM method uses Kernel tricks to create decision boundaries among classes. That means, this algorithm deploys different kernel functions based on the application to achieve this. There exist diverse kernel functions to use for SVM classifier. In this study, Radial Basis Gaussian (RBF) kernel function has been utilized to make the features linearly separable. The RBF kernel model follows the mathematical equation represented in Eq. 11. The equation measures the Euclidean distance between the origin of the RBF function illustrated in Figure 3-11 and observed data. Then, the distance value will be multiplied to a constant coefficient called gamma which is obtained through grid search. Next, the observed data will be classified based on the computed threshold by the algorithm and the output of the Gaussian function. It can be seen from the RBF kernel that if the observed data is close to the origin, data point will belong to a higher section of the kernel and if it is located far away from the origin, it will belong to a lower section of the kernel. Different colors in the Figure 3-11 represent decision boundaries created for the classes.

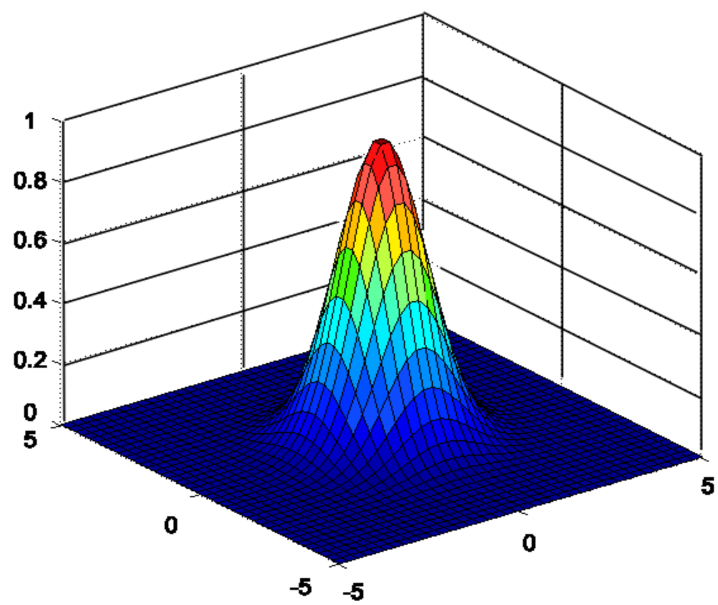

Figure 3-11. Radial Basis Gaussian function

$$K(X,L) = e^{-\gamma\|(X-L)\|^2}$$ *Eq. 11*

X and L represent the observed data point and origin of the RBF kernel (Eq. 11), respectively. The impact of the gamma value on SVM model is in the way that if this value increases it can lead to the overfitting of the model and if it decreases it can lead to the underfitting of the model. Therefore, finding the appropriate value of the gamma plays an important role on the model performance. After finding the right parameters of the SVM model by preforming grid search, the model was trained with the training data and its performance was investigated with the appropriate metrics that are discussed in the following section.

1.8.6.3 MLP

Due to the superiority of artificial neural networks (ANN) in modeling the extremely complex functions and data relationships, a class of ANN approach called multi-layer perceptron (MLP) is considered for constructing the prediction model. The three main layers in artificial neural network structure are input layers, hidden layers, and output layers (Figure 3-12. MLP network). The nodes of each layer are fully connected with certain weights to every node in the following layer. Except the input layer, all the layers utilize an activation function. Weighted inputs from previous layers are summed together and feed into the activation function in the next layer. The weights are obtained with an optimization algorithm called gradient decent.

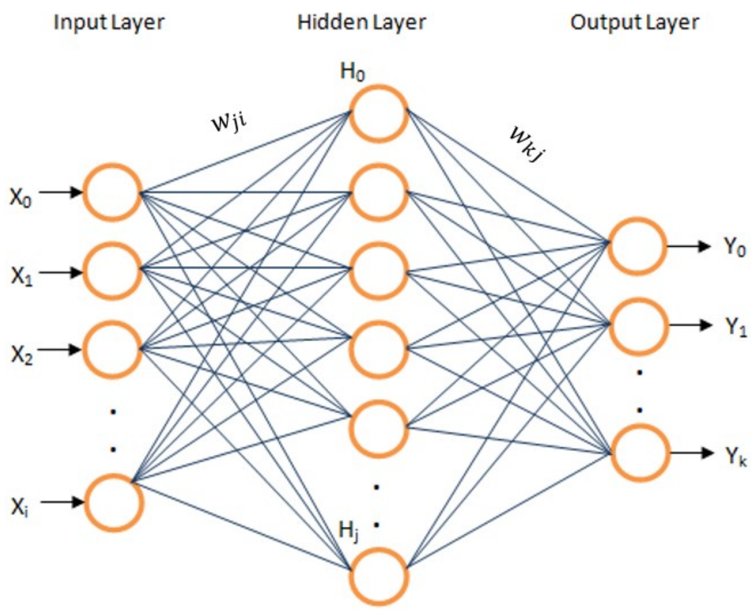

Figure 3-12. MLP network

The training steps of the two-layer feed-forward backpropagation algorithm is described as follow:

- $Step\ 1$: Initializing all the weights' function and bias for the training data.
- $Step\ 2$: Using the Eq. 12 and Eq. 13 for neurons output computations in the hidden layer and output layer are as follows:

$$h_j(x) = f(\sum w_{ji} x_i + \theta_j) \qquad \textit{Eq. 12}$$

$$o_k(x) = f(\sum w_{kj} h_j(x) + w_k) \qquad \textit{Eq. 13}$$

$$f(x) = \max(0, x) \qquad \textit{Eq. 14}$$

where θ_j represents the bias, the term w_{ji} and w_{kj} correspond to the weights for node j to i and j to k, h_j and o_k are the output values of the hidden and output layers, and $f(x)$ is the Relu activation function.

- $Step\ 3$: Calculation of the error and updating the weights by utilizing the Eq. 15 and Eq. 16. The weight and bias variables are updated by utilizing the stochastic gradient decent method.

$$w^* = \underset{w}{\operatorname{argmin}} \sum_{n=1}^{N} loss\left(o^{(n)}, t^{(n)}\right) \qquad \textit{Eq. 15}$$

$$w_{ki} \leftarrow w_{ki} - \eta \frac{\partial E}{\partial w_{ki}} \qquad \textit{Eq. 16}$$

Where w^* stands for a weight that makes the error between output value of the network and target value minimum. w_{ki} is a weight between node k to i. E is the error between the target value and output value.

- $Step\ 4$: Updating all the weights functions and bias. Repeating the steps 2 and 3 for all training data.
- $Step\ 5$: Repeating steps 2-4 until reaching to an acceptable error convergence.

1.8.7 Evaluation Metrics

To assess a machine learning model functionality, evaluation metrics are required to quantify its predictive performance. Selecting a practical model for an application is highly dependant on these quantities. There are standard evaluation metrics that are utilized widely to evaluate classifiers such as accuracy, precision, recall and F-score. As represented in Eq. 17, accuracy is a measurement that determines the number of correct predictions out of the total number of the predictions. Two other important factors beside accuracy are precision and recall. Precision (Eq. 18) measures the fraction of samples assigned the positive class that belong to the positive class while recall (Eq. 19) represents how well the prediction of positive class has been performed. Also, these two factors reflect the performance of the model in false positive and false negative predictions. It can be seen from Eq. 18 and Eq. 19 that smaller number of false positive predictions results in higher precision value and similarly, the smaller number of false negative predictions results in higher recall value. Precision and recall metrics can be combined together to make a single metric that can balance both scores. This single metric is called F-score. Eq. 20 expresses that the higher value of recall and precision will lead to the higher value of F-score. It can be concluded from the equations that a model which has the highest values of evaluation metrics can be selected for a prediction application. Confusion Matrix is another type of evaluation metrics which compares the real target values with the predicted target values by the ML model in a $N * N$ Matrix in which N shows the number of classes. The performances of the developed models in this study are evaluated in the following section.

$$Accuracy = \frac{Number\ of\ Correct\ predictions}{Total\ Number\ of\ predictions} \qquad \text{Eq. 17}$$

$$Precision = \frac{True\ positive}{True\ positive + False\ positive} \qquad \text{Eq. 18}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ negative} \qquad \text{Eq. 19}$$

$$F1 = 2 \times \frac{Precision * Recall}{Precision + Recall} \qquad \text{Eq. 20}$$

1.9 Results & Discussions

The average of accuracies, recall, precision and F-score of the models obtained from the 10-fold cross validation method over training data are represented in Figure 3-13 and Figure 3-14. As demonstrated in Figure 3-13, the averaged accuracy of the MLP and SVM models over training data are quite the same and they both have achieved a high accuracy in recognition of the different free weights. However, as Figure 3-14 illustrates the SVM model has slightly higher precision and F-score values compared to MLP model.

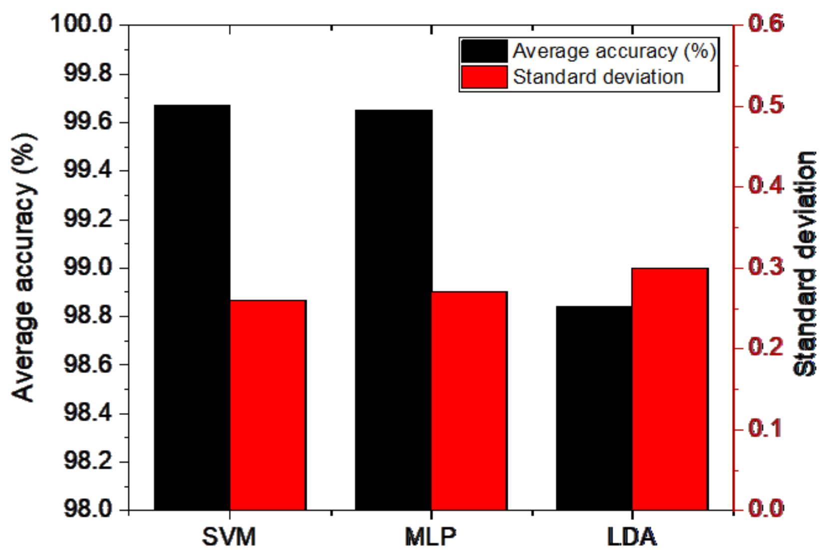

Figure 3-13. Average accuracies of 10-fold cross validation over training data and their standard deviation for three developed models

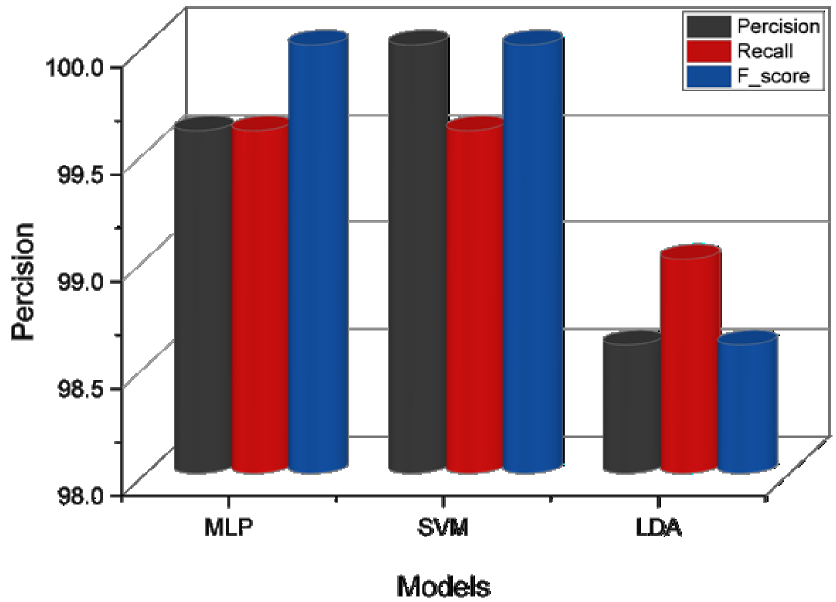

Figure 3-14. Average precisions, recalls and fscores of 10-fold cross validation over training data and their standard deviation for three developed models

The models' performances over test data are shown in Figure 3-15,Figure 3-16, Figure 3-17, and Figure 3-18. It is shown in Figure 3-16 and Figure 3-17 that MLP and SVM models have reached higher accuracies than LDA model over test data. It can also be seen from Figure 3-18 that SVM model accuracy 99.8% is slightly higher than MLP model accuracy 99.6%. Confusion matrices of the models show that all the models have difficulties in recognizing $8lb$ dumbbell. LDA confusion matrix Figure 3-15 illustrates that this model has the highest misclassification error in detection of $2lb$ in comparison with other weights. Overall, all the performances of all models in this study were significant and did not have considerable differences in detecting any weights. As a result, LDA model was selected for this part of study since is very simple and computationally efficient when compared to models such as SVM and MLP.

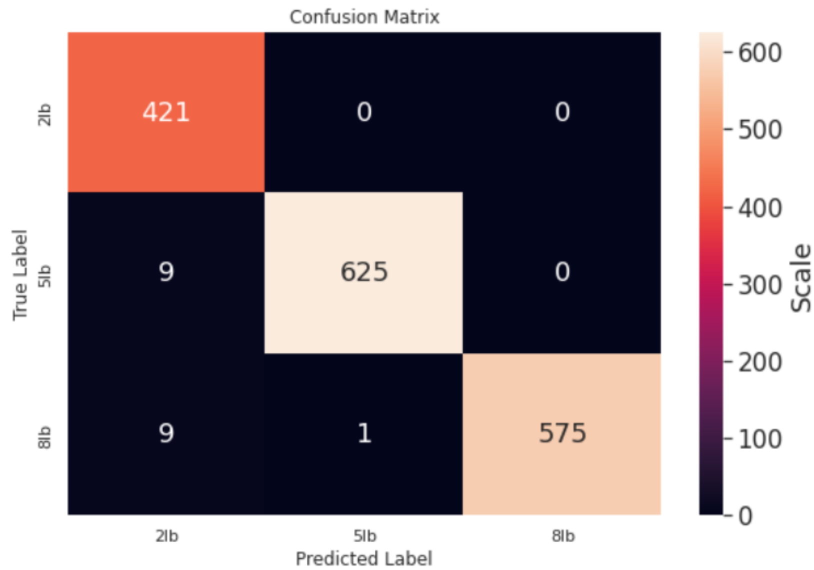

Figure 3-15. Confusion matrices for LDA *model*

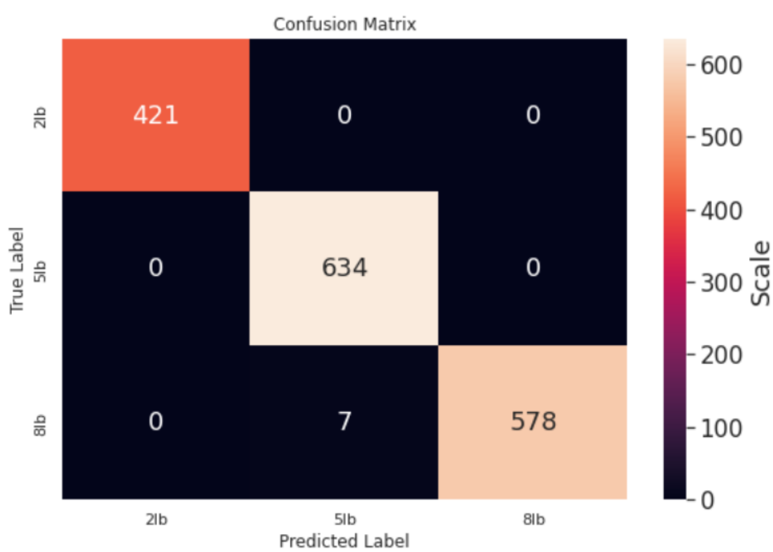

Figure 3-16. Confusion matrices for MLP *model*

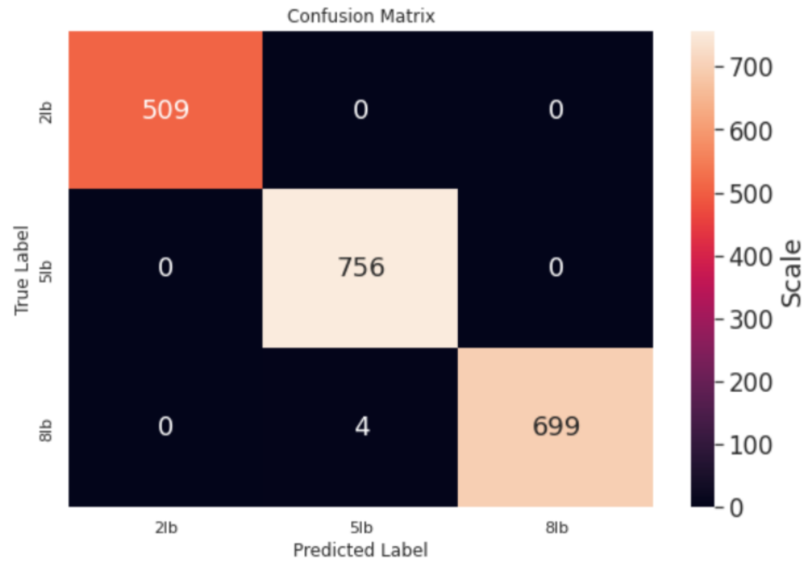

Figure 3-17. ***Confusion matrices for SVM model***

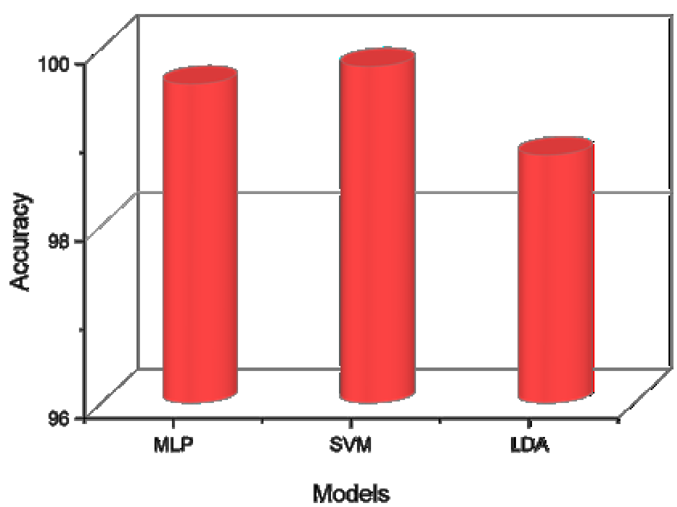

Figure 3-18. ***Accuracy of the models over test data***

1.10 Conclusion

A smart glove prototype deploying an IMU, an accelerometer and three piezoresistive sensors integrated into fabric was developed in this study. The detailed design of this prototype was discussed, and its performance in tracking force sensors was investigated in a study with six healthy participants. Three machine learning classifiers, LDA, SVM and MLP were trained, validated, and tested using Sklearn package in Python for the purpose of weight prediction. Comparing the performances of the developed models by using evaluation metrics including accuracy, precision, recall and f-score, revealed that SVM algorithm works better than the other classifiers for this application with an average accuracy of 99.67% over 10-fold cross validated models and 99.8% accuracy over test data. It can be concluded that this developed wearable system can provide automatic feedback to gym users about lifted weight to increase the efficiency and progress of workouts.

Chapter 4.

Evaluation of Supervised Learning Algorithms for Autonomous Recognition of Gym Activities

1.11 Introduction

This chapter is toward step 3 and 4 of the thesis's objectives to compare the performance of four common machine learning models for the recognition of common gym activities based on single wrist worn IMU data.

Inertial measurement units (IMUs) have been utilized in several research studies for developing classifiers to track and monitor human activities, however many studies have focused on recognizing daily activities such as walking, sleeping, standing, and cycling. The studies that have been performed on recognition of gym activities usually rely on multiple wearables data that a user requires to wear while doing workouts. Although this solution can provide more data and consequently higher accuracy recognitions, wearing multiple wearables can cause user discomfort and interfere with normal physical activity routines. Thus, in this section we investigate the performance of decision tree (DT), k nearest neighbors (KNN), support vector machine (SVM) and Random Forest (RF) machine learning models in autonomous detection of nine common strength training activities using a single wrist worn IMU data. At the end of the chapter a method for counting activity repetitions is also proposed.

1.12 Methods and System Architecture

In this section we present the methods and experimental works conducted in this study as presented in Figure 4-1.

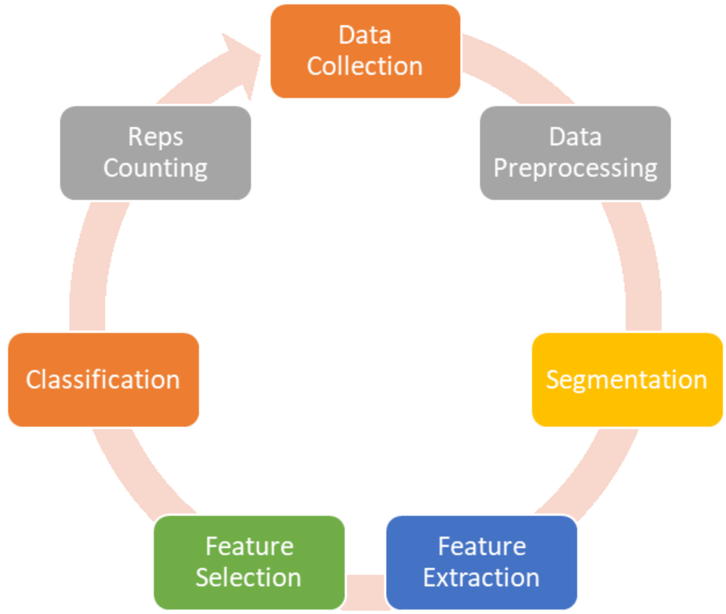

Figure 4-1. Activity recognition steps

1.13 Experiment Setup and Data Collection

In this study we have gathered Euler angles of the right wrist to investigate if they can be used to reach higher accuracy when using machine learning models to identify nine different common workout activities including standing triceps extension, standing dumbbell hammer curls, seated cable back rows, wide stance squat, overhead shoulder press, straight arm pullover, single arm dumbbell bench rows, dumbbell bent-over raise, side shoulder dumbbell raises and dumbbell bent over lateral rear delt raises (Figure 4-2). The reason for choosing wrist data is the popularity of the wristband in wearable devices, user comfortability and a wide range of information that can be provided from the sensors located on wrist [56] . Therefore, the best sensor placement for activity recognition in a smart glove was figured to be the wrist of a user.

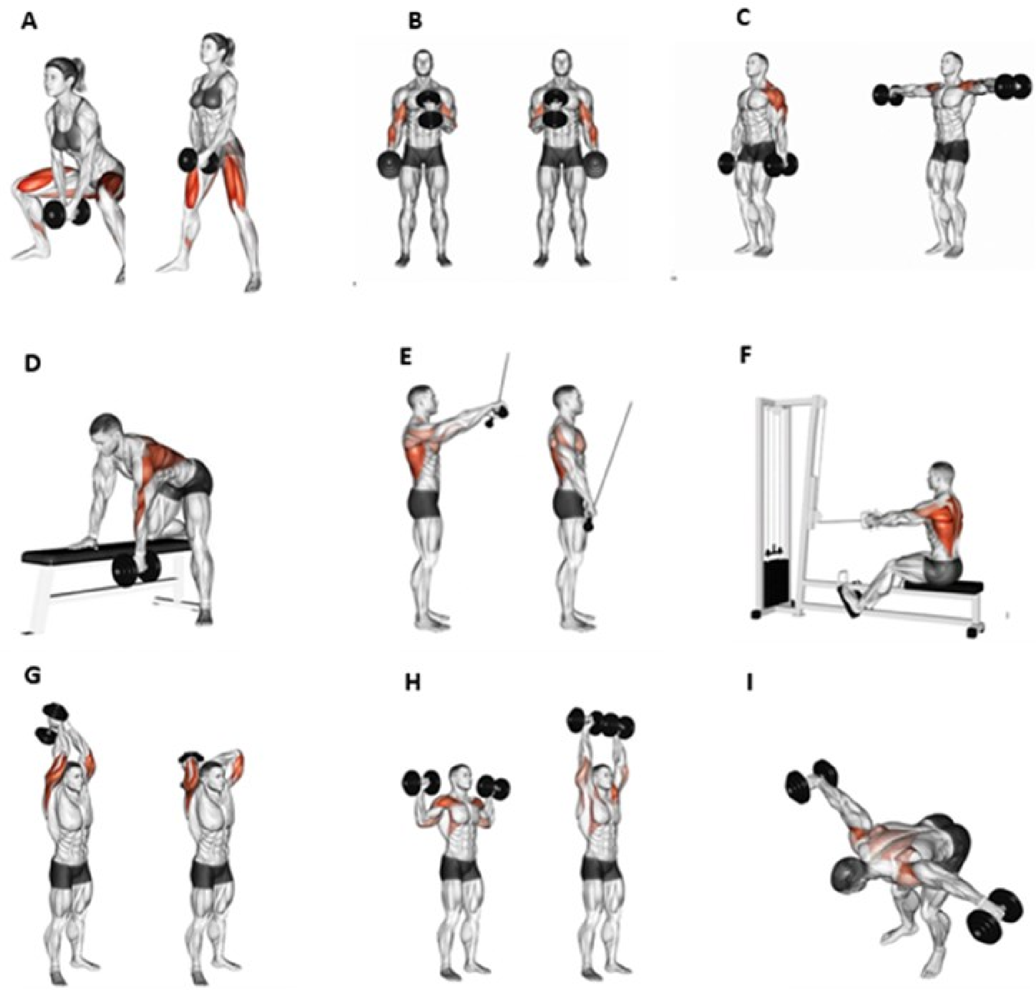

Figure 4-2. Illustration of 9 common strength training workouts used in this study. *[97], [98]*A) Seated cable back rows. B)Hammer curl. C)Side shoulder dumbbell raises. D)Dumbbell bent-over raises. E)Overhead shoulder press. F)Single arm dumbbell bench rows. G)Straight arm pullover. H)Wide stance squat. I) standing triceps extension

Nine workouts as depicted in Figure 4-2 were designed to collect orientation data of the wrist to analyze the proposed system's capability of recording and classifying activities and counting activities repetitions. One hour and a half workout session experiment was designed and ran for activity detection objective. Twelve healthy participants for the study (five men and seven women) in a range of 20-35 years old were recruited to perform the designated activities. Activities for activity recognition were selected based on a personal trainer's suggestion. These activities include common workouts which target basic set of muscles including shoulders, forearms, triceps, chest, legs, and abs that are practical for both amateurs and professionals to practice.

Before starting any experiments, participants were asked to provide the informed consent form. Next, the nine activities detection were introduced to each of the participants. All the activities were asked to be performed for three sets of fifteen repetitions. Wrist Euler angles were gathered with sampling rate of $100Hz$ through the mobile app. The data were then sent to the researcher's computer after the experiment session was done.

1.14 Data Preprocessing

Before applying preprocessing method to the raw data, by observing the Yaw raw signals we figured that due to the noises that signals contained, they were not practical to be used in the application and we continued with Pitch and Roll signals.

Preprocessing of raw data is required to minimize the noise effects due to changes in the users' behavior, movement, and environmental conditions like malfunctioning of gym equipment. The most common noise elimination method are lowpass filters, moving average filter, and Kalman filter. Gaussian-smoothing filter for time series data is a slight adoption of the moving average filter. The difference is in the moving average method each data point is replaced by the average of previous and following data points, whereas in the Gaussian smoothing method, previous and following data points are weighted according to a Gaussian function. In our study, this filter outperformed conventional moving average filter.

The formula of Gaussian smoothing filter is represented in Eq. 21 and Eq. 22 .

$$y_t = \sum_{i=t-k}^{t+k} x_i \, g_i \qquad \text{Eq. 21}$$

$$g = e^{\frac{-4ln(2)t^2}{w^2}}$$ *Eq. 22*

In the above mathematical formula, *k* is number of data points in the filter kernel, *t* is time, *x* is the data point, and g is the Gaussian function. The *w* term shown in *g* function is called full width at half maximum (FWHM). If we consider the filter kernel as a gain function, this term shows the width of the function when gain is equal to half of the maximum. The purple line in Figure 4-3 illustrates FWHM. This parameter is particularly important when designing a Gaussian filter because it defines how much smoothing has to be applied to the signal.

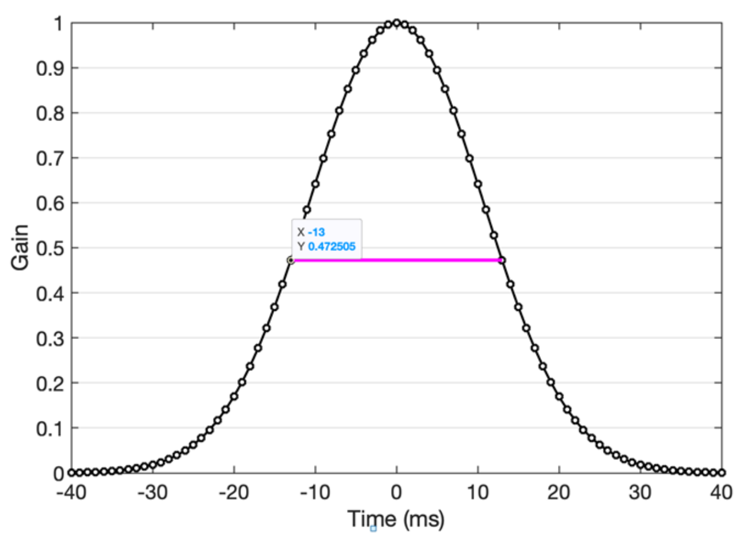

Figure 4-3. Gaussian filter kernel

Another important factor in designing this filter is the number of data points in the filter kernel represented by k. Choosing an appropriate value for k requires two considerations: First, k should be sufficiently large so that the Gaussian function is close to zero on both sides and the other one is that k should be set to a value that does not make the filter kernel to go too far from zero. This is because a too long filter can cause edge effects.

In this project, we set the value of k to 40 and w to 25, respectively. The last step involves normalizing the g function values. Figure 4-4 illustrates the implementation of Gaussian filter on one of the sport's raw data.

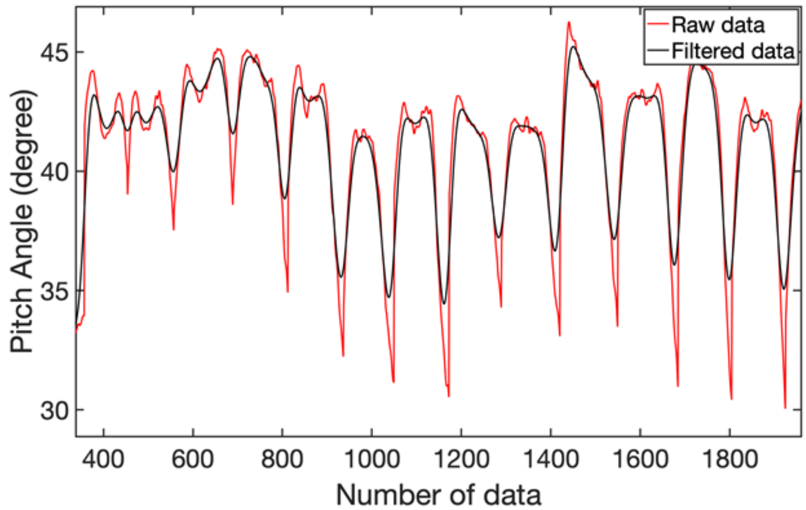

Figure 4-4. Implementation of Gaussian filter on raw data- black is raw data and red is filtered data

1.15 Data Segmentation and Feature Extraction

As described in chapter 2, to generate the inputs for machine learning models, it is necessary to divide the data into segments which can share common distinctive characteristics. For this purpose, a non overlapping sliding window having fixed window size interval of two seconds was used over the filtered data. The window length was determined empirically by implementing a grid search method over windows with length $500\ ms$ to $3s$ to find the best performance of the machine learning models.

Next, the feature extraction was executed in the time domain with eight types of statistical features derived from data segments (e.g., mean, root mean square, maximum, minimum, standard deviation, variance, skewness, and kurtosis.(Table 4-1)). Sixteen different features were gathered in total from Pitch and Roll sensor signals.

Table 4-1. **Extractable statistical features formula from time series data**

Statistical Features	Formula	
Mean	$\bar{x} = \frac{\sum_{i=0}^{N} x_i}{N}$	*Eq. 23*
Root Mean Square	$RMS = \sqrt{1/n \sum_{i=0}^{n} x_i^2}$	*Eq. 24*
Standard Deviation	$\sigma = \sqrt{\frac{\sum (x_i - \bar{x})^2}{N}}$	*Eq. 25*
Variance	$\sigma^2 = \frac{\sum (x_i - \bar{x})^2}{N}$	*Eq. 26*
Kurtosis	$Kurt = \frac{\sum_{i=1}^{N} \frac{(X_i - \bar{X})}{N}}{\sigma^4}$	*Eq. 27*
Skewness	$Skew = \frac{\sum_{i=1}^{N} (X_i - \bar{X})^3}{(N-1)\sigma^3}$	*Eq. 28*

1.16 Feature Selection

To address the high processing cost arising from many features, Univariate feature selection algorithm from Scikit-learn Python package was applied on our data to find the most relevant and high-quality features. The algorithm works by ranking the best features based on the scores gained from a univariate statistical measure. The univariate statistical measure used in our application, was F-score which works only for categorical targets and numerical inputs and is based on the Analysis of Variance (ANOVA) statistical test. ANOVA checks the variance between the groups of features and variance within the groups of features. The one-way analysis of variance includes the following steps:

- Collecting the samples
- Calculation the variance between the samples
- Calculation the variance within the samples
- Calculation the ratio of the variance between to within the samples
- Calculation the F-score

Table 4-2 represents the required mathematical equations for ANOVA calculation.

Table 4-2. ANOVA mathematical equations

Source of variation	Sum of squares (SS)	Degrees of freedom (DF)	Mean squares (MS)	$F\ score$
Within samples	$SSW = \sum_{j=1}^{k}\sum_{j=1}^{l}(X - \bar{X}_j)^2$	$df_w = k - 1$	$MSW = \frac{SSW}{df_w}$	$F = \frac{MSB}{MSW}$
Between samples	$SSB = \sum_{j=1}^{k}(\bar{X}_j - \bar{X})^2$	$df_b = n - k$	$MSB = \frac{SSB}{df_b}$	
Total	$SST = \sum_{j=1}^{n}(\bar{X}_j - \bar{X})^2$	$df_t = n - 1$		

Where, p is the total number of populations, n is the total number of samples in a population, s is the standard deviation of the samples and N is the total number of observations. The larger the measure, the more contribution a group feature has to the targets. The algorithm then chose the best 10 features for the ML models including Pitch standard deviation, Pitch root mean square, Pitch minimum, Pitch maximum, Pitch mean, Roll mean, Roll maximum, Roll minimum, Roll standard deviation and Roll root mean square.

1.17 Classification

After extracting features and selecting the practical ones, the next step is to find the right classifier to generate a machine learning model. To train a machine learning model, a set of training data is required. Therefore, the data was split into two groups: training data and test data. Generated classifiers performances were then assessed using the test data. 70 percent of the data were considered as a training set and 30 percent of them as a test set. Most of the common shallow classifiers that have been employed in different activity recognition tasks were utilized in this study. Further, their performances were compared and investigated using accuracy, precision, recall, and f scores evaluation metrics to find the most practical model in this application. All models are fine-tuned using grid search approach. A 10-fold cross validation method was used in which data was split into 90 percent for training set and 10 percent as the validation set. 10-fold cross validation method was applied to avoid overfitting and to assess the performance of the developed machine learning on new subsets of data. The accuracy of the model was then determined out of the average of accuracies of the 10fold cross validated models.

1.17.1 Decision Tree

Decision tree model as the name suggests, creates a tree like structure for prediction purposes. A Decision tree starts by analyzing the whole dataset and then it splits it into subgroups or features that are called nodes. There exist three different nodes in this model which are Root node, Decision node and Terminal node or Leaf node as illustrated in Figure 4-5. Root node is the first node in the Decision tree model that splitting process starts from it. Decision node is a node that splits into further sub nodes until it reaches to a leaf node. Leaf node is a terminal node that splitting process is terminated at this node. The algorithm splits the nodes at the most informative features using the Gini Index measure Eq. 29.

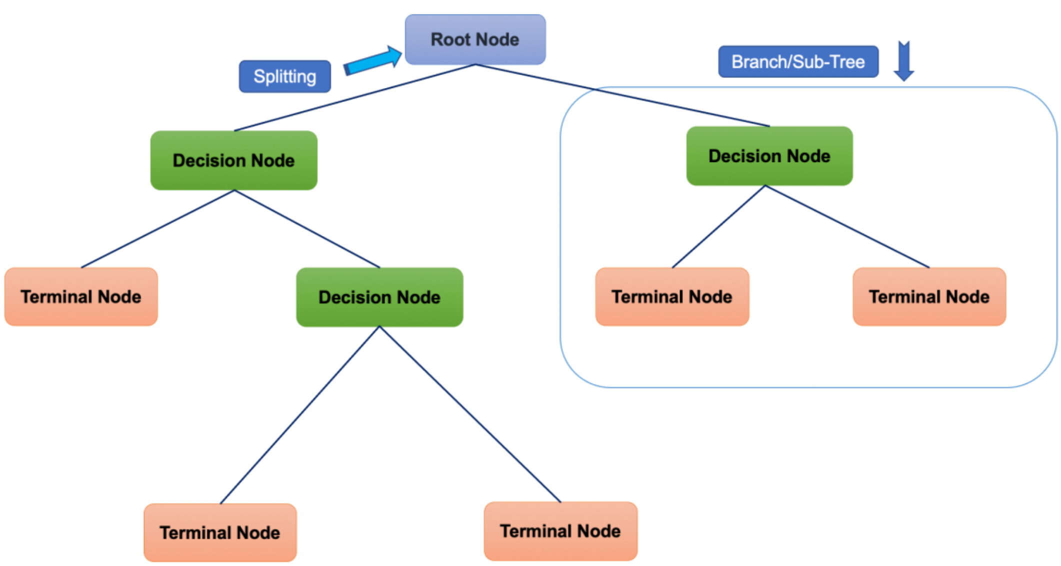

Figure 4-5. Decision tree structure

Gini index determines impurity of the subset of data in each splitting process. Impurity is used to assess the homogeneity of data. Data is considered pure or homogenous if it includes an only single class. The greater number of classes in the data, the more impure it is, and the splitting is not considered practical. Gini index value is between the range of zero to 0.5 Figure 4-6. The closer the outcome of the Gini index function to 0.5, the more impurity exists within the data.

$$Gini = 1 - \sum_{i=1}^{C}(p_i)^2 \qquad \textit{Eq. 29}$$

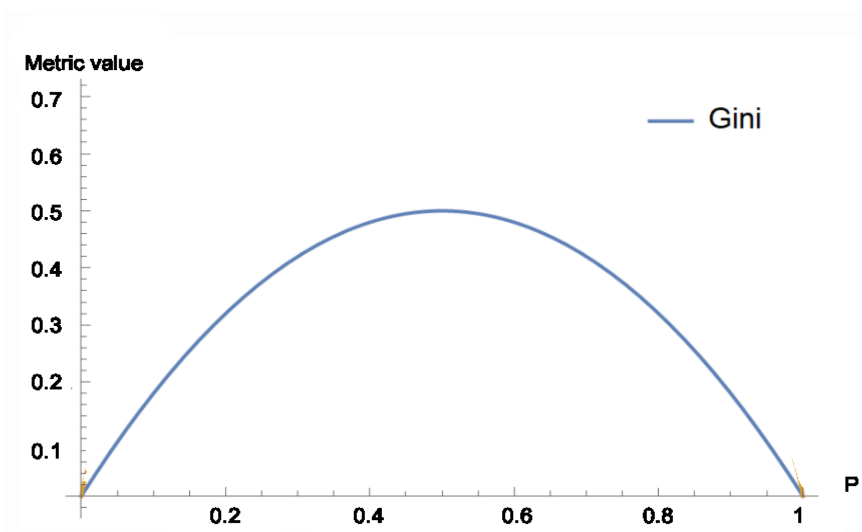

Figure 4-6. Gini index curve

The training steps in Decision tree algorithm are explained as follow:

- Select Root node based on the lowest Gini index value
- On each iteration of the algorithm Gini index is calculated and the lowest value is used for selecting a decision node

- Set D is split to produce the subsets of data
- The algorithm continues to recur on each subset until it reaches a leaf node

Decision tree was applied to the training data and its performance was investigated and reported in the next section.

1.17.2 KNN

K nearest neighbours is a simple machine learning model that does not require any learning. This model stores all the dataset and classifies a new observation based on a similarity measurement between the new observed data and its k nearest neighbours Figure 4-7. This model often exploits Euclidean distance Eq. 30 to determine the similarity of the data points. The majority vote algorithm is then applied to the outputs obtained from Euclidean distance to classify the new data point. In the KNN algorithm finding the right value for the K hyperparameter plays an important role in the development process. Selecting a smaller value for the K will lead to overfitting of the model and inversely, selecting a large value for that will lead to underfitting of the model. After setting an appropriate value for this hyperparameter empirically, this model was applied to the training set and its performance was investigated using evaluation metrics.

$$d\ (x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \qquad \text{Eq. 30}$$

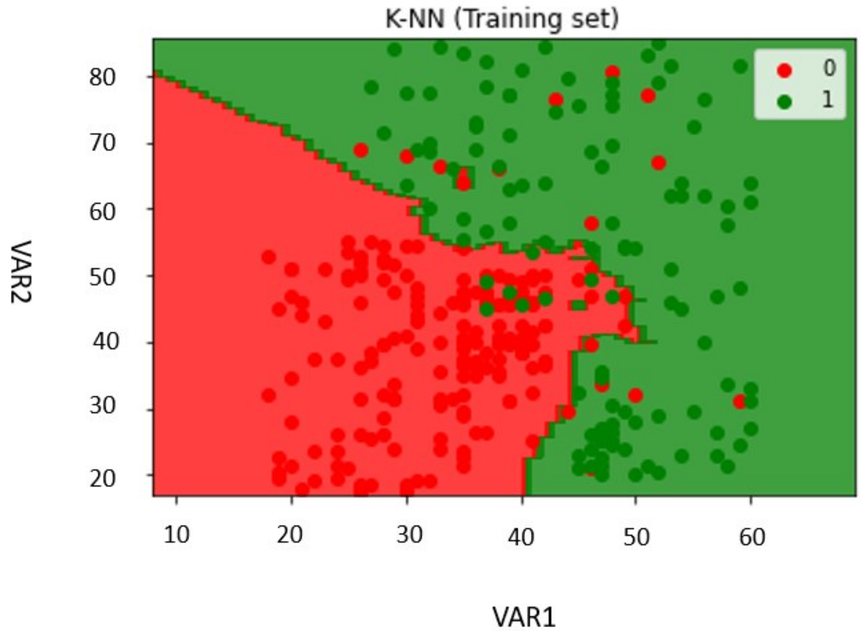

Figure 4-7. KNN performance over two classes of the data

1.17.3 SVM Model

Support Vector Machine (SVM) is one of the most feasible machine learning models in the application of activity recognition. As mentioned previously, there exist diverse kernel functions to use for SVM classifier development. Since Our application is nonlinear and we require a kernel function that makes the features linearly separable, we chose Radial Basis Gaussian (RBF) kernel function in our SVM model. Practical parameters of the SVM model were obtained by preforming grid search. Next the model was trained with the training data and its performance was investigated with the appropriate metrics that are discussed in the following section.

1.17.4 Random Forest Model

Random Forest machine learning model is an ensemble learning model which applies the technique of bootstrap aggregating, or bagging, to a set of weak learners to achieve better predictive performance. The weak or base learners that Radom Forest (RF) utilizes, is decision tree models which suffer from overfitting if it is used individually. In the bagging technique shown in Figure 4-8, random samples of data with replacement are selected repeatedly from the training set and decision trees model are fitted to these samples. After training the classification model, a new observant is classified by taking a majority vote from the outputs generated from the trees. Optimal number of the trees, maximum depth of the tress and number of the splits in the data are obtained empirically in this model.

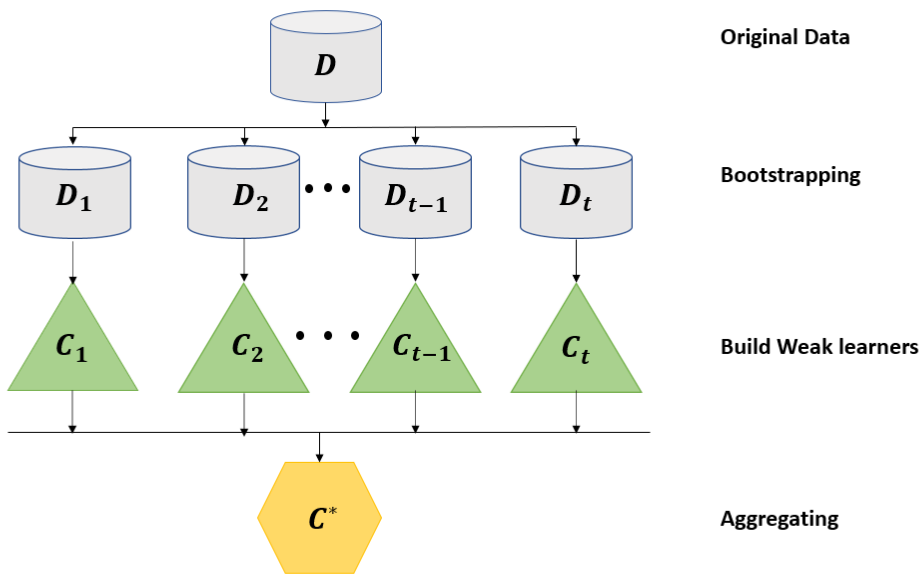

Figure 4-8. Bagging ensemble method

Step by step of a RF model is:

- Picking random K data points with replacement from a training set based on grid search
- Building the decision tree associated to these K data points
- Choosing the N number of trees by doing grid search and repeating steps 1 & 2
- Applying the majority voting to predict the output of an observation

After training the model with the training dataset, the model was evaluated with the same statistical measures as the ones used for other ML models. The results are discussed in the following section.

1.18 Repetition Counting

For precise repetition counting, the peak detection algorithm was used in which initially the type of sport activity was detected from the ML model. The signal peak values of each activity were counted based on their minimum peak height, minimum peak distance, and the signal width and height range characteristics. The plots for the repetition counting model for certain sports repetitions are presented in Figure 4-9.

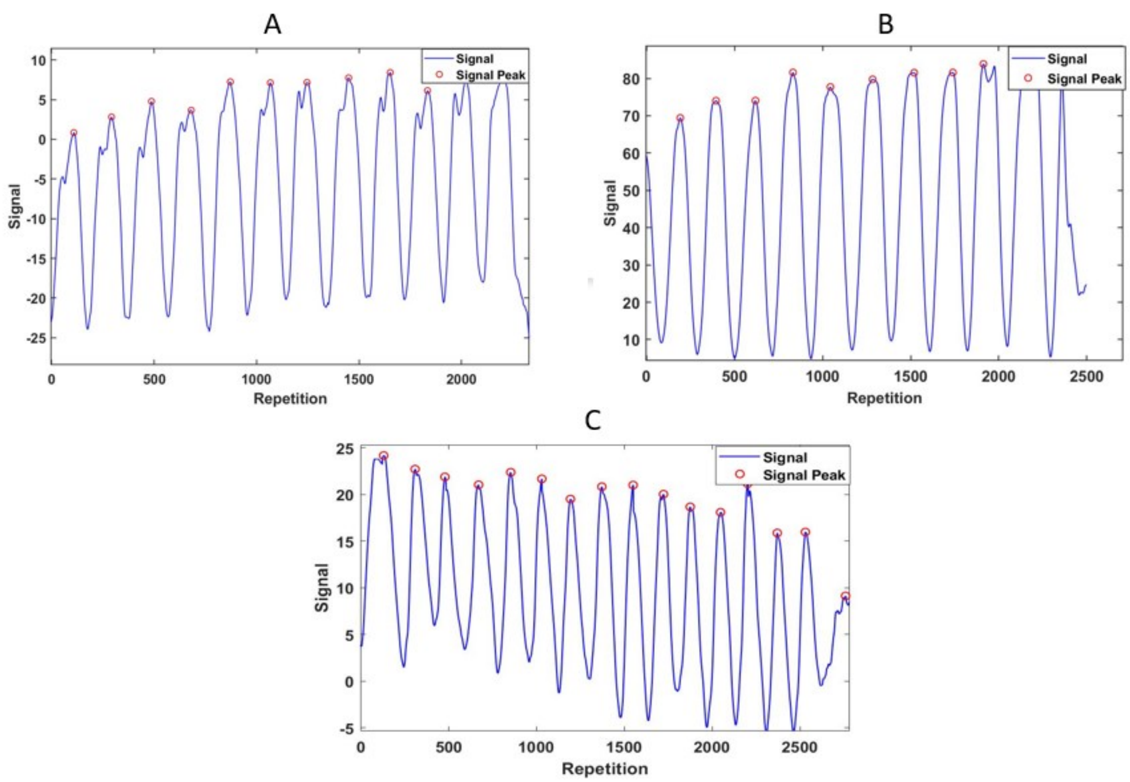

Figure 4-9. Sample of a repetition counting model on specific sports repetitions. A) Hammer Curl. B) Squat. C) Pullover

1.19 Results

1.19.1 Activity Recognition

Classifiers' performances are evaluated and validated with 10-fold cross validation algorithm. The average values of accuracies, precisions, recalls and F-scores are determined from cross validated models over training data. As represented in Figure 4-10 and Figure 4-11, random forest model can make the most accurate prediction with the highest values of accuracy, precision, recall and F-score. It can be observed that, although SVM and DT classifiers have reached higher accuracies than KNN model, these models have lower recall values. This results in more numbers of false negative predictions. The high value of false negative can significantly exert a negative influence on the machine learning performance and should be considered as one of the major criteria in model selection.

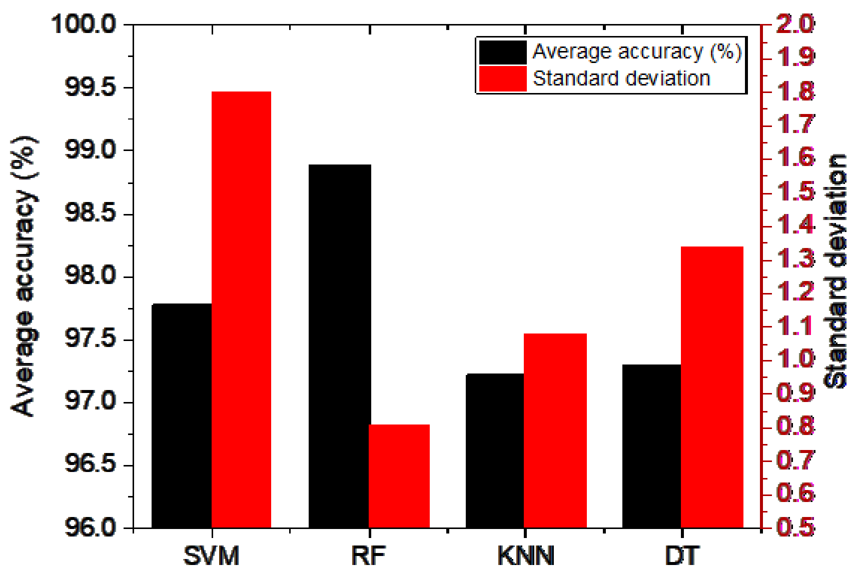

Figure 4-10. Average accuracies of 10-fold cross validation over training data and their standard deviation for the four developed models

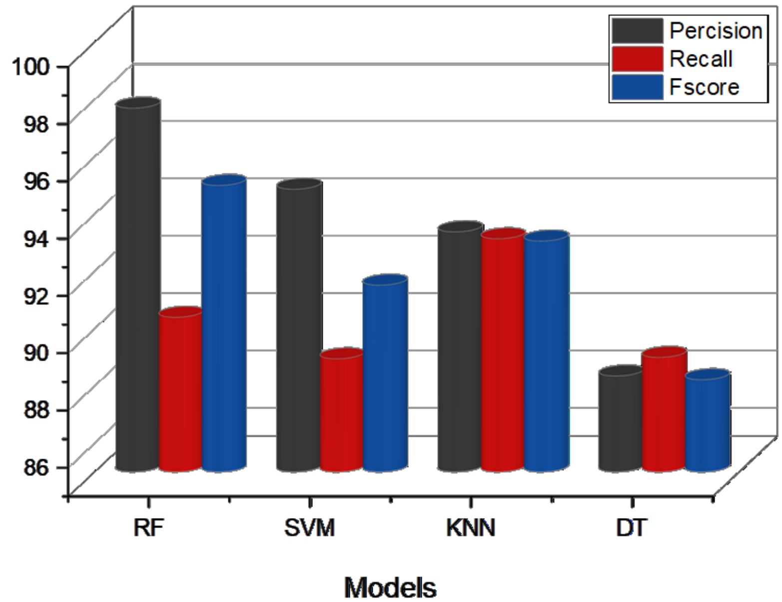

Figure 4-11. Average precisions, recalls and fscores of 10-fold cross validation over training data and their standard deviation for the four developed models

The overall comparison of model performances over test data also demonstrated that Rf model outperforms other models in recognition of sport activities. It can be seen from models' confusion matrices in Figure 4-12,Figure 4-13,Figure 4-14 and Figure 4-15 that some sports like seated cable back rows, shoulder press and triceps can be recognized by all the developed models accurately while an activity like pullover is not easy to be identified even with the most accurate developed model such as random forest. Moreover, it can be observed that SVM, KNN and DT models have difficulties in distinguishing two similar activities, dumbbell bent over, and side shoulder raises. However, it is illustrated that random forest model can recognize dumbbell bent over, and side shoulder raises without any error. The overall accuracies of the models over test data are illustrated in the Figure 4-16. As this figure expresses, the KNN model demonstrates the least accuracy while Rf reached the highest score.

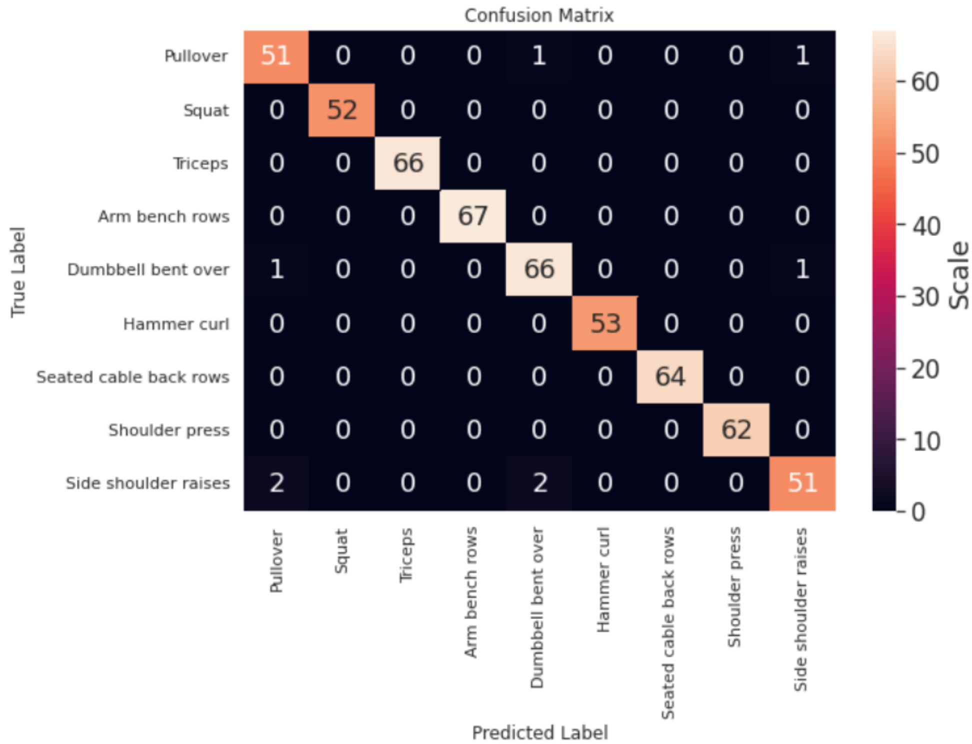

Figure 4-12. Confusion matrix for the Decision Tree model

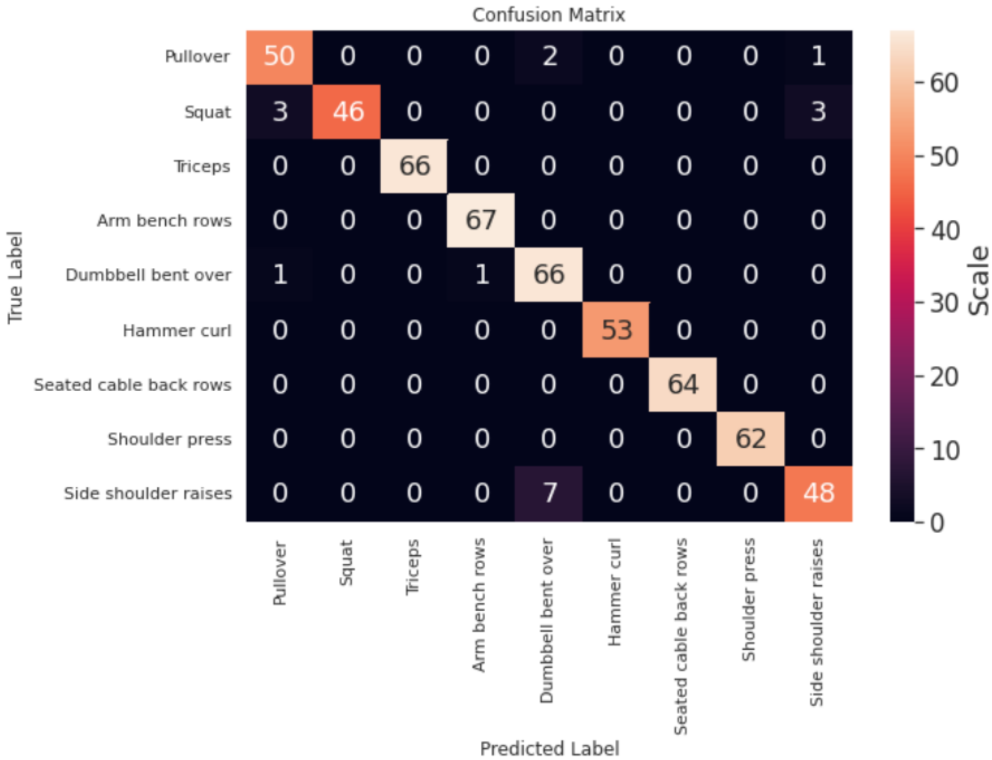

Figure 4-13. Confusion matrix for the KNN model

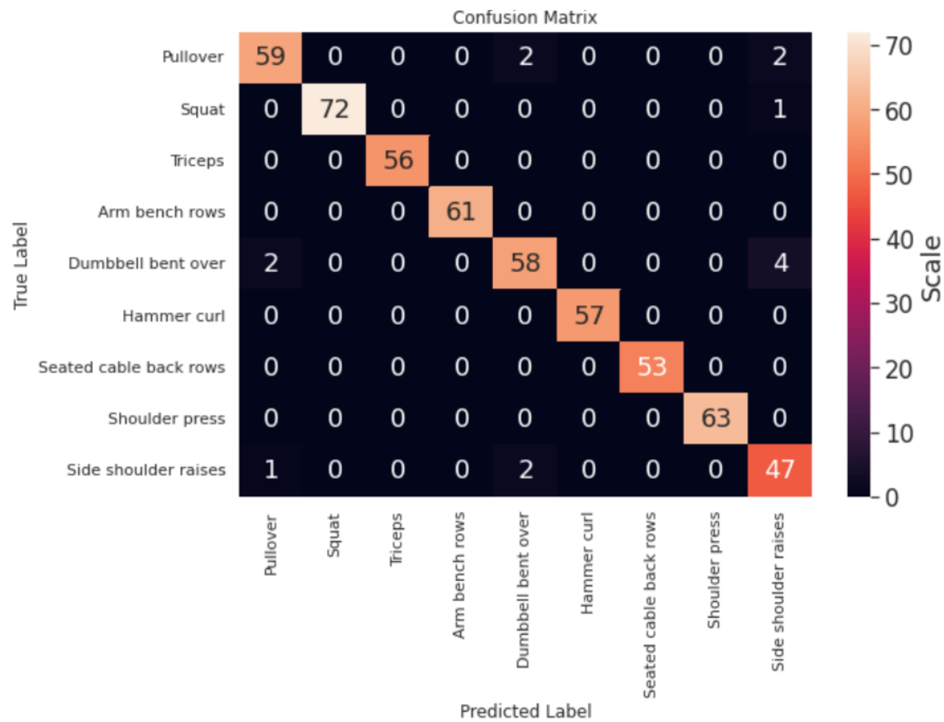

Figure 4-14. **Confusion matrix for the SVM model**

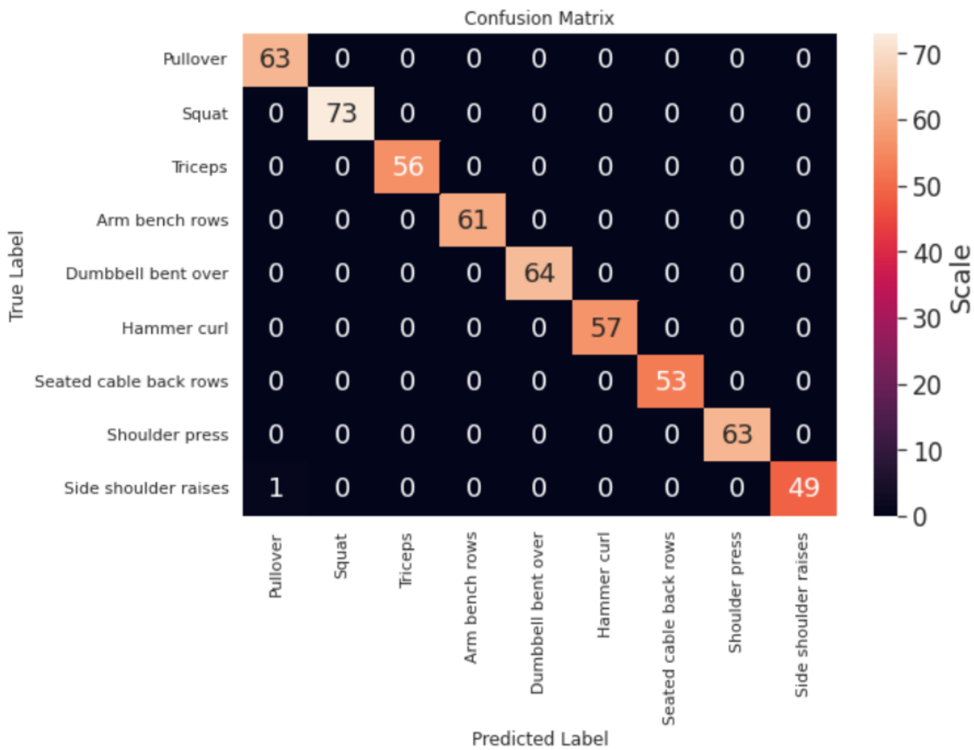

Figure 4-15. Confusion matrix for the RF model

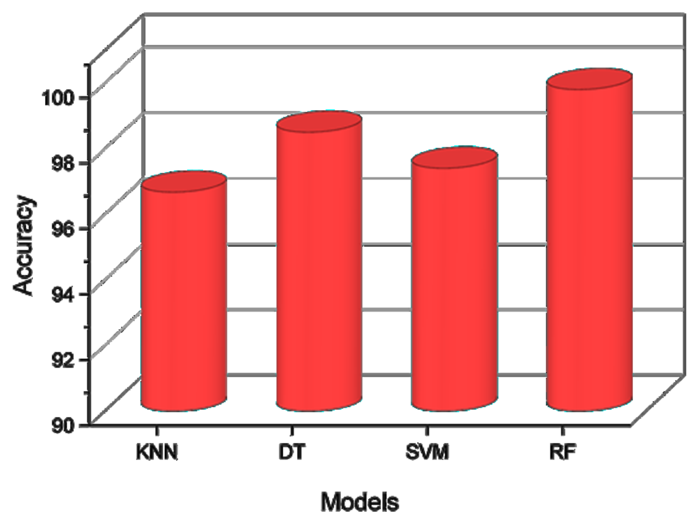

Figure 4-16. Accuracy of the models over test data

1.19.2 Repetition Counting

By selecting the RF model for the activity recognition application, repetition counting was developed in the next step. This algorithm finds the signal peaks based on the signal characteristics of a specific sport activity. In the first step, RF detects the activity type and sends the class label of the activity to the repetition counting algorithm, then the algorithm will search for the peaks. This developed technique was able to find activities repetitions with the overall average accuracy of 96% over all types of sports. As illustrated in Figure 4-17, the algorithm has a weak performance in finding the repetitions of arm bench rows and pullover while has a great performance in finding the peaks of the other sport activities.

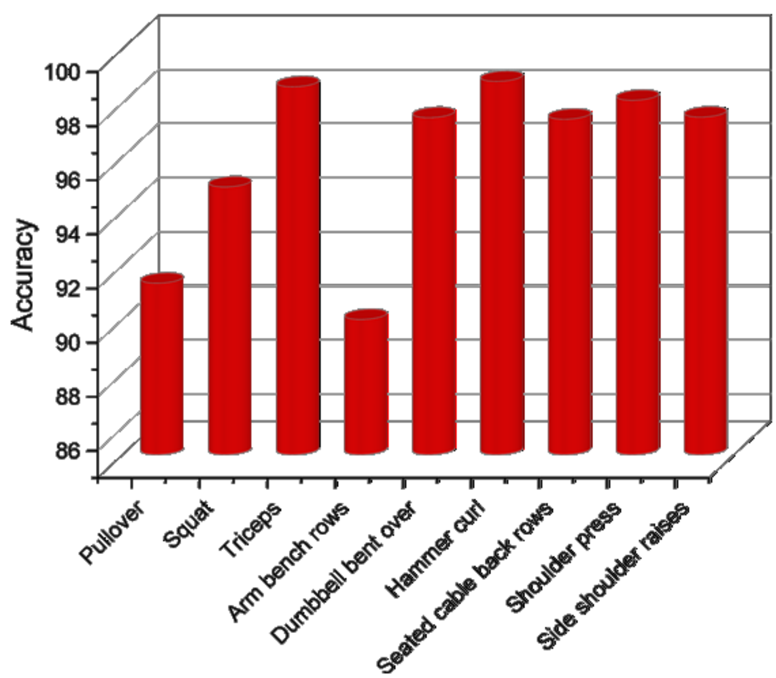

Figure 4-17. Accuracy of repetition counting algorithm over each sport type

1.20 Conclusion

In this study, four common machine learning models were investigated for gym activities recognition application using Euler angles data from a single wrist-worn inertial sensor. Data from nine different gym activities were collected from twelve healthy individuals and exploited in this experiment. Evaluation factors showed that the Random Forest model can predict sport activity with high accuracy, precision, and recall. It can be concluded that although certain activities such as dumbbell bent over and side shoulder rises are extremely similar, our model is accurate enough to distinguish these sports from each other. Moreover, our system is capable of recognizing a leg exercise such as Squat as well as arm exercises. A repetition counting method was developed which works by leveraging finding signal peaks algorithm. When an activity is recognized by the RF model, this algorithm finds peaks based on the specific characteristics of the identified activity signal such as width, height, minimum peak height, and minimum peak distance. The accuracy of 96% was achieved from this algorithm. The developed model for activity recognition and repetition counting can be exploited in gym fitness wristbands or wrist of a smart glove to report what sport activity has been done with its number of repetitions to users or personal trainer of the users to let them evaluate their performances at gym and maximize their performance efficiency by providing practical feedback.

Chapter 5. Conclusion

The current widespread wearables mostly focus on daily activities monitoring and calories measurement. They cannot provide information and feedback regarding weights used during workouts or monitor activities throughout the exercise automatically. In this study, we introduce a novel multifunctional wearable sensor-based platform for automatic recognition of weight training activities, weights utilized during training and numbers of activities repetitions. The main goal of this paper is to assist individuals in maximizing the performance progress, efficiency and avoid overtraining and overreaching by providing feedback in weight training activity. The proposed wearable glove consists of force sensors, IMU and accelerometer for monitoring forces, hand and wrist orientations. To reach the highest accuracy for the objectives of the study, weight prediction and activity recognition, most of the commonly used classifiers in this context were developed and their performances were investigated. Machine learning algorithms including random forest, k nearest neighbors, support vector machine and decision tree were studied for activity recognition purpose and, three other classifiers including support vector machine, neural network, and linear discriminant analysis were assessed for weight detection objective. The classifiers performances were compared and evaluated by evaluation metrics, accuracy, recall, precision and f-score over both training and test data. In activity recognition study, random forest outperformed other classifiers with the average accuracy of 98.89% over 10-fold cross validated models and 99.8% accuracy over test data. In weight detection study, SVM outperformed other classifiers with the average accuracy of 99.67 % over 10-fold cross vali-dated models and 99.8% accuracy over test data. Also, repetition counting model based on peak finding algorithm reached an average accuracy of 96% over all the exercises.

Due to the wide range of gym sport activities, it can be impossible to collect data for all types of sports. In future, different learning methods such as transfer learning can be implemented and evaluated on this wearable to include as many activities as possible for the end users. Besides, the system capability to detect higher weights in different forms from dumbbells requires to be investigated in future studies to provide better feedback system and richer information for the trainees. One of the limitations of the current force sensory system is the drift caused by long term usage of it. This study has not covered any solution regarding this issue and it is highly recommended for the future studies to consider this problem when conducting experiments over wider range of the free weights.

References

[1] W. R. Thompson, "Worldwide Survey of Fitness Trends for 2021 Apply It!," 2020. [Online]. Available: www.acsm-healthfitness.org

[2] J. A. Bennie, J. Shakespear-Druery, and K. de Cocker, "Muscle-strengthening Exercise Epidemiology: a New Frontier in Chronic Disease Prevention," *Sports Medicine - Open*, vol. 6, no. 1, Dec. 2020, doi: 10.1186/s40798-020-00271-w.

[3] W. J. Kraemer, N. A. Ratamess, and D. N. French, "Resistance Training for Health and Performance," 2002.

[4] R. A. Winett and R. N. Carpinelli, "Potential health-related benefits of resistance training," *Preventive Medicine*, vol. 33, no. 5. Academic Press Inc., pp. 503–513, 2001. doi: 10.1006/pmed.2001.0909.

[5] W. L. Westcott, "Resistance Training is Medicine: Effects of Strength Training on Health," 2012. [Online]. Available: http://journals.lww.com/acsm-csmr

[6] L. A. Tucker and K. Maxwell, "Effects of Weight Training on the Emotional Well-Being and Body Image of Females: Predictors of Greatest Benefit."

[7] G. Aroganam, N. Manivannan, and D. Harrison, "Review on Wearable Technology Sensors Used in Consumer Sport Applications," *Sensors (Basel, Switzerland)*, vol. 19, no. 9. NLM (Medline), Apr. 28, 2019. doi: 10.3390/s19091983.

[8] R. T. Li, S. R. Kling, M. J. Salata, S. A. Cupp, J. Sheehan, and J. E. Voos, "Wearable Performance Devices in Sports Medicine," *Sports Health*, vol. 8, no. 1. SAGE Publications Inc., pp. 74–78, Jan. 01, 2016. doi: 10.1177/1941738115616917.

[9] J. M. García-Gómez, I. de La Torre-Díez, J. Vicente, M. Robles, M. López-Coronado, and J. J. Rodrigues, "Analysis of mobile health applications for a broad spectrum of consumers: A user experience approach," *Health Informatics Journal*, vol. 20, no. 1, pp. 74–84, Mar. 2014, doi: 10.1177/1460458213479598.

[10] J. J. P. C. Rodrigues, I. M. C. Lopes, B. M. C. Silva, and I. de La Torre, “A new mobile ubiquitous computing application to control obesity: SapoFit,” *Informatics for Health and Social Care*, vol. 38, no. 1. pp. 37–53, Jan. 2013. doi: 10.3109/17538157.2012.674586.

[11] M. H. Iqbal, A. Aydin, O. Brunckhorst, P. Dasgupta, and K. Ahmed, “A review of wearable technology in medicine,” *Journal of the Royal Society of Medicine*, vol. 109, no. 10. SAGE Publications Ltd, pp. 372–380, Oct. 01, 2016. doi: 10.1177/0141076816663560.

[12] X. Li, Z. Zhou, J. Wu, and Y. Xiong, “Human posture detection method based on wearable devices,” *Journal of Healthcare Engineering*, vol. 2021, 2021, doi: 10.1155/2021/8879061.

[13] J. J. Guiry, P. van de Ven, and J. Nelson, “Multi-sensor fusion for enhanced contextual awareness of everyday activities with ubiquitous devices,” *Sensors (Switzerland)*, vol. 14, no. 3, pp. 5687–5701, Mar. 2014, doi: 10.3390/s140305687.

[14] M. Shoaib, S. Bosch, O. Durmaz Incel, H. Scholten, and P. J. M. Havinga, “Fusion of smartphone motion sensors for physical activity recognition,” *Sensors (Switzerland)*, vol. 14, no. 6, pp. 10146–10176, Jun. 2014, doi: 10.3390/s140610146.

[15] M. Shoaib, S. Bosch, O. D. Incel, H. Scholten, and P. J. M. Havinga, “Complex human activity recognition using smartphone and wrist-worn motion sensors,” *Sensors (Switzerland)*, vol. 16, no. 4, Apr. 2016, doi: 10.3390/s16040426.

[16] F. J. Ordóñez and D. Roggen, “Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition,” *Sensors (Switzerland)*, vol. 16, no. 1, Jan. 2016, doi: 10.3390/s16010115.

[17] S. Härtel, J. P. Gnam, S. Löffler, and K. Bös, “Estimation of energy expenditure using accelerometers and activity-based energy models-validation of a new device,” *European Review of Aging and Physical Activity*, vol. 8, no. 2, pp. 109–114, Oct. 2011, doi: 10.1007/s11556-010-0074-5.

[18] Mody University of Science and Technology. School of Engineering and Technology and Institute of Electrical and Electronics Engineers, *2020 International Conference on Emerging Trends in Communication, Control and Computing : copyright information, proceedings : February 21-22, 2020*.

[19] *2018 2nd East Indonesia Conference on Computer and Information Technology (EIConCIT)*. IEEE, 2018.

[20] A. Kadar Muhammad Masum, E. Hoque Bahadur, A. Shan-A-Alahi, M. Akib Uz Zaman Chowdhury, M. Reaz Uddin, and A. al Noman, "Human Activity Recognition Using Accelerometer, Gyroscope and Magnetometer Sensors: Deep Neural Network Approaches; Human Activity Recognition Using Accelerometer, Gyroscope and Magnetometer Sensors: Deep Neural Network Approaches," 2019.

[21] P. Düking, L. Giessing, M. O. Frenkel, K. Koehler, H. C. Holmberg, and B. Sperlich, "Wrist-worn wearables for monitoring heart rate and energy expenditure while sitting or performing light-to-vigorous physical activity: Validation study," *JMIR mHealth and uHealth*, vol. 8, no. 5, May 2020, doi: 10.2196/16716.

[22] C. S. Ho *et al.*, "Feasibility of the Energy Expenditure Prediction for Athletes and Non-Athletes from Ankle-Mounted Accelerometer and Heart Rate Monitor," *Scientific Reports*, vol. 10, no. 1, Dec. 2020, doi: 10.1038/s41598-020-65713-7.

[23] J. H. Park, D. G. Jang, J. W. Park, and S. K. Youm, "Wearable sensing of in-ear pressure for heart rate monitoring with a piezoelectric sensor," *Sensors (Switzerland)*, vol. 15, no. 9, pp. 23402–23417, Sep. 2015, doi: 10.3390/s150923402.

[24] A. H. E. Akpa, M. Fujiwara, H. Suwa, Y. Arakawa, and K. Yasumoto, "A smart glove to track fitness exercises by reading hand palm," *Journal of Sensors*, vol. 2019, 2019, doi: 10.1155/2019/9320145.

[25] E. R. Komi, J. R. Roberts, and S. J. Rothberg, "Measurement and analysis of grip force during a golf shot," *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology*, vol. 222, no. 1, pp. 23–35, Mar. 2008, doi: 10.1243/17543371JSET9.

[26] X. Liang, H. Heidari, and R. Dahiya, "Wearable capacitive-based wrist-worn gesture sensing system," in *Proceedings - 2017 1st New Generation of CAS, NGCAS 2017*, Sep. 2017, pp. 181–184. doi: 10.1109/NGCAS.2017.80.

[27] M. Donati *et al.*, "A flexible sensor technology for the distributed measurement of interaction pressure," *Sensors (Switzerland)*, vol. 13, no. 1. pp. 1021–1045, Jan. 2013. doi: 10.3390/s130101021.

[28] D. M. Bravata *et al.*, "Using Pedometers to Increase Physical Activity and Improve Health A Systematic Review." [Online]. Available: https://jamanetwork.com/

[29] D. Merom *et al.*, "Promoting Walking with Pedometers in the Community. The Step-by-Step Trial," *American Journal of Preventive Medicine*, vol. 32, no. 4, pp. 290–297, Apr. 2007, doi: 10.1016/j.amepre.2006.12.007.

[30] C. Shen, B. J. Ho, and M. Srivastava, "MiLift: Efficient Smartwatch-Based Workout Tracking Using Automatic Segmentation," *IEEE Transactions on Mobile Computing*, vol. 17, no. 7, pp. 1609–1622, Jul. 2018, doi: 10.1109/TMC.2017.2775641.

[31] J. Qi, P. Yang, M. Hanneghan, S. Tang, and B. Zhou, "A hybrid hierarchical framework for gym physical activity recognition and measurement using wearable sensors," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 1384–1393, Apr. 2019, doi: 10.1109/JIOT.2018.2846359.

[32] A. H. E. Akpa, M. Fujiwara, H. Suwa, Y. Arakawa, and K. Yasumoto, "A smart glove to track fitness exercises by reading hand palm," *Journal of Sensors*, vol. 2019, 2019, doi: 10.1155/2019/9320145.

[33] Z. G. Xiao and C. Menon, "A review of force myography research and development," *Sensors (Switzerland)*, vol. 19, no. 20. MDPI AG, Oct. 02, 2019. doi: 10.3390/s19204557.

[34] T. Stefanou, G. Chance, T. Assaf, A. Lenz, and S. Dogramadzi, "Wearable Tactile Sensor Brace for Motion Intent Recognition in Upper-Limb Rehabilitation," *Proceedings of the IEEE RAS and EMBS International Conference on Biomedical*

Robotics and Biomechatronics, vol. 2018-August, pp. 148–155, Oct. 2018, doi: 10.1109/BIOROB.2018.8487721.

[35] C. Ahmadizadeh, L. K. Merhi, B. Pousett, S. Sangha, and C. Menon, "Toward Intuitive Prosthetic Control: Solving Common Issues Using Force Myography, Surface Electromyography, and Pattern Recognition in a Pilot Case Study," *IEEE Robotics and Automation Magazine*, vol. 24, no. 4, pp. 102–111, Dec. 2017, doi: 10.1109/MRA.2017.2747899.

[36] A. K. Godiyal, M. Mondal, S. D. Joshi, and D. Joshi, "Force myography based novel strategy for locomotion classification," *IEEE Transactions on Human-Machine Systems*, vol. 48, no. 6, pp. 648–657, Dec. 2018, doi: 10.1109/THMS.2018.2860598.

[37] Z. Gang Xiao and C. Menon, "Does force myography recorded at the wrist correlate to resistance load levels during bicep curls?", doi: 10.1016/j.jbiomech.2018.11.035.

[38] J. Fontecha, F. J. Navarro, R. Hervás, and J. Bravo, "Elderly frailty detection by using accelerometer-enabled smartphones and clinical information records," *Personal and Ubiquitous Computing*, vol. 17, no. 6, pp. 1073–1083, Aug. 2013, doi: 10.1007/s00779-012-0559-5.

[39] S. Mehrang, J. Pietilä, and I. Korhonen, "An activity recognition framework deploying the random forest classifier and a single optical heart rate monitoring and triaxial accelerometer wrist-band," *Sensors (Switzerland)*, vol. 18, no. 2, Feb. 2018, doi: 10.3390/s18020613.

[40] O. D. Incel, M. Kose, and C. Ersoy, "A Review and Taxonomy of Activity Recognition on Mobile Phones," *BioNanoScience*, vol. 3, no. 2, pp. 145–171, Jun. 2013, doi: 10.1007/s12668-013-0088-3.

[41] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, "Deep learning for sensor-based activity recognition: A survey," *Pattern Recognition Letters*, vol. 119, pp. 3–11, Mar. 2019, doi: 10.1016/j.patrec.2018.02.010.

[42] F. Li, K. Shirahama, M. A. Nisar, L. Köping, and M. Grzegorzek, “Comparison of feature learning methods for human activity recognition using wearable sensors,” *Sensors (Switzerland)*, vol. 18, no. 2, Feb. 2018, doi: 10.3390/s18020679.

[43] W. S. Lima, E. Souto, K. El-Khatib, R. Jalali, and J. Gama, “Human activity recognition using inertial sensors in a smartphone: An overview,” *Sensors (Switzerland)*, vol. 19, no. 14, Jul. 2019, doi: 10.3390/s19143213.

[44] A. K. Dey *et al.*, *UbiComp ’12 : proceedings of the 2012 ACM Conference on Ubiquitous Computing : September 5-8, 2012, Pittsburgh, USA*.

[45] W. Sousa, P. Sadarc, E. Souto, R. Jalali, J. Rodrigres, and K. El-Khatib, “A comparative analysis of the impact of features on human activity recognition with smartphone sensors,” in *WebMedia 2017 - Proceedings of the 23rd Brazillian Symposium on Multimedia and the Web*, Oct. 2017, pp. 397–404. doi: 10.1145/3126858.3126859.

[46] A. M. Khan, A. Tufail, A. M. Khattak, and T. H. Laine, “Activity recognition on smartphones via sensor-fusion and KDA-based SVMs,” *International Journal of Distributed Sensor Networks*, vol. 2014, 2014, doi: 10.1155/2014/503291.

[47] G. Bieber, P. Koldrack, C. Sablowski, C. Peter, and B. Urban, “Mobile physical activity recognition of stand-up and sit-down transitions for user behavior analysis,” 2010. doi: 10.1145/1839294.1839354.

[48] E. Mitchell, D. Monaghan, and N. E. O’Connor, “Classification of sporting activities using smartphone accelerometers,” *Sensors (Switzerland)*, vol. 13, no. 4, pp. 5317–5337, 2013, doi: 10.3390/s130405317.

[49] J. Beutel *et al.*, *SenSys 2010 : proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems, Zurich, Switzerland, November 3-5, 2010*.

[50] A. Henpraserttae, S. Thiemjarus, and S. Marukatat, “Accurate activity recognition using a mobile phone regardless of device orientation and location,” in *Proceedings - 2011 International Conference on Body Sensor Networks, BSN 2011*, 2011, pp. 41–46. doi: 10.1109/BSN.2011.8.

[51] S. Reddy, M. Mun, J. Burke, D. Estrin, M. Hansen, and M. Srivastava, “Using mobile phones to determine transportation modes,” *ACM Transactions on Sensor Networks*, vol. 6, no. 2, Feb. 2010, doi: 10.1145/1689239.1689243.

[52] M. Shoaib, S. Bosch, O. D. Incel, H. Scholten, and P. J. M. Havinga, “Complex human activity recognition using smartphone and wrist-worn motion sensors,” *Sensors (Switzerland)*, vol. 16, no. 4, Apr. 2016, doi: 10.3390/s16040426.

[53] M. Shoaib, S. Bosch, O. Durmaz Incel, H. Scholten, and P. J. M. Havinga, “Fusion of smartphone motion sensors for physical activity recognition,” *Sensors (Switzerland)*, vol. 14, no. 6, pp. 10146–10176, Jun. 2014, doi: 10.3390/s140610146.

[54] M. Hynes, H. Wang, E. McCarrick, and L. Kilmartin, “Accurate monitoring of human physical activity levels for medical diagnosis and monitoring using off-the-shelf cellular handsets,” *Personal and Ubiquitous Computing*, vol. 15, no. 7, pp. 667–678, Oct. 2011, doi: 10.1007/s00779-010-0345-1.

[55] M. Hynes, H. Wang, E. McCarrick, and L. Kilmartin, “Accurate monitoring of human physical activity levels for medical diagnosis and monitoring using off-the-shelf cellular handsets,” *Personal and Ubiquitous Computing*, vol. 15, no. 7, pp. 667–678, Oct. 2011, doi: 10.1007/s00779-010-0345-1.

[56] R. M. Al-Eidan, H. Al-Khalifa, and A. M. Al-Salman, “A review of wrist-worn wearable: Sensors, models, and challenges,” *Journal of Sensors*, vol. 2018. Hindawi Limited, 2018. doi: 10.1155/2018/5853917.

[57] D. Das, S. M. Busetty, V. Bharti, and P. K. Hegde, “Strength training: A fitness application for indoor based exercise recognition and comfort analysis,” in *Proceedings - 16th IEEE International Conference on Machine Learning and Applications, ICMLA 2017*, 2017, vol. 2017-December, pp. 1126–1129. doi: 10.1109/ICMLA.2017.00012.

[58] S. Mehrang, J. Pietilä, and I. Korhonen, “An activity recognition framework deploying the random forest classifier and a single optical heart rate monitoring and triaxial accelerometer wrist-band,” *Sensors (Switzerland)*, vol. 18, no. 2, Feb. 2018, doi: 10.3390/s18020613.

[59] H. Park, S. Y. Dong, M. Lee, and I. Youn, “The role of heart-rate variability parameters in activity recognition and energy-expenditure estimation using wearable sensors,” *Sensors (Switzerland)*, vol. 17, no. 7, Jul. 2017, doi: 10.3390/s17071698.

[60] S. S. Bangaru, C. Wang, S. A. Busam, and F. Aghazadeh, “ANN-based automated scaffold builder activity recognition through wearable EMG and IMU sensors,” *Automation in Construction*, vol. 126, Jun. 2021, doi: 10.1016/j.autcon.2021.103653.

[61] A. M. Khan, M. H. Siddiqi, and S. W. Lee, “Exploratory data analysis of acceleration signals to select light-weight and accurate features for real-time activity recognition on smartphones,” *Sensors (Switzerland)*, vol. 13, no. 10, pp. 13099–13122, Sep. 2013, doi: 10.3390/s131013099.

[62] M. Schneider, M. Velten, and J. Haupert, “The objectrules framework providing ad-hoc context-dependent assistance in dynamic environments,” in *Proceedings - 2010 6th International Conference on Intelligent Environments, IE 2010*, 2010, pp. 122–127. doi: 10.1109/IE.2010.30.

[63] M. Schneider, M. Velten, and J. Haupert, “The objectrules framework providing ad-hoc context-dependent assistance in dynamic environments,” in *Proceedings - 2010 6th International Conference on Intelligent Environments, IE 2010*, 2010, pp. 122–127. doi: 10.1109/IE.2010.30.

[64] Q. V. Vo, M. T. Hoang, and D. Choi, “Personalization in mobile activity recognition system using K-medoids clustering algorithm,” *International Journal of Distributed Sensor Networks*, vol. 2013, 2013, doi: 10.1155/2013/315841.

[65] P. Siirtola and J. Röning, “Recognizing Human Activities User-independently on Smartphones Based on Accelerometer Data,” *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 1, no. 5, p. 38, 2012, doi: 10.9781/ijimai.2012.155.

[66] H. Martín, A. M. Bernardos, J. Iglesias, and J. R. Casar, “Activity logging using lightweight classification techniques in mobile devices,” *Personal and Ubiquitous*

Computing, vol. 17, no. 4, pp. 675–695, Apr. 2013, doi: 10.1007/s00779-012-0515-4.

[67] R. S. Bivand *et al.*, “BOOK REVIEWS EDITOR: THOMAS M. LOUGHIN Applied Spatial Data Analysis with R Bayesian Disease Mapping: Hierarchical Modeling in Spatial Epidemiology Survival and Event History Analysis: A Process Point of View,” *Biometrics*, vol. 65, pp. 660–673, 2009, Accessed: Sep. 26, 2021. [Online]. Available: http://www.sph.sc.edu/alawson/default.htm

[68] F. Attal, S. Mohammed, M. Dedabrishvili, F. Chamroukhi, L. Oukhellou, and Y. Amirat, “Physical Human Activity Recognition Using Wearable Sensors,” *Sensors 2015, Vol. 15, Pages 31314-31338*, vol. 15, no. 12, pp. 31314–31338, Dec. 2015, doi: 10.3390/S151229858.

[69] H. Koskimaki and P. Siirtola, “Recognizing gym exercises using acceleration data from wearable sensors,” in *IEEE SSCI 2014 - 2014 IEEE Symposium Series on Computational Intelligence - CIDM 2014: 2014 IEEE Symposium on Computational Intelligence and Data Mining, Proceedings*, Jan. 2015, pp. 321–328. doi: 10.1109/CIDM.2014.7008685.

[70] S. Ishii, A. Yokokubo, M. Luimula, and G. Lopez, “Exersense: Physical exercise recognition and counting algorithm from wearables robust to positioning,” *Sensors (Switzerland)*, vol. 21, no. 1, pp. 1–16, Jan. 2021, doi: 10.3390/s21010091.

[71] S. Reddy, M. Mun, J. Burke, D. Estrin, M. Hansen, and M. Srivastava, “Using mobile phones to determine transportation modes,” *ACM Trans. Sensor Netw*, vol. 6, no. 13, 2010, doi: 10.1145/1689239.1689243.

[72] S. Dernbach, B. Das, N. C. Krishnan, B. L. Thomas, and D. J. Cook, “Simple and complex activity recognition through smart phones,” *Proceedings - 8th International Conference on Intelligent Environments, IE 2012*, pp. 214–221, 2012, doi: 10.1109/IE.2012.39.

[73] J. Yang, “Toward Physical Activity Diary: Motion Recognition Using Simple Acceleration Features with Mobile Phones,” 2009.

[74] D. Morris, T. S. Saponas, A. Guillory, and I. Kelner, “RecoFit: Using a wearable sensor to find, recognize, and count repetitive exercises,” in *Conference on Human Factors in Computing Systems - Proceedings*, 2014, pp. 3225–3234. doi: 10.1145/2556288.2557116.

[75] E. Velloso, A. Bulling, H. Gellersen, W. Ugulino, and H. Fuks, “Qualitative activity recognition of weight lifting exercises,” *ACM International Conference Proceeding Series*, pp. 116–123, 2013, doi: 10.1145/2459236.2459256.

[76] S. Balli, E. A. Sağbaş, and M. Peker, “Human activity recognition from smart watch sensor data using a hybrid of principal component analysis and random forest algorithm,” *Measurement and Control (United Kingdom)*, vol. 52, no. 1–2, pp. 37–45, Jan. 2019, doi: 10.1177/0020294018813692.

[77] Z. G. Xiao and C. Menon, “A review of force myography research and development,” *Sensors (Switzerland)*, vol. 19, no. 20. MDPI AG, Oct. 02, 2019. doi: 10.3390/s19204557.

[78] X. Jiang, L. K. Merhi, Z. G. Xiao, and C. Menon, “Exploration of Force Myography and surface Electromyography in hand gesture classification,” *Medical Engineering and Physics*, vol. 41, pp. 63–73, Mar. 2017, doi: 10.1016/j.medengphy.2017.01.015.

[79] R. Chengani, M. L. Delva, M. Sakr, and C. Menon, “Pilot study on strategies in sensor placement for robust hand/wrist gesture classification based on movement related changes in forearm volume,” in *2016 IEEE Healthcare Innovation Point-of-Care Technologies Conference, HI-POCT 2016*, Dec. 2016, pp. 46–49. doi: 10.1109/HIC.2016.7797693.

[80] T. Stefanou, G. Chance, T. Assaf, A. Lenz, and S. Dogramadzi, “Wearable Tactile Sensor Brace for Motion Intent Recognition in Upper-Limb Rehabilitation,” in *Proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics*, Oct. 2018, vol. 2018-August, pp. 148–155. doi: 10.1109/BIOROB.2018.8487721.

[81] D. Giovanelli and E. Farella, “Force Sensing Resistor and Evaluation of Technology for Wearable Body Pressure Sensing,” *Journal of Sensors*, vol. 2016, 2016, doi: 10.1155/2016/9391850.

[82] K. Aoike, K. Nagamune, K. Takayama, R. Kuroda, and M. Kurosaka, “Gait analysis of normal subjects by using force sensor and six inertial sensor with wireless module,” in *2016 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2016 - Conference Proceedings*, Feb. 2017, pp. 1257–1260. doi: 10.1109/SMC.2016.7844414.

[83] P. Fang *et al.*, “Fabrication, structure characterization, and performance testing of piezoelectret-film sensors for recording body motion,” *IEEE Sensors Journal*, vol. 18, no. 1, pp. 401–412, Jan. 2018, doi: 10.1109/JSEN.2017.2766663.

[84] G. P. Sadarangani, X. Jiang, L. A. Simpson, J. J. Eng, and C. Menon, “Force myography for monitoring grasping in individuals with stroke with mild to moderate upper-extremity impairments: A preliminary investigation in a controlled environment,” *Frontiers in Bioengineering and Biotechnology*, vol. 5, no. AUG, Jul. 2017, doi: 10.3389/fbioe.2017.00042.

[85] Z. G. Xiao and C. Menon, “Performance of Forearm FMG and sEMG for Estimating Elbow, Forearm and Wrist Positions,” *Journal of Bionic Engineering*, vol. 14, no. 2, pp. 284–295, Apr. 2017, doi: 10.1016/S1672-6529(16)60398-0.

[86] X. Jiang, Z. G. Xiao, and C. Menon, “Virtual grasps recognition using fusion of Leap Motion and force myography,” *Virtual Reality*, vol. 22, no. 4, pp. 297–308, Nov. 2018, doi: 10.1007/s10055-018-0339-2.

[87] E. Fujiwara and C. K. Suzuki, “Optical fiber force myography sensor for identification of hand postures,” *Journal of Sensors*, vol. 2018, 2018, doi: 10.1155/2018/8940373.

[88] H. Truong *et al.*, “CapBand: Battery-free Successive Capacitance Sensing Wristband for Hand Gesture Recognition,” *Proceedings of the 16th ACM Conference on Embedded Networked Sensor Systems*, vol. 18, p. 14, doi: 10.1145/3274783.

[89] IEEE Robotics and Automation Society, IEEE Engineering in Medicine and Biology Society, IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics 5 2014.08.12-15 São Paulo, and BioRob 5 2014.08.12-15 São Paulo, *5th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics, 2014 12-15 Aug. 2014, São Paulo, Brazil*.

[90] V. Ravindra and C. Castellini, “A comparative analysis of three non-invasive human-machine interfaces for the disabled,” *Frontiers in Neurorobotics*, vol. 8, no. JAN, 2014, doi: 10.3389/fnbot.2014.00024.

[91] A. Kadkhodayan, • Xianta Jiang, and C. Menon, “Continuous Prediction of Finger Movements Using Force Myography,” *Journal of Medical and Biological Engineering*, vol. 36, doi: 10.1007/s40846-016-0151-y.

[92] *2016 6th IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob).* IEEE, 2016.

[93] W. M, K. NH, and C. W, “Pressure signature of forearm as predictor of grip force,” *Journal of rehabilitation research and development*, vol. 45, no. 6, pp. 883–892, 2008, doi: 10.1682/JRRD.2007.11.0187.

[94] X. Wang, Z. Liu, and T. Zhang, “Flexible Sensing Electronics for Wearable/Attachable Health Monitoring,” *Small*, vol. 13, no. 25. Wiley-VCH Verlag, Jul. 05, 2017. doi: 10.1002/smll.201602790.

[95] L. J, L. MJ, and A. J, “Evaluating and improving the performance of thin film force sensors within body and device interfaces,” *Medical engineering & physics*, vol. 48, pp. 206–211, Oct. 2017, doi: 10.1016/J.MEDENGPHY.2017.06.017.

[96] S. ’Kamarul, B. ’Humairah, “Tensile Properties of Silicon Rubber via Experimental Analytical Method Adaopting Hyperelastic Constitutive models,” *Journal of Engineering and Applied Sciences*, 2017.

[97] “Gymwolf - Gym and Cardio workout tracker.” https://www.gymwolf.com/exercises (accessed Sep. 26, 2021).

[98] "WorkoutLabs: Simple Fitness for Everyone." https://workoutlabs.com/ (accessed Sep. 26, 2021).