# Daily Life Activity Recognition with a Head Mounted IMU on Older Adults

## Which Features to Extract?

by


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# Daily Life Activity Recognition with a Head Mounted IMU on Older Adults; Which Features to Extract?

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**Abstract**– As the population aged 65 and above increases, falls among these older adults emerge as a significant public health concern, leading to disabilities and economic burdens. Preventative strategies and personalized fall risk assessments are essential for mitigating fall risks. Human Activity Recognition in early fall risk detection by monitoring everyday activities in older adults could assess patients fall risks. However, current literature has overlooked the older adult demographic by only measuring adults younger than 65, under representing the older population. This research specifically focuses on identifying key features from head-mounted Inertial Measurement Unit (IMU) data using machine learning to classify Sit-to-Walk (STW) and Walk-to-Sit (WTS) movements, which are commonly associated with high risk of fall. In addition these movements can be essential in monitoring changes in performance to asses fall risk. We analyzed five activities STW, WTS, Sitting, Swing phase, and Others. Using three feature selection methods (Mutual Information Gain, ANOVA, Recursive Feature Elimination) on 116 extracted features we were able to rank the features and select the top ten. The study then evaluated the accuracy of three classifiers (Logistic Regression, Random Forest, and K-Nearest Neighbor or Support Vector Machine) with these features. Results indicated that the ANOVA and Random Forest classifier combination achieved the highest total accuracy of 95%, with Random Forest performing exceptionally well in STW and WTS classifications, reaching up to 81% accuracy. Commonly selected features across all methods included the accelerometer's maximum x-axis measured and its energy in both time and frequency domains. This model's performance is comparable with existing literature and validates its effectiveness in fall risk detection.

## 1 Introduction

In Europe, the adult population over 65 years old is growing, as evidenced by the CDC's Morbidity and Mortality Weekly Report, which shows a doubling of this age group within three decades. Specifically, from 2000 to 2030, the percentage of the older adult population will increase from 12.6% to 20.3% [12, 16]. This demographic shift highlights a significant public health challenge: falls among older adults. Globally, falls are a major public issue, resulting in numerous fatal and non-fatal injuries, disability, and medical expenditure, particularly among the older population. In fact, every year, a third of the world's population over 65 experiences a fall [1, 26]. With the older demographic increasing , both the number of fall injuries and the resulting expenditures are expected to increase substantially.

With advancing age the possibility of falling increases. Intrinsic factors that play a role in older adult's risk of falling are the deterioration in function of their sensory, neuromuscular, and musculoskeletal system. There are fall prevention programs at patient level that can reduce the risk of falling by tackling these intrinsic factors. Interventions such as muscle strengthening, gait training, evaluation for assistive devices, medication modification, seated exercises and balance training are some methods that may help prevent falling [24]. These intervention methods are most effective with a personalized program by early detection using personalized fall risk assessments [5, 10].

For older adults, certain daily life activities are associated with an increased risk of falling, including walking, climbing stairs, pushing/pulling objects, Sit-to-Walk (STW), and bending over [3, 20]. Notably, STW is an activity often associated with many falls in adults during the standing up movement and directly shifting into walking. Similarly, the Walk-to-Sit (WTS) movement, which requires bending over, is also associated with a increased number of falls in older adults [28, 7, 23, 25]. In older adults, the adoption of compensatory methods, such as using their arms for assistance during activities like Sit-to-Walk (STW), can serve as early indicators of progressive physical decline. Identifying these compensatory strategies at an early stage can help assess the risk of falls. Therefore, by detecting activities like STW and Walking Task Speed (WTS) where compensatory strategies are commonly employed, we can direct areas where personalized fall risk assessments should be applied. This enables us to identify older adults at high risk of falling who may benefit from targeted prevention programs.

The use of IMU sensors in assessing fall risk has demonstrated promising predictive value. It has also been a preferred choice for data acquisition in Sensor-based monitoring of activities also known as Human Activity Recognition (HAR). HAR, has been a growing field within biomedical engineering that can recognize when activities are performed using sensors and employing machine-learning algorithms [9]. Currently, there is an ongoing project in Technische Universiteit Delft (TUDelft) that is building a fall prevention system. Using an Inertial Measurement Unit (IMU) sensor housed in glasses and a ML algorithm the project aims to detect the activities and monitor changes overtime to help assess the risk of fall for older adults. The use of only one sensor has shown to be sufficient for recognition [6]. Because there is a high prevalence of glasses worn in the older population [22], devices such as glasses with IMU sensors can reduce the sense of obstruction and improve usability when collecting HAR data [19]. In addition, sensors worn on the head compared to the wrist or legs can be less susceptible to noise [17].
Thus, the chosen method of data collection for both activity recognition and fall risk assessment is an IMU housed in glasses.

There have been three studies that utilized head-worn IMU sensor to recognize daily life activities. Amongst these studies a diverse range of activities were classified. In a study by Novac Pierre-Emmanuel, et al. (2022) the authors aimed to build a dataset that collected IMU data from smart glasses [21]. 20 participants were measured, 8 women and 12 men with an average age of 36. 8 activities were identified including standing, sitting, walking, lying, climbing up/down stairs, running, and drinking. For Al Huda, et al. (2017) they also used an IMU sensor placed on the head to recognize activities [2]. Information about the participants used in this study were not provided, however five activities were measured: Standing, Walking, Moving up/down stairs, Running, and Jumping. Finally, in another study that used head worn IMU sensor, Wolff, et al. (2018) collected data in completely natural environments and with a diverse participant group [29]. Activities measured were running, walking, inline-skating, cycling, standing, sitting, reading, and lying. 11 year old children were measured for all these activities, athletes were used for inline-skating and cycling, and an older adult for sitting, walking and reading. However, these studies and many more similar ones did not measure data from older adults and hence possibly creating a bias dataset if it were ever used in fall prevention for older adults. In addition, no studies have looked into classifying Sit-to-Walk and Walk-to-Sit in participants.

This research aims to determine the most contributing features of head-mounted IMU data for a ML model to classify Sit-to-Walk and Walk-to-Sit in older adults. Establishing these features will contribute in the fall prevention project in TUDelft where daily life activities need to be recognized and monitored for changes to help assess an older adults fall risk.

# 2 Methods

This section describes the methods for data acquisition, organization, preprocessing, and processing. Data labeling, organization, and feature extraction were completed using MATLAB R2022a with 'Image processing and Computer vision' and 'Signal Processing Toolbox' installed. For feature selection and training/testing different classification models, Python programming language v3.9 with an Scikit-Learn package was used.

## 2.1 Data Acquisition

In Netherlands, this study conducted measurements in the homes of 19 healthy participants over 65 years old with no current muscular, skeletal, neurological or psychiatric disorders, alcoholism, balance issues, or recent surgeries in the past year. Participants were recruited through personal channels and informed with the risks of participating. An example of a consent form can be found in the Appendix.

Participants were instructed to perform three tasks three times each. Each task began and ended in a seated position. Participants, for their tasks, washed their hands in a kitchen sink, retrieved a book from a table, and walked around the room. The chair participants started in was in one room where they would have space to walk around and retrieve a book. The seat was also placed as close to the kitchen sink to limit the time needed for the participant to return to their seated position.

For this study an Inertial Measurement Unit (IMU, 120Hz, Movella Dot) and a Gopro 7 Black

(120fps) were used to record the activity of the participants. While video and IMU recording, A hammer test was conducted on the sensor; The sensor was placed on a flat surface and struck with a rubber hammer to generate an isolated peak in the raw data as depicted in Appendix B. After the hammer test, the IMU was placed above the right ear of each participant using a headband (Figure 1) and participants were instructed to perform their task. Finally, another hammer test was conducted after the completion of the activity. The IMU had six degrees of freedom for its accelerometer and gyroscope. the x-axis of the IMU measured the vertical displacement and yaw, the y-axis measured the horizontal displacement and roll, and the z-axis measured the lateral displacement and pitch.

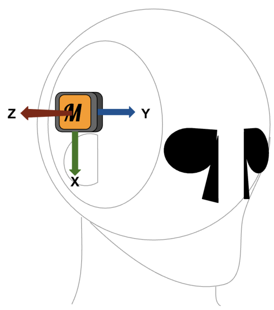



Figure 1: IMU placement and axis direction

The GoPro used to video record the hammer tests and tasks of the participants was held at a distance from the participant where their seated position and the room was in frame. Position of the camera was dependant on the homes of the participants. Once the sensor was secured on the heads of participants, they would begin preforming the task at their own tempo. Each recording was the span of one task and the duration of each task was dependant on the participant and their prefered tempo. For each participant a total of 9 video were recorded.

## 2.2 Data Extraction

From data acquisition all the participants performed the same movements to complete their task. Participants performed quiet sitting in the chairs while they waited for instructions. They also performed STW to execute their task and WTS after completing their task and returning to their seat. Data corresponding

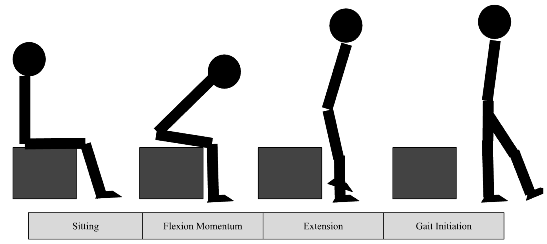



Figure 2: Phases for Sit-to-Walk

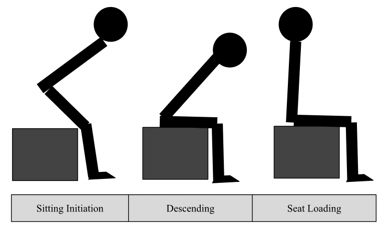



Figure 3: Phases for Walk-to-Sit

to Sitting, STW, and WTS were isolated for preprocessing. In addition, the first swing phase (SP) and Other movements after were isolated. IMU data was manually labeled with these five movement classes based on video recording. Each movement was predefined to precisely label the beginning and ending of each.

**Video Labeling and Synchronization**

Using Video Labeler Application on MATLAB, frames of the video were labeled with 11 possible movements: 1) The first hammer test before the task, 2) Sitting, 3) Flexion Momentum (FM), 4) Extension, 5) Gait initiation, 6) Swing Phase (SP), 7) Other, 8) Sitting initiation, 9) Descending 10) Seat Loading, and finally 11) the last hammer test after task completion. For each label, key characteristics were used to determine the beginning and end of each phase. For example, (1) was defined by the frame that captured the sensor and hammer's first moment of contact. The movements are defined with these labels.

**Sitting** When the sensor was placed on the heads of the participants and they waited for instructions to begin the execution of their task, they were sitting still on the chairs. Their torsos were leaning back, and their feet were parallel to each other. Their hands were either at their sides or resting on their legs. This marked the beginning of label (2).

**Sit-to-Walk** When the participants were instructed to execute their task, they transitioned from a seated position immediately into a walking movement. This movement was divided into three phases [13, 8, 4]. The first phase, flexion momentum (3), The participant swayed their torso forward and down while their feet would slightly adjust back until their bottom was lifted slightly above the seat. The moment the bottom was seen hovering above the chair marked the end of (3). The second phase, Extension (4), the participants extended their knees and moved their hips forward lifting the torso back. In addition, the participant shifted their weight to one leg and lifted their heel on the other leg. The frame that showed the heel lift marked the end of (4). The final phase, Gait Initiation (5), was when the participant fully lifted their foot off the ground and moved it forward until its heel came into contact with the floor initiating the gait phases for walking. The contact of the foot with the floor marked the end of (5). Figure 2 illustrates the three phases of STW after quiet sitting.

**Swing Phase**
After Sit-to-Walk the participant initiated the first swing phase (6) of the gait, fully transitioning them into walking. Gait initiation from STW differs from the first swing phase of the gait due to the transition from a stationary phase; The body needs to make a series of adjustments to initiate the first step of gait. Thus, the swing phase after gait initiation in STW is defined separately. Swing phase was described as the moment the participant lifted their foot off the floor and swung it forward until their heel made contact with the floor; This marked the end of (6).

**Other**
For this project, the focus in movements was more on STW and WTS. However, other activities were isolated to see if STW and WTS could be distinguished from the rest such as Sitting and Swing Phase. However, a third movement defined as 'Other' (7) was considered. 'Other' refers to any movement that occurred within a few seconds after swing phase. This could possibly be walking or standing. The number of frames labeled as Other was equal to the amount of frames found in Sit-to-Walk.

**Walk-to-Sit**
There were a few articles that investigated the Stand-to-Sit (STS) movement [18, 14]. The phases identified in STS were used to separate WTS into three phases (Figure 3); Sitting Initiation (8), Descending (9), and Seat Loading (10). Sitting Initiation was when the person performed torso and knee flexion. The frame that first showed the participant bend their knees and move their torso forward until the frame right before the waist begins to descend marked the frames for (8). Then, in descending phase (9), the person continued knee flexion and vertically descended their bottom onto the seat. The frame that showed the bottom of the participant come into contact with the seat marked the end of (9). Finally, in seat loading the torso was moved back and the feet would adjust forward. The frame that showed the torso lean completely back marked the end of (10).

| | Feature | Abbreviation |
|---|---|---|
| Time | Mean | M |
| | Standard Deviation | STD |
| | Mean Absolute Deviation | MAD |
| | Root Mean Square | RMS |
| | Maximum | Max |
| | Minimum | Min |
| | Energy | E |
| | Inter-quartile Range | IQR |
| | Entropy | EN |
| | Zero Crossing Rate | ZCR |
| | Cross-Correlation | CC |
| | Signal Magnitude Area | SMA |
| Frequency | Mean | M |
| | Standard Deviation | STD |
| | Mean Absolute Deviation | MAD |
| | Root Mean Square | RMS |
| | Maximum | Max |
| | Minimum | Min |
| | Energy | E |
| | Inter-quartile Range | IQR |
| | Entropy | EN |

Table 1: Features Extracted in Time Domain and Frequency Domain

The last hammer test (11) was then then defined by the frame that captured the sensor and hammer first come into contact after the task was completed.

The Video Labeler Application exported the labels as a ground truth table where it was then converted into array structures using a MATLAB script. The array structures were then used to locate the data points in the IMU raw data that corresponded to each label. The labeled data for each movement was then grouped; Sitting (2), STW (3,4,5), Swing Phase (6), Other (7), and WTS (8, 9, 10). A detailed guide to produce these array structures are in Appendix C, the activities isolated from the raw data are shown in Appendix D, and the organization of the datasets before feature extraction are illustrated in figure 4. There are six separate datasets for each activity, one for each signal of the IMU. The datasets hold multiple cell arrays. Each cell array is associated with a trial of a participant.

## 2.3 Feature Extraction

Before features were extracted a Buttersworth filter was used to exclude gravitational acceleration from the accelerometer data. The filter was first order and low passing with a cut off frequency of 18Hz [11]. The signal that remained was considered the acceleration measured from the body. Each cell array in each signal dataset was segmented using a sliding window of

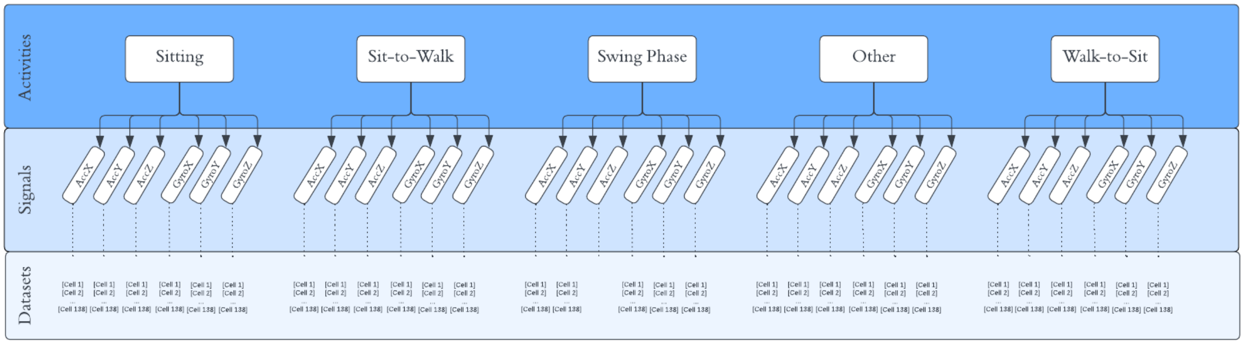



Figure 4: array structure of organized dataset for each activity's signals

50 data points and an overlap of 20%. For each segmentation a list of features were extracted (table 1 lists these features) and labeled with the activity it is associated with. A total of 116 features were extracted and a one hot key code of the activity were arranged into a matrix. Moving forward the activities were referred to as classes and table 2 defines each class. For a short description of each feature extracted refer to Appendix E

| Class | Activity |
|---|---|
| 0 | Sitting |
| 1 | Sit-to-Walk |
| 2 | Swing Phase |
| 3 | Walk-to-Sit |
| 4 | Other |

Table 2: Activities associated with each class

## 2.4 Train-Test Split

The data set that included all the features extracted was then split into training set (80%) and testing set (20%). The data split was at participant level, meaning, 80% of all participants were used to train and 20% were used to test.

## 2.5 SMOTE Class Balancing

In the five classes, Class 0 showed a larger sample size compared to the other classes, as shown in figure 5. This imbalance in samples created an unequal representation between classes. Synthetic Minority-Oversampling Technique (SMOTE) was a method to generate extra samples to the classes with fewer samples. SMOTE selects a minority class instance and identifies its k nearest neighbors within the minority class. It then randomly selects one of these neighbors and generates a synthetic example by choosing a random point along the line connecting the selected instance and its neighbor. This process is repeated until the number of samples matches with the majority class, effectively creating synthetic instances to balance class distribution. SMOTE was thus employed on the training data set to balance the minority classes with Class 0.

## 2.6 Scaling Data

Scaling was applied to the balanced data to help mitigate some features from dominating others due to having larger magnitudes. This ensured all features were contributing equally to the machine learning model. Scaling can improve performance, making it more robust and accurate across various features with different scales. Scaling was done by subtracting the mean and dividing by the standard deviation for each feature.

## 2.7 Feature Selection Methods

To further improve the performance of the classifying models by reducing the dimensionality of the data and to determine the most contributing features in the set, feature selection methods were employed. For this research we looked into two Filter techniques and one Wrapper technique [27]. The benefits of the filter methods ranked the features independently from the chosen model to classify based on a predetermined criterion, such as statistical significance or information gain. This independence allowed for a quick and computationally efficient feature selection process and was applicable to any classifier. With a wrapper technique, such as Recursive Feature Elimination (RFE) it was dependant on the classifier and thus the chosen features were only effective with that chosen model, however the benefit to this technique is it finds features that interact with each other and improves the models performance.

#### 2.7.1 Mutual Information Gain

Mutual Information Gain is a filter technique that was employed onto three classifiers. It measured the dependants between individual features and the targeted class. Mathematically it is defined as:

$$I(X;Y) = \sum_{x \in X, y \in Y} p(x,y) \log \left( \frac{p(x,y)}{p(x)p(y)} \right)$$

Here, p(x,y) is the joint probability distribution of X and Y, and p(x) and p(y) are the marginal probability distributions of X and Y, respectively. It measures how much knowing one of these variables reduces uncertainty about the other; it's zero if the variables are independent and increases as the dependence between them grows. By measuring these dependencies, features were ranked based on the relevance to classify all the classes. With this technique a chosen number of top features were used to train the classifier and evaluate their performance.

#### 2.7.2 ANOVA

Using Analysis of Variance (ANOVA), we identify features with significantly varying means across classes. Features are ranked by their p-values, with lower values indicating greater importance in class differentiation. The top-ranked features are then used to train the classifier. the p-value threshold was 0.5, meaning anything lower was considered significant.

#### 2.7.3 Recursive Feature Elimination

RFE determines the importance of features based on the performance of a machine learning model. It passes through the entire feature set and eliminates a feature with the least importance every iteration until a predetermined amount are left. RFE is model dependant because it utilizes the model to rank the features importance. With this technique three classification models were used to train and test a chosen number of top features. Each model defines importance differently. In the case of Logistic Regression and Support Vector Machin (SVM) feature importance is determined by coefficient magnitude. For Random Forest its based on the reduction of a criterion like Gini impurity or mean squared error each feature provides when used in trees. Features that lead to larger average reductions are considered more important.

### 2.8 Classification Model

The classification task for this project is multi-class with five different movements. A one-vs-rest approach of classification is used. With the selected features from the three techniques three different models are used. The models chosen are commonly used in HAR research. Mutual Information Gain and ANOVA use Logistic Regression, Random Forest, and K-Nearest neighbor. For RFE, Logistic Regression, Random Forest Classification, and Support Vector Classification were used. RFE typically requires a model that can provide some form of ranking of feature importance and K-nearest neighbor does not have this built in, therefore SVM is used as the third classifier for RFE. For each model the number of top features used to train and test were evaluated, starting at one and increasing by ten until all the features are used. Table 3 details the hyper parameters used for each classifier.

### 2.9 Metric for Evaluation

Evaluating the performance of a classification model is essential to determine its effectiveness in recognizing and the targeted movement and comparing it with other models in the project and in other literature. Accuracy is a widely used metric in classification tasks, it provides a straightforward measure of the model's ability to correctly classify instances into their respective activity categories. Accuracy is defined as the ratio of correctly classified activities to the total number of activities in the dataset.

$$Accuracy = \frac{CorrectlyClassified}{TotalActivities}$$

## 3 Results

### 3.1 Data Description

A total of 19 participants had their movements measured in this study. However, due to inconsistencies in sampling rates 16 participants were sampled at 120Hz and 3 at 60Hz—the latter group was excluded from the analysis. Among the remaining participants, the average age was 76 years, with a standard deviation of 7 years. The gender distribution included 11 females and 5 males.

From the sliding window, we obtained 1285 Sitting samples, 604 STW samples, 144 SP samples, 544 WTS samples, and 604 Other samples. After splitting the data and employing SMOTE each movement had 1010 samples for training. Figure 5 shows the number of samples in the training set before and after SMOTE was employed.

| Model | Hyper-parameters |
|---|---|
| Random Forest | number of decision trees = 100, importance criterion = Gini impurity |
| Logistic Regression | number of iteration for solver to converge = 10000, solver = 'liblinear' |
| K-Nearest Neighbor | K = 5 |
| Support Vector Machine | kernel = linear |

Table 3: Hyper-parameters used for each classifier

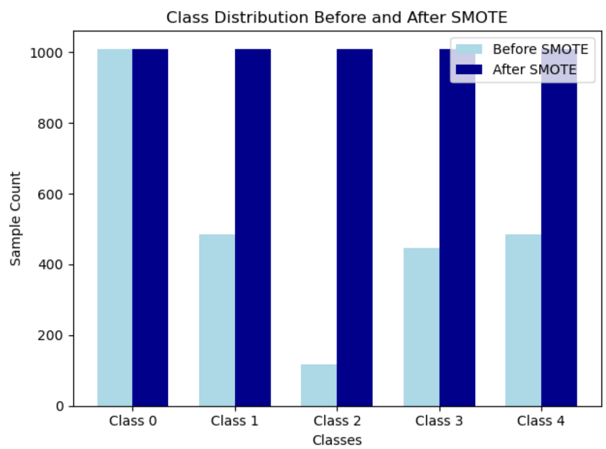



Figure 5: Sample count in the training set before and after SMOTE

## 3.2 Mutual Information Gain

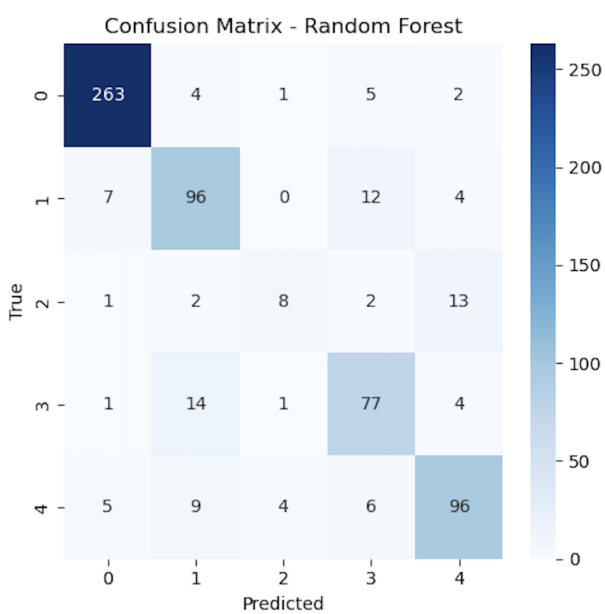
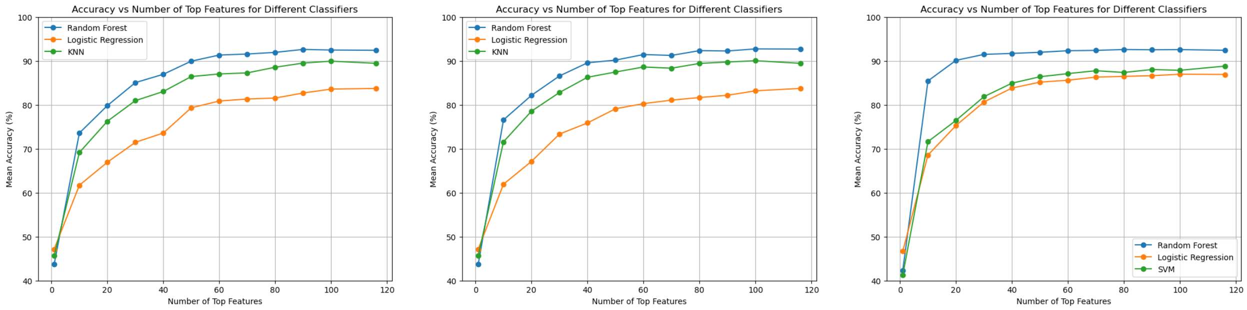



Figure 7: Confusion Matrix of Random Forest

The first 10 features ranked in Mutual Information Gain showed the greatest increase of accuracy for each classifier with shorter increases as the number of top features increased (figure 6). The first 10 features ranked are listed in table 4. For Random Forest Classification the number of features becomes less significant after the model was trained with 60 features as accuracy showed little change. After 90 features the model decreased in accuracy. For Logistic Regression, after 60 features the models accuracy started to plateau in accuracy however it would never drop. Similarly can be seen with K-Nearest neighbor, where after 60 features the increase in accuracy slowly diminishes until it begins to slightly drop after 100 features are used. Logistic Regression showed the poorest performance between the three models with a maximum of 83% accuracy achieved. Within each class Sitting was predicted with the most accuracy, followed by Other, STW, WTS, and lastly SP. Finally, the confusion matrix (Figure 7) showed how the models predicted each class with in its best performance with True Positives, True Negatives, False Positives and False Negatives displayed. STW was predicted as WTS more than any other class as well as WTS was predicted most as STW. The accuracy for STW was 77% and 75% for WTS.




(a) Mutual Information Gain (b) ANOVA (c) Recursive Feature Elimination

Figure 6: Top features performance from each selection method

## 3.3 ANOVA

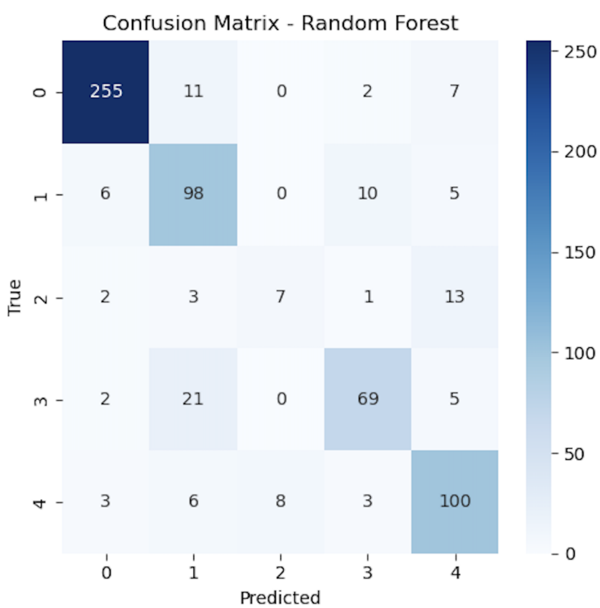



Figure 8: Confusion Matrix for Random Forest

In ANOVA (Figure 6) the top ten features showed the greatest increase of accuracy for each classifier with the accuracy plateauing after 60 features, previously seen in Information Gain. The first 10 features ranked are listed in table 4. Random Forest Classification showed the best performance amongst the three, followed by KNN and then Logistic Regression. . Within each class Sitting was predicted with the most accuracy, followed by Other, STW or WTS, and lastly SP. Finally, the confusion matrix (Figure 8) showed how the models predicted each class with the number of True Positives, True Negatives, False Positive, and False Negative displayed. STW was predicted as WTS more than any other class as well as WTS was predicted most as STW. The accuracy measured for STW was 71% and 81% for WTS.

## 3.4 Recursive Feature Elimination

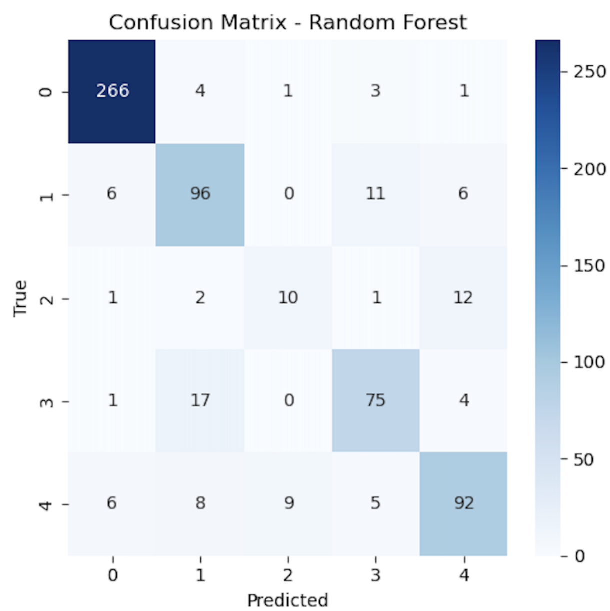



Figure 9: Plot of data extracted from the IMU accelerometer corresponding to each activity.

Similar to the previous methods RFE showed the greatest increase of accuracy for each classifier when using the first top 10 features with shorter increases as the number of top features increased (Figure 6. The first 10 features ranked are listed in table 4. Random Forest Classifier, the best performing model, begins to show little to no change in accruacy after 30 features are chosen. In Logistic Regression the model shows a similar effect after 80 features and for SVM, after 60 features. Within each class Sitting was predicted with the most accuracy, followed by Other, STW or WTS, and lastly SP. Finally, the confusion

| Top 10 Features | | | | |
|---|---|---|---|---|
| IG | ANOVA | RFE-RF | RFE-LR | RFE-SVM |
| SMA_Acc | SMA_Gyro | AccX_Max | AccX_Max | AccX_Mean |
| AccXf_Energy | AccYf_Mean | AccX_Energy | AccX_Energy | AccX_STD |
| AccX_Energy | AccYf_STD | AccXf_Mean | AccXf_Mean | AccX_RMS |
| AccXf_Max | AccYf_MAD | AccXf_MAD | AccXf_Max | AccX_Max |
| AccX_RMS | AccYf_Max | AccXf_Energy | AccXf_Energy | AccX_Energy |
| AccXf_STD | AccYf_Min | AccY_MAD | AccXf_IQR | AccXf_Mean |
| AccXf_MAD | AccYf_Energy | AccY_IQR | AccY_Energy | AccYf_Energy |
| AccY_RMS | AccZ_STD | AccYf_Mean | AccYf_Max | GyroX_RMS |
| AccXf_Mean | AccZ_MAD | GyroX_RMS | GyroZ_Mean | GyroXf_MAD |
| AccY_Energy | AccZ_RMS | GyroXf_Max | CCAccXY | GyroZ_Energy |

Table 4: ten features that were ranked as the best for each method of feature selection

matrix showing how the models predicted each class (Figure 9) showed STW was predicted as WTS more than any other class and vise versa. The accuracy of STW was 76% and 79% for WTS

### 3.5 Top 10 Features Used

From Table 4 we are able to see the top ten chosen features. These ten features are considered the most contributing features of the 116 features extracted and based on the performance showed the most impact in accuracy for each model. Comparing the 5 lists, we can see that the most frequently appearing features are AccX_Max, AccXf_Energy, and AccX_Energy, ranked in the top 10 by IG, RFE-RF, and RFE-LR. These three features appear in three different methods. Features that appear in two methods are AccXf_Max, AccX_RMS, AccXf_STD, AccXf_MAD, AccY_RMS. These features were ranked in the top 10 by IG and RFE-RF. No features appeared in the top rankings for all five methods. In Appendix E the three most common features are explained.

## 4 Discussion

This study's objective was to determine the best features to recognize the transfer movement sit-to-walk and walk-to-sit in a population age 65 years and older head mounted IMU. The selected features were then classified by three different models to evaluate their performance in accuracy. The top ten features selected were listed and a relationship between the amount of selected features and accuracy of the model was graphed.

### 4.1 Findings

The analysis showed that the top ten features selected by three methods—Mutual Information Gain, ANOVA, and Recursive Feature Elimination—significantly improved the most in classification accuracy, especially using the Random Forest Classifier. In Mutual Information Gain, the model achieved a 75% accuracy with 10 features and its best at 93% accuracy with 90 features. With ANOVA, the top 10 features achieved 70% accuracy, increasing to 95% with 90 features. For Recursive Feature Elimination, the model reached 88% accuracy with 10 features and 93% with 40 features. Notably, using the full feature set didn't significantly impact accuracy, suggesting immunity to the curse of dimensionality. The Random Forest Classifier was consistently the most effective across all methods, especially in classifying specific categories like STW and WTS. When looking into other HAR literature that utilized head mounted IMU sensor to recognize activities such as [21] we can compare how some activities performed in accuracy with this study. Sitting in our study had a higher accuracy of 95% in recognition compared to Novac, et al. who achieved 77%. However, their study looked into classifying more than five activities including other static movements which may have compromised their accuracy, while in this study sitting was the only static movement measured. Notable is the overall accuracy in Novac's research. They had total accuracy ranging from 75% to 81% while in our study the range of total accuracy at its best performance was above 90%. Similarly, in Wolff, et al.'s study they were able to achieve a total accuracy of 86.79% with eight activities measured [29].This indicates that the method used in our study to recognize the measured activities is on par with established approaches in the field, however the difference in activities measured could contribute to the difference in accuracy and why our study was able to perform with higher accuracy than other literature.

Observing the top ten features from each method an interesting pattern emerged. First, the majority of features chosen by all methods, except ANOVA, were from the x-axis of the Accelerometer, while ANOVA predominantly selected features from the y-axis of the accelerometer. And very few moments were features chosen from the z-axis of the accelerometer. The limited displacement in the lateral direction of the body when performing any of the activities compared to vertical or horizontal displacement could contribute as to why features in the z-axis of the accelerometer were rarely selected as a top feature.

Furthermore, the appearance of gyroscope features appeared to be lesser compared to accelerometer features. For instance, in the top 10 features of the Information Gain method, no gyroscope features were used. ANOVA incorporated one gyroscope feature, RFE-RF two, RFE-LR one, and RFE-SVM three. The contribution of pitch, roll, or yaw in each movement was not as crucial to distinguish movements such as STW and WTS. For example in both of these movements there is few instance where the body needs to rotate around the x-axis (yaw). This rotation is also not seen in quiet sitting or walking. The only case where rotation does occur is if the person was looking around during their movement. This could provide an explanation as to why the x-axis gyroscope of all the axis was selected in the top features. The same explanation can be used for rotation around the y-axis (roll) and z-axis (pitch) of the gyroscope. This observation suggests that while gyroscope features contribute to classification accuracy, most models could potentially be equally effective without them, similarly stated in Wolff et al. (2018) [29].

Within the top 10 features, three features appeared across three different methods of feature selection: The maximum value of a window in the x-axis of the accelerometer, the energy measured in the frequency domain of the x-axis of the accelerometer, and the energy in the time domain of the x-axis of the accelerometer. There appearance across multiple methods suggests these features are robustly relevant to the dataset, likely capturing a fundamental aspect of the data. We can also assume that these features are less likely the result of method-specific bias. These features contribute greatly in distinguishing the measured activities, a bio mechanical interpretation of these features in STW and WTS can be found in the intensity of these movements. Typically, in human activity recognition there are static and dynamic activities. Sitting and standing are considered static due to the lack of movement and STW and WTS can be considered dynamic due to the constant movement. Differentiation static and dynamic movements using an IMU can be done in multiple ways. For example, Kong, et al. (2021) looked at the mean absolute deviation for each activity and found a clear distinction in the deviation from the mean for each activity; Static activities had less deviation from the mean and dynamic activities had more deviation [15]. The same can be applied for STW, WTS and Sitting. We can distinguish STW and WTS from sitting using the feature Energy in both the time and frequency domain because of the intensity found in these movements. The flexion of the trunk and extension of the knees to lift the body vertically creates high amounts of energy for the x-axis of the accelerometer in STW, comparatively the flexion of the trunk and knees in WTS. For sitting, the body does not move as much and therefore the energy measured from the accelerometer is relatively low. Similarly the selection of maximum values in the x-axis of the accelerometer can be explained with the sudden vertical displacement of the body in STW that occurs in a few milliseconds. This quick acceleration would produce a larger value in the x-axis accelerometer compared to sitting or other activities. If you were to look at WTS, it also would have a vertical displacement of the body that occurs in a few milliseconds, however it is a downward acceleration that may help distinguish it from STW. If these features are present in the subset selected for the classification model they are likely to improve the performance. However, we cannot be certain that these features are not also correlated with other features in the set and are therefore dependant to another to fully utilize its effectiveness.

## 4.2 Limitation

In the process of annotating video data for identifying specific transfer movements, there existed potential biases in labeling. Despite the researcher's efforts towards precision, certain indicators marking the start or end of a movement occasionally fell outside the camera's view. This limitation could introduce inaccuracies in defining the exact moments of each movement.

The alignment method used to annotate and extract data relevant to these movements was subject to a potential error margin of 10 samples based on the length of the signal associated with the hammer test. Such a deviation in sample alignment might have influenced the characteristics of the features extracted later in the analysis. This aspect of data handling is necessary to be cautious when interpreting the results, minor misalignment's could have a larger effect on the data further down the process. When the data for each signal was segmented a window of 50 samples iwth 20% overlap was chosen. This choice was arbitrary, and could have had a significant impact on the performance of the classification model, further investigation on what is the optimal window size and overlap needs to be conducted to see if it has any effect.

Furthermore, the dataset showed an imbalance, with a significantly higher number of samples representing sitting as compared to transfer movements. To address this, an up-sampling technique was employed to balance the data for transfer movements. However, this introduction of synthetic data poses its own challenges, as it could potentially affect the feature selection process. The synthetic nature of the up-sampled data might not perfectly replicate the real-world scenarios it is meant to represent, thus impacting the study's conclusions. Down-scaling could be an alternative technique to balance the classes however this would dispose valuable information from the Sitting activity, in addition the use of up scaling can help generate more data for minority classes to determine the most important features.

Additionally, the hyperparameters used in the analysis were not at their optimal setting. Optimized hyperparameter is an important step in machine learning models, as it significantly affects the model's ability to accurately make predictions. This could have an impact on the interpretation of the results for the features.

### 4.3 Future Work

For future research, there are several ways our methods for recognizing transfer movements in the elderly can be improved and expanded. Enhancements in data acquisition are crucial; gathering more samples of each transfer movement will provide a richer and more balanced dataset. This broader data collection will enable more robust and comprehensive analysis, leading to more accurate and reliable models.

Developing a more precise method for extracting relevant data is another key area needed for improvement. This involves improving techniques to isolate the exact moments and characteristics of each transfer movement, thereby reducing noise and improving the quality of the dataset. With this improvement we can train a model to more accurately identify individual activities or transfer movements. A possible solution to this is applying a method similarly found in a study conducted by Raman et al. (2020). In their research, they utilized a Network Time Protocol (NTP) as a reference source to achieve synchronization among multiple sensors. In our own study, we can employ the NTP method to synchronize both the camera and the head-mounted sensor. This would provide a synchronization with a latency as small as 414 microseconds.

Increasing the amount of features extracted from the data. By analyzing a larger feature set, we can potentially find more effective features. Introducing more activities in the dataset is another important step. If we we want to monitor more activities in elderly this will allow us to test the robustness of the selected features, ensuring that they can continue to effectively distinguish Sit-to-Walk movements from other activities.

A way to expand the research in recognizing transfer movements is looking into classifying the different phases of the transfer movements. By recognizing the different phases and complimenting it with a fall risk assessment tool we can have better insight in the changes that occur over time.

## 5 Conclusion

Features extracted from a head-mounted IMU on an older population were effective in accurately classifying STW and WTS movements. Recognition of these movement and observing changes in their performance over time would help assess the fall risk in a patient. Using feature selection methods such as Mutual Information Gain, ANOVA, and Recursive Feature Elimination 116 features were ranked. From the selection, features in the x-axis accelerometer were the most crucial features to distinguish different movements, while features extracted from gyroscopes had less of an impact in the models performance and can be neglected. Features such as the maximum values and energy in the x-axis of the accelerometer showed the most robustness for each model, with Random Forest Classifier as the best amongst them. The accuracy from these models were comparable to other literature and therefore our method and feature choice can be used to recognize daily life activities in older adults. Furthermore, current datasets lack a large sampling of older adults above the age of 65 years old. Our datasets collected from this population age can fill this gap and be used for future work in building models to recognize activity in an older population.

## 6 Acknowledgements

I want to express my deepest gratitude for the guidance given to me throughout my thesis by my supervisors Eline van der Kruk, Chirag Raman, and Niels Waterval who all have shown patients and knowledge I strive to achieve. I would also like to thank my family and friends who supported me greatly.

# References


[1] URL: `https://www.who.int/news-room/fact-sheets/detail/falls`.

[2] Fais Al Huda, Herman Tolle, and Rosa Andrie Asmara. "Realtime Online Daily Living Activity Recognition Using Head-Mounted Display." In: *Int. J. Interact. Mob. Technol.* 11.3 (2017), pp. 67–77.

[3] Robert L Berg, Joseph S Cassells, et al. "Falls in older persons: risk factors and prevention". In: *The second fifty years: Promoting health and preventing disability*. National Academies Press (US), 1992.

[4] Thomas Buckley et al. "Age impairs sit-to-walk motor performance". In: *Journal of Biomechanics* 42.14 (2009), pp. 2318–2322.

[5] Suiyao Chen et al. "Personalized fall risk assessment for long-term care services improvement". In: *2017 Annual Reliability and Maintainability Symposium (RAMS)*. IEEE. 2017, pp. 1–7.

[6] Ömer Faruk Ertuğrul and Yılmaz Kaya. "Determining the optimal number of body-worn sensors for human activity recognition". In: *Soft Computing* 21.17 (2017), pp. 5053–5060.

[7] Marcia L Finlayson and Elizabeth W Peterson. "Falls, aging, and disability". In: *Physical Medicine and Rehabilitation Clinics* 21.2 (2010), pp. 357–373.

[8] Gunilla E Frykberg et al. "Temporal coordination of the sit-to-walk task in subjects with stroke and in controls". In: *Archives of physical medicine and rehabilitation* 90.6 (2009), pp. 1009–1017.

[9] Fuqiang Gu et al. "A survey on deep learning for human activity recognition". In: *ACM Computing Surveys (CSUR)* 54.8 (2021), pp. 1–34.

[10] Jennifer Howcroft, Jonathan Kofman, and Edward D Lemaire. "Review of fall risk assessment in geriatric populations using inertial sensors". In: *Journal of neuroengineering and rehabilitation* 10 (2013), pp. 1–12.

[11] Ramy Hussein et al. "Robust recognition of human activities using smartphone sensor data". In: *2017 International Conference on the Frontiers and Advances in Data Science (FADS)*. IEEE. 2017, pp. 92–96.

[12] Eleni Kanasi, Srinivas Ayilavarapu, and Judith Jones. "The aging population: demographics and the biology of aging". In: *Periodontology 2000* 72.1 (2016), pp. 13–18.

[13] Andy Kerr, Brian Durward, and KM Kerr. "Defining phases for the sit-to-walk movement". In: *Clinical biomechanics* 19.4 (2004), pp. 385–390.

[14] KM Kerr et al. "Analysis of the sit-stand-sit movement cycle in normal subjects". In: *Clinical Biomechanics* 12.4 (1997), pp. 236–245.

[15] Weiheng Kong, Lili He, and Hailong Wang. "Exploratory data analysis of human activity recognition based on smart phone". In: *IEEE Access* 9 (2021), pp. 73355–73364.

[16] Carol T Kulik et al. *Aging populations and management*. 2014.

[17] Oscar D Lara and Miguel A Labrador. "A survey on human activity recognition using wearable sensors". In: *IEEE communications surveys & tutorials* 15.3 (2012), pp. 1192–1209.

[18] Yi-Ting Lin and Heng-Ju Lee. "Comparison of the lower extremity kinematics and center of mass variations in sit-to-stand and stand-to-sit movements of older fallers and nonfallers". In: *Archives of rehabilitation research and clinical translation* 4.1 (2022), p. 100181.

[19] Kevin Moore et al. "Older adults' experiences with using wearable devices: qualitative systematic review and meta-synthesis". In: *JMIR mHealth and uHealth* 9.6 (2021), e23832.

[20] Aarti Nagarkar and Snehal Kulkarni. "Association between daily activities and fall in older adults: an analysis of longitudinal ageing study in India (2017–18)". In: *BMC geriatrics* 22.1 (2022), pp. 1–7.

[21] Pierre-Emmanuel Novac et al. "UCA-EHAR: A Dataset for Human Activity Recognition with Embedded AI on Smart Glasses". In: *Applied Sciences* 12.8 (2022), p. 3849.

[22] Benjamin Otte et al. "Self-Reported eyeglass use by US Medicare beneficiaries aged 65 years or older". In: *JAMA ophthalmology* 136.9 (2018), pp. 1047–1050.

[23] Tomislav Pozaic et al. "Sit-to-stand transition reveals acute fall risk in activities of daily living". In: *IEEE journal of translational engineering in health and medicine* 4 (2016), pp. 1–11.

[24] Patricia Quigley et al. "Fall prevention and injury protection for nursing home residents". In: *Journal of the American Medical Directors Association* 11.4 (2010), pp. 284–293.

[25] Kilian Rapp et al. "Epidemiology of falls in residential aged care: analysis of more than 70,000 falls from residents of bavarian nursing homes". In: *Journal of the American Medical Directors Association* 13.2 (2012), 187–e1.

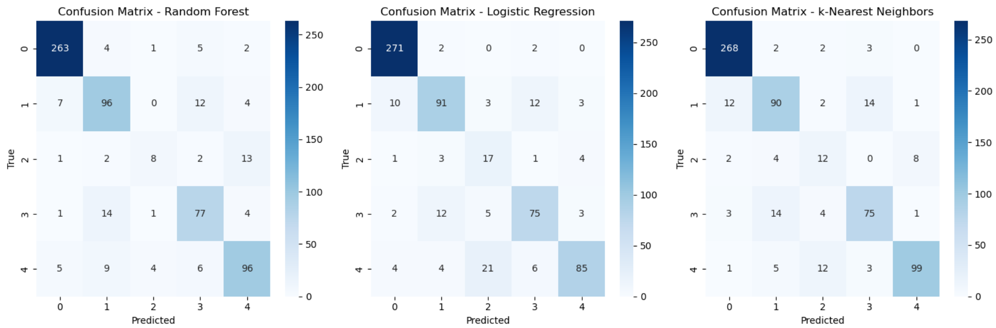
[26] David A Sleet, Daphne B Moffett, and Judy Stevens. "CDC's research portfolio in older adult fall prevention: a review of progress, 1985-2005, and future research directions". In: *Journal of safety research* 39.3 (2008), pp. 259–267.

[27] Jozsef Suto, Stefan Oniga, and Petrica Pop Sitar. "Feature analysis to human activity recognition". In: *International Journal of Computers Communications & Control* 12.1 (2017), pp. 116–130.

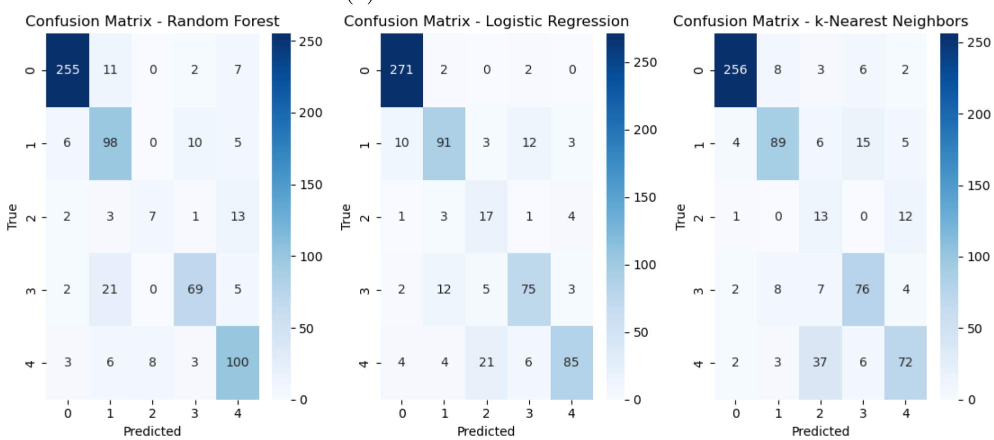
[28] AM Tromp et al. "Fall-risk screening test: a prospective study on predictors for falls in community-dwelling elderly". In: *Journal of clinical epidemiology* 54.8 (2001), pp. 837–844.

[29] Johann P Wolff et al. "Activity recognition using head worn inertial sensors". In: *Proceedings of the 5th international Workshop on Sensor-based Activity Recognition and Interaction*. 2018, pp. 1–7.

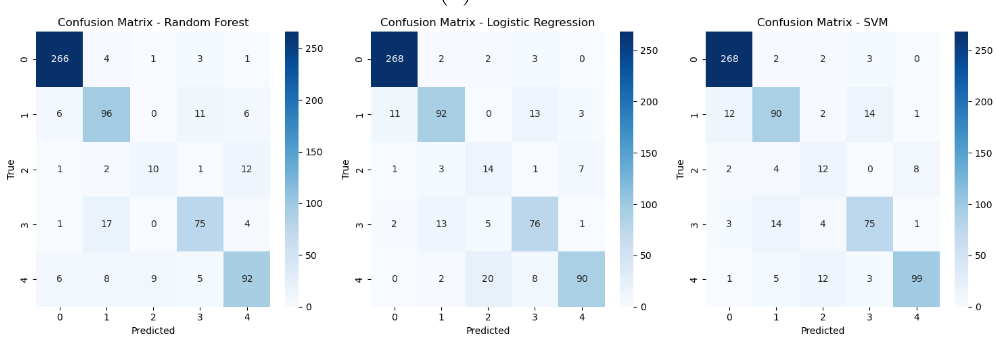
# A Appendix: Confusion Matrix of Each Classifier For Each Method of Feature Selection




(a) Mutual Information Gain




(b) ANOVA




(c) Recursive Feature Elimination

# B Appendix: Matlab Plotting of IMU Raw Data

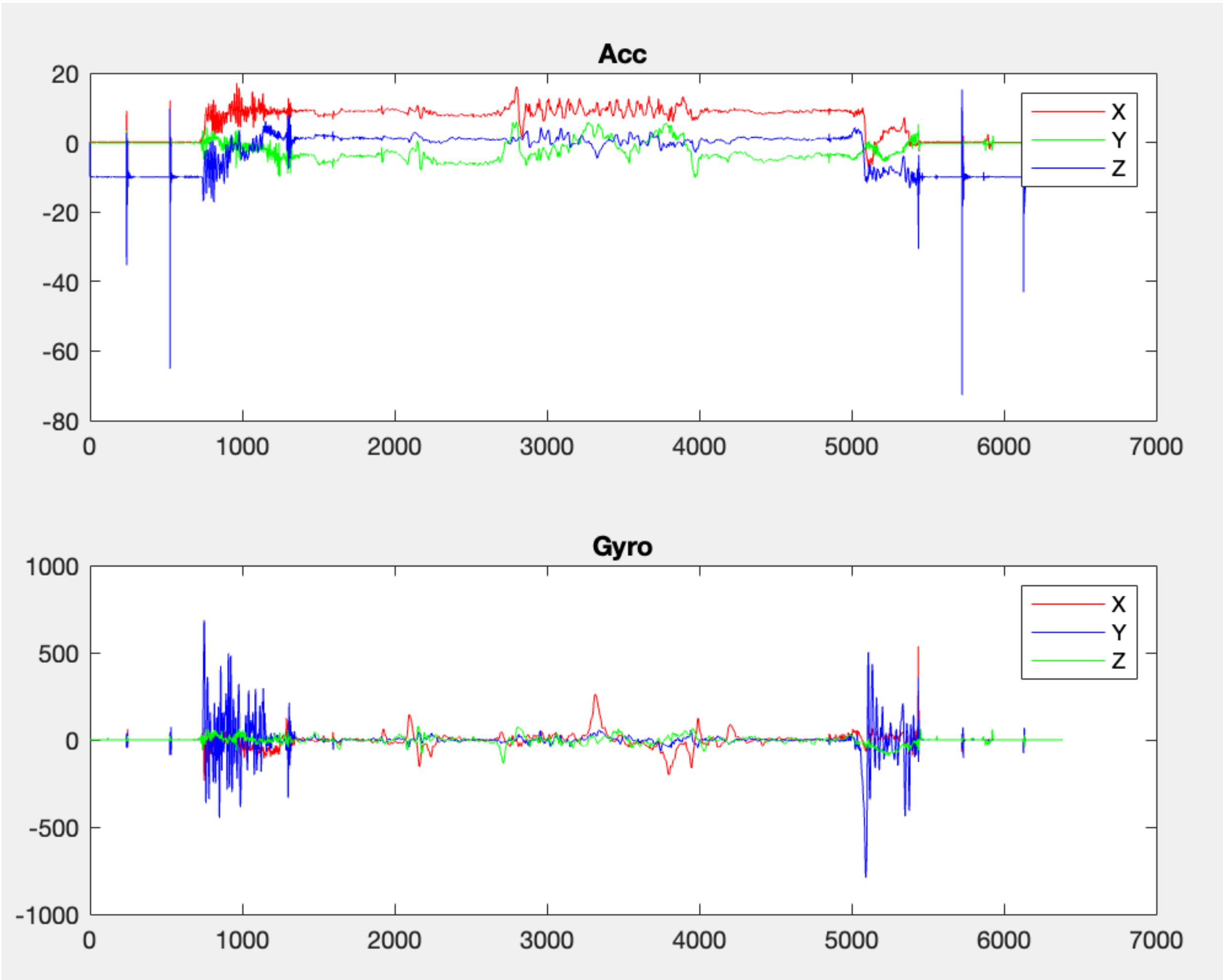



Figure 11: Raw data from the IMU plotted in MATLAB

# C Appendix: IMU Data Extraction for each Activity

**Video Frame Location**

After exporting the ground truth table of the labelled videos a script in MATLAB is used to convert it into structure arrays that gives the location of the first and last frame of the video for each activity. Below are examples of the structure array, with the first value indicating the first frame location and the second value indicating the last frame.

$$Video.P16.T1\_3.Sitting : [2512, 2918]$$

$$Video.P16.T1\_3.Sit2Walk : [2919, 3094]$$

**IMU Peak Search**

For the IMU data a script, written in MATLAB, is used to find the first peak that would correspond to the hammer test. A threshold of -8 to -11 is used to find the peak. The outcome of this script is another structure array that gives the location of the peak for all participants and their trials. Some peak locations were determined to be an error due to noise surpassing the threshold. Manual changes to any suspecting peak location errors are then managed. Below is an example of one of the fields in the structure array. The value indicates the location in the dataset where the first peak appears.

$$synchframes.P16.T1\_3 : 205$$

The final peak corresponding to the hammer test after task completion in the IMU data would be located in the last seconds. This final peak was located with a window that shares similar size to the number of frames between the contacts of the first and last hammer test. The window starts at the first peak found in the synchframe structure array and runs through the signal until the end of the window finds the last peak under a threshold of -8 to -11. The location of the first peak is then adjusted in the synchrame structure array and later used to extract the relevant data.

$$synchframes.P16.T1\_3 : 209$$

**IMU Data Extraction**

Using the two structured arrays *synchframe* and *Video* we can then extract the IMU data points that corresponds with the frames of each activity. A new structured array that provides IMU data of each activity for each participant is then produced. Figure 12 shows a plotting of this data. Activities found are Sitting, STW, Swing phase, Other, and WTS. SwingPhase and Other will be activities used to see if we can recognize STW and WTS against other activities present.

$$IMU.P16.T1\_3.Sit2Walk : [1000 \times 11]$$

$$IMU.P16.T1\_3.Walk2Sit : [1000 \times 11]$$

**Data restructuring**

Now that we have an array of each movement per participant the data is then restructured. The data is then separated for each signal in each movement. This completes the Data extraction and we can now move on to the pre-processing step.

$$Data.Sitting.AccX : [[Cell.1], [Cell.2]...[Cell138]]$$

$$Data.Sitting.AccY : [[Cell.1], [Cell.2]...[Cell138]]$$

$$Data.Sitting.GyroX : [[Cell.1], [Cell.2]...[Cell138]]$$

$$Data.Sitting.GyroY : [[Cell.1], [Cell.2]...[Cell138]]$$

# D Appendix: Data extraction of IMU for Each Activity

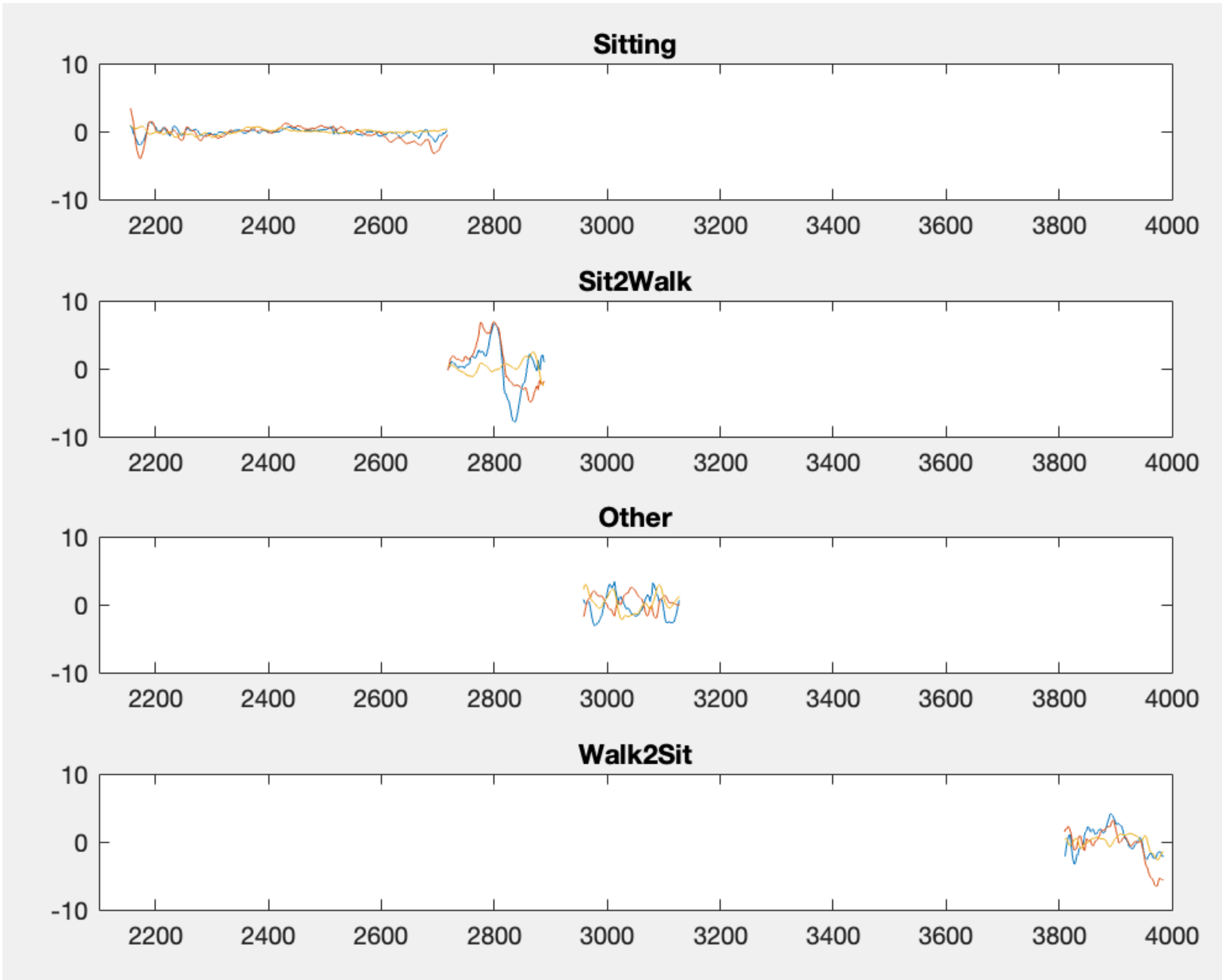



Figure 12: Plot of data extracted from the IMU accelerometer corresponding to each activity.

# E Appendix: Explination of Features Selected

| | |
|---|---|
| Mean | Calculates the sum of all values in the signals window then divides it by the total number of data points in the window in the time or frequency domain |
| Standard Deviation | quantifies the degree of dispersion or variability within a signals window. It is calculated by finding the square root of the average of the squared differences between each data point and the mean of the window. This can be found in the time or frequency domain. |
| Mean Absolute Deviation | Calculates the average amount by which each data point is different from the mean value of the window. This can be found in the time or frequency domain. |
| Root Mean Square | Another method in finding the "average" value in a window, but considers both positive and negative values. Data is squared, then the mean of these squared values is found, and finally it takes the square root of that mean. This can be found in the time or frequency domain |
| Maximum | The maximum value of a signals window in the time or frequency domain. |
| Minimum | The minimum value of a signals window in the time or frequency domain |
| Energy | Quantifies the signal's total power by summing the squared magnitudes of the frequency or time components in the signals window. |
| Inter-quartile Range | Specifically represents the range between the first quartile (25th percentile) and the third quartile (75th percentile) of the signals window in either the time or frequency domain. It indicates how much the middle 50% of the window's data varies. |
| Entropy | measures the level of disorder or uncertainty in a signals window. |
| Zero Crossing Rate | The rate at which a signal transitions from positive to zero to negative or negative to zero to positive. This can only be calculated in the time-domain |
| Cross-Correlation | Measures the similarity between two different signal windows to see how much they match or align in the time domain. |
| Signal Magnitude Area | quantifies the overall magnitude experienced by a body in the time domain. |

# Informed Consent

This informed consent form is for individuals who are invited to participate in this TU Delft study about Feature analyses of inertial data of sit-to-walk movement.

**Researchers:** Omri Raizman
**Supervisors:** Eline van der Kruk
**Organization Name:** Delft University of Technology (TUDelft)
**Faculty:** Mechanical, Materials, and Maritime Engineering (3ME) Faculty, TU Delft

Below is a brief introduction to the study and your role in it. If you agree to participate after reading this information, please sign the certificate of consent at the end of this form. You will receive a full copy of your signed Informed Consent Form, upon request.

## Information Sheet

**Introduction:** The risk of falls in elderly is often associated with transfer movements, such as sit-to-walk and walk-to-sit. These seemingly simple tasks can become challenging as individuals age due to various factors. Muscle strength and flexibility decline, leading to a decreased stability and balance control. Diminished physical functions can result in difficulties during transitions from sitting to walking, where walking occurs directly after standing skipping the stabilization phase. We believe proactively identifying the risks associated with transition movements could help reduce the incidence of falls. With this study we can measure inertial data using an inertial measuring unit containing an accelerometer, gyroscope and magnetometer (These sensors are often found in your mobile devices). With the inertial data we then look for distinguishable features that can be used to recognize these transfer movements in a machine learning algorithm.

**Who can participate in this study**
Healthy subjects ages 65 years and above, who are proficient in english.

**Who should not participate in the study**

- no prior muscular or skeletal injuries,
- no history of neurological or psychiatric disorders,
- no alcoholism,
- no history of balance problems
- no surgeries done in the past year
- Incompetence to give informed consent

**What does the study involve**
I will come to the participant's household in the Netherlands.

***What is expected of me***

Throughout the experiment I will be recording with a GoPro camera. I will also ask the participants to wear eSense earbuds as the inertial measure unit sensor. I will ask the participants to perform basic tasks in the house from a seated position. Activities in this experiment are 1) Wash their hands, 2) Retrieve a book from a shelf, 3) Stand up and walk within their homes. If the activity is considered difficult the participant can ask for the experiment to stop, or to take longer breaks. These activities will be asked to be performed five times. This experiment should take no longer than 1 hour depending on the participants.

**Possible harms or side effects of participating**: There are no known physical or physiological risks associated with the non-invasive attachment of the sensor to the head and the performance of the activities. At your request, the experiment can be stopped immediately if you feel uncomfortable.

**Data Policy**: Personal information such as your age in years, home address, phone number, gender, previous falls are asked before the experiments. During the experiments, identifiable (full-body) video recordings will be made of you performing the tasks. All the recorded data will be anonymized and stored safely without access to external parties. Personal data, which links your anonymized data to yourself, will be stored separately and only the researchers may have access to it. The video recordings will not be kept for longer than 2 months. Any other identifiable data (such as name, email address, telephone number) are stored separately from the recorded data and will not be kept for longer than 2 months. All information will be archived so that no one except the researchers and supervisors as listed above will have access to the data. On request, you will have access to your data. All data is made anonymous for publication purposes. The anonymized data will be processed and uploaded to an online repository in the advent of a possible publication. Informed consent forms with data indicating the participant does not fall under the exclusion criteria will be secured in a locked cabinet and kept for two years before being discarded.

**Participant's rights**: Participation in this research study is completely voluntary. Even after you agree to participate and begin the study, you are still free to withdraw at any time and for any reason. You have the right to ask that any data you have supplied to that point be withdrawn/destroyed, without penalty. You have the right to omit or refuse to answer or respond to any question that is asked, without penalty. You have the right to have your questions about the procedures answered (unless answering these questions would interfere with the study's outcome). If any questions arise as a result of reading this information sheet, you need to ask the investigators before the start of the experiment

**Cost, reimbursement, and compensation**: No cost, reimbursement, or compensation are applicable for this study.

**For further information:** The investigators and supervisors listed above will gladly answer your questions about this study at any time. If you are interested in the final results of this study, you can contact one of the investigators or supervisors. For questions, please contact Omri Raizman at

| PLEASE TICK THE APPROPRIATE BOXES | Yes | No |
|---|---|---|
| **A: GENERAL AGREEMENT – RESEARCH GOALS, PARTICIPANT TASKS AND VOLUNTARY PARTICIPATION** | | |
| 1. I have read and understood the study information or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction. | ☐ | ☐ |
| 2. I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason. | ☐ | ☐ |
| 3. I understand that taking part in the study involves video recordings being made that are identifiable and will be kept for 2 months. I agree that those video recordings are made during the experiments. | | |
| 4. I understand that during the experiment, sensor data is recorded by an Inertial Measure Unit sensor (accelerometer, gyroscope, and magnetometer) on the head in the form of eSense earbuds. | ☐ | ☐ |
| **B: POTENTIAL RISKS OF PARTICIPATING (INCLUDING DATA PROTECTION)** | | |
| 5. I understand that taking part in the study also involves collecting specific personally identifiable information (PII), such as gender, email address and phone number, and associated personally identifiable research data (PIRD), such as video recordings, with the potential risk of my identity being revealed. | ☐ | ☐ |
| 6. I understand that personal information and recorded data will be stored separately to minimize the threat of a data breach, and protect my identity in the event of such a breach. | ☐ | ☐ |
| 7. I understand that personal information collected about me that can identify me, such as name, email address and phone number, will not be shared beyond the study team. | ☐ | ☐ |
| 8. I understand that the identifiable personal data, such as video recordings, I provide will be destroyed a maximum of 2 months after | ☐ | ☐ |
| **C: RESEARCH PUBLICATION, DISSEMINATION AND APPLICATION** | | |
| 9. I understand that after the research study the de-identified information I provide might be used for future reports and publications | ☐ | ☐ |
| **D: (LONGTERM) DATA STORAGE, ACCESS AND REUSE** | | |
| 10.I give permission for the de-identified data such as force plate data and motion capture data that I provide to be archived in TU Delft repository so it can be used for future research and learning. | ☐ | ☐ |

**Signatures**

_________________________ _________________________ _________

Name of participant [printed] Signature Date

I, as researcher, have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

_________________________ _________________ _________

Researcher name [printed] Signature Date

Study contact details for further information: Omri Raizman