RAPPORT DE STAGE
D'INGENIEUR

Fitness Tracking System

SPÉCIALITÉ : **DATA SCIENCE**

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Organisme d'accueil :

General Introduction

During the past decade, numerous practical constraints associated with carry-on sensors, such as accelerometers, gyroscopes, and GPS receivers, have been successfully addressed. This progress has facilitated the monitoring and classification of human activity based on data from wearables like smartwatches, emerging as a burgeoning research area in pattern recognition and machine learning. The driving force behind this trend is the substantial commercial potential of context-aware applications and user interfaces. Additionally, activity recognition holds promise for addressing significant societal challenges such as rehabilitation, sustainability, elderly care, and health.

In the pursuit of promoting healthier lifestyles, previous efforts have focused on tracking movements and obtaining user feedback through exercise management systems. These systems partially replace tasks traditionally fulfilled by personal trainers. For instance, in aerobic exercises like bicycling, swimming, and running, there are accelerometer and GPS-based pedometers for tracking pace and distance, ECG monitors for measuring exertion, and electronic exercise machines such as treadmills, elliptical trainers, stair climbers, and stationary bikes. Weight training, a vital component of a balanced exercise program, lacks comprehensive studies on tracking free weight exercises. Presently, only one fitness wearable brand claims to automatically identify exercises and record repetitions. However, literature on context-aware applications in the strength training domain remains limited, likely due to commercial considerations.

With ongoing advancements in context-aware applications, the prospect of creating fully digital personal trainers seems feasible. To establish the requirements for such a digital trainer, this discussion briefly explores the roles of current personal trainers. These roles include a solid understanding of human anatomy, fundamental principles of exercise science and nutrition, the ability to design and execute tailored exercise programs effectively and motivationally, and the capability to track workouts to ensure proper form and progressive overload, contributing to clients' safe achievement of fitness goals. While progress has been made in digitizing the first two roles of personal trainers in recent years, the final and crucial role concerning safety and progress is not well-implemented in today's fitness wearables and applications.

The objective of this internship is to further explore the potential of context-aware applications within the strength training domain. This exploration involves analyzing accelerometer and gyroscope data from wristbands collected during free weight workouts. The dataset comprises information from five participants engaged in various barbell exercises with medium to heavy weights. The aim is to develop and assess models capable of, akin to human personal trainers, tracking exercises, counting repetitions, and detecting improper form. The methodologies employed in this internship draw inspiration from the work of Hoogendoorn and Funkuse, utilizing supervised learning approaches for classification. Various machine learning algorithms were trained using the collected dataset, and their accuracies were compared to identify the most suitable models.

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Chapter 1

Project Context

Project Context

Introduction

This section is devoted to introducing the project's context. We commence by introducing the host company where the internship transpired. Subsequently, we delve into a detailed presentation of the project, encompassing its context, challenges, and goals. Following this, we elaborate on the methodologies we employed. Lastly, we provide explanations of fundamental concepts and terminologies associated with our endeavor.

1.1 Host Company Presentation

1.1.1 General Presentation

German Links is a remarkable German-Tunisian language and communication institute that has woven a unique tapestry of success, rooted in the personal journey of its visionary founder. This extraordinary odyssey embarked upon by the founder began with an adventurous spirit, a career as an expatriate, and a passion for language and communication.

From humble beginnings, the founder embarked on a transformative path. Armed with a zeal for knowledge and a burning desire to create positive change, they undertook the role of an advisor at the town hall of Bad Waldsee in Germany. In this capacity, they were responsible for the vital aspects of social and professional integration for emigrants. Here, the founder honed their expertise in understanding the needs and challenges faced by individuals striving to build new lives in a foreign land.

Figure 1.1. German Links

The founder's journey didn't stop there. Through dedication and continuous self-improvement, they evolved from a town hall advisor into a forward-thinking entrepreneur. Today, they manage a personnel placement company in Germany that has become a beacon of hope for both immigrants seeking opportunities and employers looking for skilled talent.
German Links has not only thrived as a language and communication institute but has also contributed significantly to the community and business ecosystem. By fostering a deep understanding of cultural and linguistic nuances, German Links has become an invaluable partner for other enterprises looking to expand and engage with diverse communities.

In addition to its language and communication services, German Links has made a remarkable commitment to innovation and advancement. The institute has been a catalyst for a variety of projects aimed at the betterment of society. Notably, German Links has financed data science projects and web applications designed to benefit not just its own operations but the broader community.

These initiatives include supporting data science projects that analyze demographic trends, enabling local governments and businesses to make informed decisions regarding social integration and workforce development. Moreover, German Links has facilitated the development of web applications that streamline language education and cultural exchange, providing accessible resources to a wider audience.

In this ever-evolving journey, German Links has transcended its origins and embraced the role of a change-maker in both the social and corporate spheres. Its legacy is a testament to the power of personal dedication, cultural empathy, and a steadfast commitment to fostering innovation for the betterment of society. As German Links continues to bridge language gaps and nurture integration, it remains a beacon of inspiration for all who aspire to make a positive impact on the world.

1.2 Project Presentation

This section is dedicated to introducing the project's context, problem identification, and outlining our objectives. The project finds its origins within the framework of my Summer Internship project, marking the culmination of my engineering journey at the Private Higher School of Engineering and Technology. The execution of this project unfolded during a 2-month internship hosted by **German Links**.

1.2.1 Problem Statement

Strength training, when combined with aerobic exercises, plays a pivotal role in a well-rounded exercise program. Nevertheless, the development of automated systems for monitoring free weight exercises remains an area that has not been comprehensively studied. This internship seeks to delve further into the potential of context-aware applications in the realm of strength training. To achieve this goal, we examine the data generated by wristband accelerometers and gyroscopes during strength training sessions. The dataset collected for this internship encompasses information from five participants engaged in a variety of barbell exercises. Our primary objective is to investigate, create, and assess models capable of emulating human personal trainers by tracking exercises, counting repetitions, and identifying improper form. The methodologies employed in this report adopt a supervised learning approach for classification. We have trained several machine learning algorithms using the data we gathered and compared their accuracies to identify and assess the most suitable models for the task at hand.

1.2.2 Criticism Of The Existing

Critics of machine learning models used for tracking barbell exercises often point out several concerns related to their performance and user experience. These criticisms are expressed in a more human-friendly manner as follows:

1. **Setup and Calibration Issues:** Users often find it challenging to set up and calibrate these systems correctly. This can be time-consuming and frustrating, especially for those who are new to the technology.

2. **Maintenance and Support Issues:** Some systems might require ongoing updates, maintenance, and customer support, which could be inconsistent or insufficient, causing user frustration.

3. **Overemphasis on Numbers:** These models often focus on quantitative metrics like weight lifted and repetitions completed, which could overshadow the more qualitative aspects of exercise, such as enjoyment and overall well-being.

1.2.3 Proposed Solution

This internship seeks to address a notable gap in the existing research on applying machine learning algorithms to accelerometer data from free weight exercises. While previous work has demonstrated the potential of these algorithms to yield excellent results, there has been a notable neglect of the critical aspect of collecting high-quality datasets for strength training.

To tackle this issue, our study takes a novel approach by establishing an experimental environment that closely simulates real-world strength training workouts. One distinctive feature of our approach is the selection of exercises for the dataset. Unlike related works that often choose random sets of exercises without providing a clear rationale, we place a strong emphasis on the selection of exercises from a specific training program.

Our motivation for this approach is to ensure that the dataset is not cluttered with irrelevant or unlikely exercise combinations that one would never perform together during an actual workout. In our study, we have chosen to focus on exercises prescribed by the ”Starting Strength” program, created by Mark Rippetoe. This program is considered a cornerstone of strength training and is suitable for both beginners and experienced lifters, aiming to enhance strength effectively.

”Starting Strength” incorporates a set of fundamental barbell exercises that engage various muscle groups over the most effective range of motion, emphasizing progressive loading to stimulate the necessary adaptations for increased strength. These core exercises include the Bench Press, Deadlift, Overhead Press, Row, and Squat, as illustrated in this Figure .

By concentrating on exercises from this specific program, we aim to create a dataset that closely aligns with real-world strength training scenarios and ensures that the collected data is relevant and meaningful for individuals following this renowned strength training regimen.

1.3 Methodology

Managing a data science project can be a challenging task, as these projects require handling both vast data resources and carefully chosen and applied mathematical models. Consequently, without standardized project management methodologies, it’s easy to become lost in the intricacies of data science. Given its uniqueness, specialized and tailored methodologies have been devised to manage data science projects.

In this section, we introduce and compare two of these methodologies, and then make a selection among them.

1.3.1 SEMMA

It is a data exploration method that can be employed to address various business issues, such as fraud detection, customer retention, and churn analysis.
It comprises five phases (Sample, Explore, Modify, Model, and Assess), hence the acronym SEMMA. The figure below illustrates the distinct phases of the data science project lifecycle following the **SEMMA methodology.**

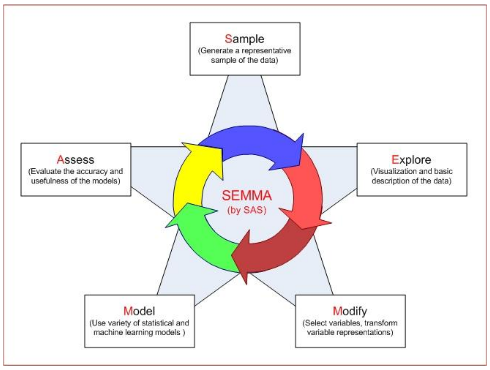

Figure 1.2. Phases of the SEMMA Methodology [**?**]

1. **Sampling (Sample)**: This step involves selecting a data sample that is both large enough to ensure it contains essential information and small enough to ensure fast processing.

2. **Exploring (Explore)**: In this step, we observe the data to discover and understand the various relationships and influences between variables. By the end of this phase, we have a better and deeper understanding of our data.

3. **Modifying (Modify)**: This step involves modifying the data by selecting the most significant variables, creating new variables that could be useful for analysis, or transforming variables if necessary. The result of this phase is a clean dataset that can be fed into the machine learning algorithm to build models.

4. **Modeling (Model)**: In this phase, various modeling techniques are applied to the previously cleaned data. Performance comparisons are made between each model and the desired outcomes, leading to the selection of the most appropriate model. Mathematical operations are carried out in this step to enhance the precision and accuracy of the results.

5. **Assessing (Assess)**: This is the final phase. At this stage, the model's performance is evaluated against test data to ensure the reliability and relevance of the modeling step. We compare our model's results with the actual results, and by analyzing the model's limitations, we attempt to correct and improve them.

1.3.2 CRISP-DM

CRISP-DM is a methodology invented in **1996**, outlining a set of stages that constitute the process of developing a **data mining project**. CRISP-DM unfolds across **six iterative phases**, spanning from business understanding to deployment, which we elucidate in this section.

1. **Business Understanding**: This phase involves understanding the project's objectives, requirements, and business constraints. The analyst formulates this knowledge into a data exploration problem and develops a preliminary plan.

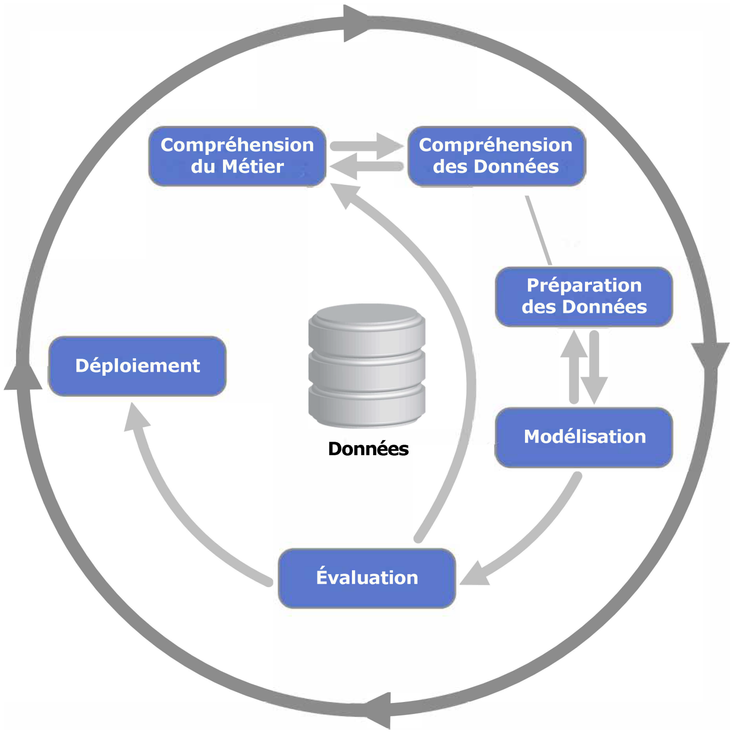

Figure 1.3. Phases of the CRISP-DM Methodology [**?**]

2. **Data Understanding**: Starting with data collection, the analyst continues operations and investigations to become familiar with the data, identify issues, and gain a better understanding of its content. In this phase, the analyst may also hypothesize hidden information.

3. **Data Preparation**: This phase encompasses all activities to construct the final dataset from the initial raw data.

4. **Modeling**: In this phase, the analyst defines and applies appropriate modeling techniques. Since some techniques have specific requirements regarding data structure, there might be a feedback loop to the previous data preparation phase.

5. **Evaluation**: In this phase, the models applied in the modeling phase are tested using suitable evaluation metrics. The goal of this evaluation is to ensure that the models are generalizable to previously unseen data. Additionally, the analyst validates that the models sufficiently cover all key requirements identified in the business understanding phase. The result of this phase is the selected final model.

6. **Deployment**: In this phase, the model selected in the **Evaluation** phase is deployed for consumption by end users. It's important to note that the code representation should also include all data preparation steps leading up to modeling. This ensures that the model will process new raw data in the same way as during model development.

1.3.3 Methodology Choice

Table 1.1 summarizes the mentioned data science project management methods.

METHODOLOGY	CRISP-DM	SEMMA
Number of Phases	6	5
Phase	Business Understanding Data Understanding Data Preparation Modeling Evaluation Deployment	———— Sample + Explore Modify Model Assess ————

Tableau 1.1. Summary table of Data Science methodologies.

In this section, we choose the appropriate methodology for our project from the two defined earlier. Let's start by comparing these two methodologies.

CRISP-DM has two additional steps compared to **SEMMA**, namely **"Business Understanding"** and **"Deployment"**.

The two phases **"Sample Data"** and **"Explore Data"** in the **SEMMA** process are present in the **"Data Understanding"** phase of the **CRISP-DM** process. Moreover, CRISP-DM is more comprehensive and documented, and it is widely used in data science projects.

Therefore, we have chosen to use the **CRISP-DM** methodology for its flexibility and well-organized steps.

1.4 Requirements Specification

Requirements specification is a crucial task before diving into project development, as it helps us have organized and clear ideas about what needs to be implemented.

This phase involves understanding the system behavior by defining the needs and requirements of the solution. In the following, we present the **business objectives**, which express the concrete functionalities of the product, as well as the **data science objectives**, which are quality indicators of the execution of the business objectives.

1.4.1 Business Objectives

Business objectives for tracking barbell exercise can vary based on the type of business or product involved. Here are some potential business objectives for implementing a barbell exercise tracking system:

- **Commercial Fitness Equipment Sales:** For companies that manufacture or sell fitness equipment, the objective could be to enhance the appeal of their products by integrating tracking technology, thus increasing sales and market share.
- **Subscription-Based Fitness Apps:** If a business offers a subscription-based fitness app, the goal might be to attract and retain more subscribers by providing a unique and effective tracking feature, ultimately boosting revenue.
- **Health and Wellness Services:** For companies in the health and wellness industry, the aim could be to offer personalized exercise tracking solutions that improve client outcomes, leading to positive reviews and more referrals.
- **Gym and Fitness Center Management:** Gyms and fitness centers can utilize tracking systems to enhance member engagement, retention, and overall satisfaction, ultimately increasing membership numbers and revenue.
- **Rehabilitation and Physical Therapy:** For businesses in the rehabilitation or physical therapy sector, the objective might be to use tracking to monitor patient progress and improve rehabilitation outcomes, which can lead to increased patient referrals.
- **Data Analytics and Insights:** Companies specializing in data analytics could aim to develop and sell insights extracted from exercise tracking data, providing valuable information to other businesses in the fitness and health industry.
- **Research and Development:** Some organizations might focus on research and development, seeking to advance the understanding of exercise science through the collection and analysis of data generated by tracking systems.

1.4.2 Data Science Objectives

The data science objectives for this project encompass the development of advanced text classifiers to enhance the Parental Advisory Platform's effectiveness in identifying and addressing inappropriate content. The objectives include:

- **Exercise Classification and Recognition:** Develop machine learning models that accurately classify and recognize different barbell exercises, contributing to improved tracking and analysis.
- **Form Assessment and Feedback:** Create algorithms to assess exercise form, providing real-time feedback to users and trainers to help ensure proper and safe execution.
- **Repetition Counting:** Develop systems that accurately count the number of repetitions performed in each set, reducing the need for manual tracking and enhancing workout efficiency.

- **Performance Metrics:** Implement data science techniques to extract performance metrics, such as power output, bar speed, and range of motion, to help users optimize their workouts.
- **Exercise Progress Analysis:** Use data analytics to track users' progress over time, identifying trends and improvements in their performance.
- **User Personalization:** Develop recommendation systems that personalize workout routines and weight selections based on individual user data and goals.
- **Anomaly Detection:** Create algorithms to detect deviations from proper form or unusual workout patterns, helping prevent injuries and improve safety.
- **Data Visualization:** Design data visualization tools and dashboards that make it easy for users and trainers to interpret and track exercise data.
- **Integration with Wearable Devices:** Develop data science solutions that integrate with wearable fitness devices, providing a seamless and comprehensive fitness tracking experience.

Chapter 2

Project Pipeline

Introduction

This chapter focuses on the theoretical and mathematical explanations of different algorithms, models, and concepts. These explanations form the basis for implementing the project. By understanding the inner workings and mathematical principles behind these methods, you'll make informed and innovative choices during the project's execution.

2.1 Data Understanding

2.1.1 Data Collection

While other works focused solely on accelerometer data, most current smart devices contain more carry-on sensors, like a gyroscope, which could provide additional information. Moreover, the sensors were placed in strange places like a band around the torso or a workout glove. If the goal is to create a commercial product out of these endings, then it should be implemented in something more practical, like a smartwatch, which already contains all of the required sensors. Therefore, MbientLab's wristband sensor research kit was used to collect data for this experiment. The wristband mimics the placement and orientation of a watch while allowing for controlled experiments. Data was collected using the default settings of the sensors: accelerometer: 12.500HZ and gyroscope: 25.000Hz. In order to collect a representative dataset, 5 participants were asked to perform the barbell exercises in 3 sets of 5 repetitions. Just as in the Starting Strength program. In another training session, the participants were asked to perform the same exercises but in 3 sets 10. These sets of higher reps will be used to see how models generalize over different weights. This resulted in a total of 150 (5x5x6) sets of data. Additionally, in between some sets 'resting' data was collected. To keep the data as representative as possible, the test subjects had no restrictions during the resting periods. Therefore, the resting periods are a mix of standing, walking, and sitting. This data will be used to examine the state change from rest to exercise

2.1.2 Weights

To determine the appropriate weight, the one rep max (1RM) metric was used. The 1RM is the maximum amount of weight that a person can possibly lift for one repetition . 1RM can either be calculated directly using maximal testing or indirectly using submaximal estimation. The latter method is preferred as it is safer and quicker. There are several common formulas used to estimate 1RM using the submaximal method, the Epley and the Brzycki being the most common . For this experiment Epley's formula was used:

$$1RM = w\left(1 + \frac{r}{30}\right)$$

Epley's formula, as mentioned earlier, calculates the one-rep max (1RM), with 'r' representing the number of repetitions and 'w' indicating the weight used. After determining the 1RM for each exercise, Epley's formula can be further employed to calculate the appropriate weight for sets of 5 or 10 repetitions. This corresponds to approximately 85% of the 1RM for 5 reps and 75% of the 1RM for 10 reps. Utilizing this method ensures that all participants engage in the exercises with weights tailored to their individual strength levels, promoting accuracy and safety in their workouts.

Participant	Gender	Age	Weight (Kg)	Height (cm)	Experience (years)
A	Male	23	95	194	5+
B	Male	24	76	183	5+
C	Male	16	65	181	<1
D	Male	21	85	197	3
E	Female	20	58	165	1

2.2 Converting Raw Data

The initial raw dataset consisted of a total of 69,677 entries, with each entry containing an epoch timestamp and x, y, and z-values obtained from the sensor on the wristband. To work with this data effectively, the individual sensor measurements were organized into separate files, each with a unique timestamp. To minimize data loss during aggregation, we opted for a small time step of t = 0.20 seconds, resulting in five data instances per second. For numerical values, aggregation was performed using the mean, while categorical attributes (labels) were aggregated using the mode. This aggregation process led to the creation of a consolidated dataset, which served as a valuable starting point for data visualizations and analysis. In Figure 2, accelerometer data for a heavy set of each exercise is displayed. The figure vividly illustrates the uniqueness of exercise patterns, with clear peaks that make it easy to identify individual repetitions. Figure 3, on the other hand, highlights the differences in y-acceleration between medium and heavy squat sets. Medium-weight sets exhibit higher peaks, while heavy sets display deeper drops. This observation aligns with the expected behavior, as medium-weight repetitions tend to move upwards more swiftly due to lower resistance, while heavy-weight repetitions descend more rapidly due to the significant load they bear.

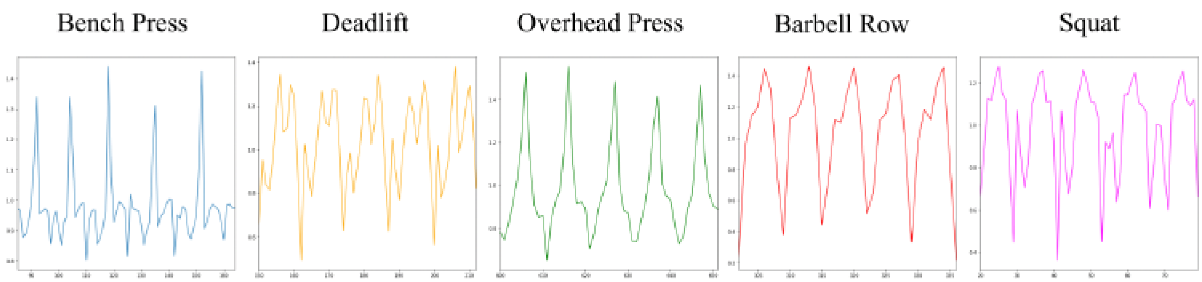

Figure 2.1. Accelerometer Data

Parts of our data that explain most of the variance are identifed. Two approaches will be discussed: Low-pass Filtering, which can be applied to individual attributes, and Principal Component Analysis, which works across the entire dataset.

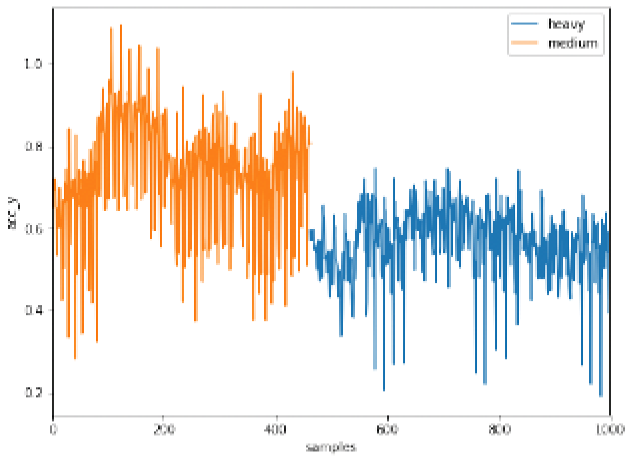

Figure 2.2. Medium and Heavy Weight squats

2.2.1 Low-pass Filter

The low-pass filter can be applied to data that is of temporal nature, and assumes that there is a form of periodicity. The Butterworth low-pass filter can remove some of the high frequency noise in the dataset that might disturb the learning process . The filter was applied to all but the target features. The visualizations showed that the movements have a frequency of around 2 seconds per repetition. After some further visual inspection of some trial-and-error results as suggested in the work of van den Bogert , the cut-of point was set at 1.3 Hz. The figure above shows the y-acceleration for a heavy bench press set before and after smoothing.

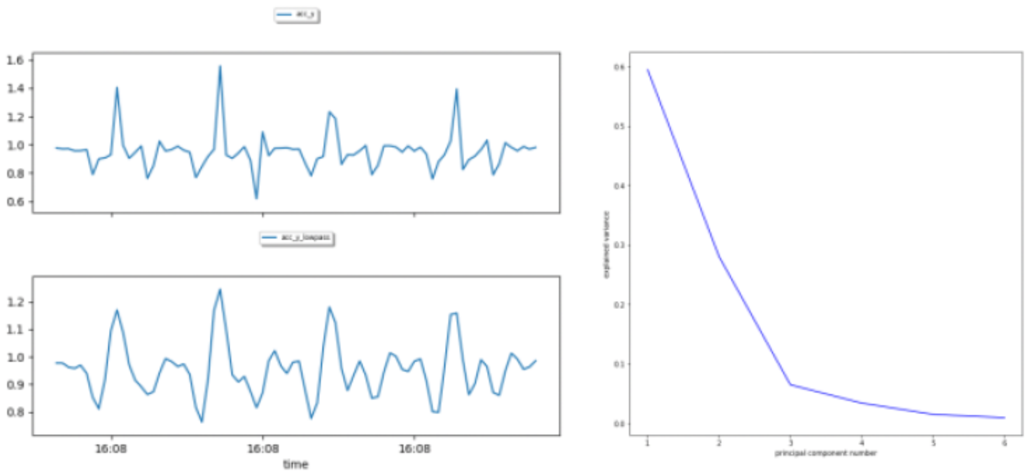

Figure 2.3. Low-pass Filter and Principal Component Number

2.2.2 Principal Component Analysis

A principal component analysis (PCA) was conducted to nd the features that could explain most of the variance. PCA was applied to all features excluding the target columns. The results are visualized in Figure 4 which shows that the explained variance drastically decreases after 3 components. Therefore, 3 components are selected and their values are included into the dataset.

2.3 Feature Engineering

This section we will discuss how additional features were derived from the original dataset including aggregated features, time features, frequency features, and clusters.

2.3.1 Aggregated Features

To further exploit the data, the scalar magnitudes r of the accelerometer and gyroscope were calculated. r is the scalar magnitude of the three combined data points: x, y, and z. The advantage of using r versus any particular data direction is that it is impartial to device orientation and can handle dynamic re-orientations . r is calculated by :

$$r_{magnitude} = \sqrt{x^2 + y^2 + z^2}$$

2.3.2 Time Domain

To exploit the temporal nature of the data, numerical data points were aggregated by taking the standard deviation (sd) and the mean of all features except the target columns over various window sizes. The sd should capture the varia-tion in the data over time. For example, the sd is expected to be higher during exercises than during resting periods. The temporal mean will indicate more about the general levels of the data, with less in uence from spiky noise. When selecting an appropriate window size, one should balance how strongly the data would be a ected by noise on the one hand, and maintaining predictive power on the other hand. Figure 5 shows the results for windows sizes of 2, 4, and 6 seconds. A windows size of 4 seconds was chosen and added to the dataset.

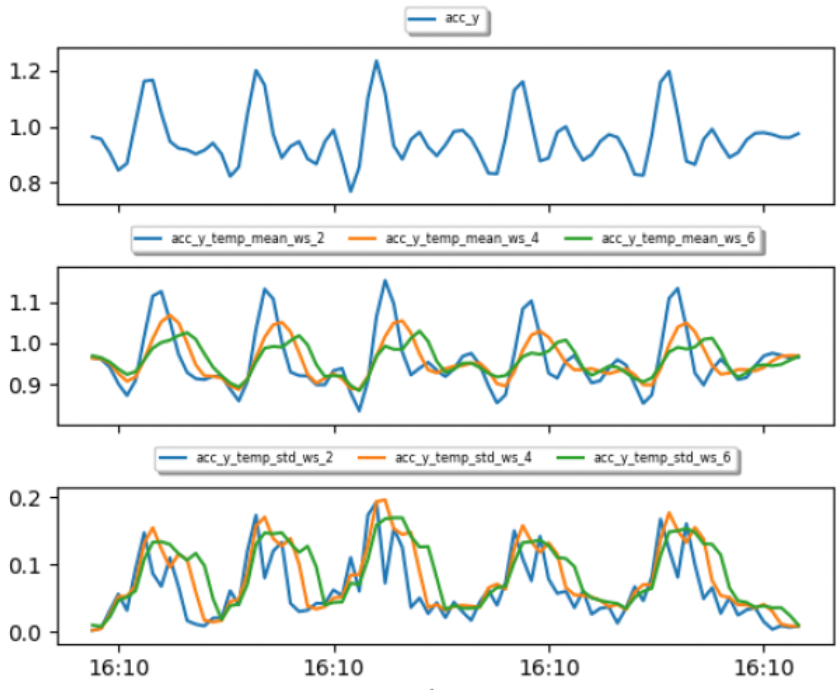

Figure 2.4. Numerical temporal aggregation with window size of 2, 4 and 6

2.3.3 Frequency Domain: Fourier Transformation

In addition to investigating the time domain, the frequency domain will also be examined. The concept of a Fourier transformation suggests that any set of measurements can be expressed as a blend of sinusoidal functions with varying frequencies. To compute the frequency characteristics, including the maximum frequency, the frequency signal weighted average, and the power spectral entropy, a Fourier Transformation was employed using a consistent window size of 4 seconds .

2.3.4 Clustering

A potential solution to predicting a label could be achieved through the utilization of a specific cluster membership. The primary focus of this approach would involve clustering the acceleration data, as the analysis indicated that the gyroscope data did not yield significant insights. After conducting various tests, it was determined that k-means clustering with a value of 4 for k was the most favorable method, as it yielded the highest silhouette score of 0.6478 when compared to alternative methods such as k-medoids and agglomerative clustering. Despite a slightly higher silhouette score for k=2, the decision was made to select 4 clusters, as this configuration effectively captured the distinct labels. The outcomes of this clustering analysis are visually presented in Figure 6. Additionally, Table 2 provides an overview of the distribution of measurements and corresponding labels. Notably, Cluster 1 predominantly encompasses bench press and overhead press data, which aligns with the similarity between these pressing movements. Cluster 2 accurately captures squat data, while cluster 3 successfully captures deadlift and row data with a perfect score. However, Cluster 4 exhibits some inaccuracies in capturing the remaining data

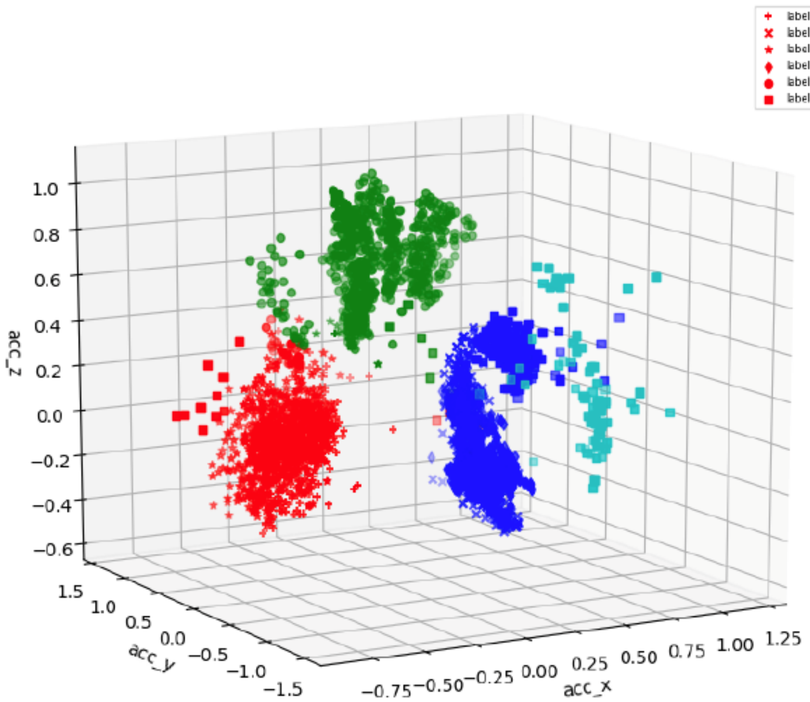

Figure 2.5. Clusters

Label	Cluster 1	Cluster 2	Cluster 3	Cluster 4
BenchPress	99.88 %	0.12 %	0.00 %	0.00 %
Deadlift	0.00 %	0.00 %	100.00 %	0.00 %
OHP	99.28 %	0.72 %	0.00 %	0.00 %
Row	0.00 %	0.00 %	100.00 %	0.00 %
Squat	2.98 %	97.02 %	0.00 %	0.00 %
Rest	4.14 %	3.78 %	50.45 %	41.62 %

Figure 2.6. Cluster Coverage

2.4 Modeling

The dataset has undergone processing and is now primed for training. It comprises of 6 fundamental features, 2 scalar magnitude features, 3 PCA features, 16 time features, 12 frequency features, and 1 cluster feature. The succeeding section will expound on the construction and assessment of models for classification, repetition counting, and form detection.

2.4.1 Classification

Due to the temporal characteristics of our dataset, the division of the training and test sets was conducted according to the exercise sets. The training dataset encompasses the initial two sets for each exercise, weight, and participant combination, while the test dataset comprises the remaining sets. This approach guarantees the availability of reliable test data that the models have not been exposed to previously.

- **Feature selection:** Forward feature selection was used to investigate which features contribute the most to performance, as useless features could impact the performance of the algorithms. Using a simple decision tree and gradually adding the best features, the results showed that after 15 features, the performance no longer significantly improved. The 5 features with the most predictive power are: pca 1, acc y, pca 3, gyr x temp std ws 4, acc r pse.

- **Regularization:** In order to punish more complex models, a regularizer was added to the objective functions. Figure 7 shows the impact of adding a regularization parameter on the performance for the training set. It indicates that the accuracy of the test set slightly improves with a higher regularization parameter, but only until a certain point. After that, the accuracy decreases on both the training and the test set.

- **Models:** First, an initial test run was done to determine the performance of a selection of models and features. This test included the following models: Neural network, Random Forest, Support Vector Machine, K-nearest Neighbours, Decision Tree, Naive Bayes. Grid search was performed on all of the models.

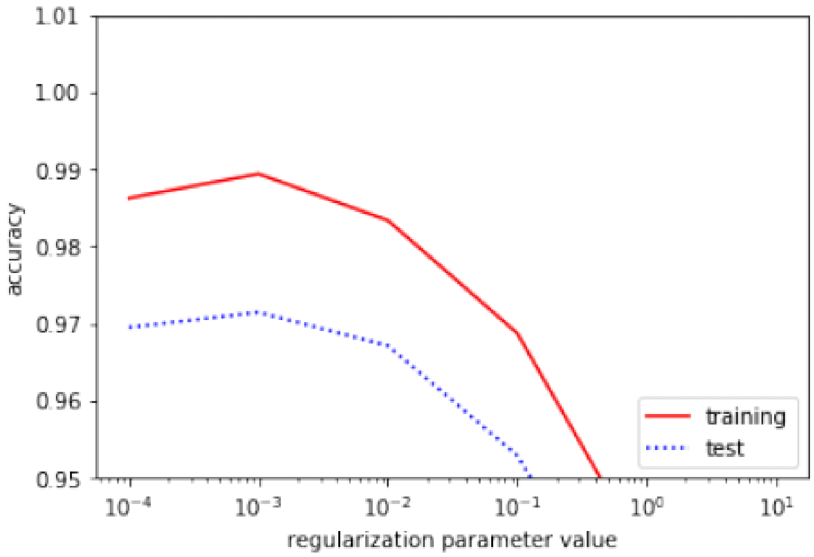

Figure 2.7. Regularization

2.4.2 Classification Results

The results per model can be seen on the left in figure 8. The colors represent the different feature sets as explained in [2]. The chapter 5 feature set contains all features. Based on these results a Random Forest was further optimized with the 15 best performing features. Using a 5-fold cross validation upon which grid search parameter tuning was performed, the following optimal parameters for the Random Forest were found: minimum samples per leaf: 2, n-estimators: 100, criterion: gini. A confusion matrix of the final predictions is shown on the right in the aobve Figure . The model achieved an overall accuracy of 98.51% with a similar precision, recall and f1-score on the test set.

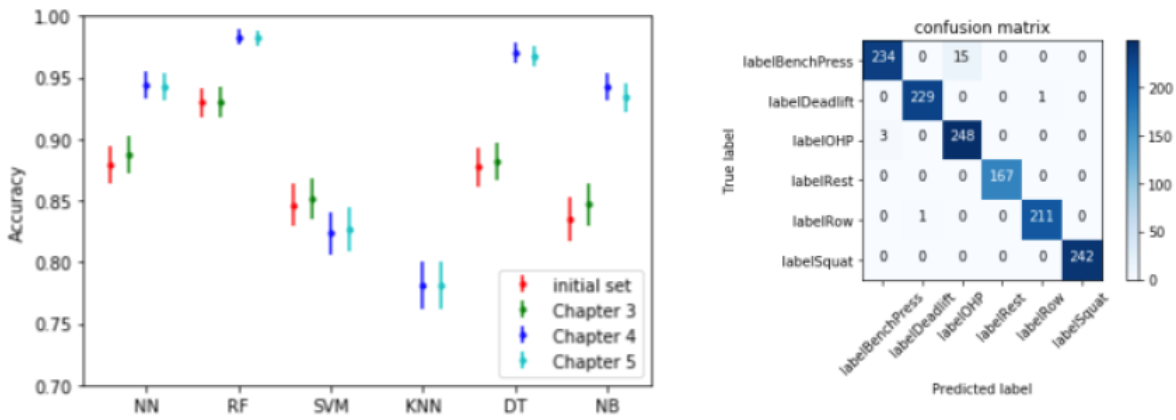

Figure 2.8. Model Performance and RF Classification Confusion Matrix

Chapter 3

General Conclusion

This internship aimed to investigate the potential of context-aware applications in the field of strength training. The motivation behind this research stemmed from the lack of emphasis on strength programs in existing literature and the limited support provided by current activity trackers. To gather relevant data, we collected data from wristband accelerometers and gyroscopes during actual strength training sessions. Five participants were involved in performing the five fundamental barbell lifts with both medium and heavy weights. To ensure the appropriateness of the weights used, we utilized the one-rep max (1RM) metric. By applying machine learning techniques inspired by the quantified self cycle, we identified the Random Forest model as the most effective exercise classification model. This model achieved an impressive overall accuracy of 98.51It is important to note that the model was not flawless, as it occasionally misclassified instances of bench press as overhead press and vice versa, as well as encountering similar issues with the deadlift and row exercises. This can be attributed, in part, to the similarities in wrist orientation during these exercises.