Exploring the Possibilities of The Most Effective Models for Exercise Tracking

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Abstract:
This paper investigates the development of context-aware applications for strength training, emphasizing the use of wristband accelerometers and gyroscopes to monitor free weight exercises. The objective is to design and evaluate machine learning models capable of identifying exercise type, counting repetitions, and detecting improper form, functioning as a virtual personal trainer. Data were collected from five participants performing a series of barbell exercises under controlled conditions. The collected sensor signals were processed, filtered, and synchronized to form a robust dataset suitable for model training and validation. Several supervised learning algorithms were applied, including Random Forest, K-Nearest Neighbors, Naïve Bayes, Decision Trees, and Neural Networks, to determine which models yield the highest classification accuracy. The results demonstrate that machine learning methods can effectively distinguish between exercise movements and detect deviations in form based on wrist sensor data. This research highlights the potential of wearable technologies and context-aware systems to enhance training safety, provide real-time feedback, and support personalized fitness programs through data-driven insights.

Chapter 1: Introduction

Recent developments in wearable sensors, such as gyroscopes and accelerometers, have accelerated the growth of activity monitoring via smartwatches and related devices, especially in the areas of machine learning and pattern recognition.
By investigating the possibilities of wristband accelerometers and gyroscopes in monitoring strength training exercises, this project tracks exercises, counts repetitions, and identifies incorrect form in an effort to create models that mimic personal trainers. Data from five participants performing barbell exercises are analyzed. In order to identify the best models for tracking exercise, the research compares various machine learning algorithms using a supervised learning methodology.
A review of related work, an explanation of data collection and processing techniques, feature extraction from the data, model construction and evaluation, and a summary of major findings round out the paper's structure.

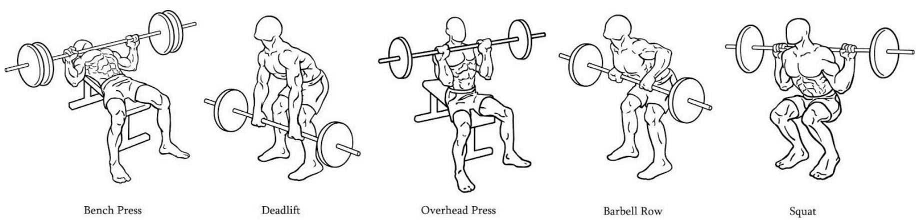


Fig. 1. Basic Barbell Exercise

Chapter 2: Approach

Group Organization and Task Assignments:

Our project depends on the efforts of Matin, Mohamad, and Arturo, each of whom makes a unique contribution to guarantee the project's overall success.

platform used:

- Google Colab

Tasks and Contributions:

Data Collection (Arturo):

- Ensuring the inclusion of barbell exercises performed by participants.
- Collaborated with Mohamad to integrate code functionality for automated recognition of exercise start and end points, optimizing data collection efficiency.

Experimental Setup, Data Synchronization, and Processing (Mohamad):

- Led the technical implementation across experimental setup and data preparation.
- Developed Python scripts to automate sensor calibration, exercise timing, and dataset synchronization across all sessions.
- Built a full preprocessing pipeline for raw sensor data, including advanced filtering, noise reduction, and augmentation to improve model generalization.
- Ensured end-to-end data quality, preparing the dataset for machine learning analysis and validation.

Model Selection and Training (Matin):

- Led the feature engineering phase, implementing Python code for Fourier transformation and k-means clustering to enrich the dataset.
- Explored and implemented machine learning algorithms, focusing on ensemble methods such as Random Forest.

Coding Collaboration (All Participants):

wrote, optimized, and reviewed Python code in a team environment while adhering to best coding practices and project-specific guidelines. Regular code review sessions were held to enhance the implemented algorithms' quality, efficacy, and maintainability.

Chapter 3: Progress and Achievements (Phase 1)

3.1 Data Collection

We collected data using MbientLab's wristband sensor research kit, which was selected due to its usefulness and similarity to a smartwatch, featuring a gyroscope and accelerometer. To test the model's generalization across varying exercise intensities, five participants—three sets of five repetitions for barbell exercises and three sets of ten repetitions for another—participated in the study. This method produced 150 sets of exercise data in total. To ensure that the dataset is comprehensive and representative of typical workout scenarios, data was also collected during "resting" periods, which included sitting, walking, and standing. This allowed for the analysis of transitions from rest to exercise.

3.2 Combination of Raw Data

The raw dataset included 69,677 entries, each of which included the wristband's x, y, and z sensor values along with an epoch timestamp. For coherence, the data—which had previously been stored in distinct files with distinct timestamps—was combined. The cleaned dataset made for more impactful visualizations. For instance, distinct exercise patterns and the ability to clearly identify repetitions from data peaks were shown in accelerometer data that was visualized for a heavy set of each exercise. The difference in y-acceleration between the medium and heavy weight squat sets was another thing to notice. The medium weight sets had deeper drops (because of the higher load causing faster downward motion) and higher peaks (because of lower resistance and faster upward motion)

3.3 Overview of Dataset Composition

The dataset comprises data from five unique participants (A, B, C, D, and E) who engaged in six different activities: Bench, Overhead Press (OHP), Squat, Deadlift (Dead), Row, and Rest. A total of 91 unique sets were recorded.

Fig. 2. Accelerometer and Gyroscope Data

3.4 . Sensor Data Distribution

The histograms provided a glimpse into the general behavior of the accelerometer and gyroscope readings:

Accelerometer:

- Readings along the X-axis are centered around zero, displaying a fairly symmetric distribution.
- The Y-axis readings are a bimodal distribution.
- The Z-axis readings are right-skewed, with a majority of the data points around zero.

Gyroscope:

- The readings across all three axes show distributions centered around zero, suggesting rotational stability for most of the data points.

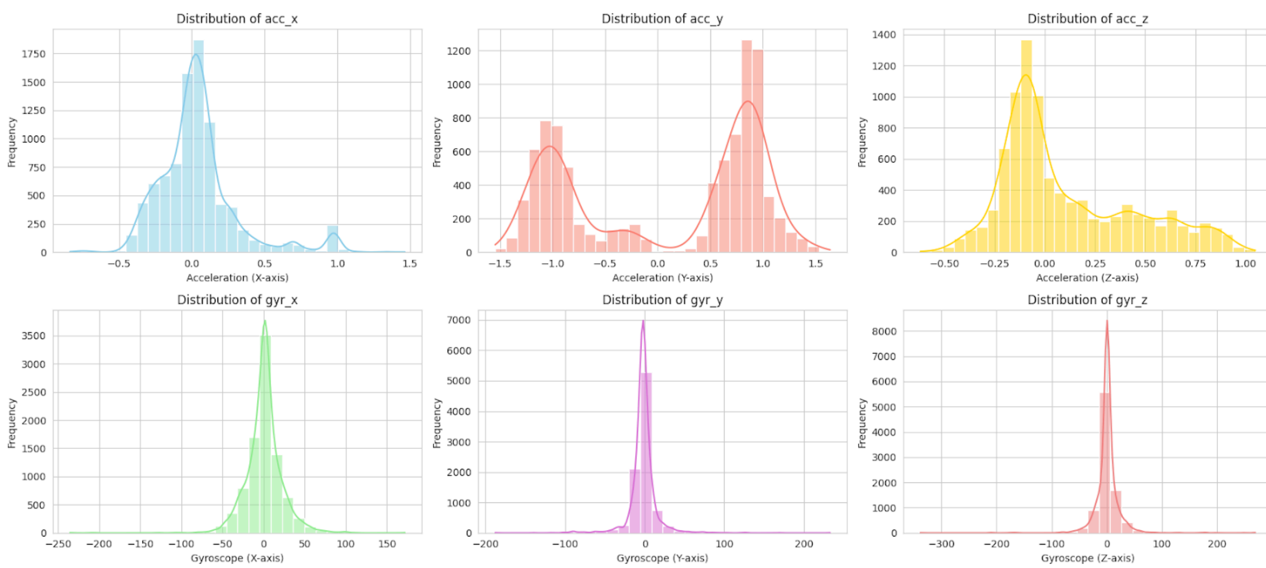


Fig. 3. Distribution of Accelerometer and Gyroscope Data Components

3.5. Activity Insights

Box plots were utilized to compare the spread and central tendency of accelerometer and gyroscope readings for each activity:

Activities like "rest" typically had compact ranges, indicating consistent measurements.

In contrast, activities like "squat" and "bench" displayed wider spreads and varied sensor readings, hinting at the diverse movements involved in these exercises.

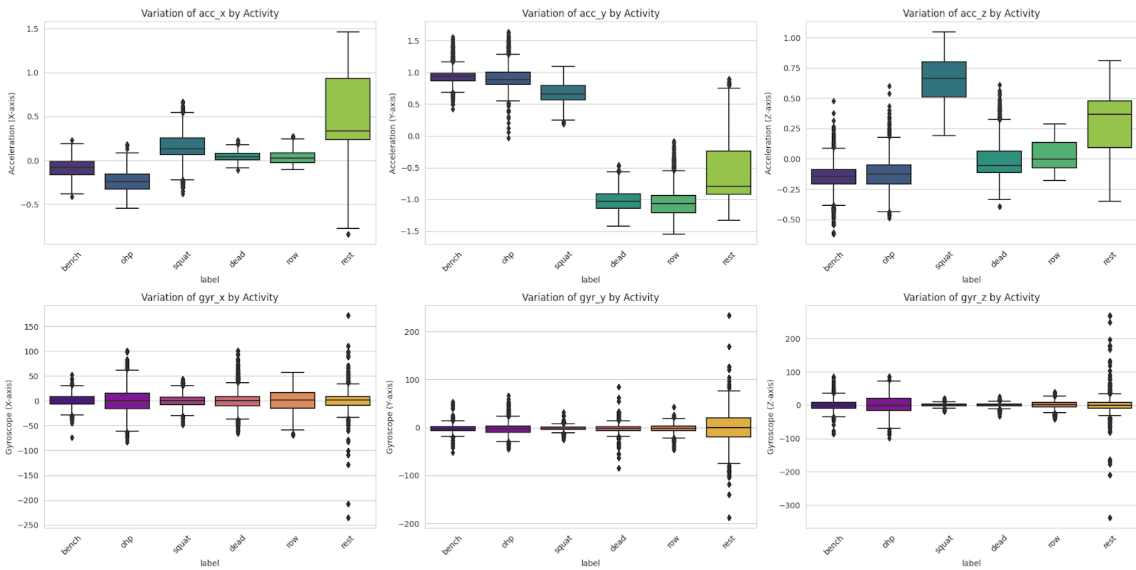


Fig. 4. Box Plots Comparing Accelerometer and Gyroscope Readings Across Activities

3.6. Participant Behavior

Each participant showcased unique movement patterns, especially evident when analyzing the "bench" activity:

Participants had distinct characteristics in their accelerometer readings, indicating different movement techniques or postures.

Variations in gyroscope readings emphasized the individualized rotational movements during the bench exercise.

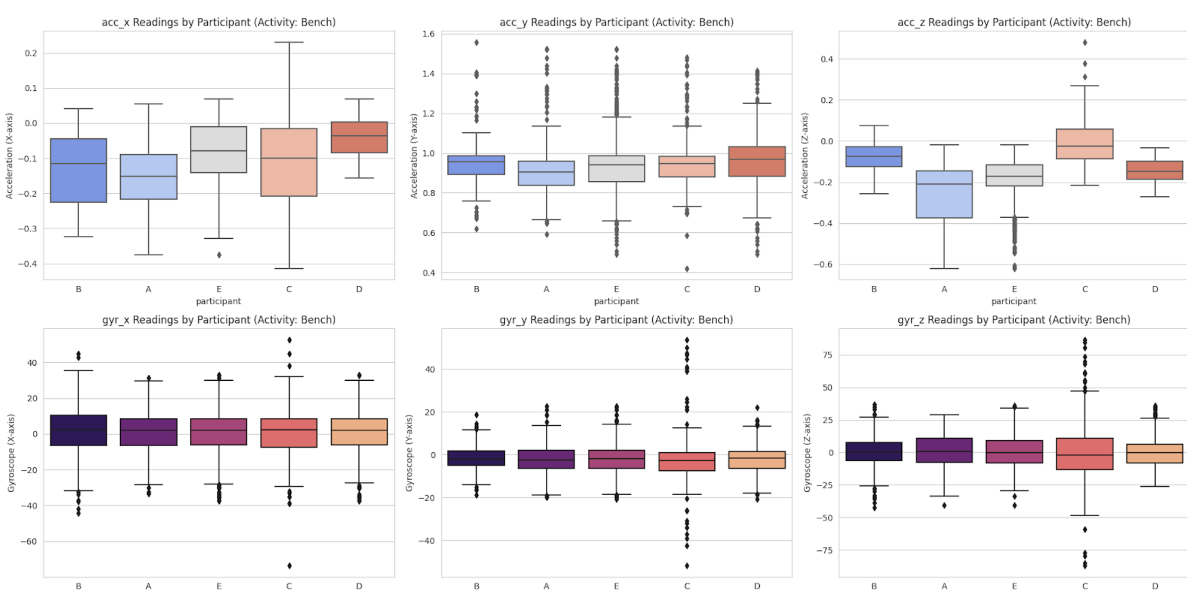


Fig. 5. Participant Behavior - Unique Movement Patterns in "Bench" Activity

3.7. Intensity Analysis

The exercise intensity, classified as "heavy" or "light," had a profound effect on the sensor readings:

"Heavy" exercises generally displayed a more compact range, suggesting controlled and consistent movements.
"Medium" intensity exercises showed wider spreads in readings, indicating varied movements.

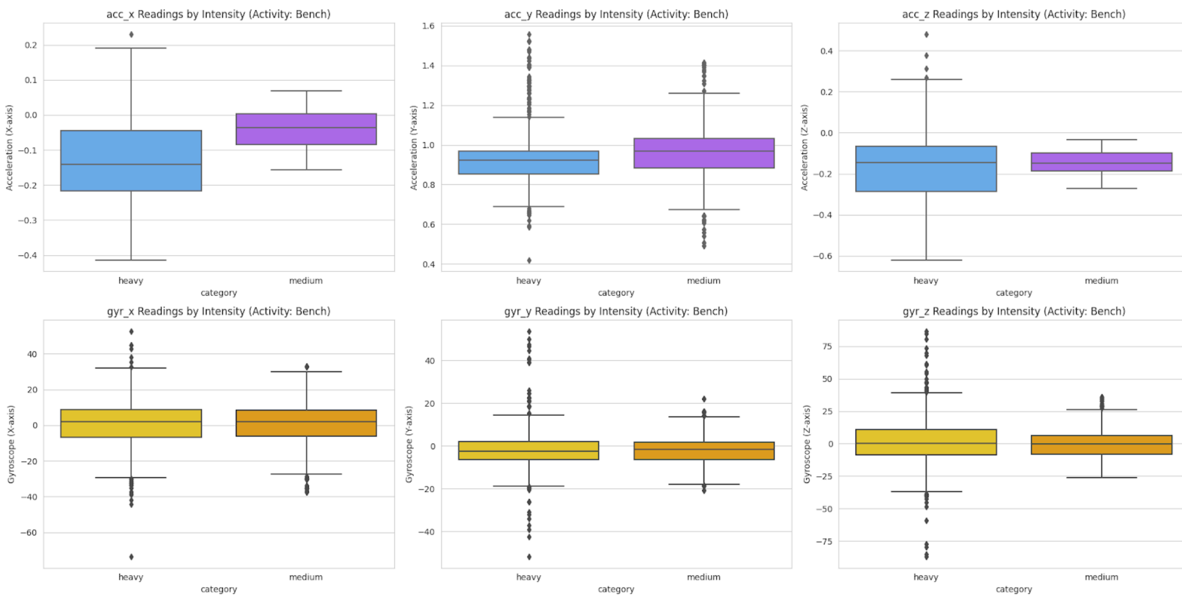


Fig. 6. Intensity Analysis of Sensor Readings

3.8. Conclusion:
Through this analysis, we've uncovered patterns in movement based on activities, participant behaviors, and exercise intensities. These insights can guide fitness trainers, athletes, or individuals in tailoring training regimes, making informed decisions, or detecting inconsistencies in workout techniques.

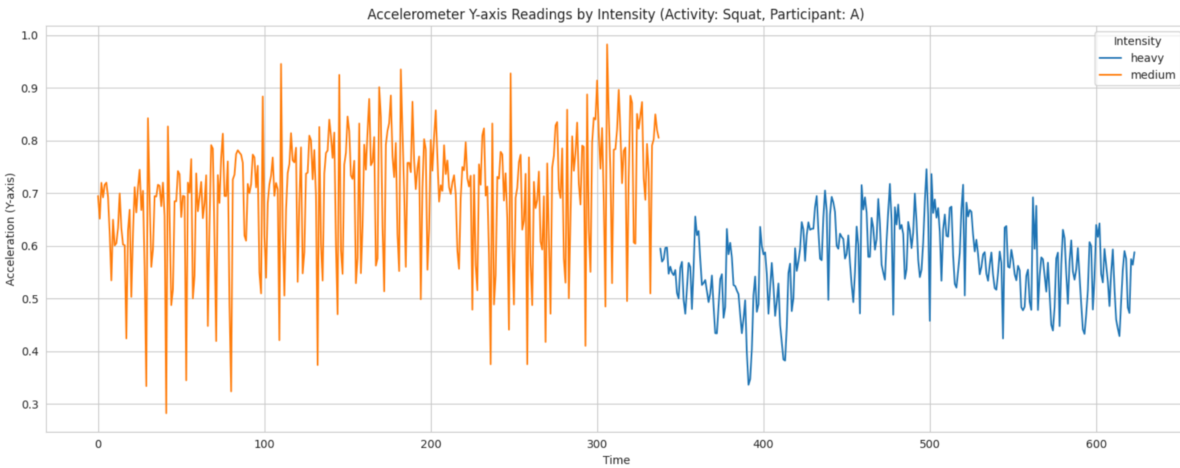


Fig. 7. Squat Activity - Accelerometer Y-axis Reading

Chapter 4: Refinement and Analysis (Phase 2)

Building upon the collected dataset, Phase 2 involved refining the data and conducting in-depth analyses to derive valuable insights. This phase includes several key steps:

4.1 Mark outliers Chauvenet

Finds outliers in the specified column of datatable and adds a binary column with the same name extended with '_outlier' that expresses the result per data point.

4.2 Low-pass Filter

The low-pass filter operates on the assumption that there is some sort of periodicity and can be applied to temporal data. Some of the high frequency noise in the dataset that might impede learning can be eliminated by the Butterworth low-pass filter. Everything was filtered out except the desired features. The fraction of the Nyquist frequency, or half of the sampling frequency, is how cutoff frequencies are expressed.

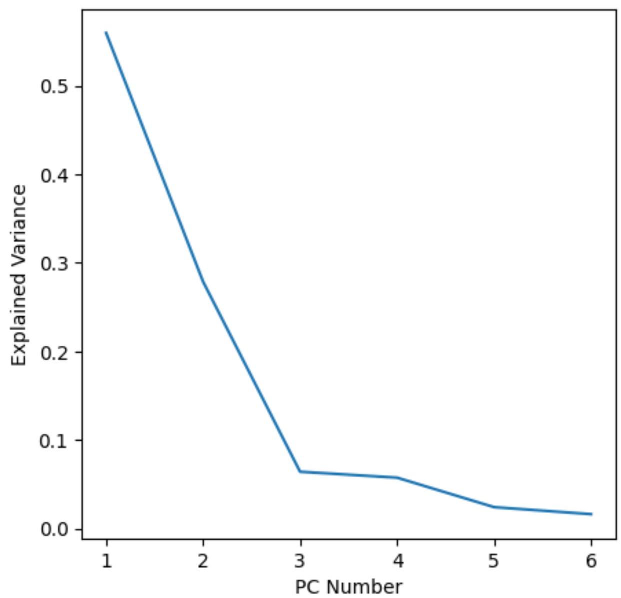


Fig. 8. Low-pass Filter and Principal Component Number

4.3 Principal Component Analysis

To identify the characteristics that could account for the majority of the variance, a principal component analysis (PCA) was performed. All features, with the exception of the target columns, underwent PCA. Figure 8 presents the results and illustrates how, after three components, the explained variance sharply drops. As a result, three components are chosen, and the dataset contains their values.

4.4 Frequency Domain: Fourier Transformation

Utilizing a fast fourier transform, determine the amplitudes of the various frequencies. In this case, the sampling rate (i.e., frequency, which is the dataset's Hertz) indicates the quantity of samples per second. Obtain frequencies within a specific window.

4.5 New dataset

Create new columns for the frequency data. Pass over the dataset (we cannot compute it when we do not have enough history) and compute the values.

4.6 Clustering

A label may be predicted in part by belonging to a particular cluster. The results indicated that the gyroscope data was not useful, so the focus will be on clustering the acceleration data. Following some experiments, the best approach was k-means clustering (k=5). Because they best represented the various labels, five clusters were selected.

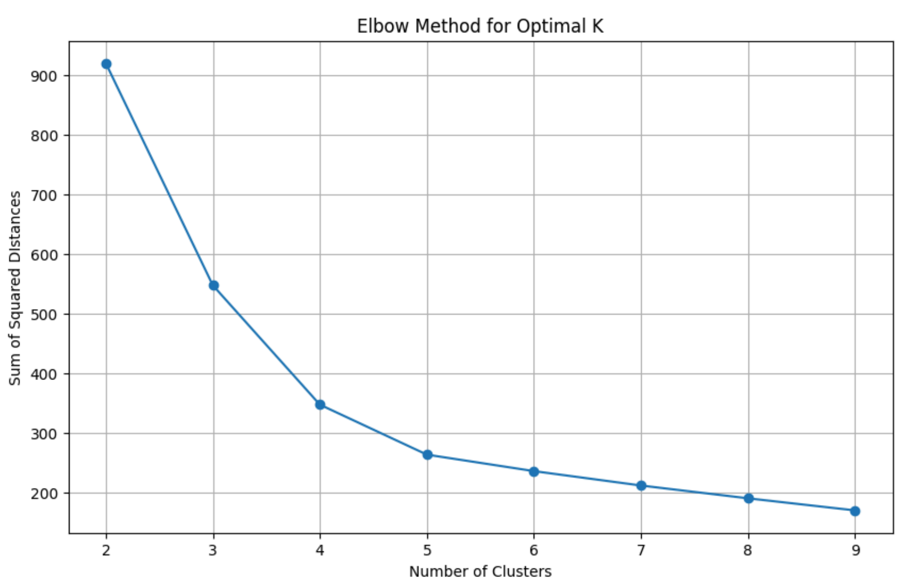
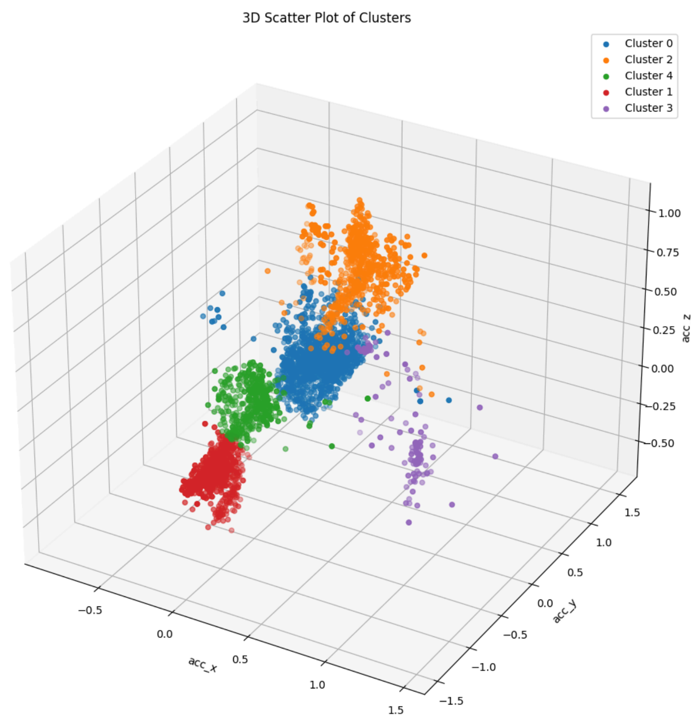


Fig. 9. KMeans

Fig. 10. Clusters



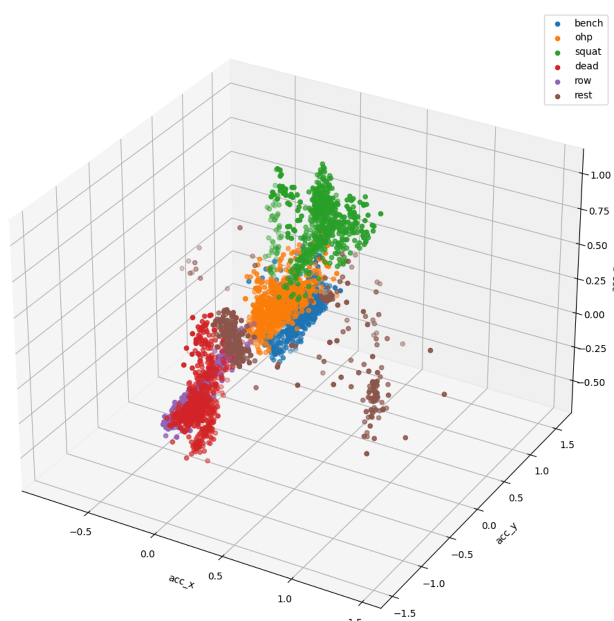


Fig. 11. Clusters labels

4.7 Predictive Modeling

Different sets of features were defined and used in our data analysis to capture different aspects of the sensor data. The raw gyroscope (gyr_x, gyr_y, and gyr_z) and accelerometer (acc_x, acc_y, and acc_z) data are included in the basic_features set. Square_features, which include squared values of accelerometer and gyroscope readings (acc_r, gyr_r) were added to provide additional dimensions and improve the ability to detect movements with varying magnitudes. Furthermore, pca_features (pca_1, pca_2, pca_3) were added to the data in order to highlight the principal components and lower dimensionality. Additionally, we took into account frequency-based (freq_features) and temporal (time_features) characteristics, which were taken from the dataset as features with the terms "temp," "freq," or "_pse," respectively. In order to capture possible clusters in the data, cluster_features was added in the end. These elements are gradually integrated into the feature sets, which begin with f_set1's fundamental features and progress to f_set4's comprehensive feature set for strong data analysis.

```python
basic_features = ['acc_x', 'acc_y', 'acc_z', 'gyr_x', 'gyr_y', 'gyr_z']
square_features = ['acc_r', 'gyr_r']
pca_features = ['pca_1', 'pca_2', 'pca_3']
time_features = [f for f in df.columns if '_temp_' in f]
freq_features = [f for f in df.columns if ('_freq_' in f) or ('_pse' in f)]
cluster_features = ['cluster']

f_set1 = list(set(basic_features))
f_set2 = list(set(basic_features + square_features + pca_features))
f_set3 = list(set(f_set2 + time_features))
f_set4 = list(set(f_set3 + freq_features + cluster_features))
```

Fig. 12. Code for Feature sets

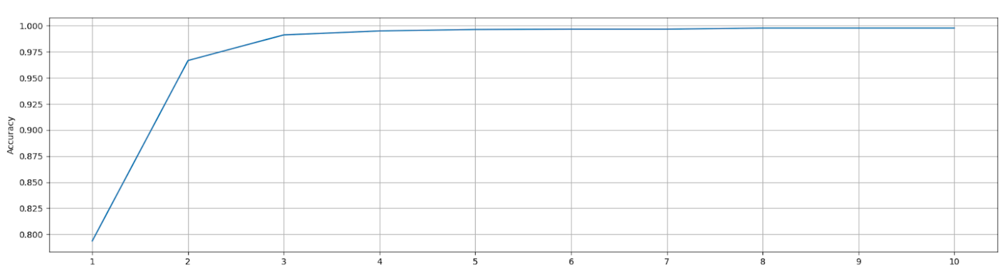


Fig. 13. number of Features

First, a preliminary test run was conducted to evaluate a range of models and features. Neural networks, Random Forests, K-nearest Neighbors, Decision Trees, and Naive Bayes were among the models used in this test.

4.8 Accuracy of the Models

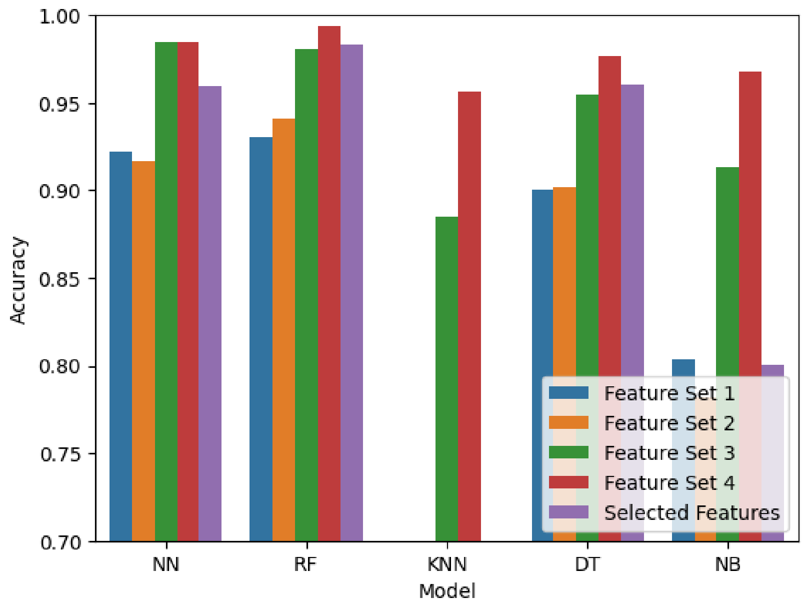


Fig. 14. Accuracy of the Models

```
acc = accuracy_score(y_test, class_test_y)
print(f'Accuracy of the model is {acc}')
```

```
Accuracy of the model is 0.9937888198757764
```

Fig. 15. Accuracy

4.9 Confusion Matrix

We used a confusion matrix, represented as a heatmap, to assess our classification model. Different classes were identified by comparing the test labels with the predicted labels in the matrix. The heatmap was improved with a color bar and blue color scheme, which made it easier to read the true labels on the y-axis and the predicted labels on the x-axis. To help with the rapid identification of the model's accurate and inaccurate classifications, we highlighted the matrix values using contrasting text colors based on a threshold calculation. The effectiveness of the model's performance in various categories was shown by this visual aid.

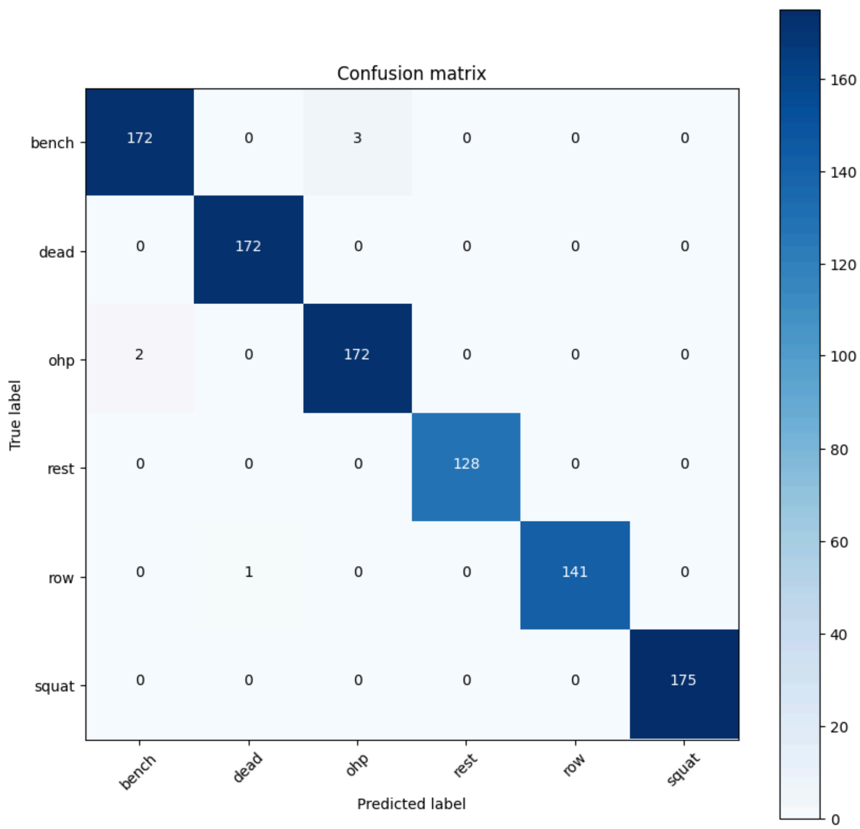


Fig. 16. Confusion Matrix

Chapter 5: Schedule

4820 (First Semester of 2023):

- **Week 3-10:**
  - Introduction: Provide an overview of the project, including its goals and the concept of quantified self.
  - Goal Setting: Define the objectives and expected outcomes of the exercise tracking models.
  - Quantified Self: Explore the concept of quantified self, emphasizing the role of wearable technology.
  - MetaMotion Sensor: Introduce the MbientLab's wristband sensor research kit and its features.
  - Dataset Preparation: Begin collecting raw data from participants during barbell exercises.
- **Week 10-16:**
  - Data Processing: Convert raw sensor data into a usable format by reading CSV files, splitting data, and performing necessary cleaning procedures.

4830 (Second Continued Semester of 2023):

- **Week 1-3:**
  - Data Visualization: Use Python scripts to visualize the collected data and plot time series data.

- **Week 3-5:**
  - Outlier Detection: Implement outlier detection techniques, including Chauvenet's criterion and local outlier factor.

- **Week 5-8:**
  - Feature Engineering: Develop algorithms for feature engineering, including frequency analysis, low-pass filtering, PCA, and clustering.

- **Week 8-11:**
  - Predictive Modeling: Explore and implement predictive models such as Naive Bayes, *Random Forest, and Neural Network.

- **Week 10-16:**
  - Project Paper: Compile the findings, methodology, and results into the final project paper.

Chapter 6: Cost

In this part, we explain the financial components of our project:

Itemized Costs:

1. **Equipment (Wristband Kit):**

The use of the Wristband Kit by MbientLab is a critical component of our research. This package, which includes accelerometers and gyroscopes, is essential for gathering complete sensor data during strength training activities. The price of the Wristband Kit is $175.34.

2. **Gym Membership:**

The crew obtained gym memberships collectively to enable the gathering of strength training workout data. The following is a breakdown of the gym membership costs:

A monthly price of $14.99 is charged to each team member, an annual fee of $49 is charged to each person, and a one-time sign-up fee of $99 is charged to each team member. To get the total cost for one person, multiply the monthly rate by 12, then add the yearly fee plus the sign-up fee. Extending this to cover the entire team of five members,
($14.99 x 12 + $49 + $99) x 5 = $1639.40

The total cost for gym memberships comes to $1639.40.

Chapter 7: Lessons learned

The development of wristband-sensor-based exercise tracking models provided our team with a valuable educational experience. Through this project, we refined our ability to collaborate effectively by establishing clear roles, maintaining consistent communication, and adapting to challenges as they arose. Flexibility proved essential to our success, particularly when unforeseen technical and logistical issues required quick problem-solving.

Each team member strengthened key competencies, including analytical reasoning, machine learning techniques, experimental design, and data collection. The interdisciplinary nature of the work demanded coordination between software engineering, signal processing, and human activity analysis, which broadened our technical and collaborative skill sets.

At the beginning of the project, we defined its scope and divided the workload into structured subtasks to ensure efficiency and accountability. Regular meetings allowed us to track progress, share insights, and address issues promptly, minimizing delays and ensuring data quality. When the originally planned wristband sensor was unavailable, the team quickly restructured the experiment using an alternative device that achieved comparable performance, demonstrating adaptability under constraints.

Mohamad led much of the data processing and automation work, while Matin and Arturo focused on modeling and data collection respectively. Each role was essential to the overall outcome, and the integration of these contributions ensured that the project met both its technical and analytical objectives.

Overall, this project strengthened our teamwork, technical proficiency, and problem-solving abilities. It emphasized the importance of adaptability and interdisciplinary cooperation in successfully executing complex engineering projects.

Chapter 8: Conclusions

To sum up, this project has demonstrated the potential of context-aware applications to enhance the accuracy, safety, and effectiveness of strength training. Using wristband accelerometers and gyroscopes, we successfully tracked and analyzed barbell exercises to provide real-time feedback and personalized recommendations. The implemented models proved capable of identifying exercise type, counting repetitions, and detecting improper form, offering a data-driven foundation for injury prevention and performance optimization.

Furthermore, integrating context-aware technology into fitness applications opens new possibilities for customized workout programs tailored to individual users' fitness levels, goals, and available time. Such systems make strength training more accessible and engaging, bridging the gap between professional coaching and personal training.

As wearable technology and data analytics continue to evolve, these advancements will enable the collection of more detailed motion and performance data. This will further improve the precision and personalization of fitness feedback, marking an important step toward intelligent, adaptive training systems. The future of context-aware applications in fitness is promising, with the potential to redefine how individuals approach physical training and health monitoring.

Acknowledgments:

We express our gratitude to our advisor, Dr. Tim H. Lin, for his guidance and support throughout this project.