MACHINE LEARNING FOR STRENGTH EXERCISE CLASSIFICATION AND REPETITION COUNTING

GROUP 3

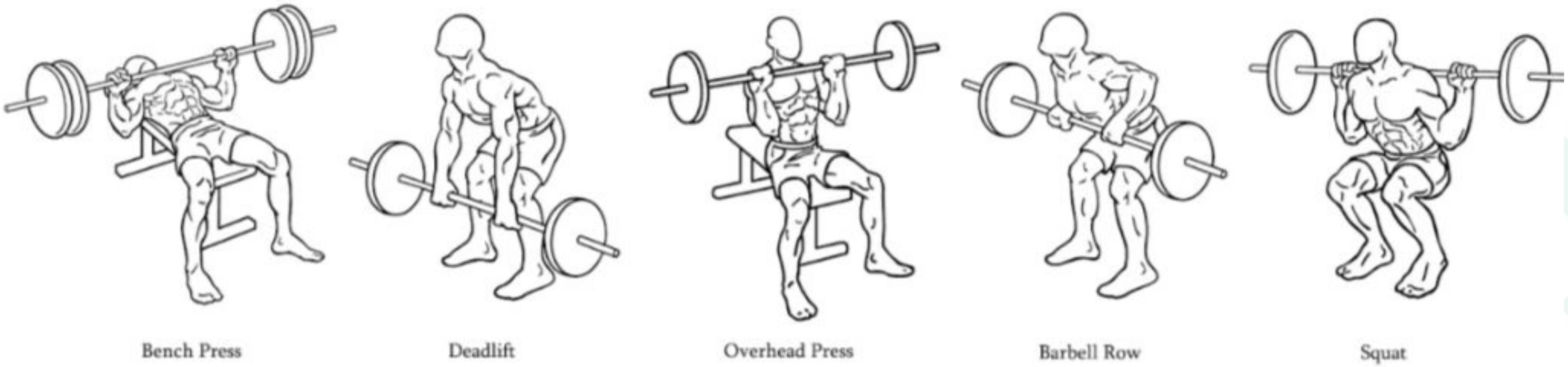
GRISHMA BELLANI
RIYA GUPTA
SHREYANSH SRIVASTAV
SHRUTYA CHAWLA
VIMANSH MAHAJAN

INDRAPRASTHA INSTITUTE *of* INFORMATION TECHNOLOGY
DELHI

ML FINAL PROJECT- GITHUB

MOTIVATION

- **Current Challenge**: Fitness wearables excel in tracking aerobic exercises but struggle with accurately monitoring free-weight exercises like barbell workouts.
- **Research Goal**: Leverage accelerometer and gyroscope data from wearables to:
  - Track barbell exercises
  - Classify barbell exercises
  - Count repetitions



LITERATURE REVIEW

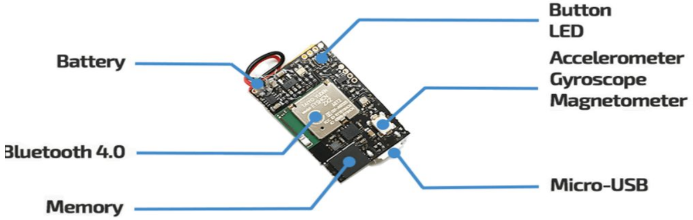
- **ML methods for the automatic evaluation of exercises on sensor-equipped weight training machines**
  - Source
  - **Objective**: Tracks movements by utilizing Support Vector Machines (SVM) and Artificial Neural Networks (ANN) to predict the quality of exercises performed by athletes.
  - **Features:** Force, weight, displacement, velocity, duration of exercise.
  - **Outcome**: Classification accuracy of 85% on validation set under 81 epochs.

- **ML Based Fitness Tracker Platform Using MEMS Accelerometer**
  - Source
  - **Objective**: Determine health status(fit/ unfit) by using Logistic Regression.
  - **Features:** Accelerometer data (X, Y, Z axes), count steps, calories taken
  - **Outcome**: Classification accuracy of 85.42%

DATASET DESCRIPTION

Source: MetaMotion sensor watches- [Link for dataset]

MetaMotion Sensor



1. Data was gathered from 5 participants over a period of 20 days with 69,677 entries.
2. The dataset consists of multiple columns, including:
   - **epoch:** Timestamp representing when the data was recorded.
   - **acc_x, acc_y, acc_z:** Acceleration values along the x, y, and z axes, respectively. This is crucial for identifying motion-related activities based on the intensity and direction of movement.
   - **gyr_x, gyr_y, gyr_z:** Gyroscopic data along the x, y, and z axes, respectively, This tracks angular velocity or rotational motion, helping to distinguish movements involving rotation or turning.
   - **participant:** Identifier for the individual performing the exercises.
   - **category:** Indicates heavy or medium weights.
   - **label:** Specifies the type of exercise performed, such as squat, bench press, or deadlift.
   - **set:** Identifies the set number within the exercise routine.
3. Additionally, **resting data** was included to capture state changes between rest and activity.

DATASET DESCRIPTION

Participants (N=5)

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

Figure 1. Participants

SNAPSHOT OF PARTICIPANTS FROM WHOM THE DATA WAS COLLECTED

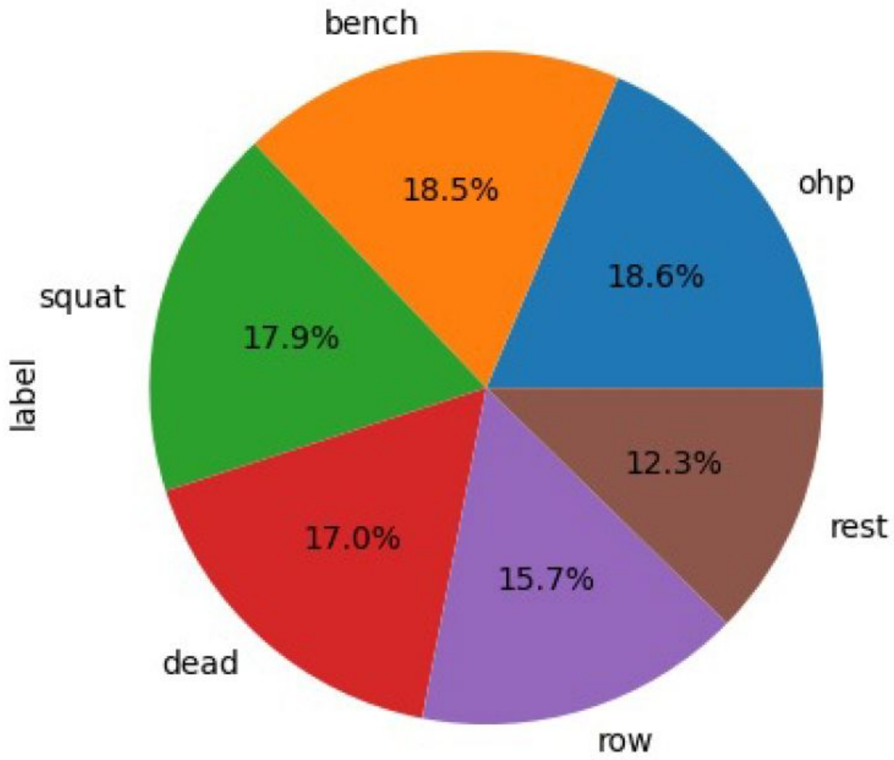


Figure 2. Distribution of labels

DISTRIBUTION OF LABELS- **No class imbalance!!!**

DATASET DESCRIPTION – PREPROCESSING STEPS

1

DATA AGGREGATION

Temporal aggregation with Δt = 200 ms (5 instances per second).

Methods:

- **Mean aggregation** for numerical data
- **Mode aggregation** for categorical data (labels) to reduce information loss

2

OUTLIER DETECTION

3 techniques evaluated:

- Local Outlier Factor (LOF)
- Interquartile Range (IQR) Method
- **Chauvenet's Criterion** (selected)

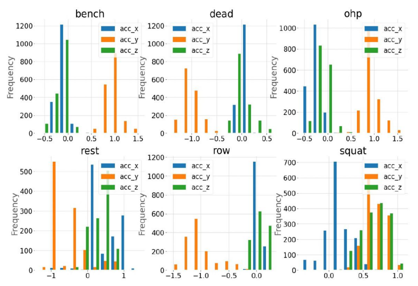


Figure 7. Normal Distribution for Accelerometer Data

3

HANDLE MISSING VALUES

- Used **data interpolation**, which estimated values based on surrounding data points to maintain data continuity and integrity.

4

LOW PASS FILTERING

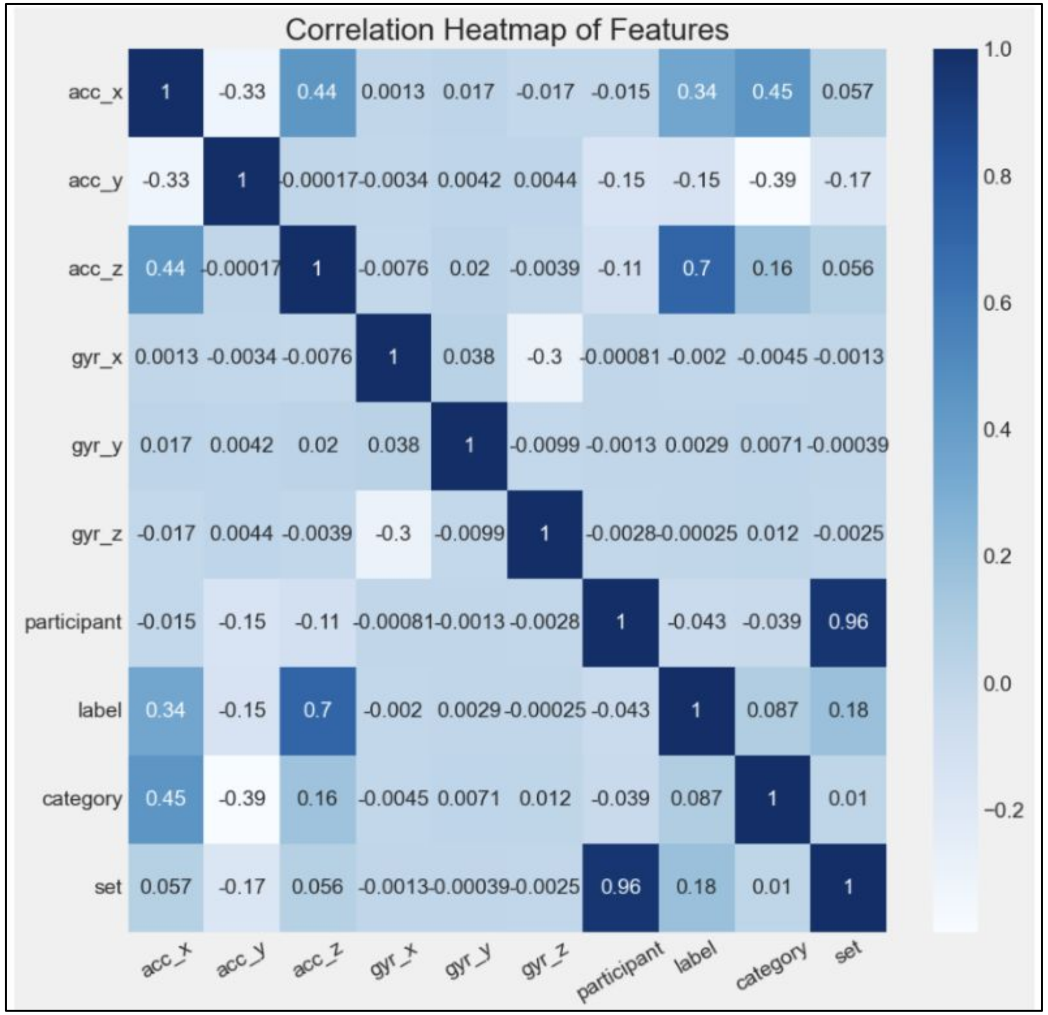
- Butterworth LPF was applied to the data to reduce high-frequency noise (excluding target columns).
- **Cut-off frequency ~ 1.3 Hz**

5

PRINCIPAL COMPONENT ANALYSIS

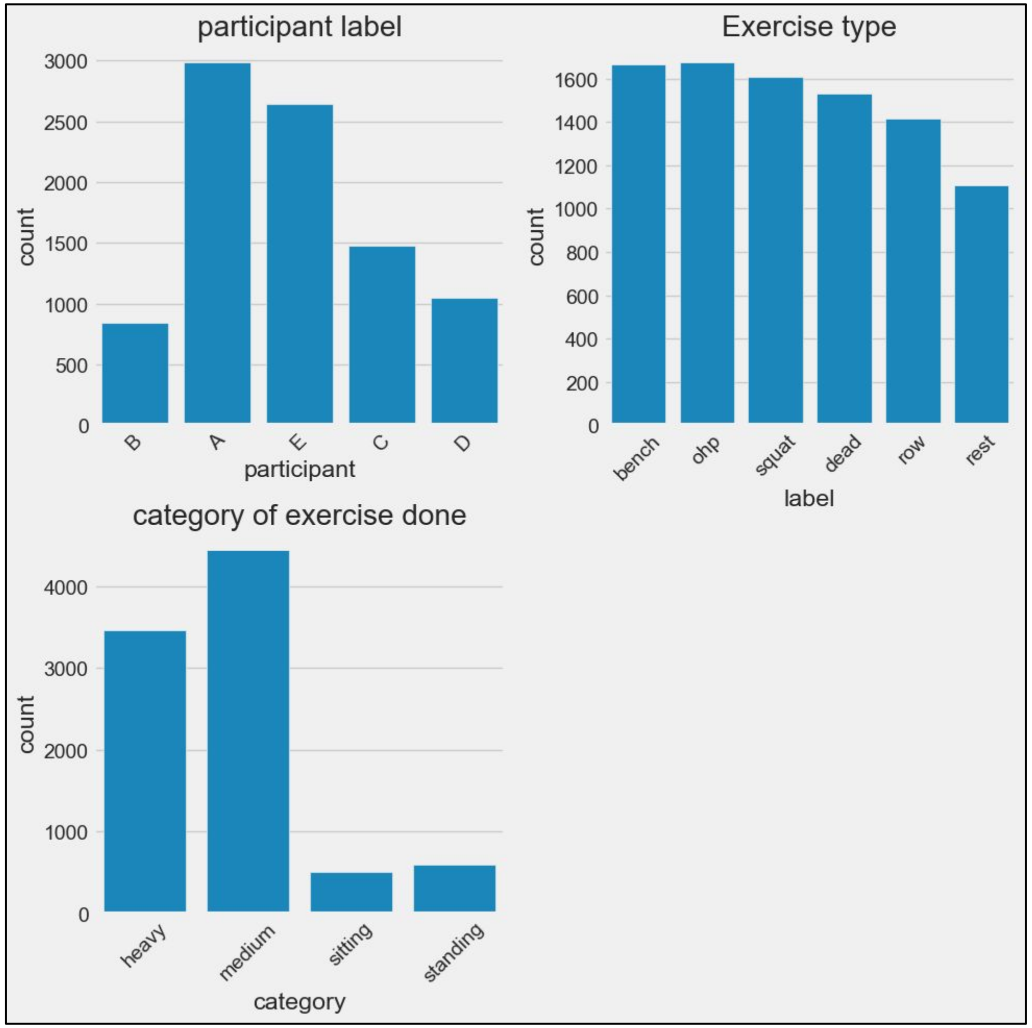
- Identified **3 principal components** that explained most variance
- Reduced dimensionality while preserving essential information

EDA: CORRELATION HEATMAP



- Accelerometer data, particularly **acc_x** and **acc_z**, are **crucial** predictors for activity classification, with **acc_z** showing a strong correlation of 0.70 with the label.
- In contrast, gyroscope data displays **weak** correlations, indicating limited influence on classification outcomes compared to accelerometer data.

EDA: BAR GRAPH



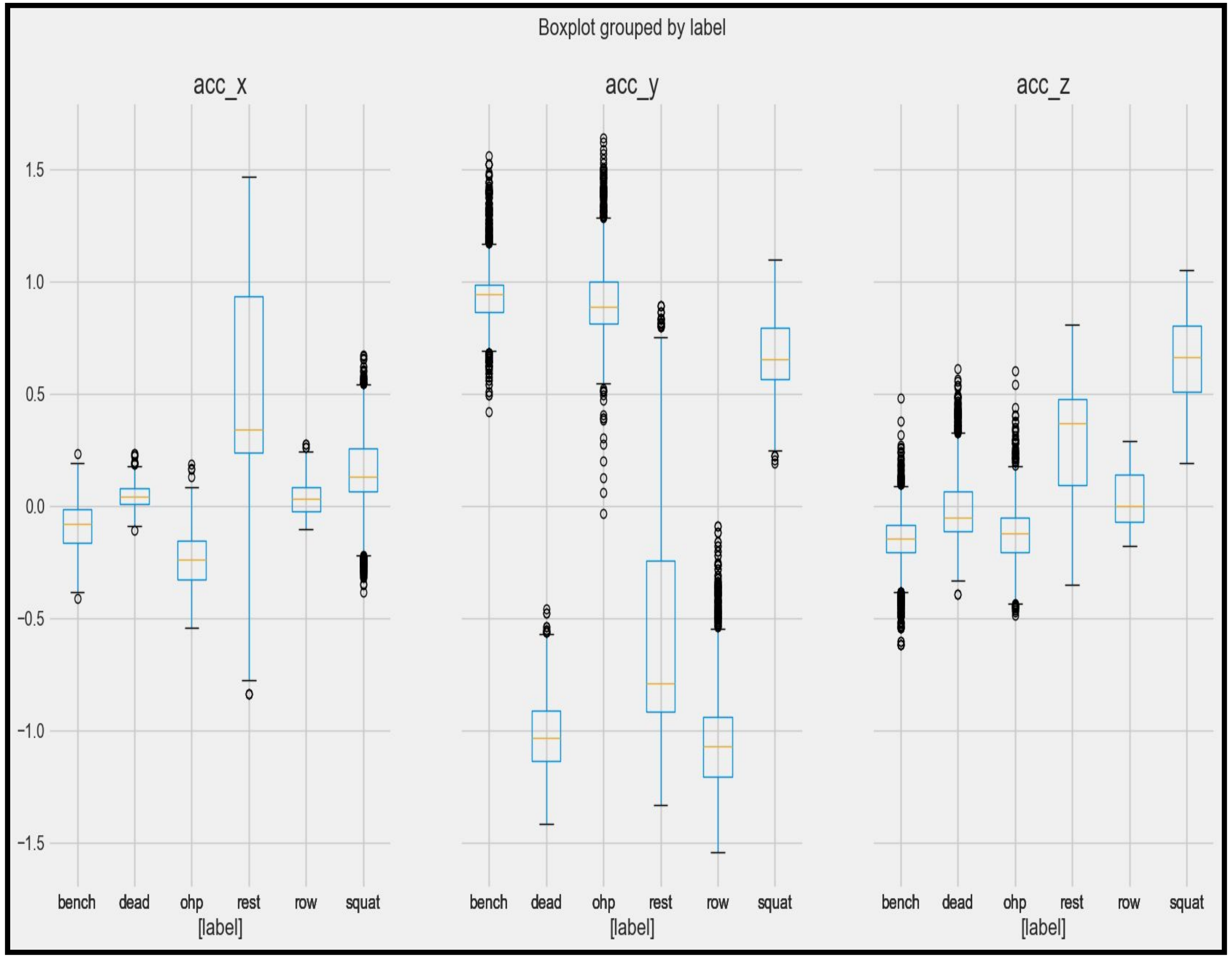
- **Participant A** contributed largely to the data.
- Almost **no class imbalance** can be observed i.e. all labels contribute almost equally.
- Most exercises are performed with **medium weights,** offering consistent data for reliable model training.

EDA: CLUSTERING GRAPH

- **Accelerometer (acc_x, acc_y, acc_z)**: **Clearly separates** exercises, especially bench, OHP, and rest; squat and deadlift show slight overlap but remain distinguishable.

- **Gyroscope (gyr_x, gyr_y, gyr_z)**: **Less distinct clusters** than acc_x, acc_y, acc_z.

EDA: BOX PLOT



- **acc_x**: Bench shows a tight distribution near 0, while rest has a broader spread, indicating variability during rest.
- **acc_y**: Rest clusters around negative values (minimal movement), while bench, dead, and row have similar medians but wider variability. OHP shows more positive values.
- **acc_z**: Bench has a narrow range with outliers, rest clusters near 0 (minimal movement), and squat shows a slightly wider spread than row.

METHODOLOGY

DATA COLLECTION

We obtained the primary dataset from **MetaMotion sensor watches**, containing a total of **69,677 entries** each consisting
of an epoch timestamp and corresponding x, y, and z values for both the accelerometer and gyroscope.

DATA PREPROCESSING

This includes Data Aggregation, EDA, Outlier Detection, Handling Missing values, Low Pass Filtering etc. to make the dataset cleaner, reduce noise, redundant features etc. to help prepare the model better.

FEATURE ENGINEERING

Sum of Squares Attributes: Captures movement intensity.

Temporal Abstraction: Captures patterns over time

Fourier Transformation: Extracts key frequency components.

K Means Clustering: Groups similar exercises based on patterns.

BUILDING THE MODEL

The dataset was split into **75:25** (train:test). We then did **forward feature selection** giving us **10 features**, followed by a **grid search** to optimize hyperparameters across models. We evaluated models like **Neural Network (MLP), Random Forest, KNN, Decision Tree,** and **Naive Bayes.** Their performance was noted and the **Random Forest model** was found to give the highest accuracy of **97.77%** which was further improved to **98.51%** after hyperparameter tuning, and further confirmed by **LazyPredict library.**

FEATURE SELECTION
HOW ADDITIONAL FEATURES WERE DERIVED?

Aggregated features

Temporal Aggregation

Frequency Domain

Clustering

+graphs

Overlapping Windows: To mitigate overfitting and eliminate overlapping windows, we selected alternate rows from the dataset, reducing its size by half.

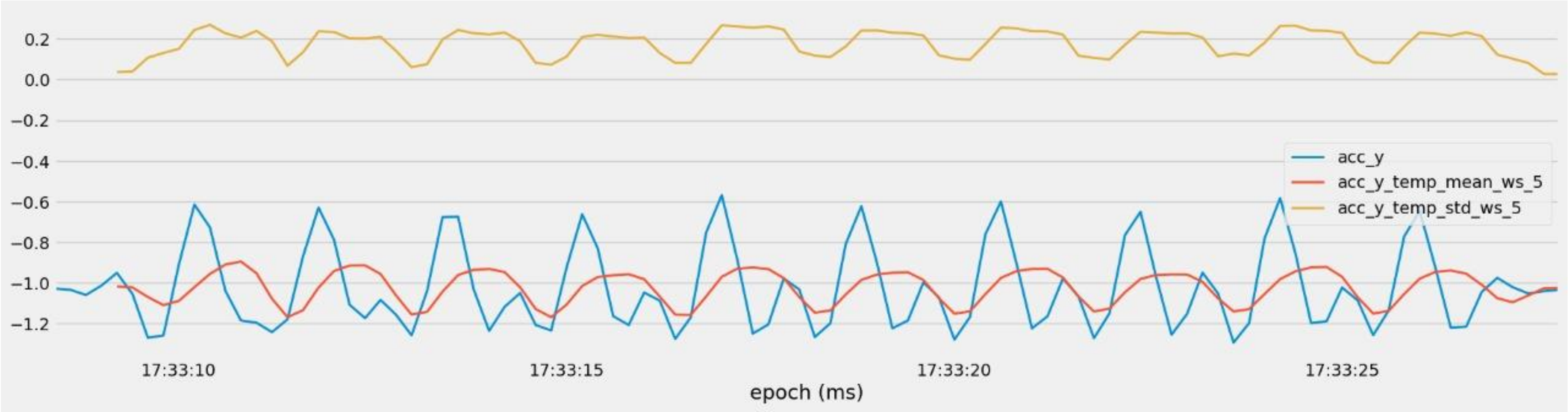
FEATURE ENGINEERING
HOW ADDITIONAL FEATURES WERE DERIVED?

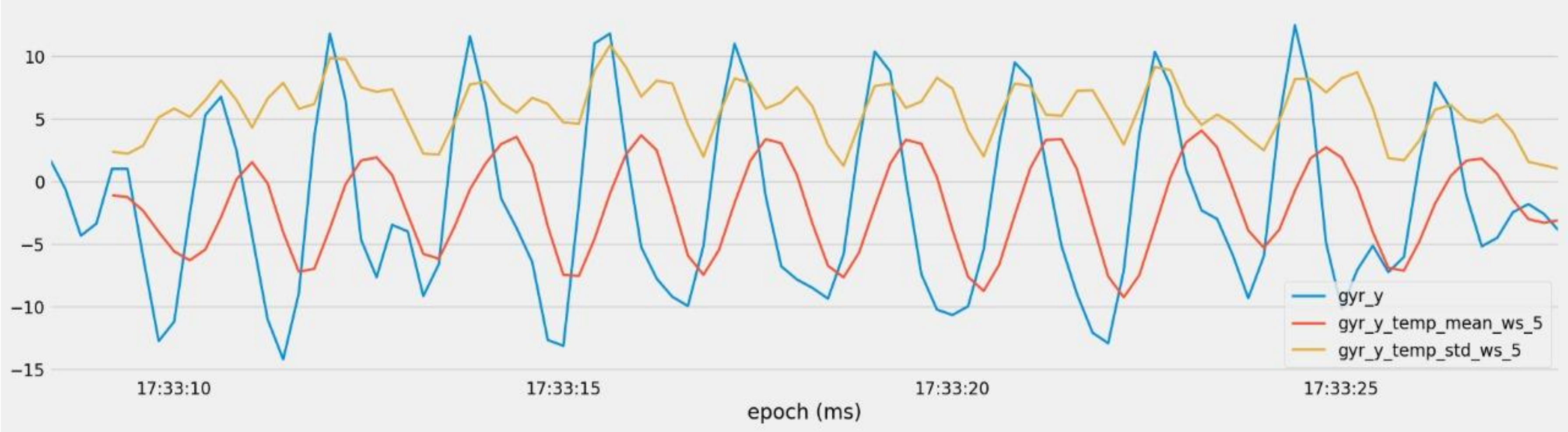
- **Aggregated Features:** The **scalar magnitudes r** of the accelerometer and gyroscope were computed in order to further utilize the data.
    - **Advantage:** It can manage dynamic reorientations and is indifferent to device orientation.

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

- **Temporal Aggregation:** It means summarizing data over a fixed period to capture patterns and reduce noise. In this case, features like mean and standard deviation were computed over 4-second windows

FEATURE ENGINEERING
HOW ADDITIONAL FEATURES WERE DERIVED?





Temporal aggregation for accelerometer(in y) and gyroscopic(in y) data respectively’

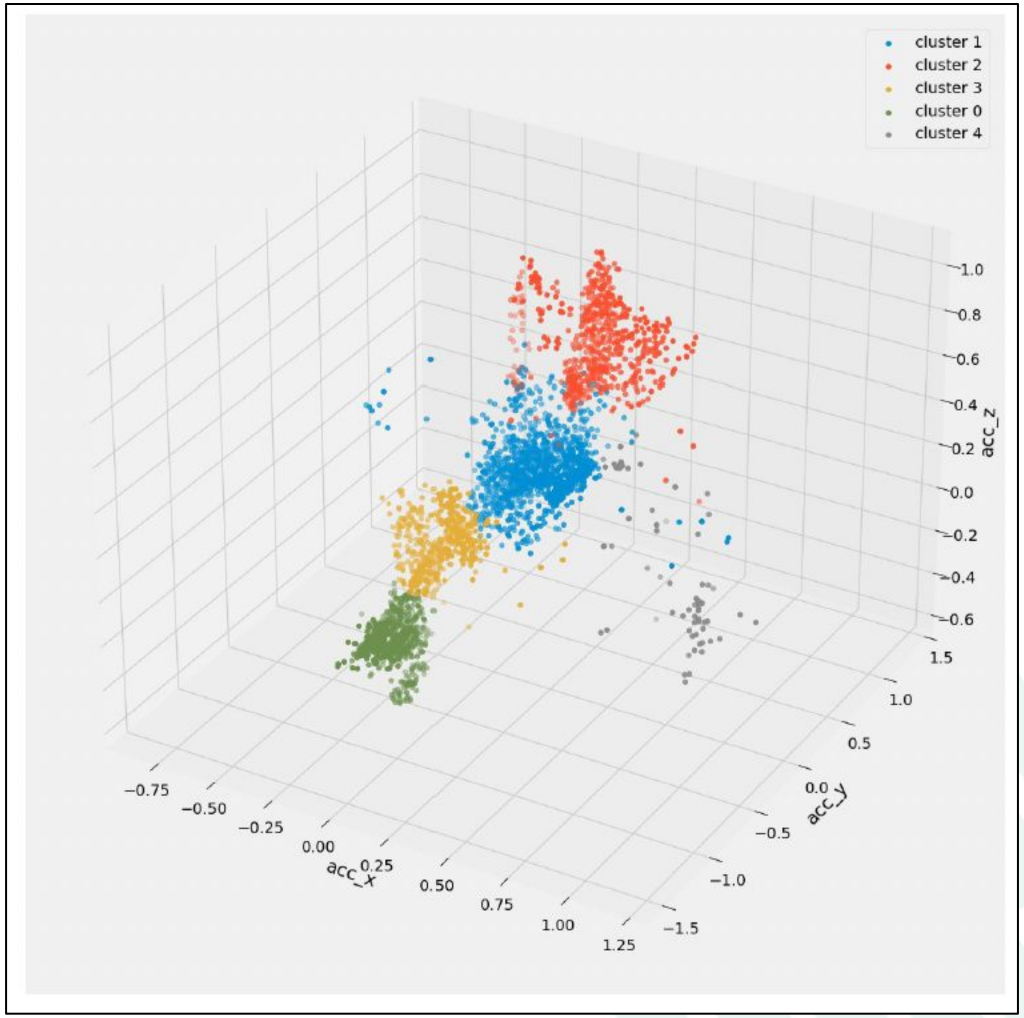
FEATURE ENGINEERING
HOW ADDITIONAL FEATURES WERE DERIVED?

- **Frequency Domain:** The analysis of frequency data using Fourier transformations helps identify patterns in movement. The data is decomposed into frequency components, including maximum frequency, signal-weighted average, and spectral entropy.
  - **Advantages:** Useful for detecting repetitive movements in strength training and distinguishing between smooth and erratic actions.

- **New Dataset**: It includes additional features, but overlapping time windows resulted in highly correlated attributes. To avoid overfitting, a maximum overlap of 50% was enforced, and instances exceeding this overlap were removed, reducing the dataset to 4505 instances. While some information was lost, this approach mitigated the risk of overfitting by reducing similar instances.

FEATURE ENGINEERING
HOW ADDITIONAL FEATURES WERE DERIVED?

- **Clustering:** Similar data points were grouped together with **k = 5.** K-means clustering was applied and it was found that:
    - Cluster 1: Bench press, overhead press data
    - Cluster 2: Deadlift
    - Cluster 3: Row
    - Cluster 4: Rest data (but fails to capture this accurately.
    - Cluster 5: Squats.

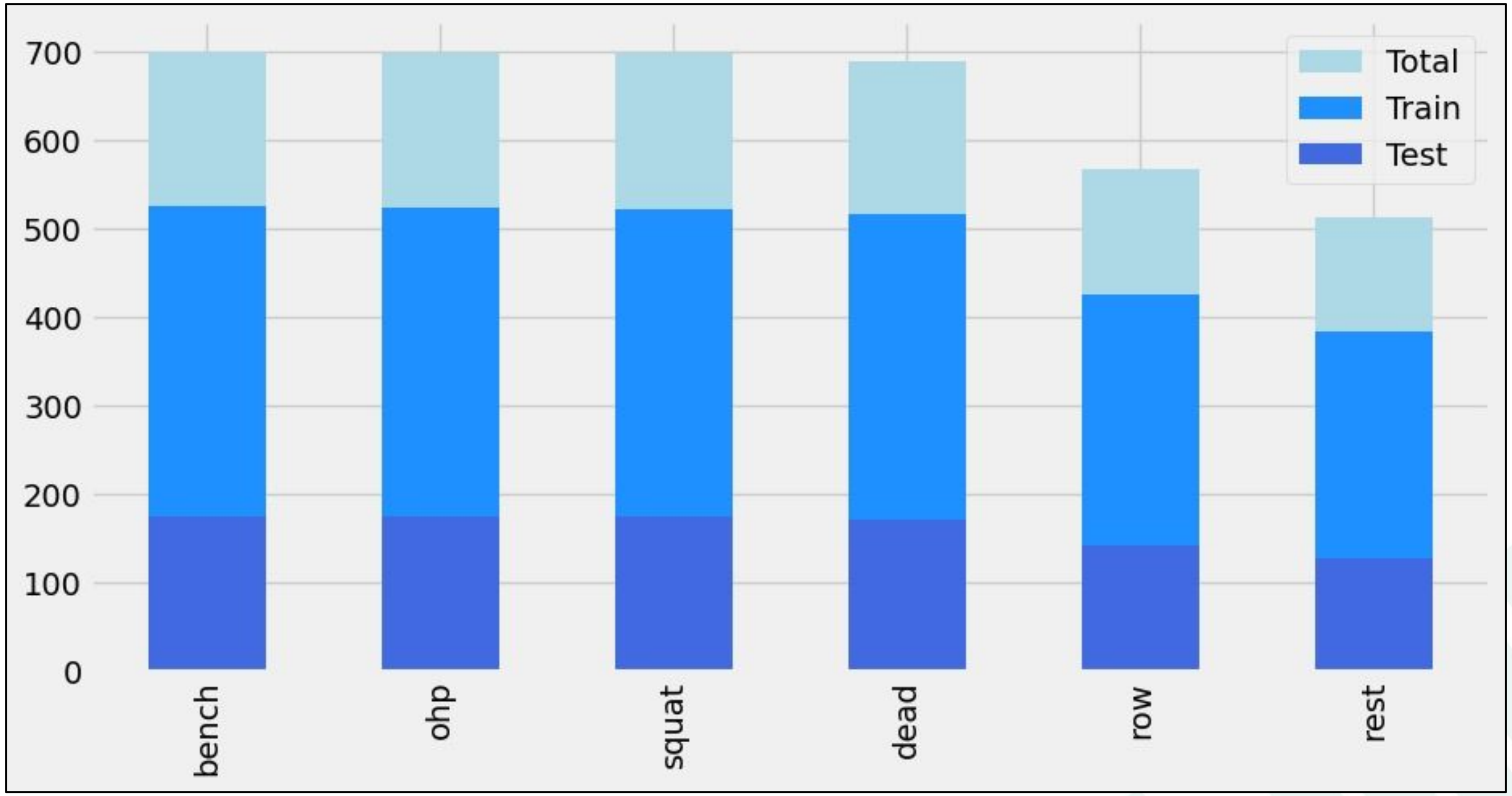


Advantage: It is possible that a membership to a certain cluster can help predict a label. The focus will be on clustering the acceleration data as the results showed that the gyroscope data was not useful.

MODELLING

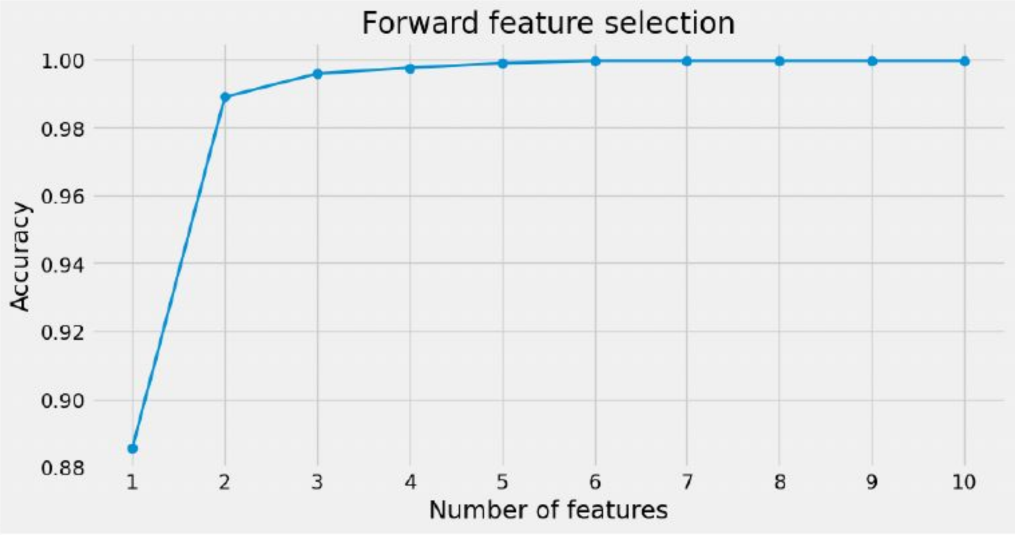
The dataset is now processed and ready for training. The dataset contains the 6 basic features, 2 scalar magnitude features, 3 PCA features, 16 time features, 12 frequency features and 1 cluster feature

- **Dataset Splitting:** The dataset was split into training and testing data with a **75:25** ratio.



MODELLING

- **Feature Selection:** Selected Features have been identified through **forward feature selection** using a simple decision tree. Results showed that after **10 features**, performance plateaued. Used **5 features sets** to test the performance of models.
- The 5 features with the most predictive power are: pca 1, acc y, pca 3, gyrx_temp_std_ws_4, acc r pse.



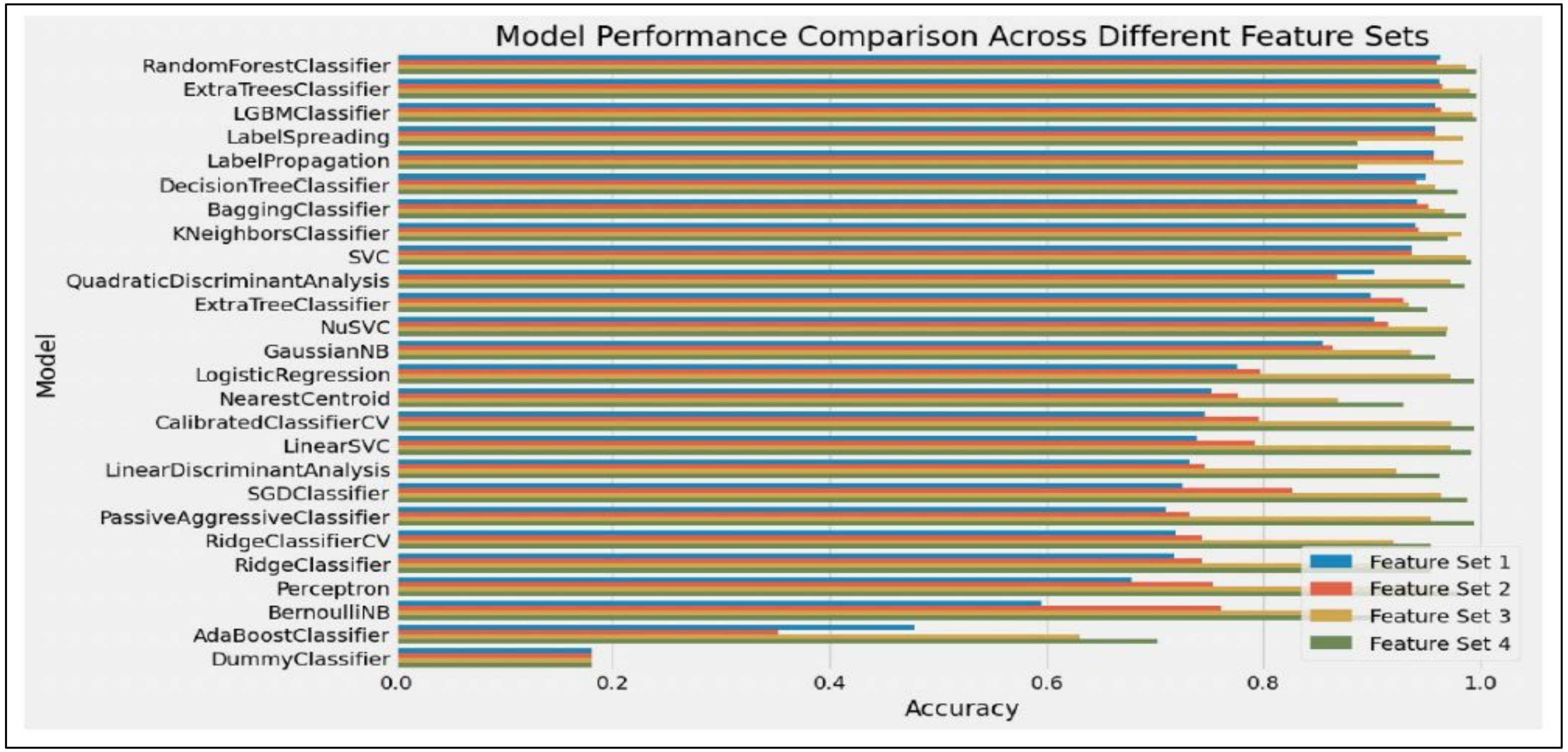
Forward feature Selection

Feature Set	List of Features
Feature Set 1	Basic Features
Feature Set 2	Basic Features + Aggregated Features + PCA Features
Feature Set 3	Feature Set 2 + Temporal aggregation Features
Feature Set 4	Feature Set 3 + Frequency Features + Cluster Features
Selected Features	pca 1, acc y, pca 3, gyr x temp std ws 4, acc r pse

Top 5

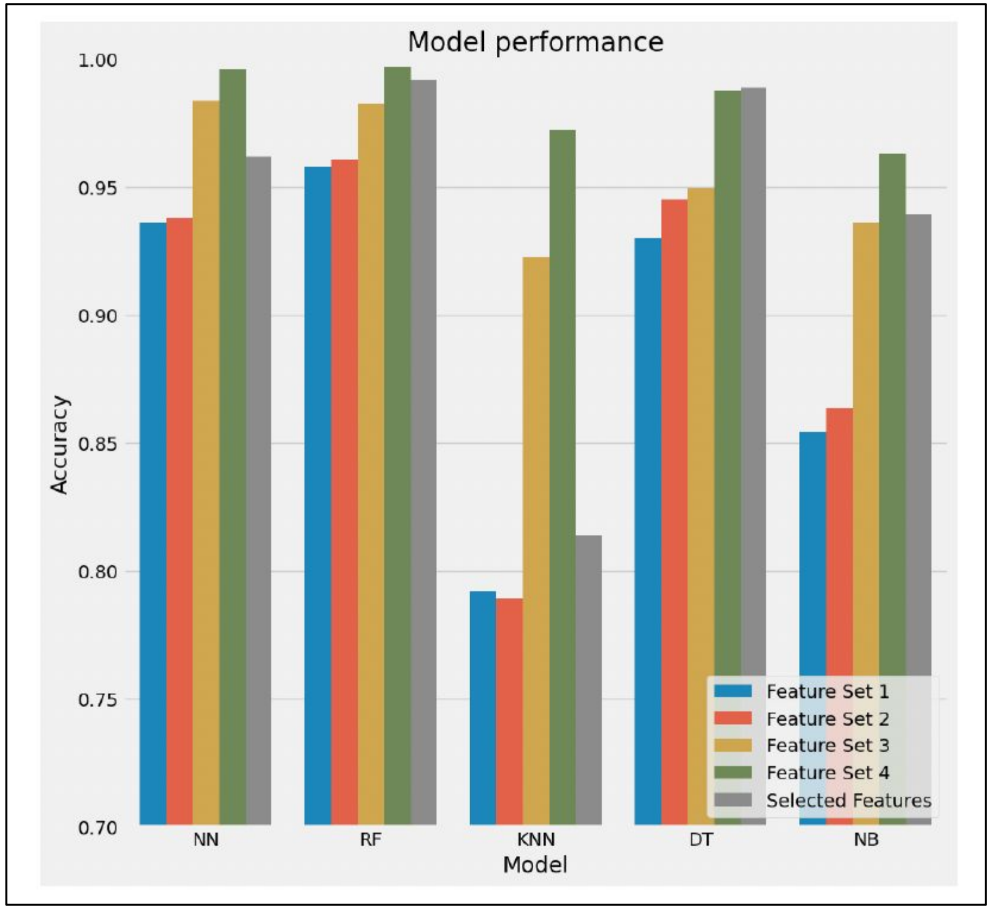
MODELLING

- **Initial Model Evaluation:** The **LazyPredict library** was employed to benchmark various models on all datasets quickly. LazyPredict provides an automated evaluation of multiple models with minimal setup. It was observed that **Random Forest** consistently outperformed other models during this initial phase.



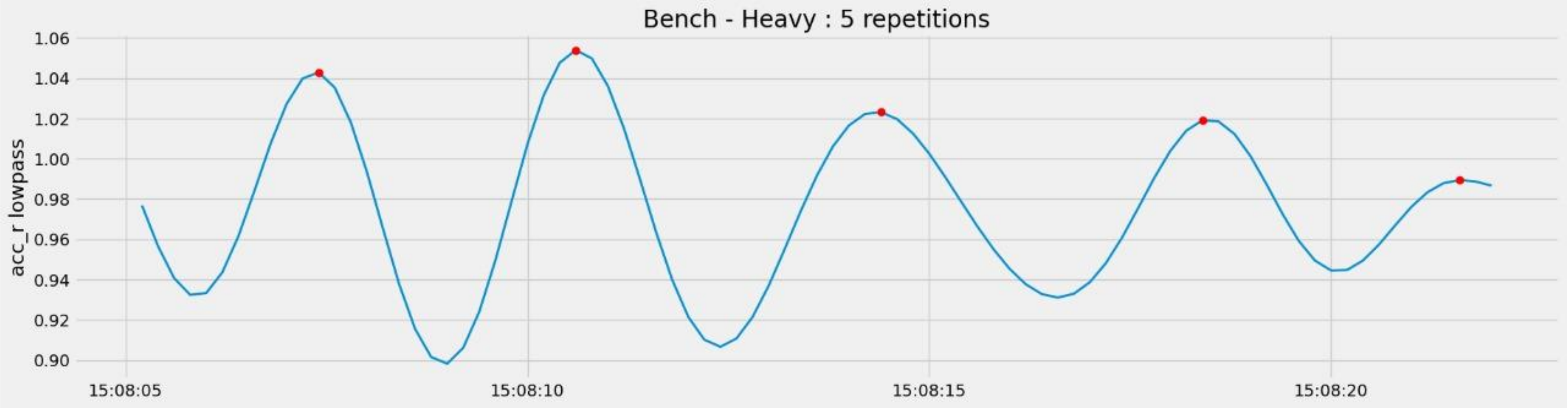
MODELLING

- **Final evaluation:** The various models tested included **Neural Network, Random Forest, KNN, Decision Tree, and Naive Bayes**. Grid search, along with regularization, was performed on all models to optimize performance across different feature sets.



COUNTING REPETITIONS

A custom algorithm was developed to count exercise repetitions using accelerometer and gyroscope data. The signal was preprocessed with a Butterworth low-pass filter, and repetitions were identified by detecting peaks in the filtered data. This approach was validated by comparing predicted repetitions against labeled ground truth, with performance measured using mean absolute error.



RESULTS & ANALYSIS

- **Feature Engineering:** Found **10 features** that had the most predictive power using Forward Feature Selection. The accuracy achieved using these selected features was **comparable** to the accuracy obtained with the full feature set.
- **Repetition Counting:** A repetition counting algorithm successfully identified exercise repetitions using accelerometer and gyroscope data. The method achieved a **mean absolute error of 0.88 repetitions per set** when compared with the labeled ground truth, demonstrating its reliability and accuracy.

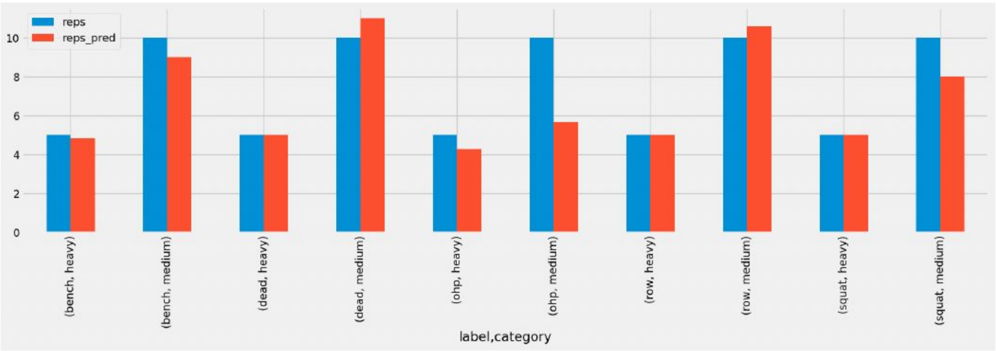


Figure 12. Counting Repetition

RESULTS & ANALYSIS

- **Data Size Reduction**: Reduced dataset from **69,677 to 9,009 entries**, retaining essential movement patterns through effective data aggregation.
- **Outliers:** Detected over **185 outliers using Chauvenet criteria,** did interpolation to maintain uniformity in data

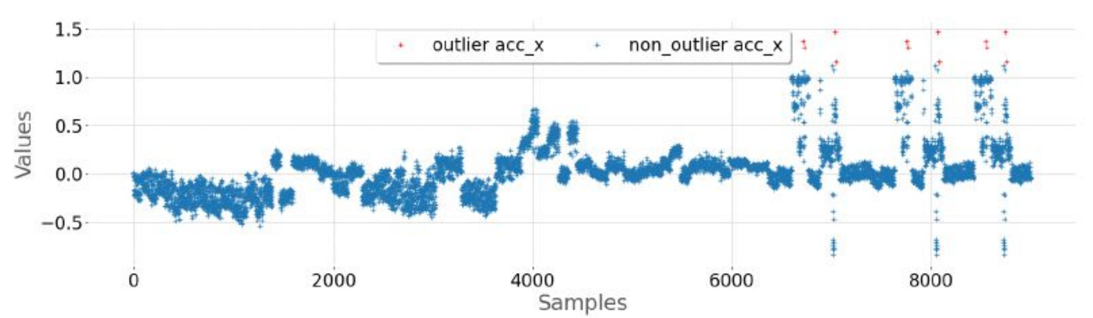


Figure 8. values(for acc_x) vs samples

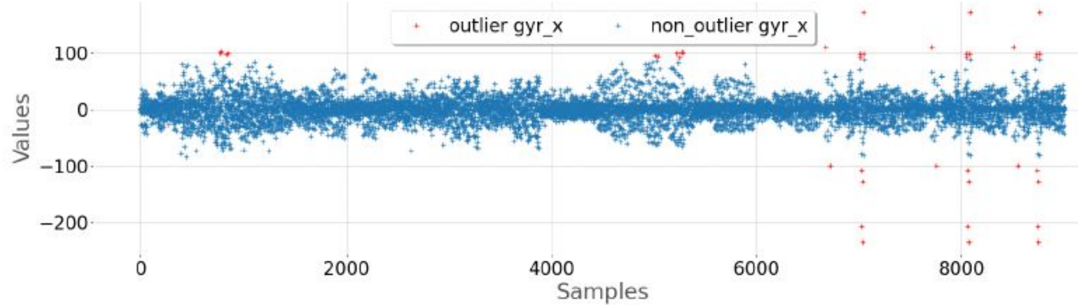
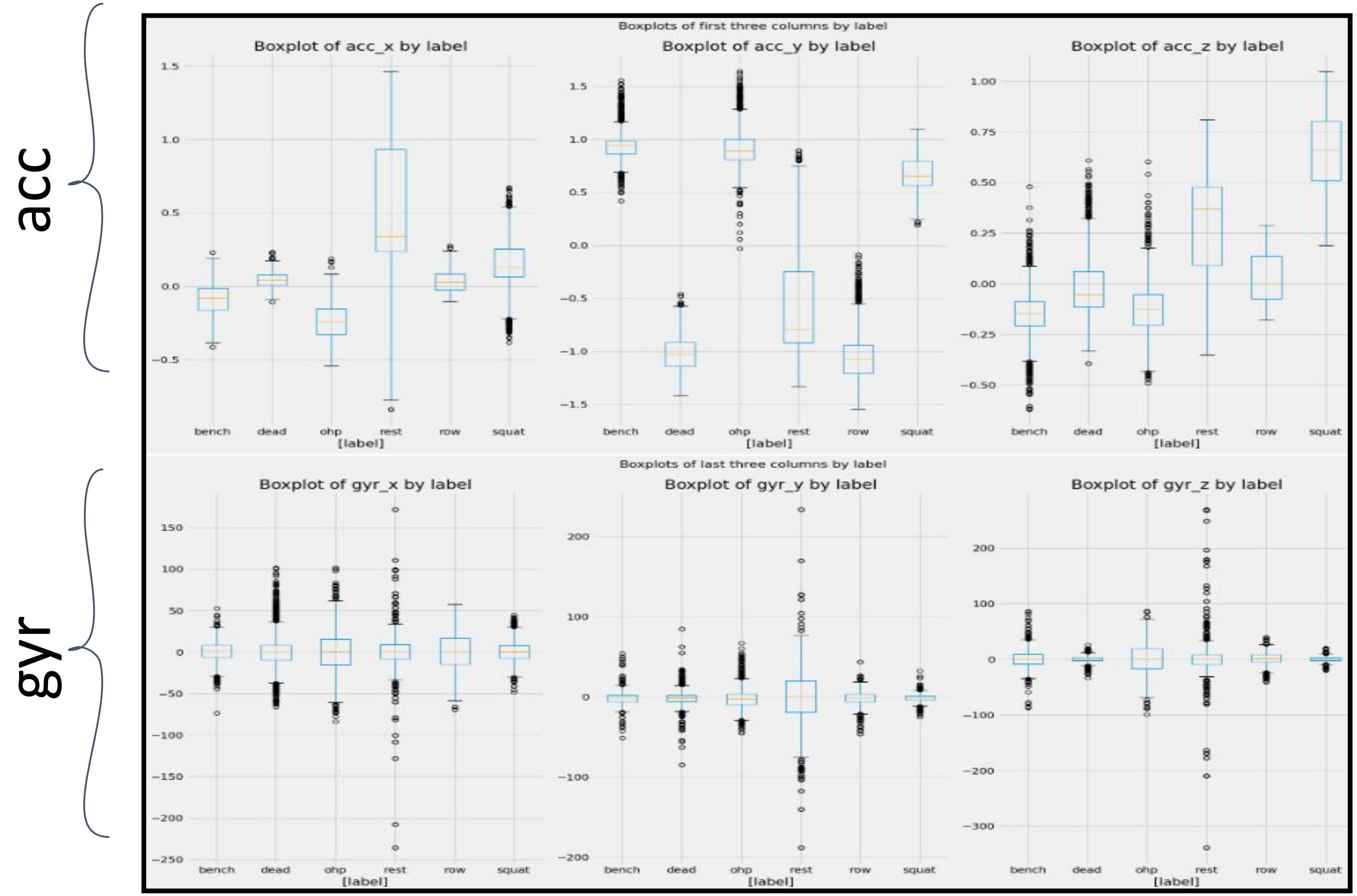


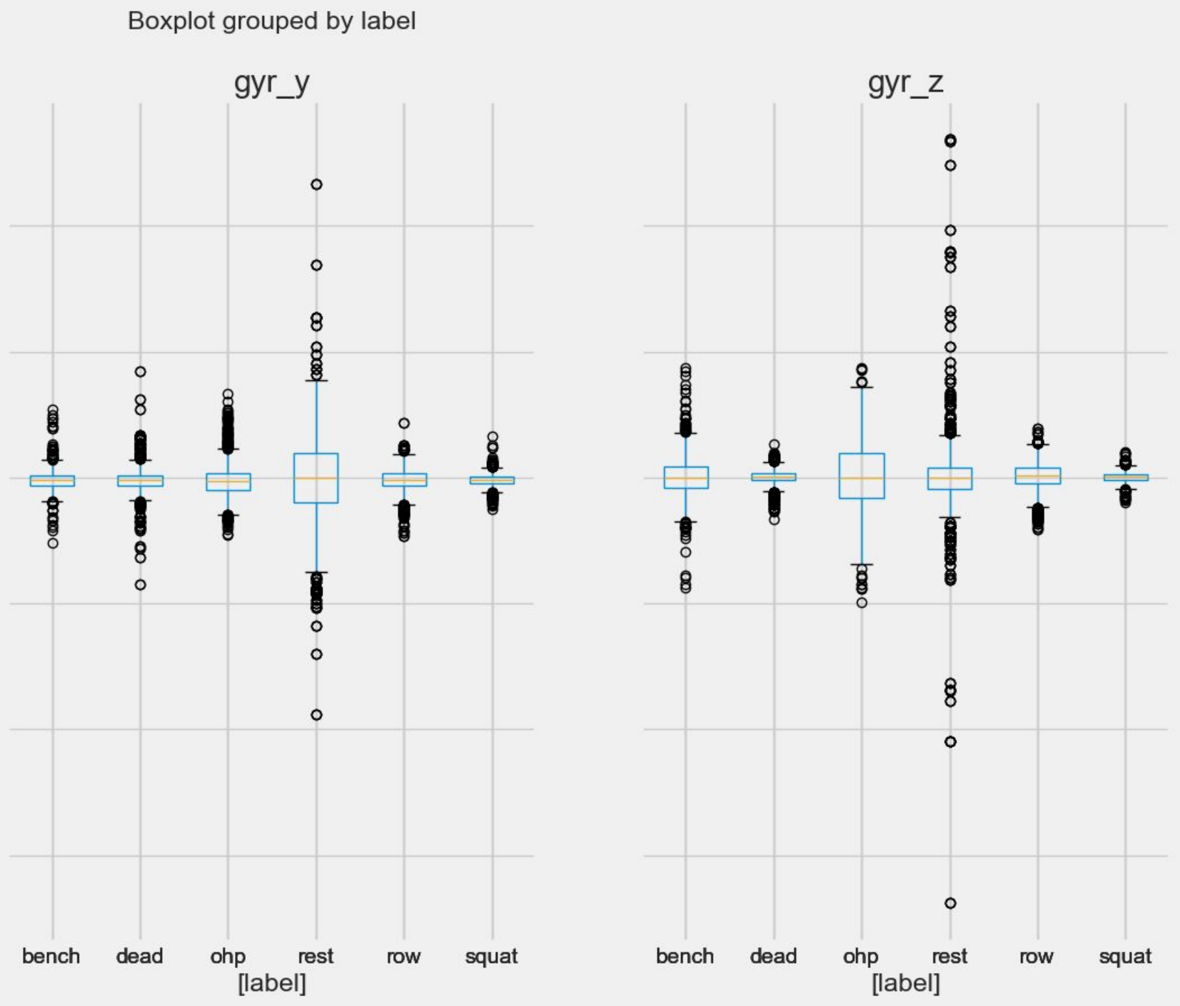
Figure 9. Value(for gyr_x) vs samples

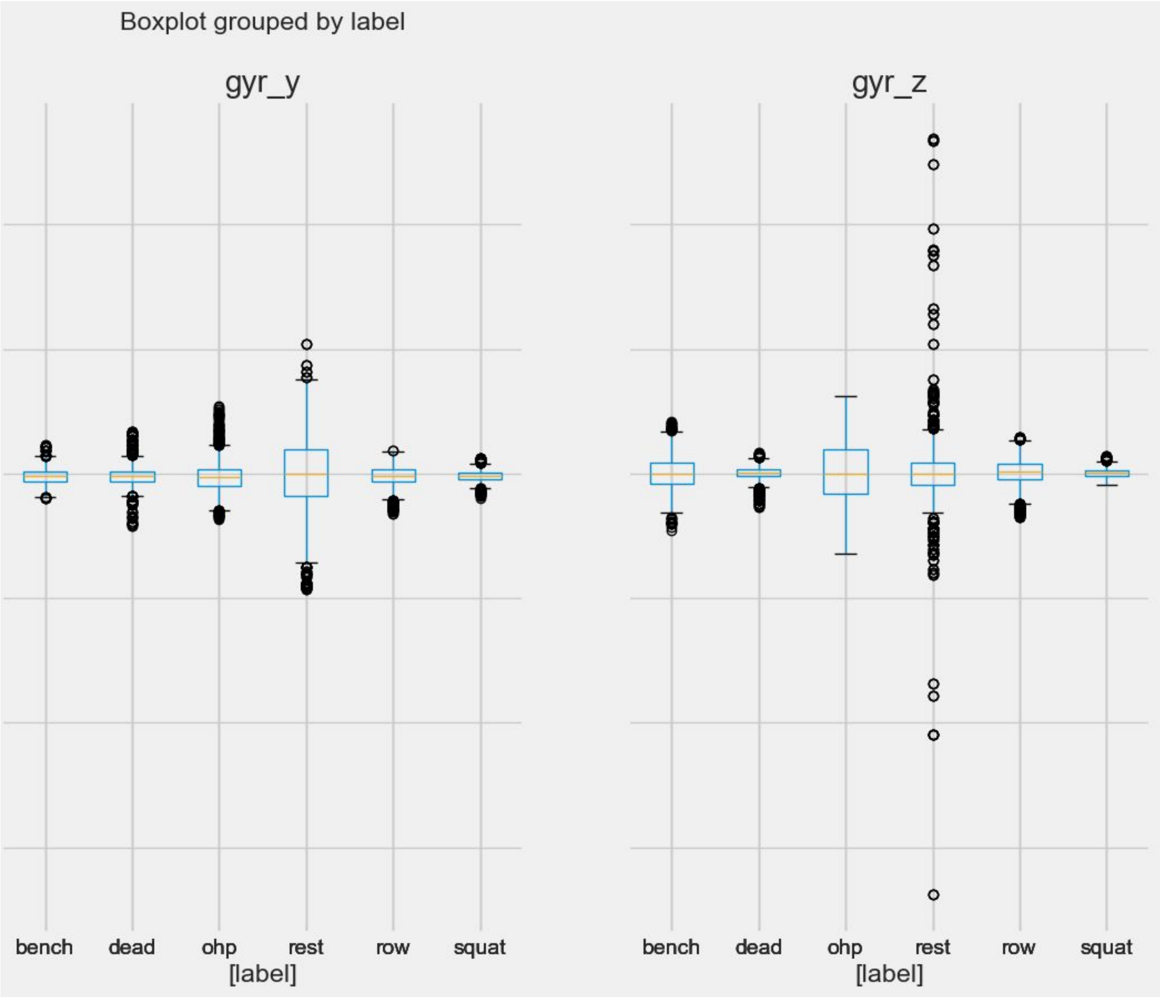
RESULTS & ANALYSIS



- **Comparison of Sensor Data**: Accelerometer data had **fewer outliers** compared to gyroscopic data, providing more consistent readings for exercise assessment.

RESULTS & ANALYSIS





Before

Removing outliers

After

RESULTS & ANALYSIS

- **Dimensionality Reduction with PCA**:
  Using 3 principal components (concluded by Elbow method) captured most data variance, simplifying analysis without significant information loss.

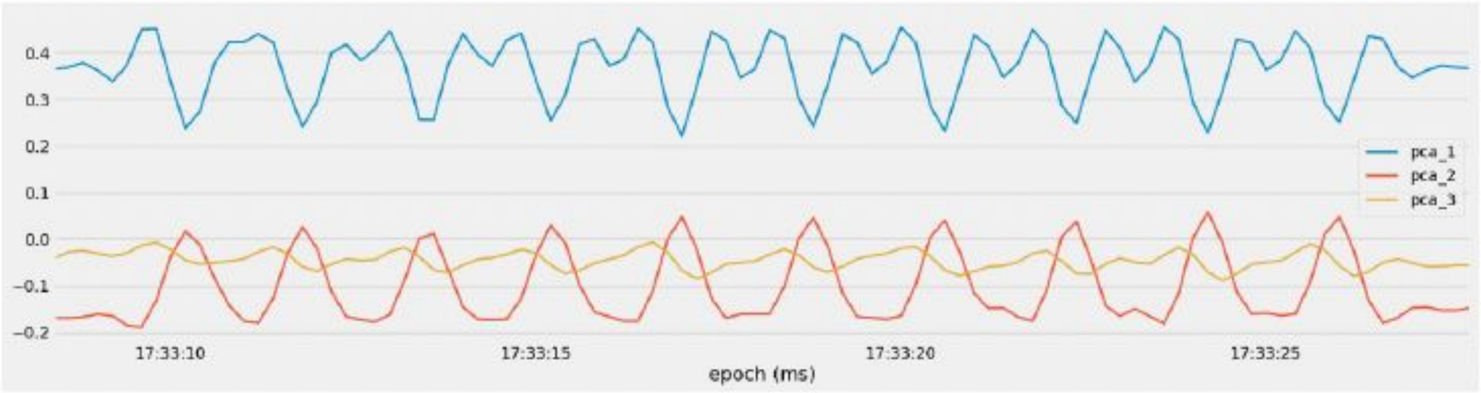
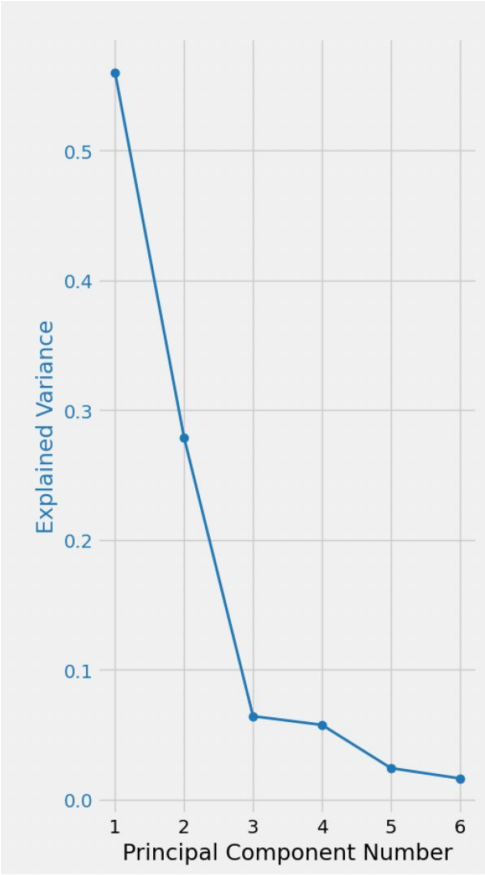
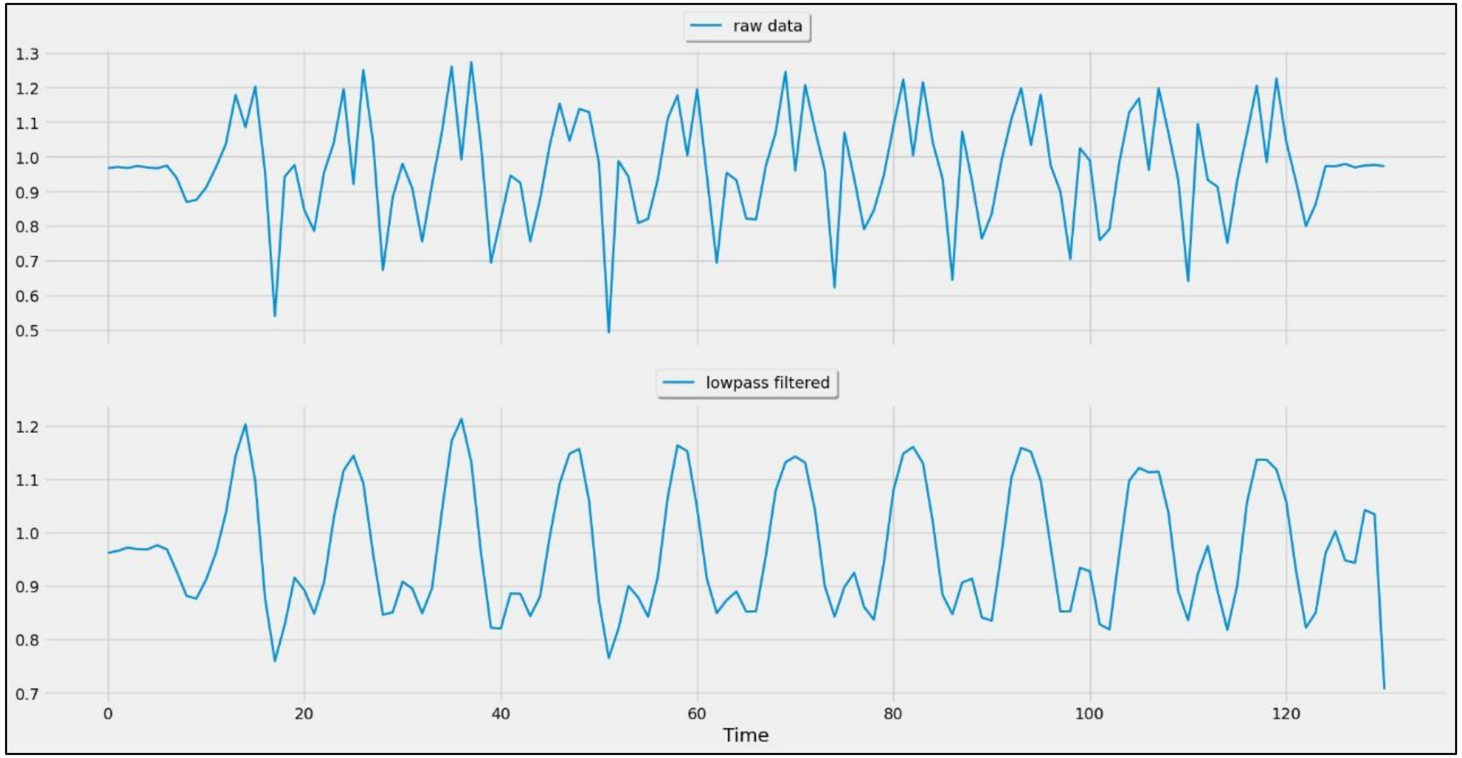


Figure 11. pca components



RESULTS & ANALYSIS

- **Noise Reduction**:
  Low-pass filtering effectively removed high-frequency noise, improving clarity in movement patterns.

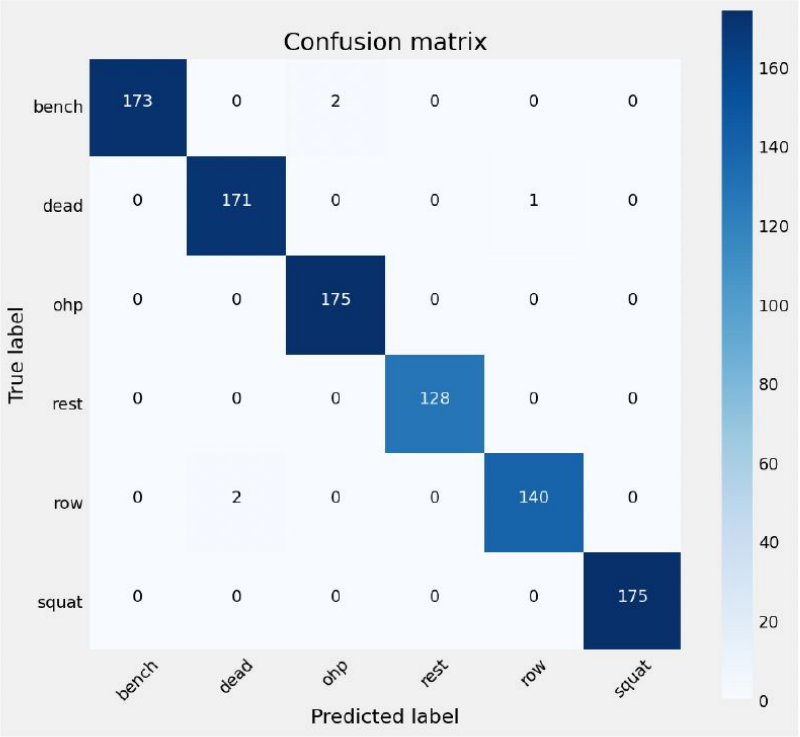


BEST MODEL

- Random Forest, followed closely by Neural Networks, demonstrated the highest performance across different feature sets. Grid search with 5-fold cross-validation was conducted to find the optimal hyperparameters, resulting in the following configuration:
    - **Minimum samples per leaf:** 2
    - **Number of estimators:** 100
    - **Criterion:** Gini
- As a result, an overall accuracy of **98.51%** was observed.

Models	Accuracy
Decision Tree	96.87%
KNN	85.79%
Naive Bayes	91.11%
Neural Networks	96.29%
Random Forests	97.77%

Table 3. Average Accuracy Across Different Feature Sets



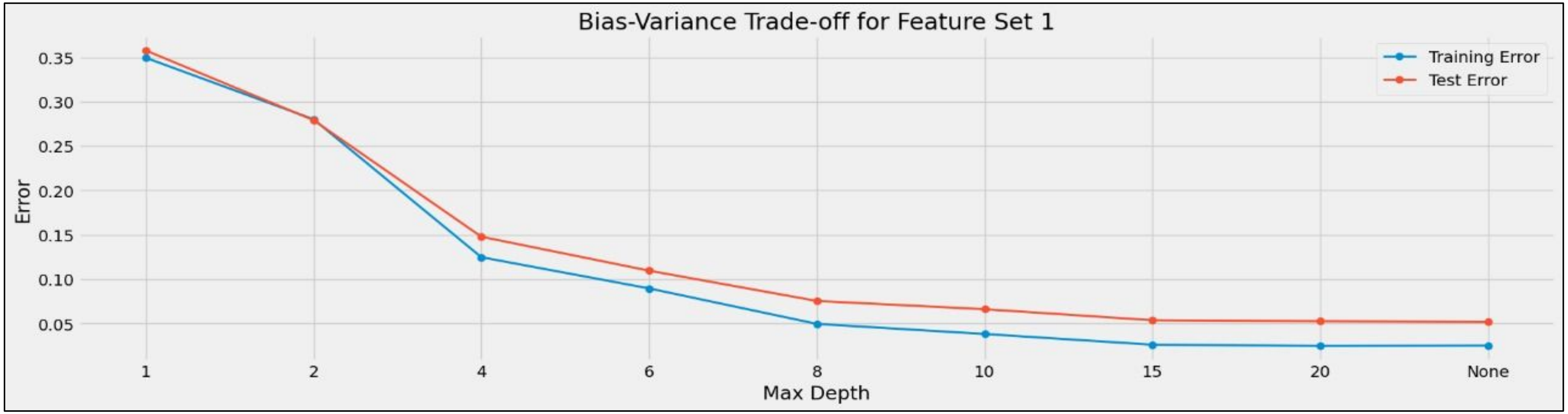
RESULTS & ANALYSIS

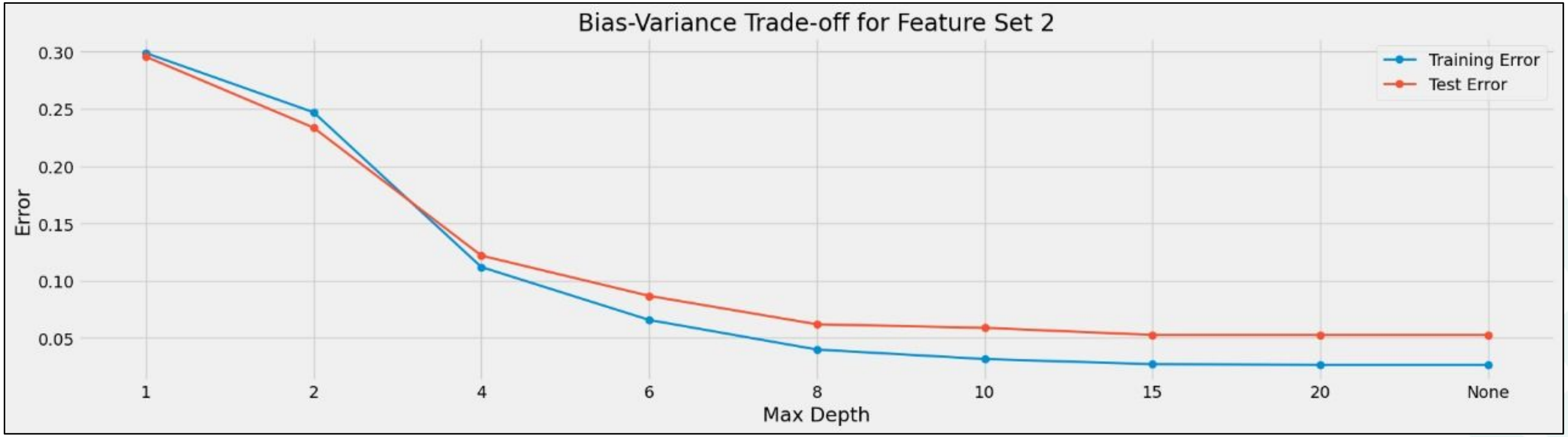
- **Models:**

  It was found that the **Random Forest Model** was the highest performing model with an accuracy of **97.77%** on the test set, which was further improved to **98.51%** after **hyperparameter tuning**.

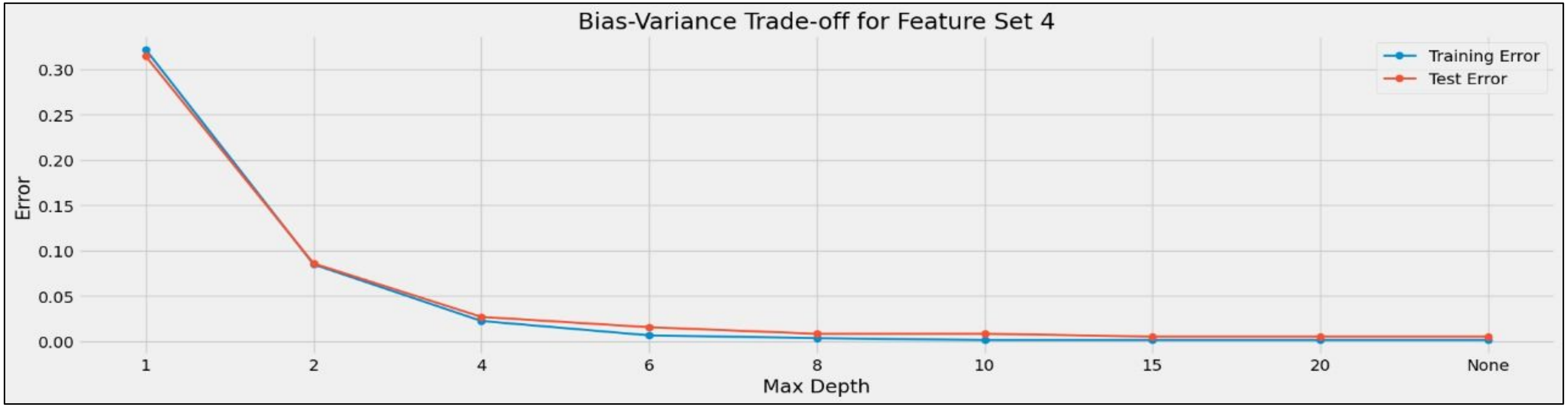
  => This indicates that the model was **highly accurate** in its predictions and can be deployed for practical purposes as well.

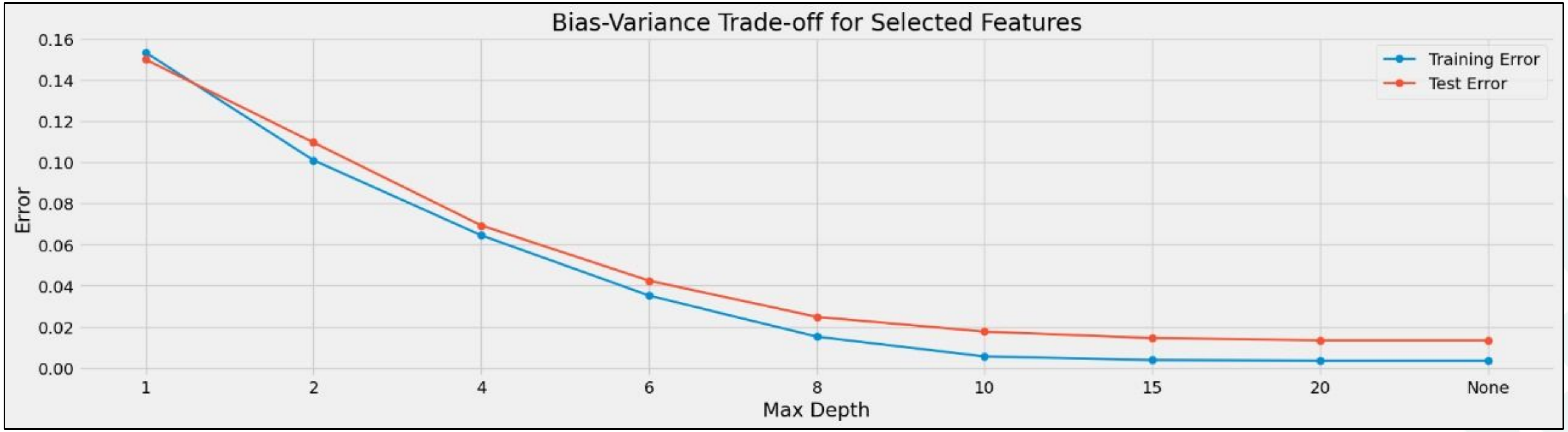
RESULTS & ANALYSIS





RESULTS & ANALYSIS





TIMELINE (MID-INTERIM)

WEEK 1-2	WEEK 3	WEEK 4	WEEK 5	WEEK 6

DATASET PREPARATION AND EXPLORATION

- Introduction to the project and finding relevant reference books, research papers etc.
- Dataset exploration: cleaning data, handling missing values, and splitting data for analysis.

DATA CONVERSION AND INITIAL EXPLORATION

- Conversion of raw sensor data.
- Prepared CSV files.
- Split dataset into training, validation, and testing sets.
- Conducted EDA to identify patterns and potential issues.

DATA VISUALISATION

- Visualization of sensor data (e.g., time series plots).
- Identified trends and patterns in the data.
- Gained insights from visualizations to guide further analysis.

OUTLIER DETECTION

- Implemented outlier detection methods like Chauvenet's criterion and Local Outlier Factor.
- Analyzed the impact of outlier removal on the dataset and prepared clean data for modeling.

FEATURE ENGINEERING

- Engineered new features using frequency analysis, and applied lowpass filters along with performing PCA.

TIMELINE (FINAL WEEKS)

WEEK 7	WEEK 8-9	WEEK 10
PREDICTIVE MODELLING	**RCA**	**FINAL ANALYSIS**
• Trained models on Naive Bayes, Neural Network (MLP), Random Forest, KNN, and Decision Tree. • Noted down their performance and evaluated results.	• We developed and refined a custom algorithm to count repetitions from the time-series data. • This helps to improve accuracy of the model.	• Final analysis and result compilation was done, along with preparation of Project Report and PPT.

CONCLUSION

This study successfully demonstrates the potential of wearable sensor technology combined with machine learning to improve the monitoring of strength training exercises. By leveraging MetaMotion sensors, extensive preprocessing, and feature engineering, we developed a Random Forest model achieving **98.51% accuracy** in classifying exercises and counting repetitions. These findings highlight the reliability of accelerometer data over gyroscope data for such tasks, and the importance of dimensionality reduction and feature selection in optimizing model performance. Our work bridges the gap between fitness technology and strength training, providing a foundation for more advanced, context-aware fitness applications in the future

FUTURE WORK

- **Temporal Abstraction**:
  - Capture patterns over varying time windows
- **Frequency Domain Features Extraction**
  - Extract frequency domain features using Fourier Transformation to analyze periodic signals within the data.
- **Clustering**:
  - Apply KMeans clustering to group similar exercise types based on sensor data patterns.
- **Predictive Modeling**:
  - Use forward feature selection and grid search to optimize models (MLP, Decision Tree, Random Forest, Naive Bayes)
- **Repetition Counting Algorithm**:
  - Develop an algorithm to count exercise repetitions based on the accelerometer and gyroscope data

CONTRIBUTIONS

- **Grishma Bellani:** Data Visualization, Outlier detection, Feature engineering, LPF & PCA, ML Model, Report
- **Riya Gupta:** Data Collection, Feature Engineering, ML Model, RCA, Result and Analysis, PPT, Report
- **Shreyansh Srivastav**: Data Pre-Processing, EDA, Outlier detection, ML Model, RCA, LPF & PCA, Report
- **Shrutya Chawla:** Data Pre-Processing, Fourier Transformation, Clustering, ML Model, Result and Analysis, Report
- **Vimansh Mahajan:** Data Collection, Fourier Transformation, Clustering, ML Model, RCA, Result and Analysis, PPT, Report

Every member of the group contributed equally to the submission.

THANK YOU!

GROUP 3

GRISHMA BELLANI
RIYA GUPTA
SHREYANSH SRIVASTAV
SHRUTYA CHAWLA
VIMANSH MAHAJAN

INDRAPRASTHA INSTITUTE *of*
INFORMATION TECHNOLOGY
DELHI

ML FINAL PROJECT