Datamining Preprocessing:
The Human Activity Recognition 70+

<u>Prepared by:</u>

Youssef Mahmoud Anis - 192100029

Youssef Muhammed Gabr -192100069

Libraries Used IN This Project:

- import numpy as np
- import pandas as pd
- import matplotlib.pyplot as plt
- import seaborn as sns
- from sklearn.preprocessing import MinMaxScaler
- from sklearn.model_selection import train_test_split

1. Explore the dataset's features and target variable.

[184]:
```
file_ids = range(501, 519)
patients = [pd.read_csv(f"{pid}.csv") for pid in file_ids]

# Combine all patients into one DataFrame
all_data = pd.concat(patients, ignore_index=True)
```

[212]:
```
print("First 10 rows of the dataset:\n")
display(all_data.head(10))
```

First 10 rows of the dataset:

	timestamp	back_x	back_y	back_z	thigh_x	thigh_y	thigh_z	label
0	2021-03-24 14:42:03.839	-0.999023	-0.063477	0.140625	-0.980469	-0.112061	-0.048096	6
1	2021-03-24 14:42:03.859	-0.980225	-0.079346	0.140625	-0.961182	-0.121582	-0.051758	6
2	2021-03-24 14:42:03.880	-0.950195	-0.076416	0.140625	-0.949463	-0.080566	-0.067139	6
3	2021-03-24 14:42:03.900	-0.954834	-0.059082	0.140381	-0.957520	-0.046143	-0.050781	6
4	2021-03-24 14:42:03.920	-0.972412	-0.042969	0.142822	-0.977051	-0.023682	-0.026611	6
5	2021-03-24 14:42:03.940	-0.988770	-0.026123	0.157227	-0.984863	-0.042725	-0.032715	6
6	2021-03-24 14:42:03.960	-1.001953	-0.016113	0.162109	-0.992920	-0.075439	-0.024170	6
7	2021-03-24 14:42:03.980	-1.000488	-0.035400	0.191406	-0.996338	-0.072754	-0.013428	6
8	2021-03-24 14:42:04.000	-0.996826	-0.056152	0.187500	-0.974609	-0.060303	-0.015625	6
9	2021-03-24 14:42:04.019	-0.978027	-0.083252	0.187500	-0.966797	-0.062500	-0.015625	6

[188]:
```
print(f"Dataset contains {all_data.shape[0]} rows and {all_data.shape[1]} columns.")
```

Dataset contains 2259597 rows and 8 columns.

We started by combining 18 different CSV files, each representing data from a different patient. These files were identified by a unique patient ID (PID), ranging from 501 to 518. Using a loop, we read each file using the read_csv function and stored them in a list called patients.

Next, we used pd.concat() to merge all these individual patient datasets into a single DataFrame called all_data, which makes it easier to work with the complete dataset as one unit.

To understand the structure of the dataset, we displayed the first 10 rows. This gave us a preview of the types of data we are working with. After that, we used .shape to check the total number of rows and columns in the dataset. It turns out the dataset contains approximately **2.25 million rows and 8 columns**.

The dataset includes:

- **timestamp**: the exact time of the data recording
- **back_x, back_y, back_z**: accelerometer readings from the lower back (in x, y, and z directions)
- **thigh_x, thigh_y, thigh_z**: accelerometer readings from the right front thigh
- **label**: the activity being performed, which is categorized as:

  1: walking
  3: shuffling
  4: stairs (ascending)
  5: stairs (descending)
  6: standing
  7: sitting
  8: lying

This setup allows us to explore how different body movements are represented in the sensor data and how we might use this for activity classification.

2. Handle missing values (if any) and outliers.

```
[190]: #mean
bx_mean = all_data ['back_x'].mean()
by_mean = all_data ['back_y'].mean()
bz_mean = all_data ['back_z'].mean()
tx_mean = all_data ['thigh_x'].mean()
ty_mean = all_data ['thigh_y'].mean()
tz_mean = all_data ['thigh_z'].mean()

print("\nBack Mean scores: ")
print(f"back_x: {bx_mean}, back_y: {by_mean}, back_z: {bz_mean}")

print("\nThigh Mean scores: ")
print(f"thigh_x: {tx_mean}, thigh_y: {ty_mean}, thigh_z: {tz_mean}")
```

```
Back Mean scores:
back_x: -0.8699343930886793, back_y: -0.03316849906111574, back_z: 0.023424907512711337

Thigh Mean scores:
thigh_x: -0.6796213034173795, thigh_y: 0.0027747422088983133, thigh_z: -0.384121996420158
```

```
[129]: #missing values
print("Missing values in each column:\n")
print(all_data.isnull().sum())
```

```
Missing values in each column:

timestamp    0
back_x       0
back_y       0
back_z       0
thigh_x      0
thigh_y      0
thigh_z      0
label        0
dtype: int64
```

We calculated the **mean values** for each of the sensor data columns:

- back_x, back_y, back_z (lower back sensors)
- thigh_x, thigh_y, thigh_z (thigh sensors)

This gives us a general idea of the average sensor readings, which can be useful later for normalization or handling missing data.

After calculating the means, we checked for any **missing values** in the dataset using **isnull().sum()**. The result showed that there are **no missing values** in any of the columns, which means the dataset is clean and we won't be using the mean here, so now we will go find outliers.

```
[10]: # IQR for Back
Q1_back = all_data[['back_x', 'back_y', 'back_z']].quantile(0.25)
Q3_back = all_data[['back_x', 'back_y', 'back_z']].quantile(0.75)
IQR_back = Q3_back - Q1_back

print("Back IQR values:\n", IQR_back)

mask_back = ~((all_data[['back_x', 'back_y', 'back_z']] < (Q1_back - 1.5 * IQR_back)) |
              (all_data[['back_x', 'back_y', 'back_z']] > (Q3_back + 1.5 * IQR_back))).any(axis=1)

# IQR for Thigh
Q1_thigh = all_data[['thigh_x', 'thigh_y', 'thigh_z']].quantile(0.25)
Q3_thigh = all_data[['thigh_x', 'thigh_y', 'thigh_z']].quantile(0.75)
IQR_thigh = Q3_thigh - Q1_thigh

print("\nThigh IQR values:\n", IQR_thigh)

mask_thigh = ~((all_data[['thigh_x', 'thigh_y', 'thigh_z']] < (Q1_thigh - 1.5 * IQR_thigh)) |
               (all_data[['thigh_x', 'thigh_y', 'thigh_z']] > (Q3_thigh + 1.5 * IQR_thigh))).any(axis=1)

# Combine both masks
final_mask = mask_back & mask_thigh
all_data_clean = all_data[final_mask]

print("\nShape after IQR-based outlier removal:", all_data_clean.shape)
print(f"Total outliers removed: {all_data.shape[0] - all_data_clean.shape[0]}")
```

```
Back IQR values:
 back_x    0.164795
back_y    0.160400
back_z    0.587646
dtype: float64

Thigh IQR values:
 thigh_x    0.916748
thigh_y    0.229004
thigh_z    0.981934
dtype: float64

Shape after IQR-based outlier removal: (1821212, 8)
Total outliers removed: 438385
```

We applied the **Interquartile Range (IQR)** method to remove outliers from the dataset.
First, we calculated the 25th (**Q1**) and 75th (**Q3**) percentiles for the **back sensor** data (back_x, back_y, back_z). The IQR was computed as Q3 - Q1, and values outside the range Q1 - 1.5*IQR to Q3 + 1.5*IQR were marked as outliers. A mask was created to identify these outlier rows.

The same steps were repeated for the **thigh sensor** data (thigh_x, thigh_y, thigh_z).
Another mask was created for outliers in the thigh readings. We then combined both masks to filter out rows that had outliers in either group.

The cleaned dataset was saved in all_data_clean. This process reduced the dataset from **2,259,597** rows to **1,822,112**. A total of **438,885 outlier rows** were removed.

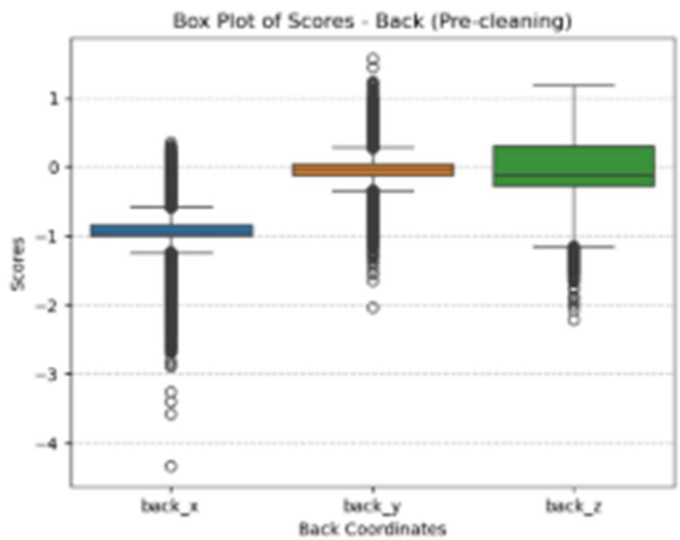
Removing these outliers helps improve the quality of the data. It ensures that extreme values won't distort analysis or model training. To see the difference between before and after of this effect we can use boxplot pre and post outliers removal.

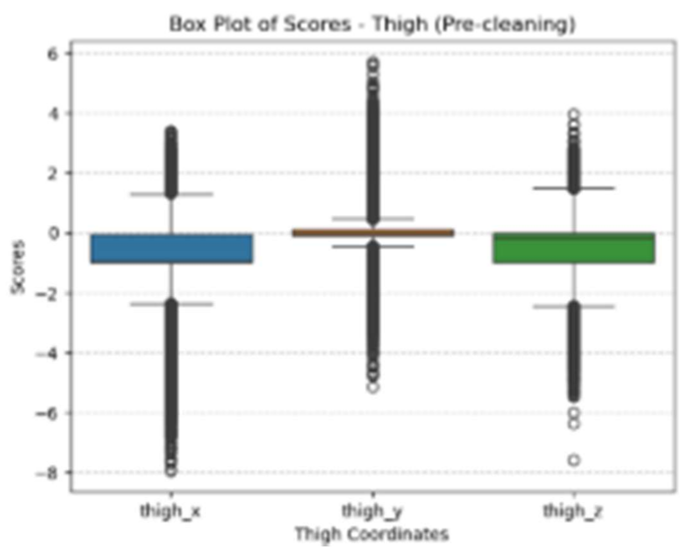
- **<u>Pre-Cleaning</u>**

[9]:

```python
# Boxplots (Pre-cleaning)
sns.boxplot(data=all_data[['back_x', 'back_y', 'back_z']])
plt.title("Box Plot of Scores - Back (Pre-cleaning)")
plt.xlabel('Back Coordinates')
plt.ylabel('Scores')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()

sns.boxplot(data=all_data[['thigh_x', 'thigh_y', 'thigh_z']])
plt.title("Box Plot of Scores - Thigh (Pre-cleaning)")
plt.xlabel('Thigh Coordinates')
plt.ylabel('Scores')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

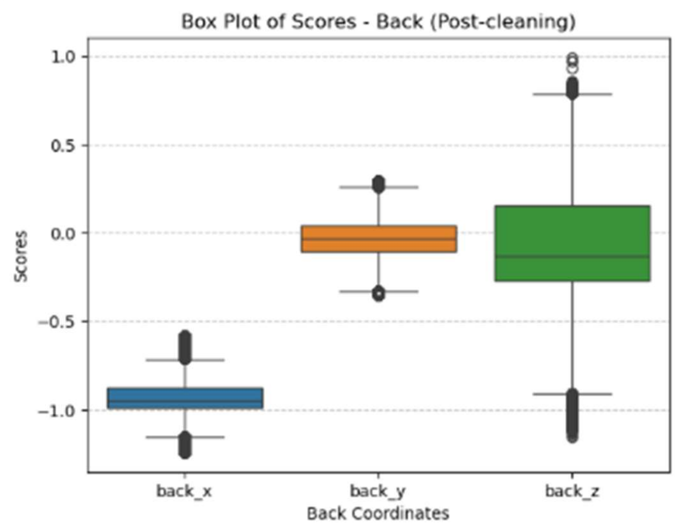


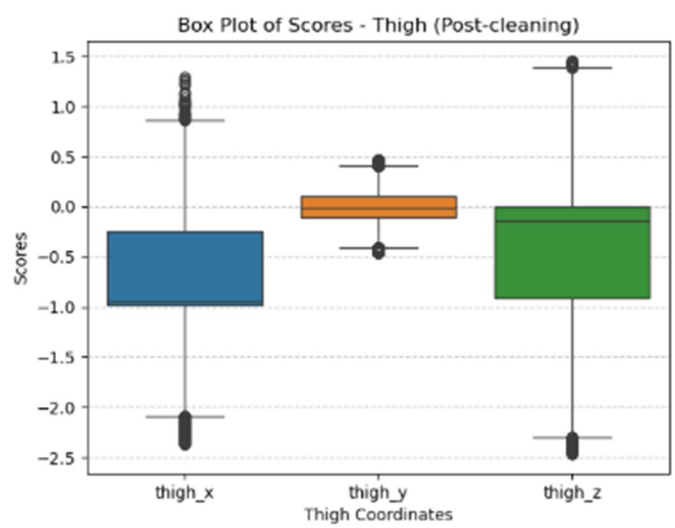


- **Post-Cleaning**

```
[222]: # BoxPlots (Post-cleaning)
sns.boxplot(data=all_data_clean[['back_x', 'back_y', 'back_z']])
plt.title("Box Plot of Scores - Back (Post-cleaning)")
plt.xlabel('Back Coordinates')
plt.ylabel('Scores')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()

sns.boxplot(data=all_data_clean[['thigh_x', 'thigh_y', 'thigh_z']])
plt.title("Box Plot of Scores - Thigh (Post-cleaning)")
plt.xlabel('Thigh Coordinates')
plt.ylabel('Scores')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```





3. Perform feature scaling or normalization.

```
[30]: # MinMax Normalization
scaler = MinMaxScaler()
features_to_scale = ['back_x', 'back_y', 'back_z', 'thigh_x', 'thigh_y', 'thigh_z']

# Apply normalization and store in new columns
all_data_clean.loc[:, [col + '_norm' for col in features_to_scale]] = scaler.fit_transform(all_data_clean[features_to_scale])

print("\nPreview of normalized features:")
display(all_data_clean[[col + '_norm' for col in features_to_scale]].head())
```

Preview of normalized features:

	back_x_norm	back_y_norm	back_z_norm	thigh_x_norm	thigh_y_norm	thigh_z_norm
0	0.365692	0.446897	0.603342	0.378216	0.380063	0.616124
1	0.394219	0.422154	0.603342	0.383495	0.369669	0.615188
2	0.439793	0.426723	0.603342	0.386702	0.414446	0.611257
3	0.432753	0.453750	0.603229	0.384497	0.452025	0.615438
4	0.406076	0.478873	0.604365	0.379151	0.476545	0.621615

We applied **Min-Max Normalization** to scale the sensor data between 0 and 1. This was done using the MinMaxScaler() from the sklearn.preprocessing module. We selected six features to normalize: back_x, back_y, back_z, thigh_x, thigh_y, and thigh_z. These features represent 3D coordinates from the back and thigh sensors. Normalization ensures all features contribute equally to model training. It also helps avoid dominance by features with larger numeric ranges. We used the .fit_transform() method to compute the min and max, then scaled the values. The normalized values were stored in new columns with a _norm suffix. For example, back_x was stored as back_x_norm, and so on. We then previewed the first few rows of the normalized dataset.

Dataset Link: DATASET

The code GitHub Link: GitHub