

Classifying Cardio Activities Using Sensor Data

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Problem Overview & Pipeline

Problem

Health Tracking devices and algorithms aren't always optimized for gym cardio equipment, even though most people do a lot of their daily physical activity at the gym.

Approach

Activity classification of the three most popular cardio activities at the UMass recreation center: stairmaster, incline treadmill, and stationary bike.

Extension

Comparing the effectiveness of an accelerometer approach to an accelerometer and gyroscope approach.



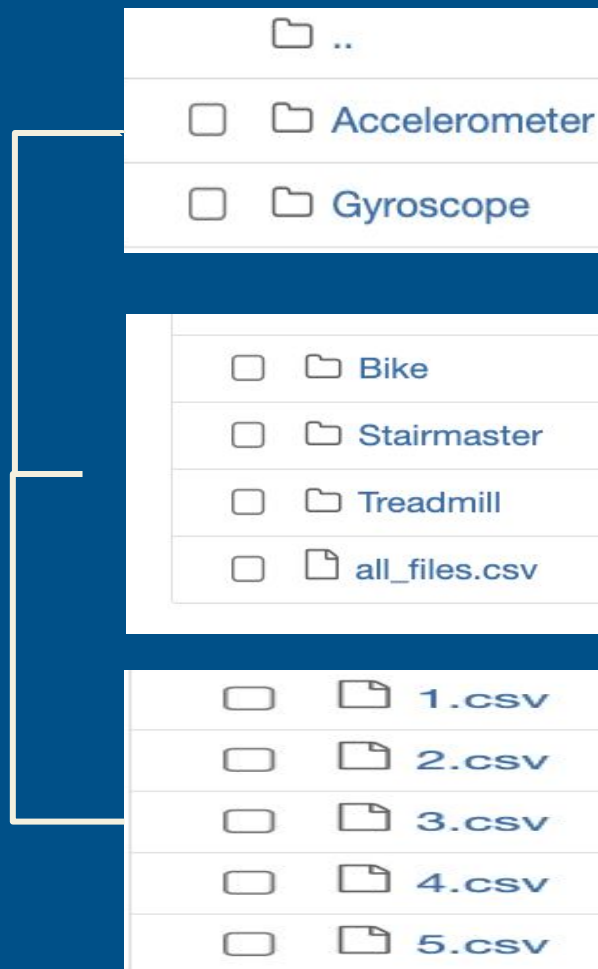
Data Collection & Processing

Data Collection

- 5 Participants recorded 5 minutes of activity on each cardio machine.
- Recorded on Sensor Logger with phone taped to participant's leg.
- We tapped start/stop after the participant was already on the cardio machine so we wouldn't have to trim the recording.
- Sampling rate was 100 Hz.

Windowing approach

- We used a window size of 10 seconds.
- No overlap, primarily for simplicity.



Technical Implementation

Feature engineering

- Calculated the magnitude of acceleration from x, y, z values.
- Applied a low pass filter to smooth the data.
- Extracted features from each data window: avg, max, min and standard deviation.
- Did this for both accelerometer and gyroscope.

Key features used

- Used time domain features from windows from the of sensor data.

Classification approach

- Used a Decision Tree Classifier to determine splits.

Model Selection and Training Methodology

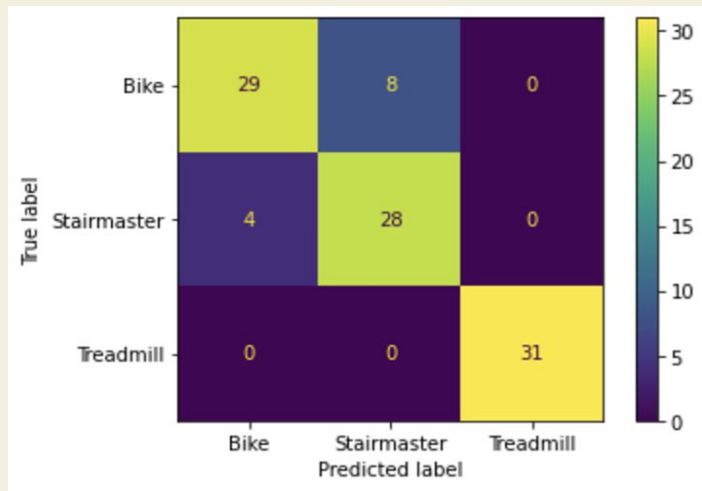
- Split the data into 70% training and 30% testing.
- Limited the tree depth to 5 to prevent overfitting.

Evaluation

- Measured model performance using accuracy and provided additional metrics like precision, recall and F1-score.

Results & Analysis

Accelerometer Only



| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Bike | 0.88 | 0.78 | 0.83 | 37 |
| Stairmaster | 0.78 | 0.88 | 0.82 | 32 |
| Treadmill | 1.00 | 1.00 | 1.00 | 31 |
| accuracy | | | 0.88 | 100 |
| macro avg | 0.89 | 0.89 | 0.88 | 100 |
| weighted avg | 0.88 | 0.88 | 0.88 | 100 |

Accuracy on test set: 0.88

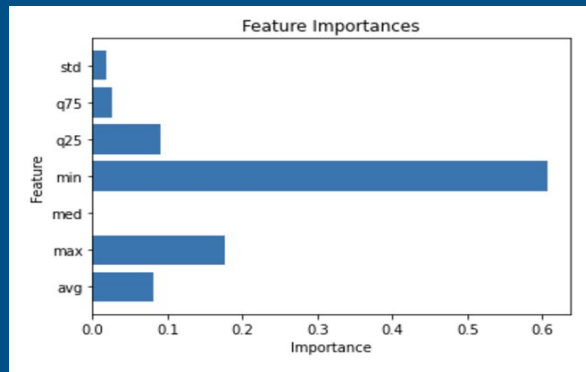
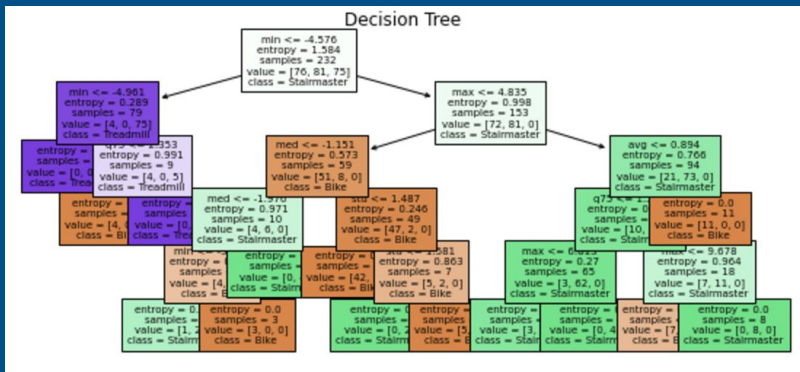
Accelerometer and Gyroscope



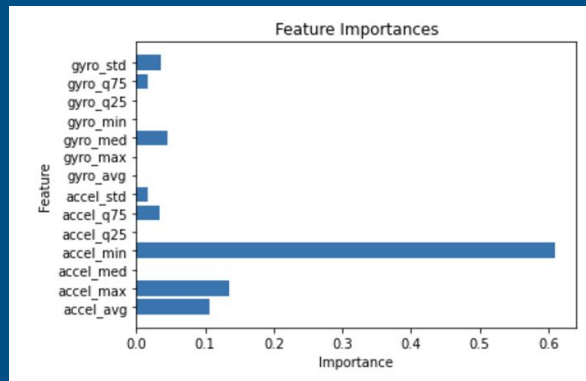
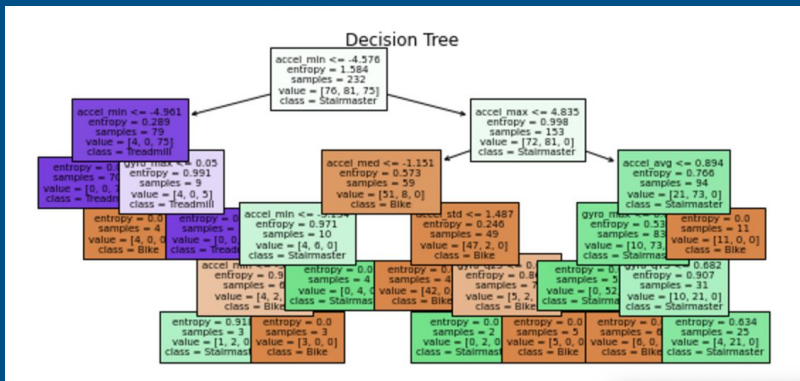
| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Bike | 0.90 | 0.70 | 0.79 | 37 |
| Stairmaster | 0.72 | 0.91 | 0.81 | 32 |
| Treadmill | 1.00 | 1.00 | 1.00 | 31 |
| accuracy | | | 0.86 | 100 |
| macro avg | 0.87 | 0.87 | 0.86 | 100 |
| weighted avg | 0.87 | 0.86 | 0.86 | 100 |

Accuracy on test set: 0.86

Results & Analysis



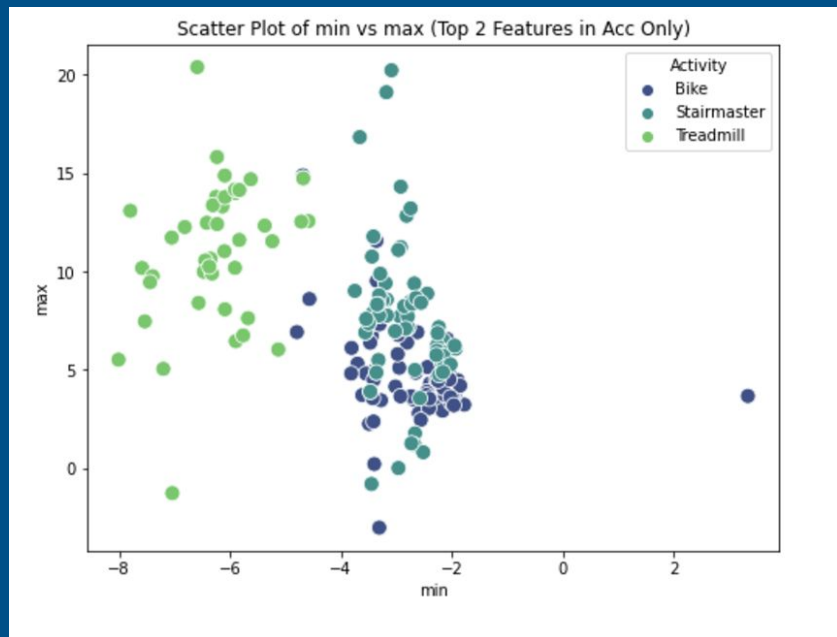
Accelerometer Only



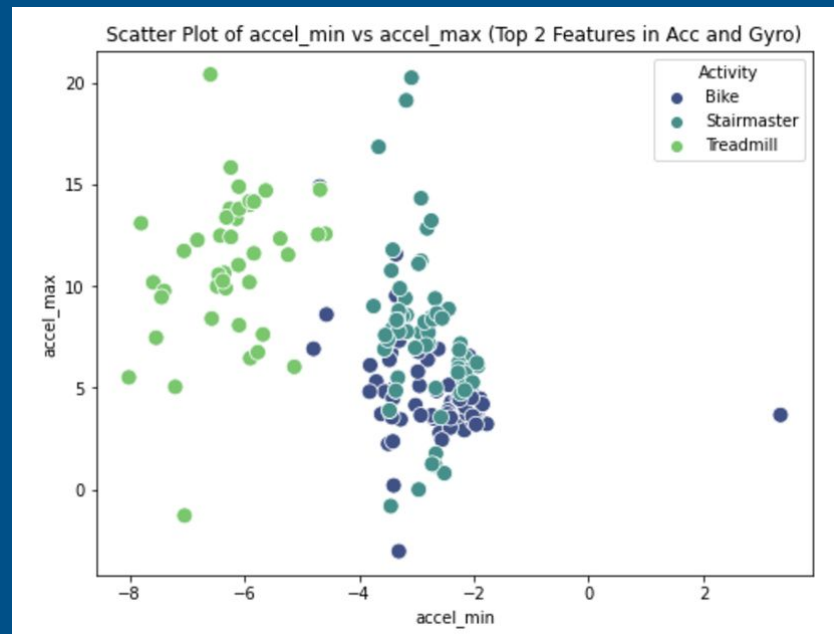
Accelerometer and Gyroscope

Results & Analysis

Accelerometer Only



Accelerometer and Gyroscope



Conclusions

What did you learn?

The gyroscope measures how much something is spinning or rotating, which might not be important for distinguishing between activities like walking on a treadmill or using a stairmaster.

This could just add unnecessary information that doesn't help the model. We could try to see if helps distinguish between just the bike and a combined stairmaster/treadmill.

What were the Main Challenges

We realised that while we were very confident in understanding and working with accelerometer data, there was a massive learning curve when it came to doing the same with gyroscope data.

Future improvements

We could have collected a lot more data and had more variation in the participants. Maybe done a bit more with feature importance.

