Predicting Stress Levels from Wearable Sensor Data

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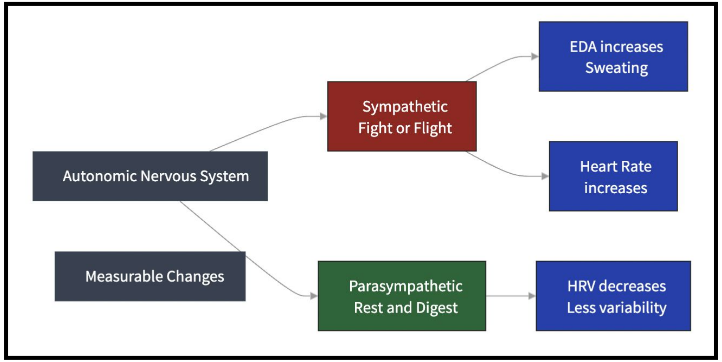
Introduction

- Wearable devices have become increasingly capable of continuously tracking physiological responses
  - ***Empatica E4 Wristband:*** Smartwatch that includes several sensors relevant to stress detection and analysis
- These detected stress signals can be used to carry out various classification tasks
  - ***Performed Task:*** Classifying whether a user is stressed, resting, or exercising

Problem & Motivation

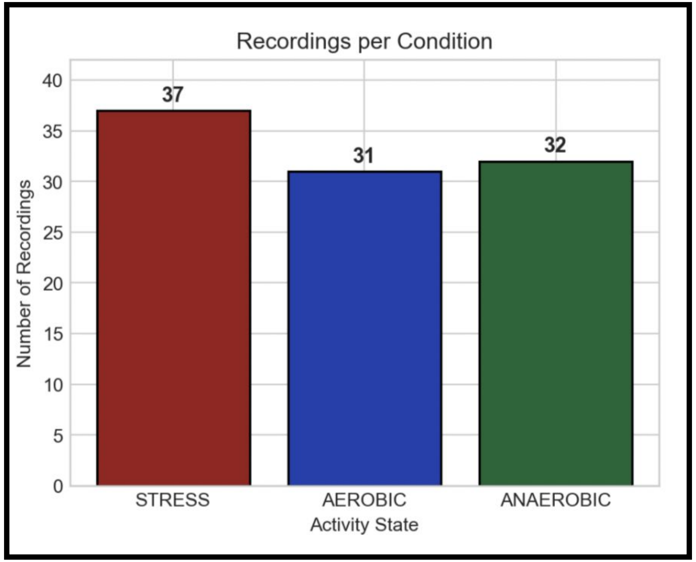
- ***Problem Statement:*** *"Can wearable sensors accurately detect and classify stress states?"*
- ***Why does it matter?***
    - Stress affects cardiovascular and autonomic nervous systems
    - Need rigorous evaluation of claims that consumer devices include stress-monitoring capabilities



Signal:	Sampling Rate:	What It Measures:
EDA	4 Hz	Skin conductance
HR	1 Hz	Beats per minute
ACC	32 Hz	3-axis movement
BVP	64 Hz	Pulse waveform
TEMP	4 Hz	Skin temperature
IBI	Variable	Beat-to-Beat intervals

Dataset Description

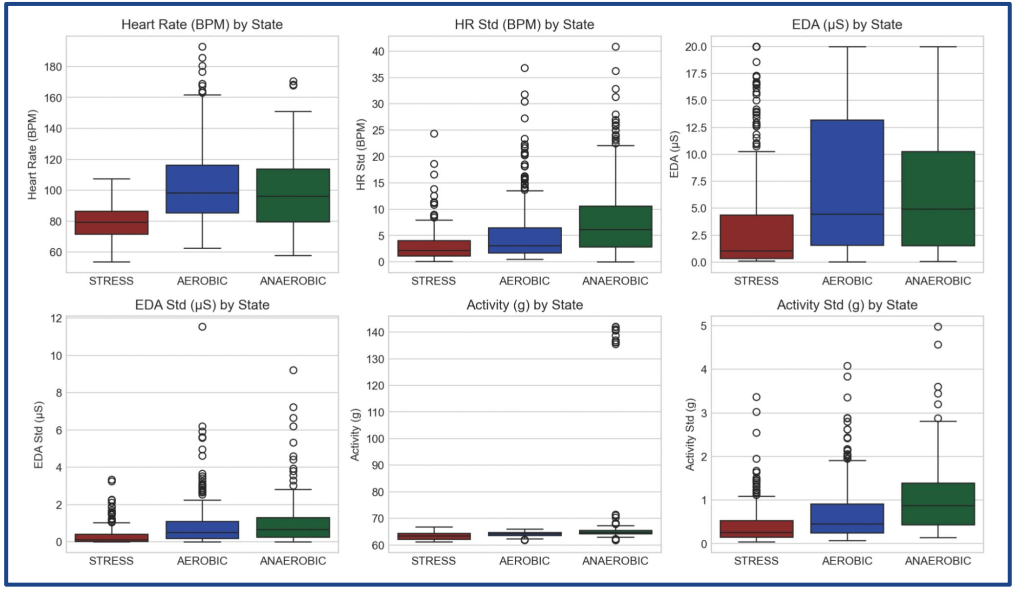
- ***Dataset:*** 100 participants, 3 controlled environments
    - **Rest (Baseline), Stress (TSST), & Physical Activity (Exercise)**
- ***Research Problem:***
    - Classify activity states (**STRESS vs. AEROBIC vs. ANAEROBIC**)
    - Tackled using multiple ML & Data Mining techniques (*Random Forest, AdaBoost, Gradient Boosting, & Clustering*)



Feature Engineering Pipeline

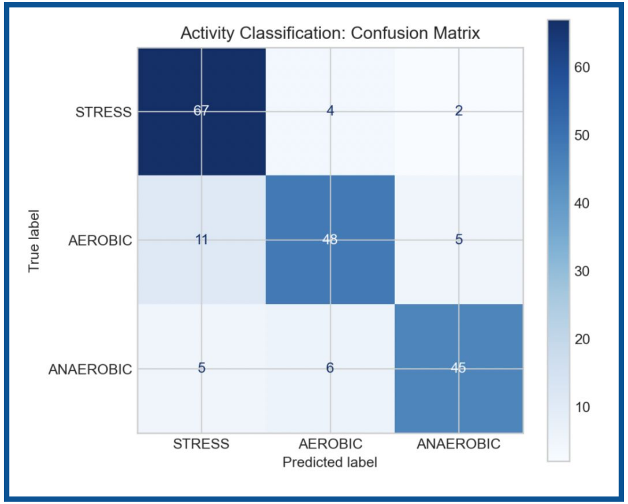
<u>From Raw Signals to Features:</u>

- Raw sensor streams → 60-second windows
- Statistical Summaries per segment (mean, std, min, max, range)
- Meaningful features extracted per window
- Filtered outliers → Condensed from thousands of raw samples to now left with a few hundred clean segments



Classification Approach & Model Selection

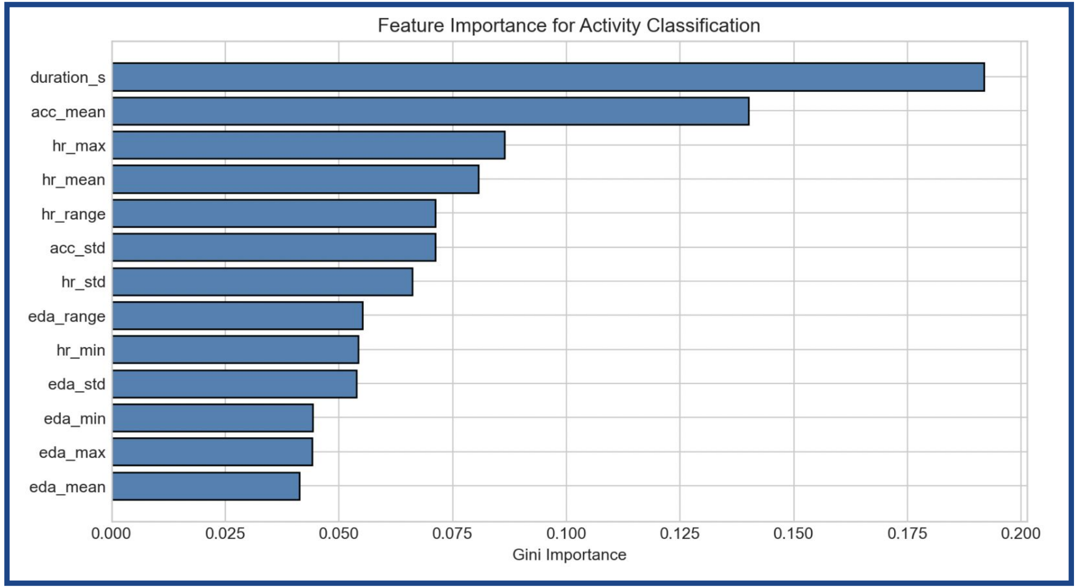
- ***Primary Model:*** Random Forest (**300 trees** with balanced weights, **75/25** train-test split)
- ***STRESS:*** 92% Recall (rarely misses stress episodes)
- ***AEROBIC/ANAEROBIC:*** Harder to separate as hinted by their Recall & F1 Scores
- *The model reliably distinguishes psychological stress from exercise*



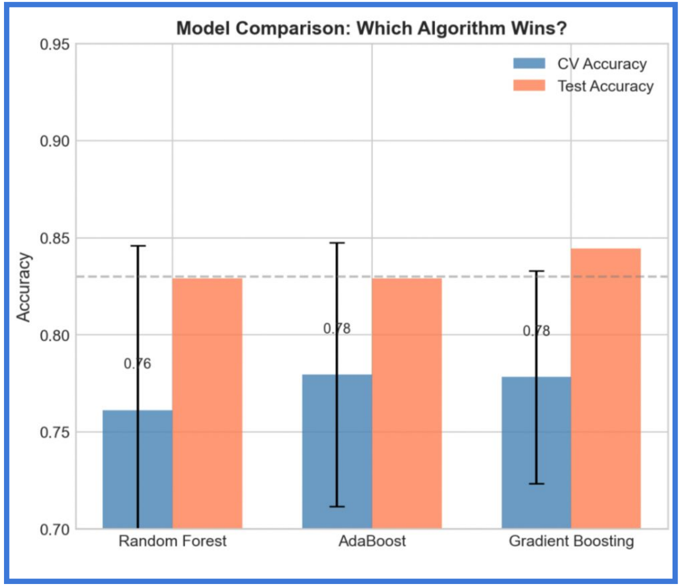
Class	Precision	Recall	F1-Score	Support
AEROBIC	0.83	0.75	0.79	64
ANAEROBIC	0.87	0.80	0.83	56
STRESS	0.81	0.92	0.86	73
Weighted Avg	**0.83**	**0.83**	**0.83**	193

Feature Importance

- ***Top Predictors:*** Duration, Accelerometer, and Heart Rate
- Movement patterns help distinguish an exercising participant from seated stress
- EDA features are ranked lower in importance than expected despite marketing claims



Model Comparison

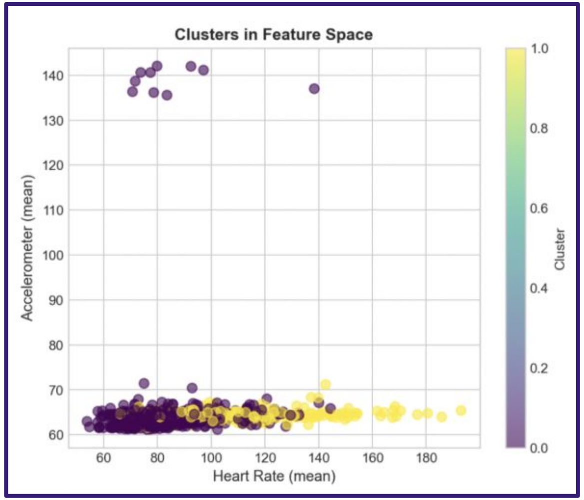


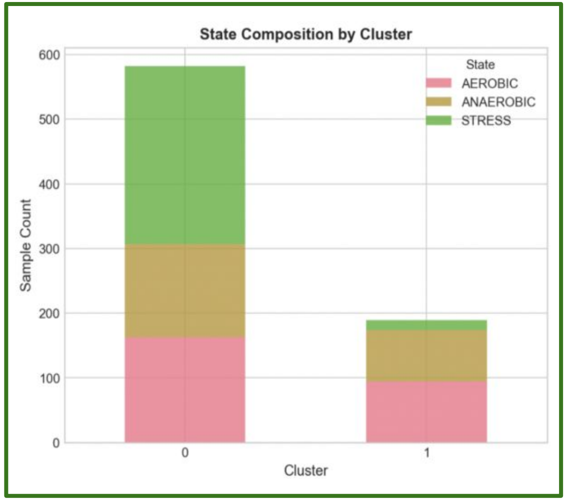
All 3 algorithms achieve a **strong accuracy of 83-85%** (**Random Forest**, **AdaBoost**, **Gradient Boosting**)

Models **agree ≈87% of the time**—with the **strongest consensus** on **being** the **STRESS class**

Unsupervised Validation

- Conducted **K-Means**
  - K = 2
  - Separated by Heart Rate
- **Low Heart Rate cluster** contains **94% of the STRESS samples**
- Confirms that the features are capturing real physiological differences between conditions





Conclusion & Key Takeaways

- Activity classification achieves ≈83% accuracy across 3 states
- Psychological stress is highly detectable
  - **Recall = 0.92** and **F1 Score = 0.87**
- ***Key Insight:*** Movement & Heart Rate outperform EDA for state classification
- ***Impact:*** Wearable devices can reliably distinguish stress from exercise and show great capabilities with discrete classification

Thank You