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Machine Learning Architectures to Classify Activities of Daily Living and Fall Types From Wearable Accelerometer Data

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Introduction

Activities of Daily Living (**ADLs**):

- self-care
- walking
- running
- going up/down the stairs

Falls

State of the art

- Classification of ADLs and falls based on accelerometer measurements *[Pires et al., 2020; Janidarmian et al., 2017, Begala et al., 2012]*

- Optimal placement at the hip *[Cleland et al., 2013]*

- Accuracy in laboratory conditions vs real-world *[Liu et al., 2022]*

Aim of the work

- Comparison of different ML approaches

- Focus on ADL and falls (multiclass classification)

- Real-world data

- Two different open datasets

ADL and Fall Datasets

Smartphone/smartphone-like accelerometers

UniZgFall *[Razum et al., 2018]*

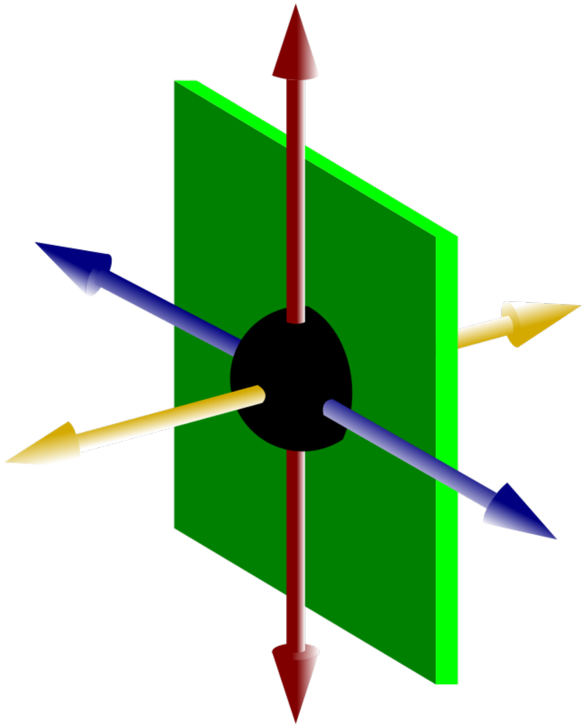
N=16, 7 types of ADL and 3 fall types

f_{sample} = 200 Hz, 468 items, unbalanced

UniMiB SHAR *[Micucci et al., 2017]*

N=30, 9 types of ADL and 8 fall types

f_{sample} = 50 Hz, 1980 items, unbalanced

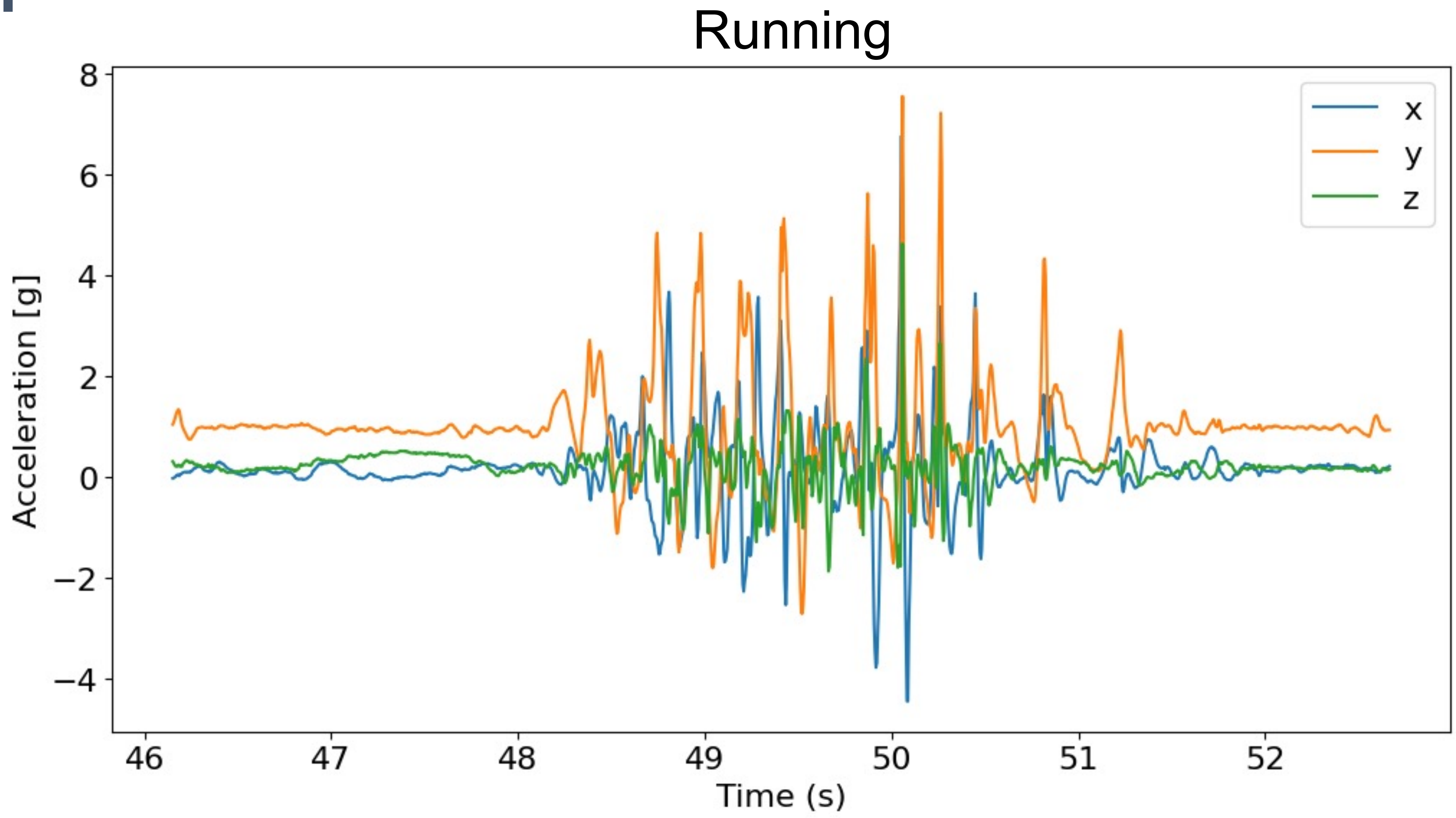


ADL and Fall Datasets

Table 1. ADLs and fall types categories in UniMiB SHAR dataset.

#	Description	Label
1	From laying on the bed to standing	StandingUpFL
2	From standing to lying on a bed	LyingDownFS
3	From standing to sitting on a chair	StandingUpFS
4	Moderate running	Running
5	From standing to sitting on a chair	SittingDown
6	Climb the stairs moderately	GoingDownS
7	Down the stairs moderately	GoingUpS
8	Normal walking	Walking
9	Continuous jumping	Jumping
10	Fall backward while trying to sit on a chair	FallingBackSC
11	Generic fall backward from standing	FallingBack
12	Falls using strategies to prevent the impact	FallingWithPS
13	Fall forward from standing	FallingForw
14	Fall right from standing	FallingLeft
15	Fall right from standing	FallingRight
16	Falls with contact to an obstacle	HittingObstacle
17	Getting unconscious	Syncope

Input data



Input data

Raw data

5150 x 3

= 25.7 s

3208 x 3

= 64.2 s

Zero-padding

Features

94: 50 in time domain, 44 FFT

#	Description	Acceleration	FFT
1	Mean	✓	✓
2	Standard deviation	✓	✓
3	Average absolute deviation	✓	✓
4	Minimum	✓	✓
5	Maximum	✓	✓
6	Maximum - minimum	✓	✓
7	Median	✓	✓
8	Median absolute deviation	✓	✓
9	Interquartile range	✓	✓
10	Negative values count	✓	✓
11	Positive values count	✓	
12	Number of values above mean	✓	
13	Number of peaks	✓	✓
14	Skewness	✓	✓
15	Kurtosis	✓	✓
16	Energy	✓	✓
17	Average resultant acceleration	✓(1 value)	✓(1 value)
18	Signal magnitude area	✓(1 value)	✓(1 value)

Machine Learning Architectures

SVM – Support Vector Machine

RF – Random Forest

CAT – CatBoost

ALL – Maximum confidence

Stratified **10-fold cross-validation**

Statistical Analysis

Accuracy and multi-class F1 score

Training time

Confusion matrix

$$F1 - score_i = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

For RF and CAT we analyzed feature importance

Kruskal-Wallis test and post hoc analysis via Dunn's test with Bonferroni correction

Hardware and Software

Ubuntu 22.04.1 LTS

Python 3.10.6

sklearn 1.2.2

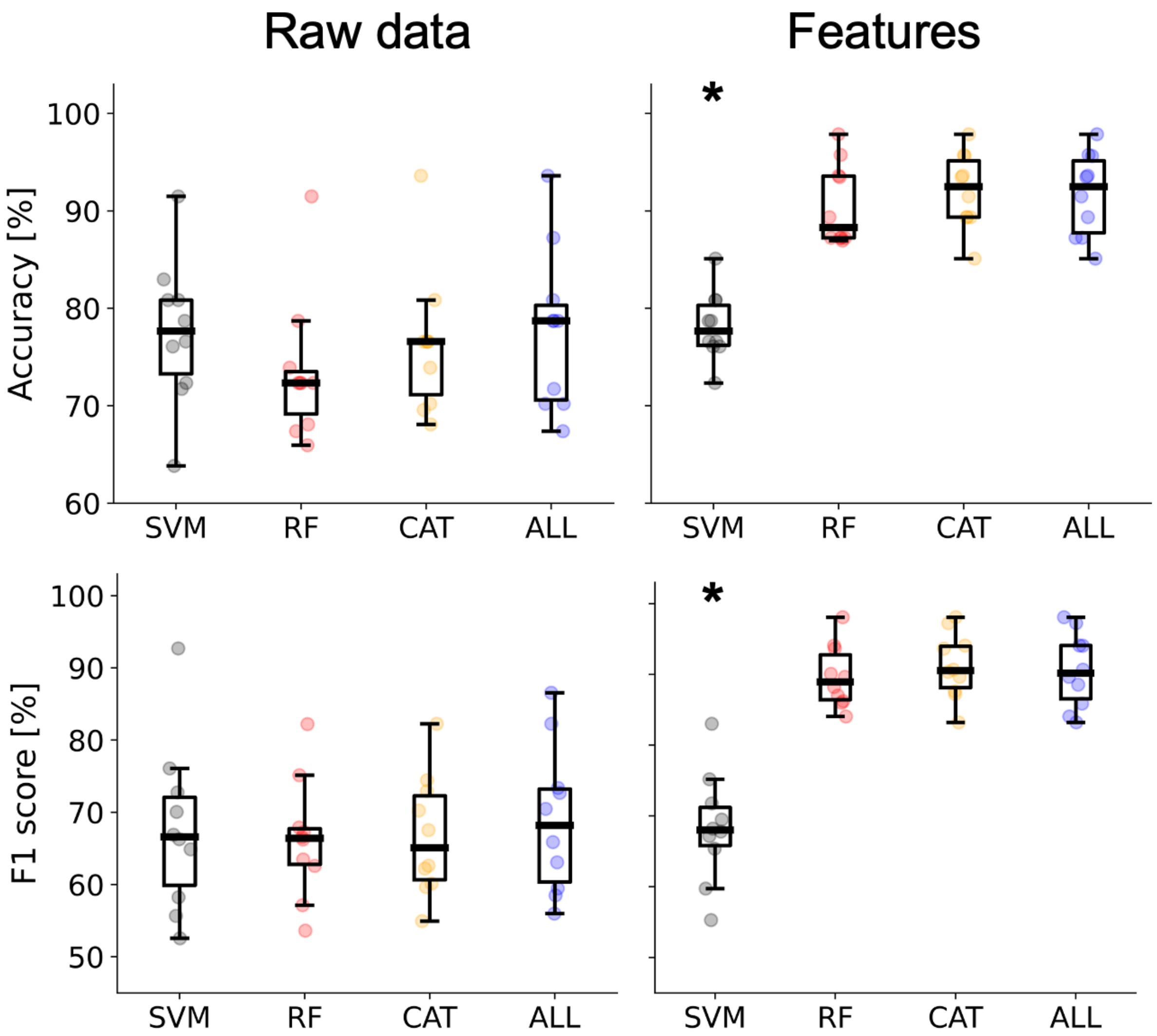
Catboost 1.1.1

Intel(R) Xeon(R) CPU E5-2690 v3 @2.60 GHz, 16 CPUs, 64 GB RAM

Open code available: https://github.com/alberto-antonietti/ml_accelerometers

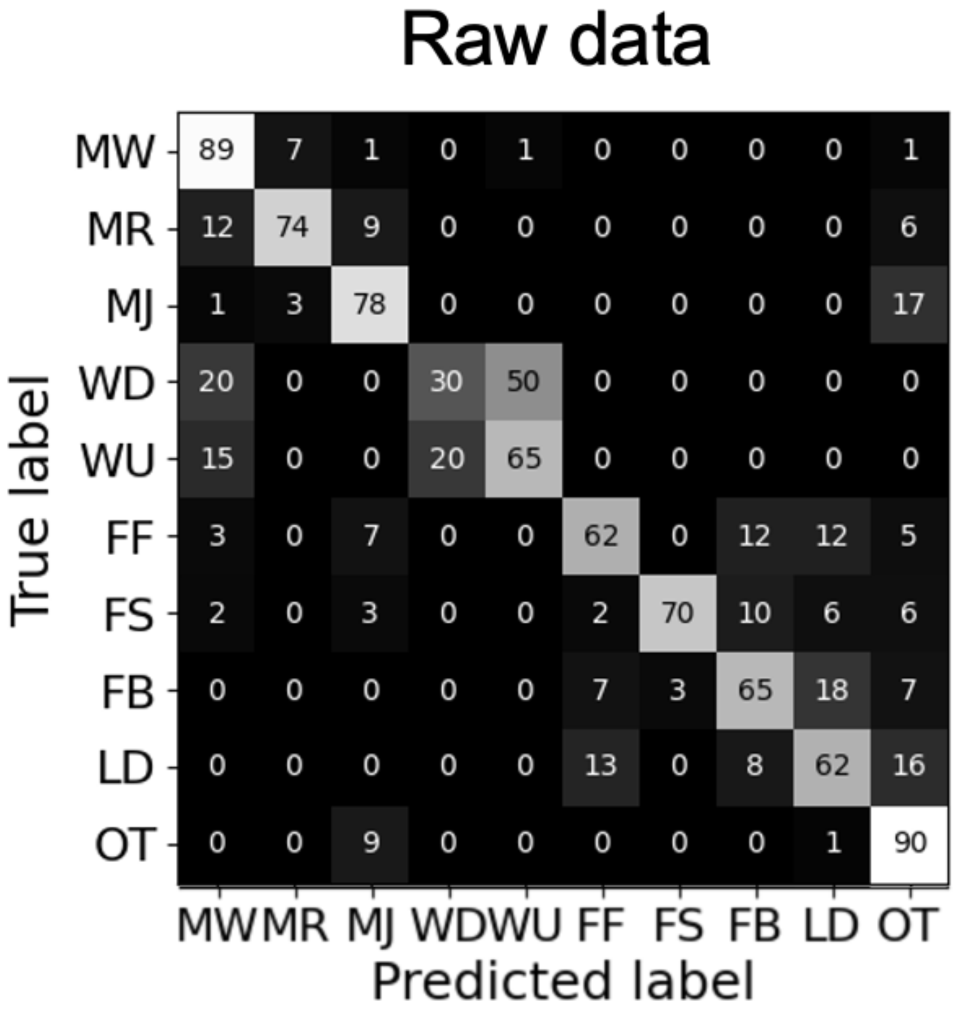
Results – UniZgFall

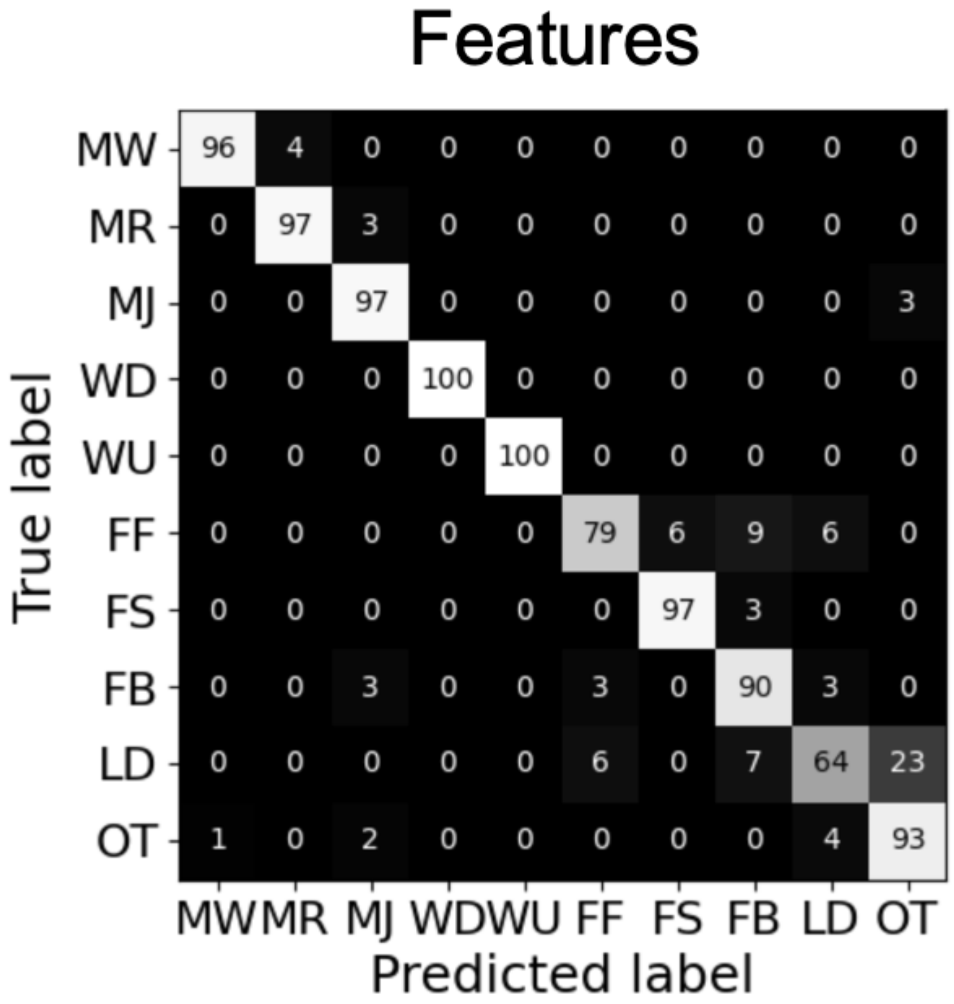
Avg Training Time
SVM 227.40 s
RF 1.79 s
CAT 1456.68 s.



Avg Training Time
SVM 0.11 s
RF 0.42 s
CAT 17.71 s.

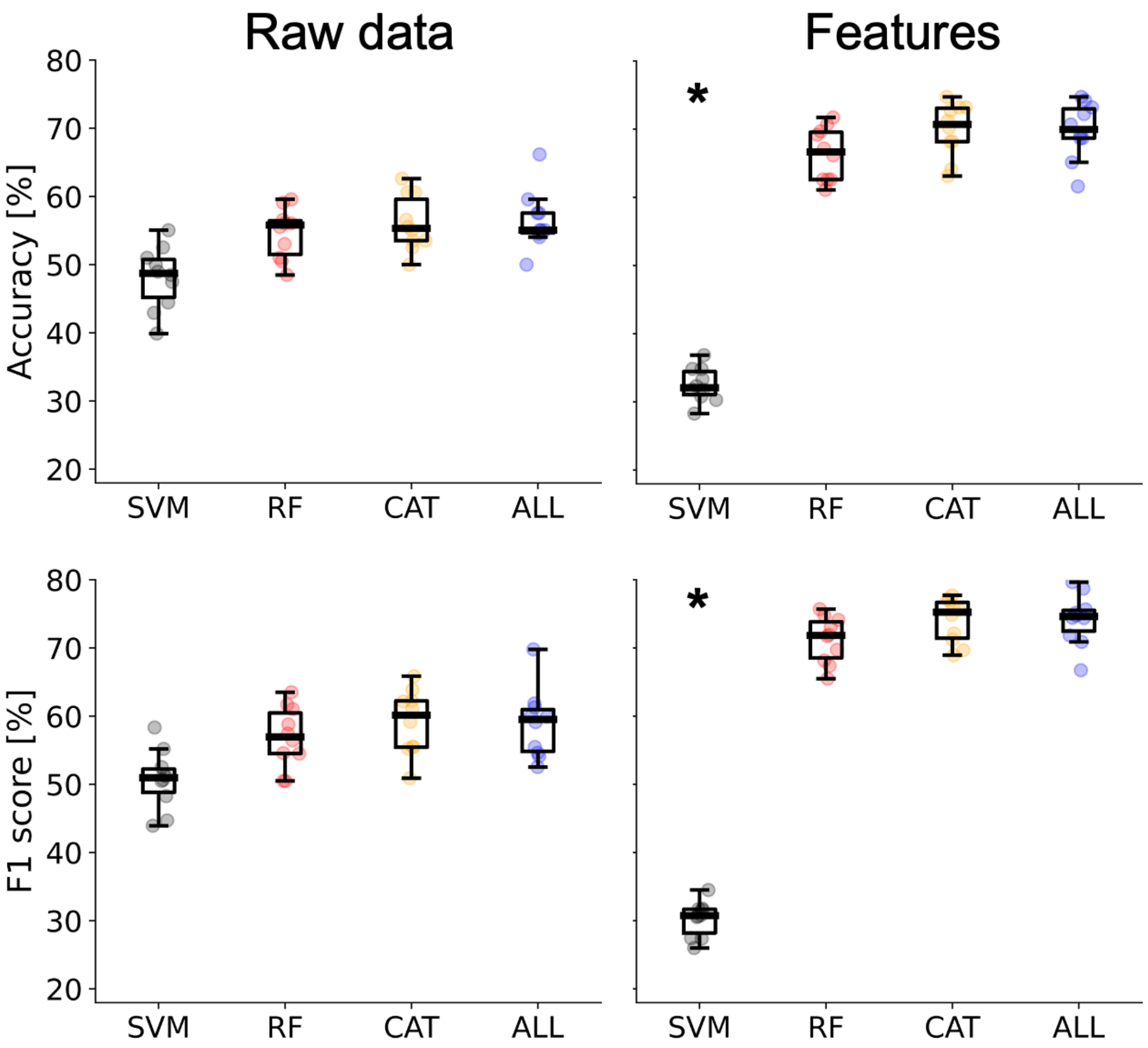
Results – UniZgFall





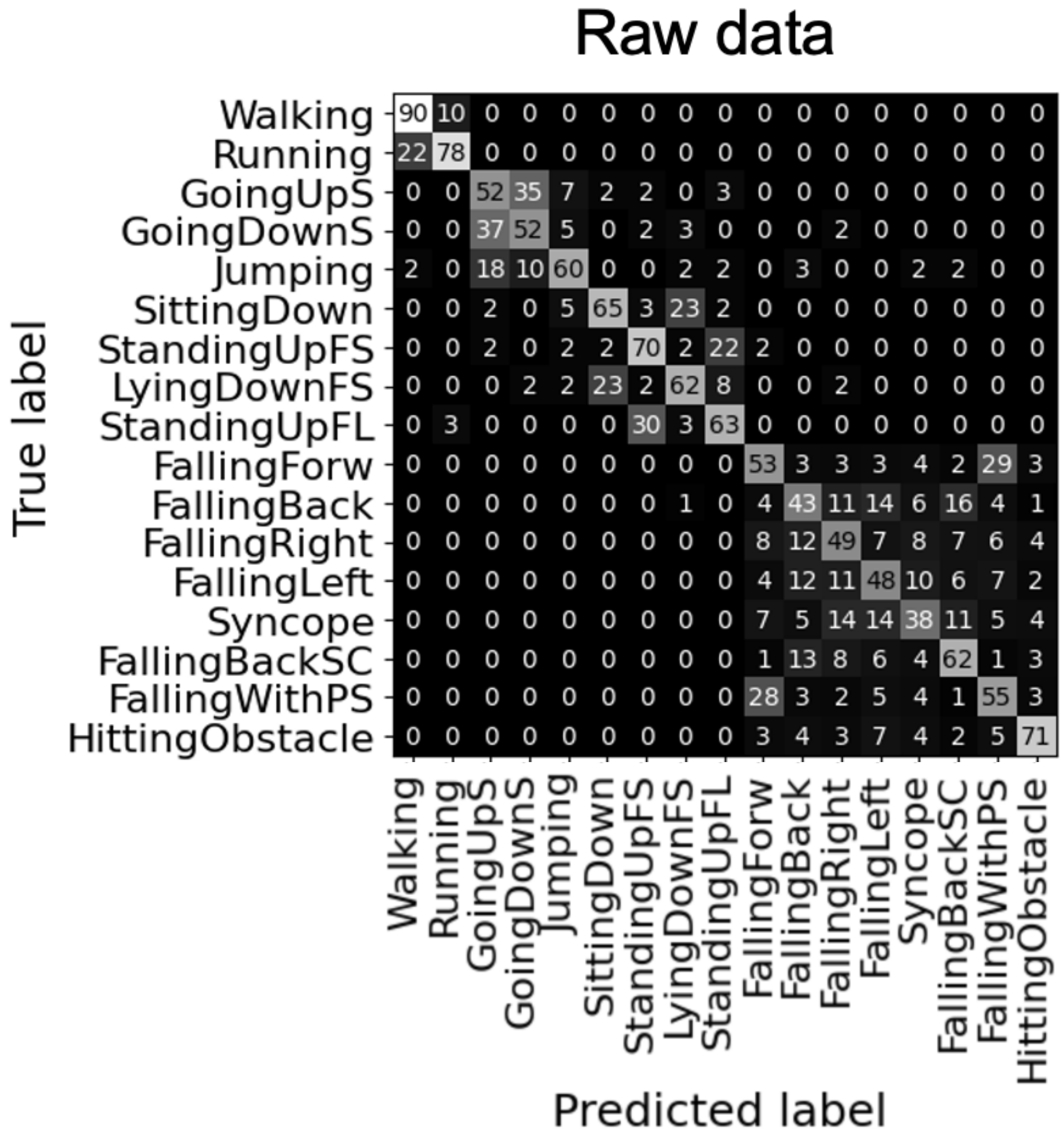
Results – UniMiB SHAR

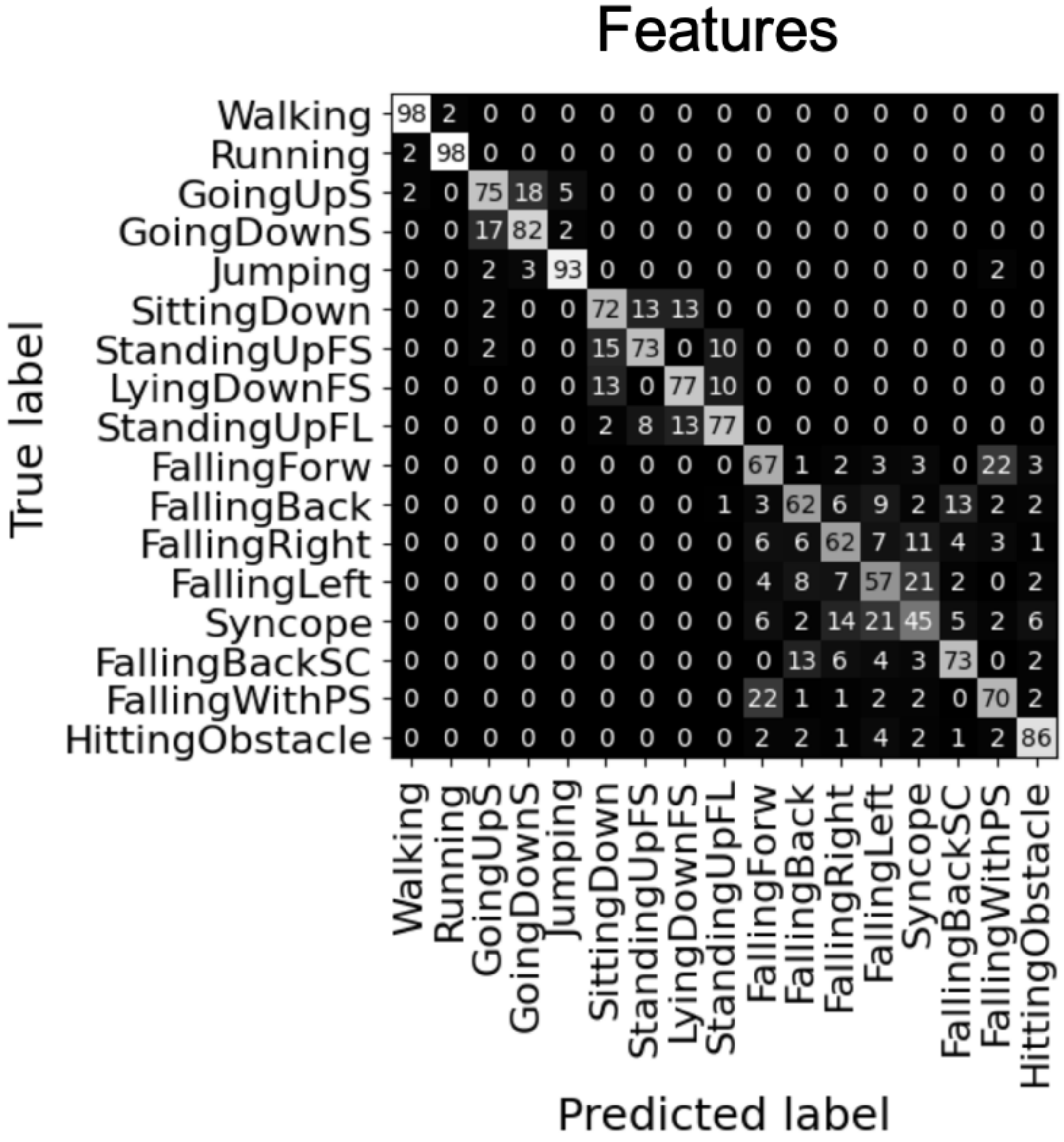
Avg Training Time
SVM 194.10 s
RF 5.34 s
CAT 1721.02 s.



Avg Training Time
SVM 2.40 s
RF 1.76 s
CAT 42.67 s.

Results – UniMiB SHAR





Explainability

$Energy$ along y axis.
Features of the y axis, as well as frequency features, were more important than the other two axes.

$$E_s = \langle x(n), x(n) \rangle = \sum_{n=-\infty}^{\infty} |x(n)|^2$$

$above\_mean$ along y and z axes.
Features of the y and z axes were slightly more important, and frequency features were less important.

Conclusions

- Robustness and generalizability

- Features are more informative than raw data

- RF and CAT performed better, RF is less demanding

- Accelerometers placed at waist → possible low user compliance

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