Projects

1. Sleep/Awake Classification

Detection of Sleep/Awake using wrist-worn Accelerometer and Heart rate data

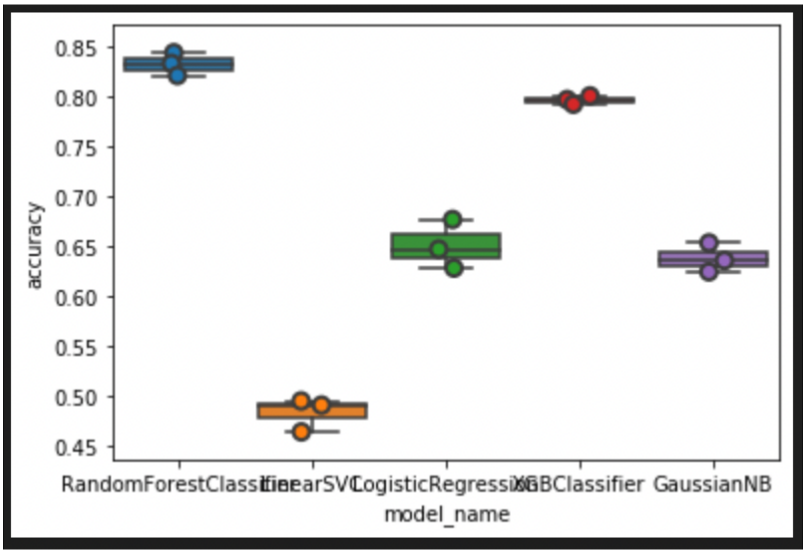
Extracted various features from Accelerometer and interpolated heartrate data, since it was inconsistent.

Features
1. Sum of values of a period of time: $\sum_{i=1}^{T} s_i$.
2. Mean: $\mu_s = \frac{1}{T}\sum_{i=1}^{T} s_i$.
3. Standard deviation: $\sigma_s = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(s_i - u_s)}$.
4. Coefficients of variation: $c_v = \frac{\sigma_s}{\mu_s}$.
5. Peak-to-peak amplitude: $max\{s_1, ..., s_T\} - min\{s_1, .., s_T\}$.
6-10. Percentiles: $10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}$
11. Interquartile range: difference between the 75^{th} and 25^{th} percentiles.
12. Lag-one-autocorrelation: $\frac{\sum_{i=1}^{T-1}(s_i-\mu_s)(s_{i+1}-\mu_s)}{\sum_{i=1}^{T}(s_i-\mu_s)^2}$.
13. Skewness: $\frac{\frac{1}{T}\sum_{i=1}^{T}(s_i-\mu_s)^3}{(\frac{1}{T}\sum_{i=1}^{T}(s_i-\mu_s)^2)^{\frac{3}{2}}}$, measure of asymmetry of the signal probability distribution.
14. Kurtosis: $\frac{\frac{1}{T}\sum_{i=1}^{T}(s_i-\mu_s)^4}{(\frac{1}{T}\sum_{i=1}^{T}(s_i-\mu_s)^2)^3} - 3$, degree of the peakedness of the signal probability distribution.
15. Signal power: $\sum_{i=1}^{T} s_i^2$.
16. Log-energy: $\sum_{i=1}^{T}\log(s_i^2)$.
17. Peak intensity: number of signal peak appearances within a certain period of time.
18. Zero crossings: number of times the signal crosses its median.
19. Correlation between each pair of axes: $\frac{\sum_{i=1}^{T}(s_i-\mu_s)(v_i-\mu_v)}{\sqrt{\sum_{i=1}^{T}(s_i-\mu_s)\sum_{j=1}^{T}(v_j-\mu_v)}}$.

Table 1: Time series features used in our representation of each window where the time series is denoted as $s_1, ..., s_T$ and T is the length of the window

These features were extracted for Accelerometer along with min, max for a specific (variable can be changed) set of seconds (like a moving window), and were into various classifiers out of which RandomForest was giving the best results. Around 84% accuracy.

Which other classifiers were used and what were their accuracies?



What is the benchmark accuracy for the dataset and how does our result compare to this?

I dont recall that, but many issues were there, like we dont had our own data and the data which we were using was from PSG while our watch will have PPG signal.
So, not sure about that.

Also, I observed only Acc features were enough to classify sleep and awake, but heart rate features are a must to classify sleep stages, for which we had very fewer data.

With 84% accuracy can we claim that min and max and other statistical features extracted from accelerometer data were enough? How can we improve this accuracy?

We may have to experiment with new additional features, i tried some more like nth_percentile and few others as well, but results didnt improve much. I think with an increment in number of datapoints the accuracy should increase.

```
FEATURES=['Mean_mag','SD_mag', 'Min_mag', 'Max_mag', 'Median_mag',
'Skewness_mag','Kurtosis_mag', 'bpm', 'Mean_bpm', 'SD_bpm',
'Min_bpm', 'Max_bpm', 'Median_bpm','Skewness_bpm', 'Kurtosis_bpm']
```

All these features were used.

Overall 700 data points were there for test set, accuracy might improve with an increase in data. Since there was class imabalnced, Sleep: 23529, Awake:2307, i balanced them to Sleep:2353,Awake:2307

2. Fall detection using Accelerometer

Detecting a Fall using Wrist-Worn Triaxial Accelerometer Considering three main stages-- Freefall, Impact and Inactivity after a fall.

1. Start of the fall: The phenomenon of weightlessness will always occur at the start of a fall. It will become more significant during free fall, and the vector sum of acceleration will tend toward 0 g; the duration of that condition will depend on the height of freefall. Even though weightlessness during an ordinary fall is not as significant as that during a freefall, the vector sum of acceleration will still be substantially less than 1 g (while it is generally greater than 1 g under normal conditions).
2. Impact: After experiencing weightlessness, the human body will impact the ground or other objects; the acceleration curve shows this as a large shock. Therefore, the second basis for determining a fall is the ACTIVITY interrupt right after the FREE_FALL interrupt.
3. Aftermath: Generally speaking, the human body,after falling and making an impact, can not rise immediately; rather it remains in a motionless position for a short period (or longer as a possible sign of unconsciousness). On the acceleration curve, this presents as an interval of a flat line. Therefore, the third basis for determining a fall situation is the INACTIVITY interrupt after the ACTIVITY interrupt.

Three Thresholds considered-- Min magnitude in a window -- For FREE FALL Detection (<120/95 mm per sec sq.) Maximum of Max min difference in a window (>2000 mm per sec sq.) Avg of max-min difference of 30 windows, with 5 samples per window equivalent to 3s (<200 mm per sec sq.)

The accuracy here on test data was above 90%, I don't recall the exact number.

It was sent to some Hospital for testing, by Prathyusha

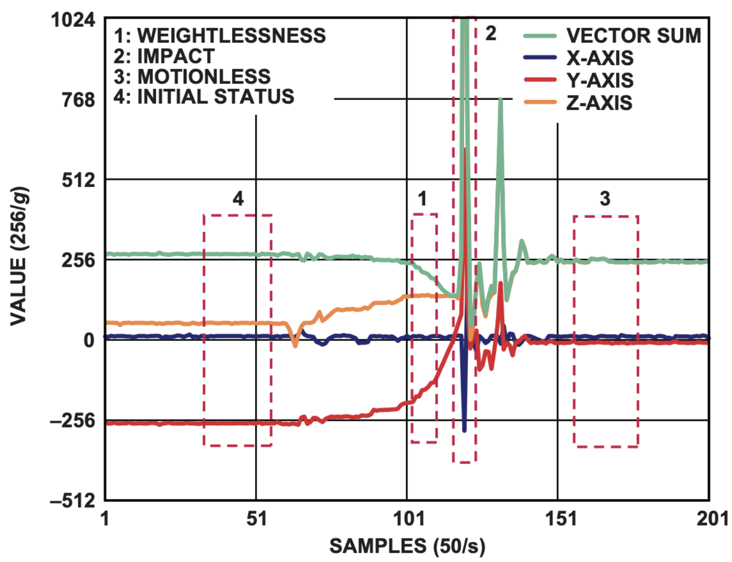


Fig: Acceleration change curves during the process of Falling

3. Arrhythmia Detection:

Algorithm to discriminate **AFIB, AFL, and NSR** heartbeat using RR interval from ECG/PPG signal. Dataset link-**ECGDataDenoised**

Data Distribution: 10,646 patients- 4690 F,5956 M participants 10s ECG Signal, Sampling frequency - 500Hz

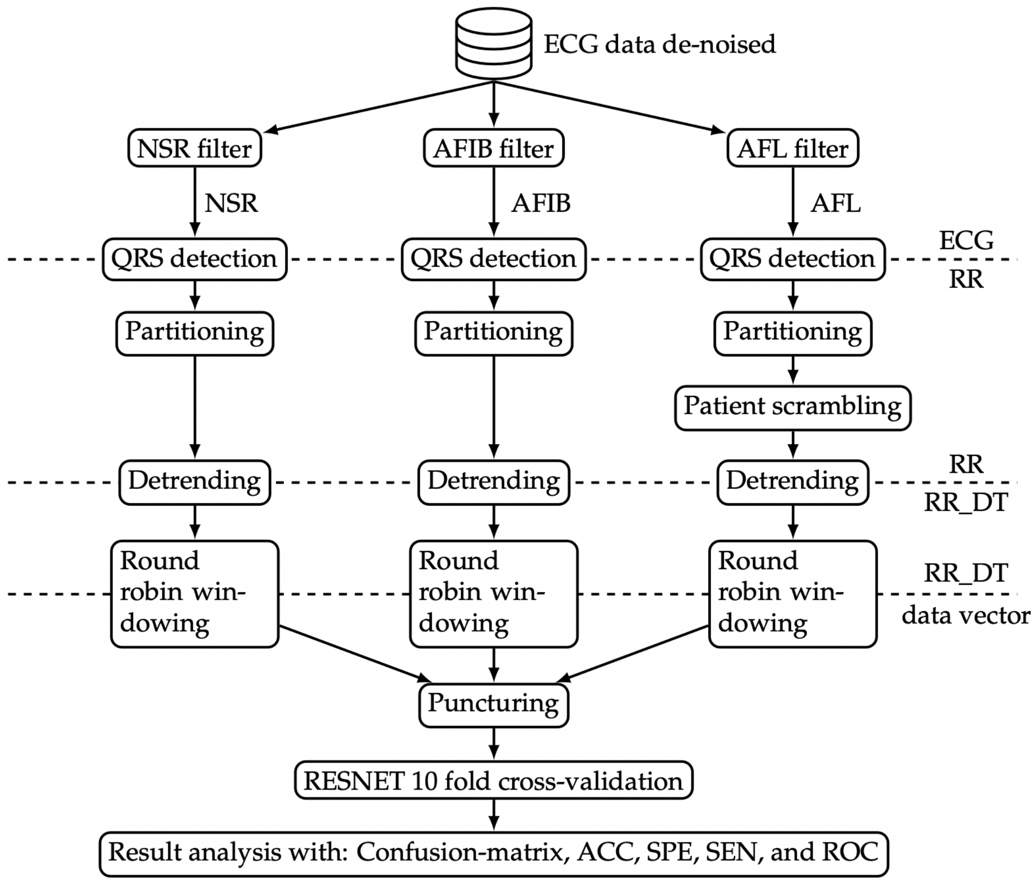


Figure 1. Block diagram of the study setup.

Methodology:

1. Extracting data and finding the RR intervals using neurokit python library.
2. Detrending of the signal using scipy detrend fn.
3. Data partition and Patient Scrambling
4. Round robin windowing technique to increase data
5. 10 fold Cross Validation using Resnet Model
6. Plotted Confusion matrices and overall accuracy for each fold

Achieved 96% accuracy on avg across all 10 folds on the test set

Is this accuracy for detection or diagnosis, that is can we just detect presence/absence of arrhythmia or are we able to classify the type of arrhythmia?

I'm not clear what do you mean from this. From an ECG singal we can classify if a person is having Arrythmia or not.

What type of detrending is used?

Mean detrending but in paper they mentioned "Detrending- (removed dc offset, keeps number of points same) detrending and low-pass filter proposed by Fisher et al. [19]. The filter combination is based on an Ornstein–Uhlenbeck third-order Gaussian process, which acts on the RR interval signal directly" , which i tried to understand, but seemed beyond my scope of knowledge.

Any other model (other than ResNet) is used?

No, Sai asked to use ResNet model, as he shared a research paper, and wanted me to incorporate that

What is the benchmark accuracy?

99% on validation set. Mine is 96% on validation and 99% on train and test set.

As I understand, we are just replicating the architecture given in the research article. Why are we getting less accuracy compared to the benchmark?

Two things are different:

1. Detrend function which i have already mentioned above needs to be incorporated.
2. Second Puncturing algorithm, which removes equidistant vectors, so that unique type of patterns can be fed into the model. This step comes after the Round robin windowing technique, which helps to make the data uniform in nature and also multiplies the amount of data vectors. But I just sliced and choose the first x-th datapoints (where x is the minimum datapoints among all the 3 classes), and hence made number of data points in class balanced.

Please include detailed results like confusion matrices for ready reference.