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EFFECTIVE NOISE REMOVAL AND UNIFIED MODEL OF HYBRID FEATURE SPACE OPTIMIZATION FOR AUTOMATED CARDIAC ANOMALY DETECTION USING PHONOCARDIOGARM SIGNALS

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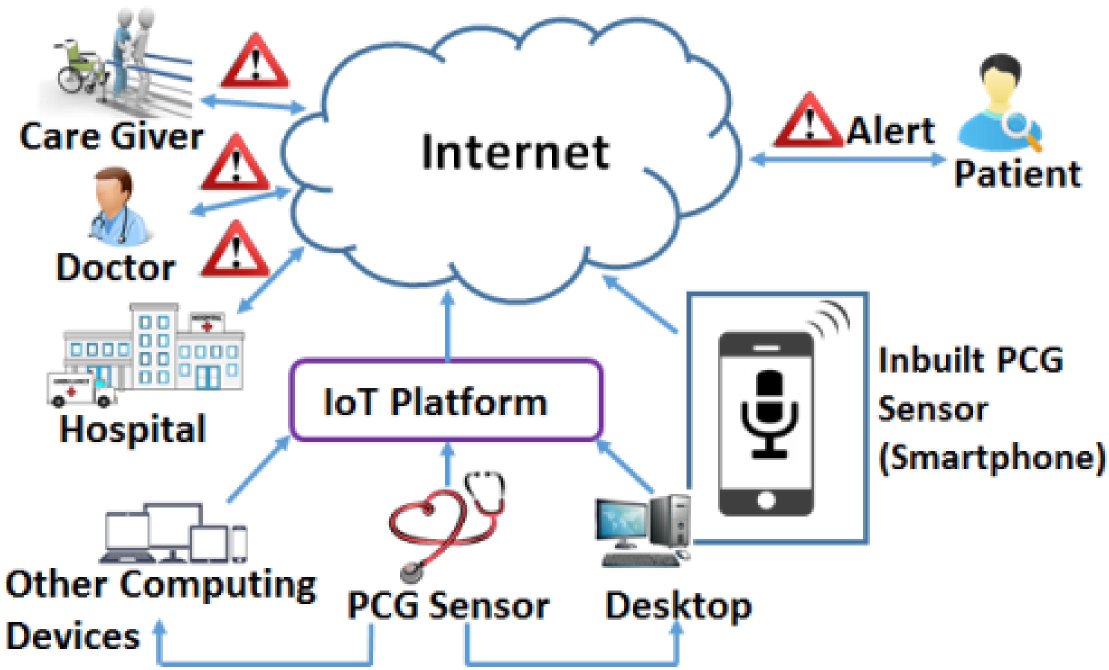
Affordable Healthcare Analytics in Internet of Things (IoT)

- **Cardiac problem is a serious issue** : An estimated 17.7 million people died from CVDs in 2015, representing 31% of all global deaths.

- "Over three quarters of CVD deaths take place in low- and middle-income countries"

- IoT revolutionizing healthcare
  - Low cost wearable sensors
  - Early screening and detection



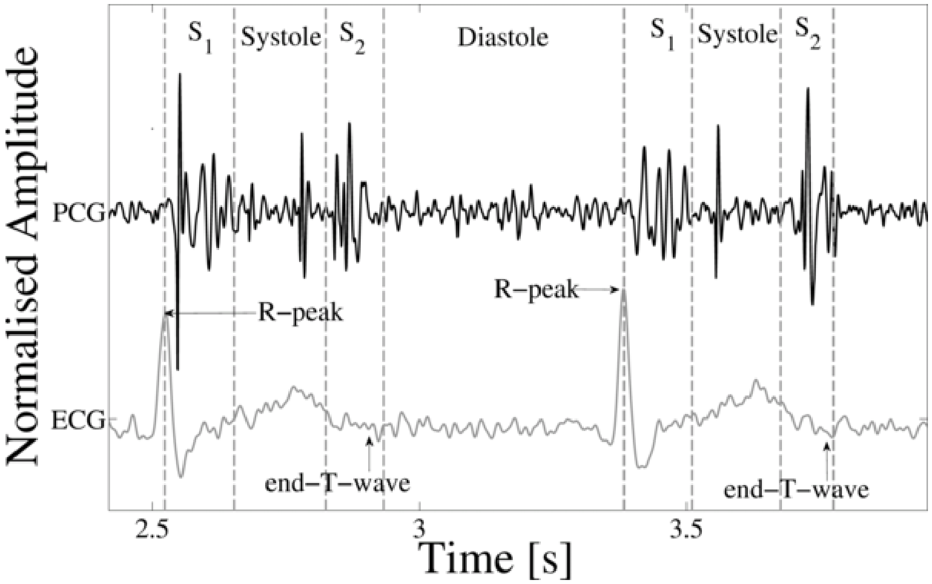
*http://www.who.int/mediacentre/factsheets/fs317/en/

Which signal?

- Phonocardiogram/Heart Sound/PCG signals
  - Transient sounds produced when heart valve opens and closes.
  - Healthy adults have two normal heart sounds S1 (‘*lub*’) - S2 (‘*dub*’) in a beat.
  - Pathological condition/Disease induces murmurs and other sounds.

- PCG signals <u>prone to noise.</u>

- <u>**Challenges**</u>
  - Accurate diagnosable quality data collection
  - Reliable Disease Prediction



https://physionet.org/challenge/2016/

What we propose?

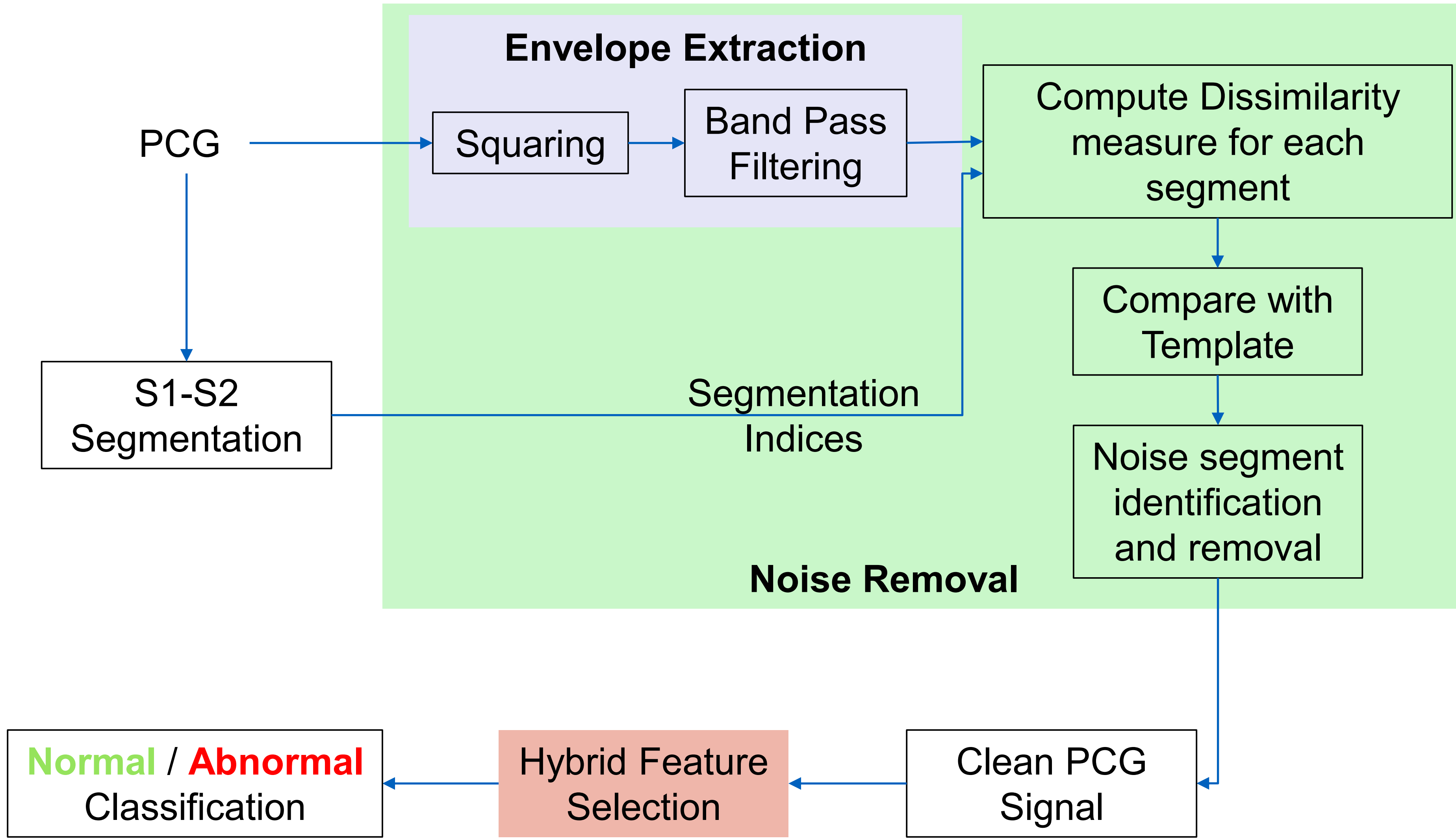
RONUN

- **Denoising**
  - Noisy PCG signal identification and rejection
- **Optimal Features**
  - Optimal feature selection through Hybrid approach
- **Classification**
  - Classification of clean PCG signal to determine the presence of cardiac abnormality.

- RONUN is an automated, preventive cardiac management solution that uses smartphone or other wearable sensor-captured heart sound, PCG signal.

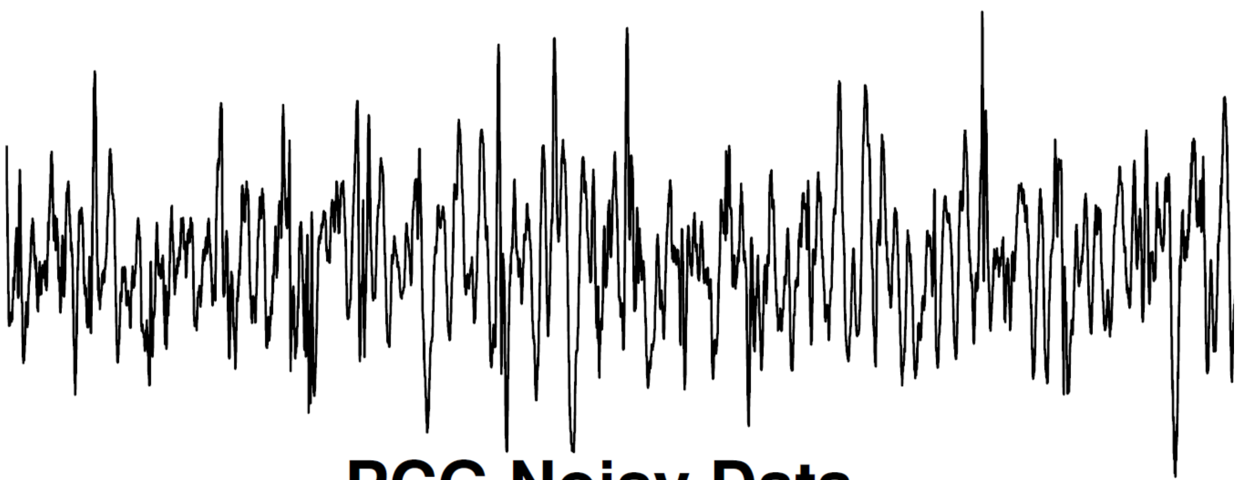
- Generates alerts by finding the pathological condition of the user.

Functional Flow



Glimpse of PCG Clean and Noisy Data

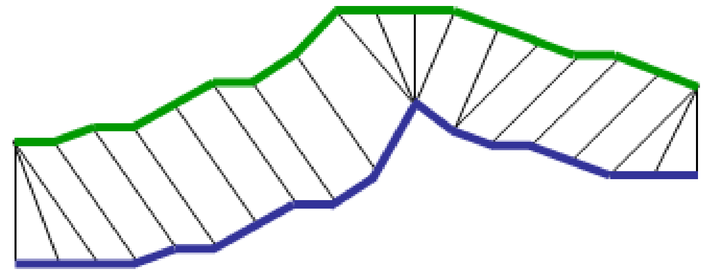
PCG Clean Data

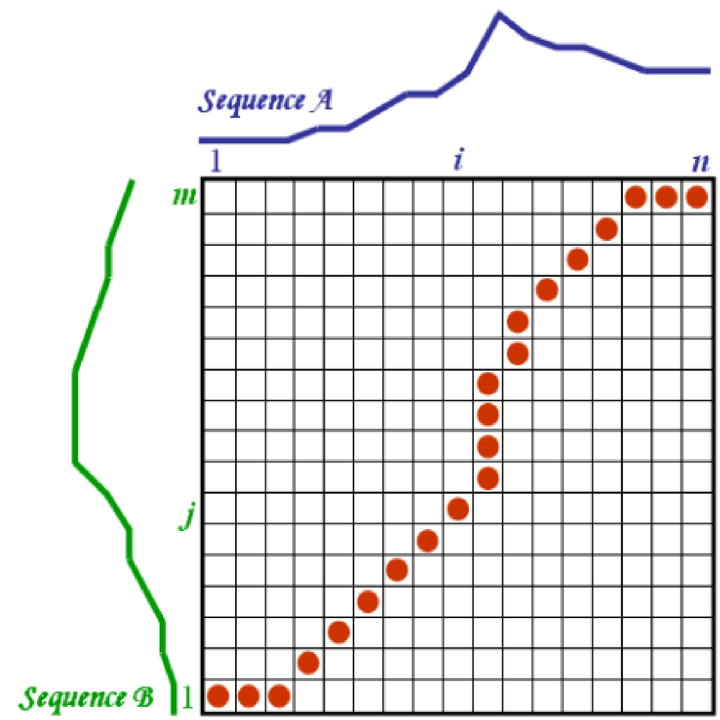


PCG Noisy Data

Semi-supervised Learning Based Noise Identification

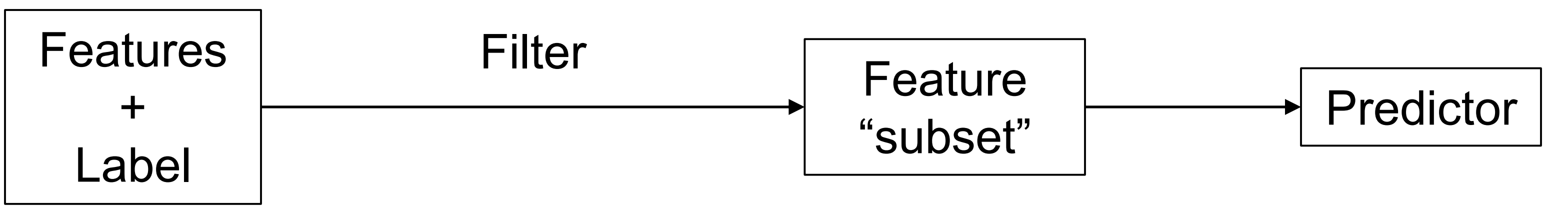
- Use a representative template
- Find most probable segment length L_p
  - Through density based clustering.
- Segmentize the signal based on heart beat
- Normalize each segment length to L_p
- Compute Dynamic Time warping (DTW) distance of each PCG segment
- DTW distances of corrupt portions are more → higher dissimilarity
- Accuracy → 84.24%



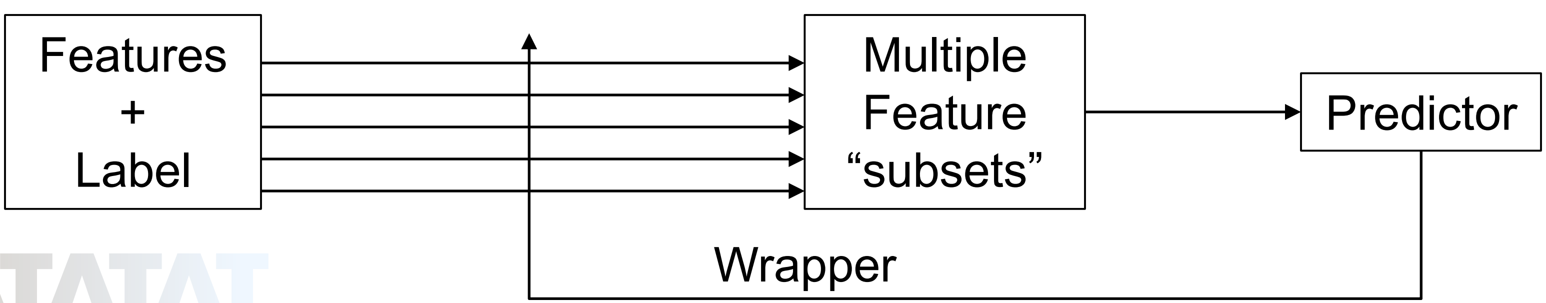


Hybrid Feature Space Optimization

- **Feature Selection and reduction** [2]
  - Improve Prediction performance
  - Provide fast and cost-efficient models
  - Better understanding of the underlying processes that generated data
- **Methods**
  - Filter



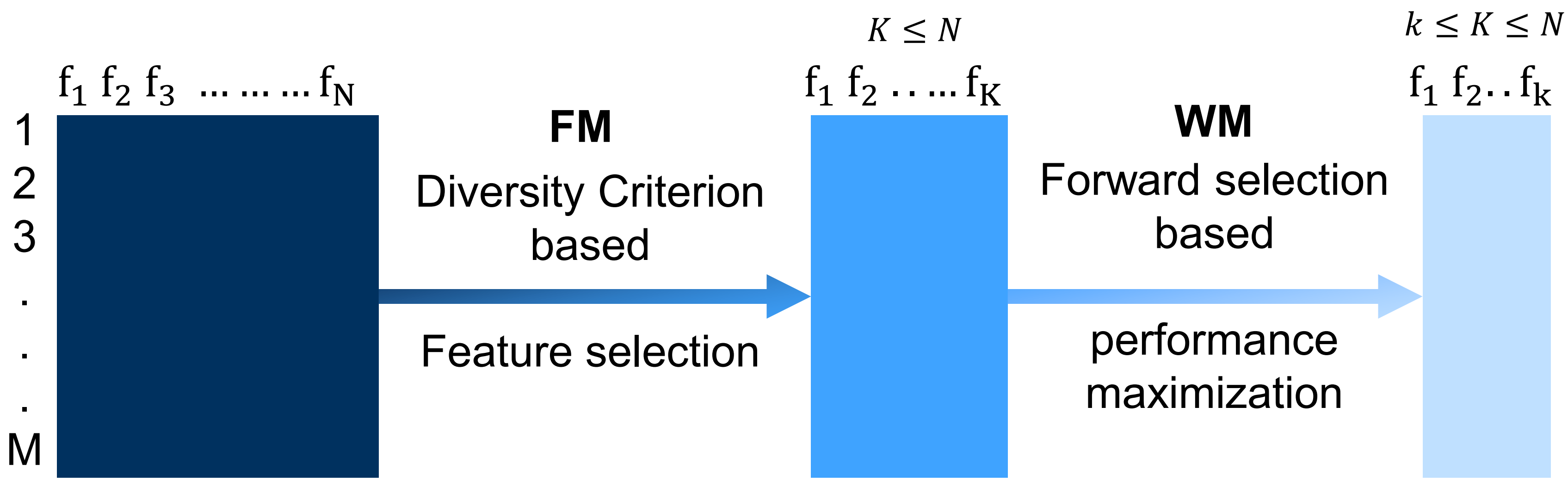
  - Wrapper



Hybrid Feature Space Optimization

- **Hybrid Feature Selection**

Given a feature set of M instances $F = \{f_1, f_2, f_3, \ldots \ldots f_N\}$ consisting N features



FM : Diversifying Features

- J different feature selection methods.
  - For example, mRMR: $R = \frac{1}{|F|^2} \sum_{f_i, f_j} I\left(f_i, f_j\right)$; $Relevance, D(F, c) = \frac{1}{|F|} \sum_{f_i} I\left(f_i, c\right)$

$$max_F \ \phi(D, R), \phi = D - R$$

- Obtain J different ranks for each feature in the feature set.
- 2-means clustering to get centroids C_1^i, C_2^i. $(C_1 < C_2)$ for i^{th} feature .
- Features are ordered in increasing order of their C_1^i values $\forall\ i = 1,2,3, \dots N$.
  - Best feature is $f_{best}\ if\ C_1^{best} < C_1^i\ \forall\ i = 1,2,3,4, \dots N$

FM : Diversifying Features

- Example:
  - 4 features $\{f_1, f_2, f_3, f_4\}$
  - K = 2
- J different feature selection methods.
  - 7 diverse selection criteria {ICAP, JMI, DISR, mRMR, MIFS, CIFE, CMIM}
- Obtain J different ranks for each feature in the feature set.

$$
\begin{aligned}
f_1 &\rightarrow [3,1,4,2,2,1,3] \\
f_2 &\rightarrow [2,3,1,4,3,4,2] \\
f_3 &\rightarrow [4,4,3,3,4,3,4] \\
f_4 &\rightarrow [1,2,2,1,1,2,1]
\end{aligned}
$$

- 2-means clustering to get centroids C_1^i, C_2^i. $(C_1 < C_2)$ for i^{th} feature .
  - $C_1^1 = 2.63,\ C_1^2 = 2.59,\ C_1^3 = 3.87, C_1^4 = 1.21$
- Features are ordered in increasing order of their C_1^i values $\forall\ i = 1,2,3, \dots N$.
  - Best feature is $f_{best}\ if\ C_1^{best} < C_1^i\ \forall\ i = 1,2,3,4, \dots N$
  - $\{f_4, f_1\}$

WM : Forward Selection Performance Maximization

- Feature ranked from filter methods are given as input.
- Choose a performance metric. For example, accuracy, F1-score, $\sqrt{Sensitivity \times Specificity}$
- Select the feature if validation performance increases else drop the feature.

Typical Features used for PCG classification

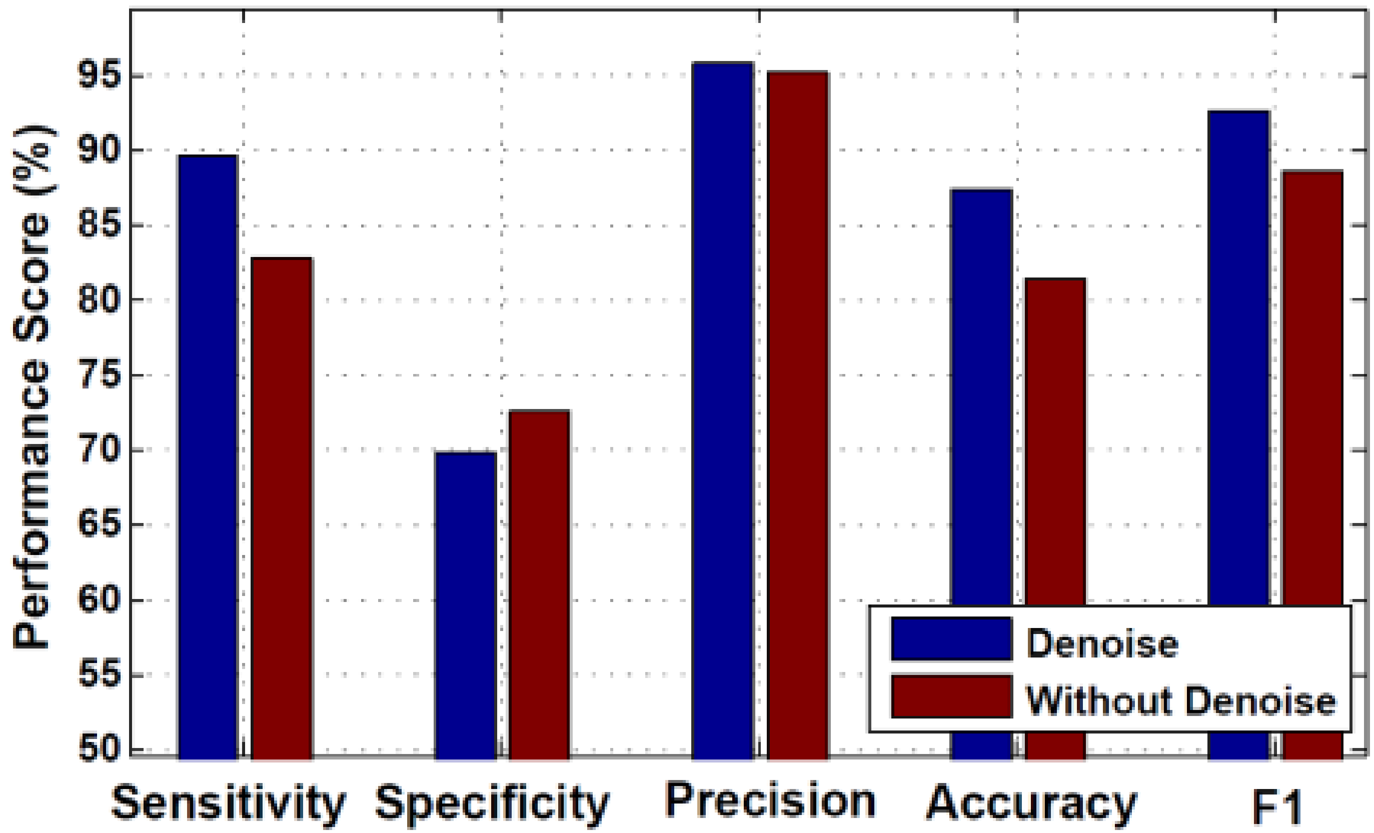
- Time domain
  - Mean, std of the RR intervals, Systole intervals, Diastole intervals
  - Mean, std ratios of interval between systole and RR in each beat
  - Mean absolute amplitude ratios between diastole period and S2 period in each heart beat.
- Frequency Domain
  - Skewness, Kurtosis of the FFT.
  - Total Normalized power in different frequency bands.
- Wavelet domain
  - 'db3' mother wavelet. 3 levels of decomposition
  - Mean and standard deviation over S1, S2, Systole diastole intervals.

Dataset Description [5]

- Digital Stethoscope
- 8 seconds to 5 minutes down-sampled at 2000 Hz
- 3153 recordings
  - 2488 Normal
  - 665 Abnormal
- Variety
  - 9 heart sound databases collected independently.
  - 7 different research teams from 7 countries and 3 continents

Performance with and without Noise Removal

- Increased abnormality detection



Stability of the features selected

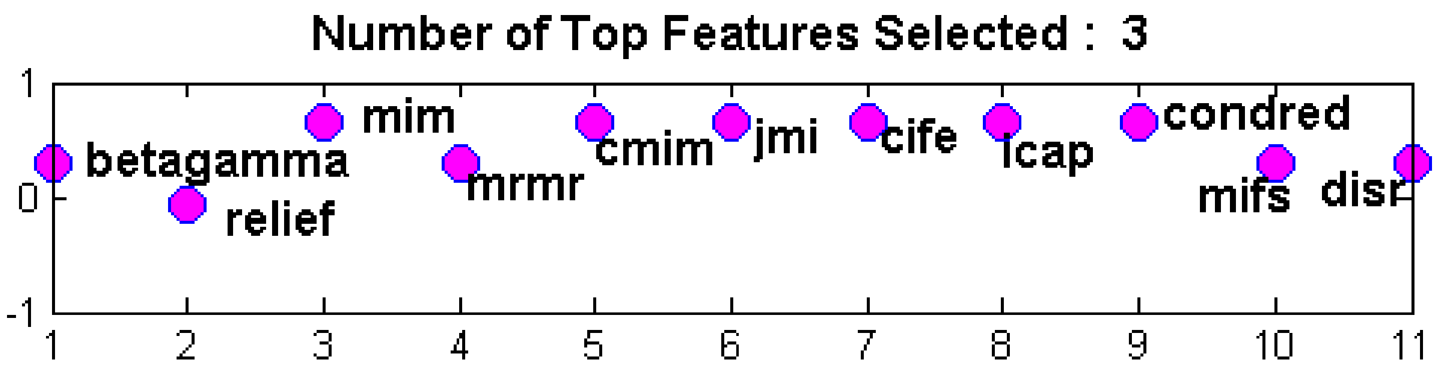
- Kuncheva's consistency index
  - The Consistency Index for two subsets $A \subset X$ and $B \subset X$, such that $|A| = |B| = k$, where $0 < k < |X| = n$, is

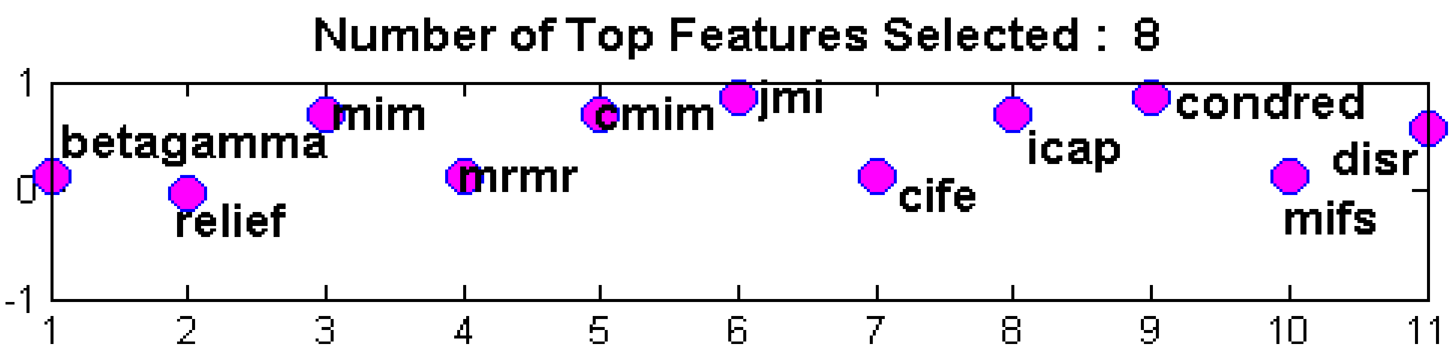
$$\omega(A,B) = \frac{\left(r - \frac{k^2}{n}\right)}{\left(k - \frac{k^2}{n}\right)} = \frac{rn - k^2}{k(n - k)}$$

k: Cardianality of A and B, r : $|A \cap B|$, n : Original number of features

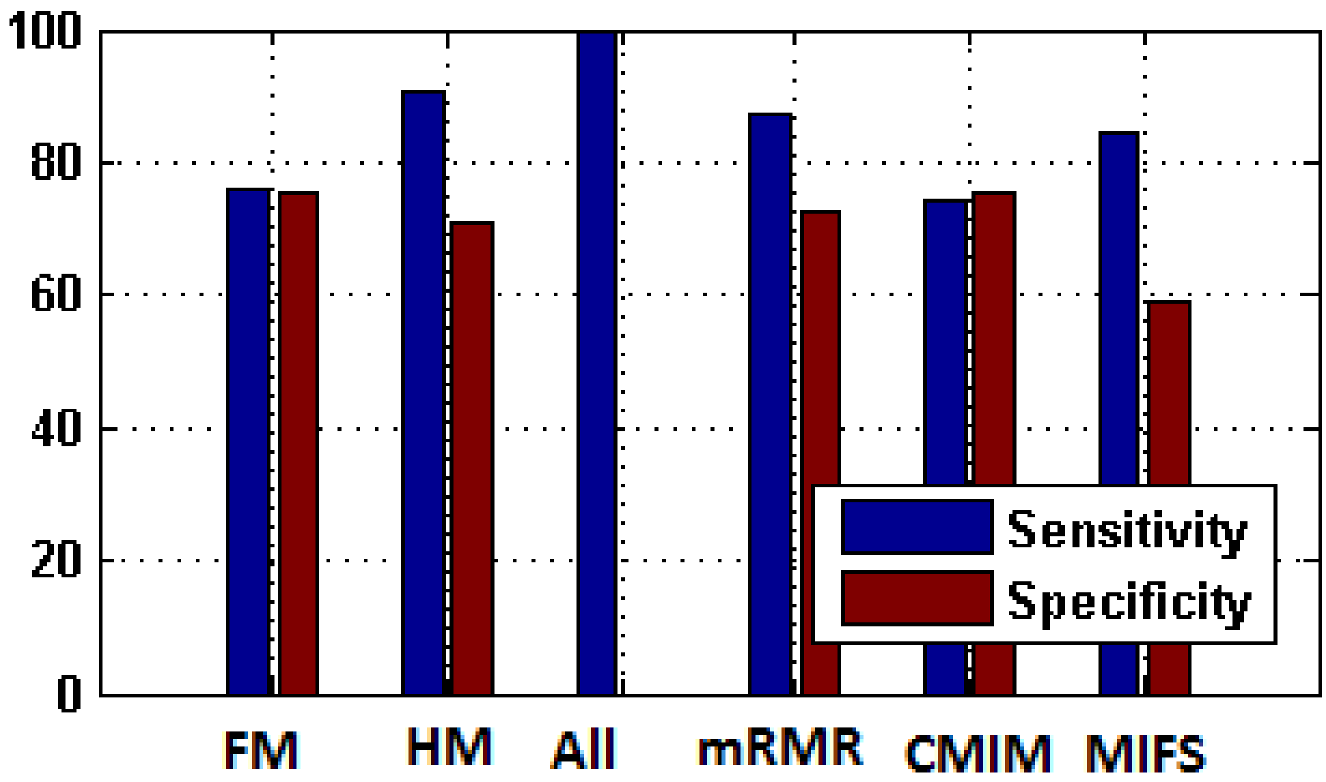
Stability of the features selected

- $\omega \geq 0.5$ ensures stability.





Ronun Abnormality Detection Performance



Concluding remarks

- Automated cardiovascular disease detection based on PCG signals.
- Appropriately pre-processed PCG signal would return higher clinical utility
- Hybrid feature space optimization

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