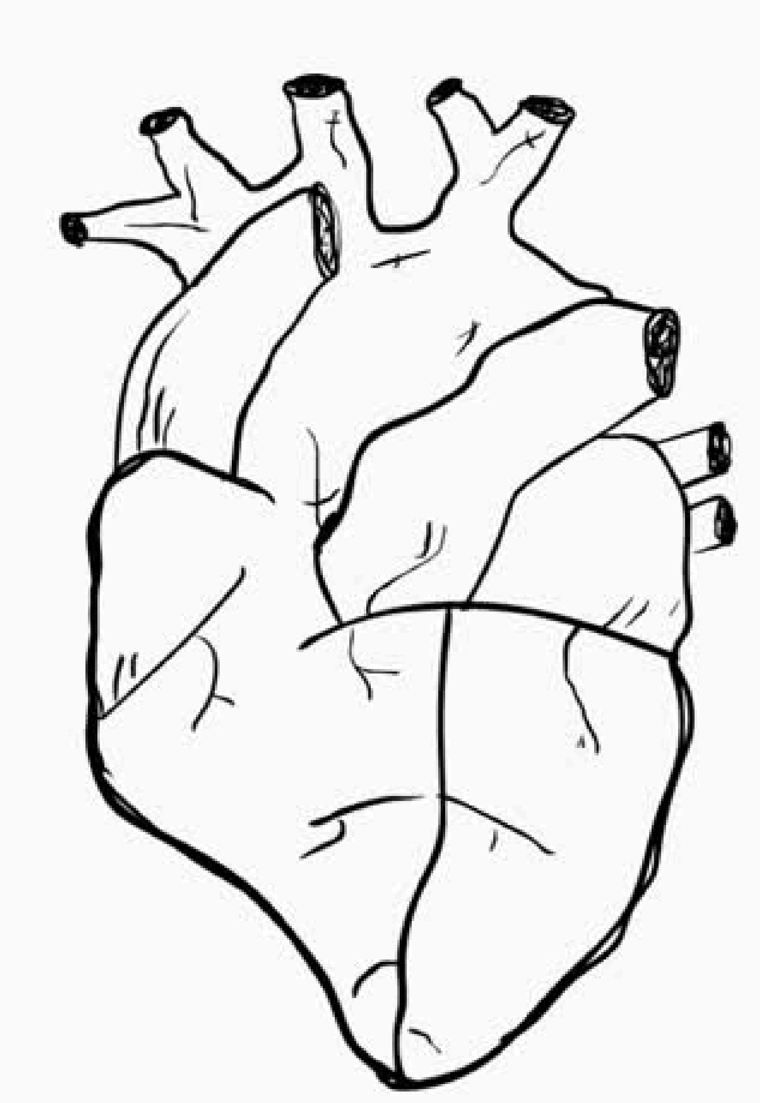
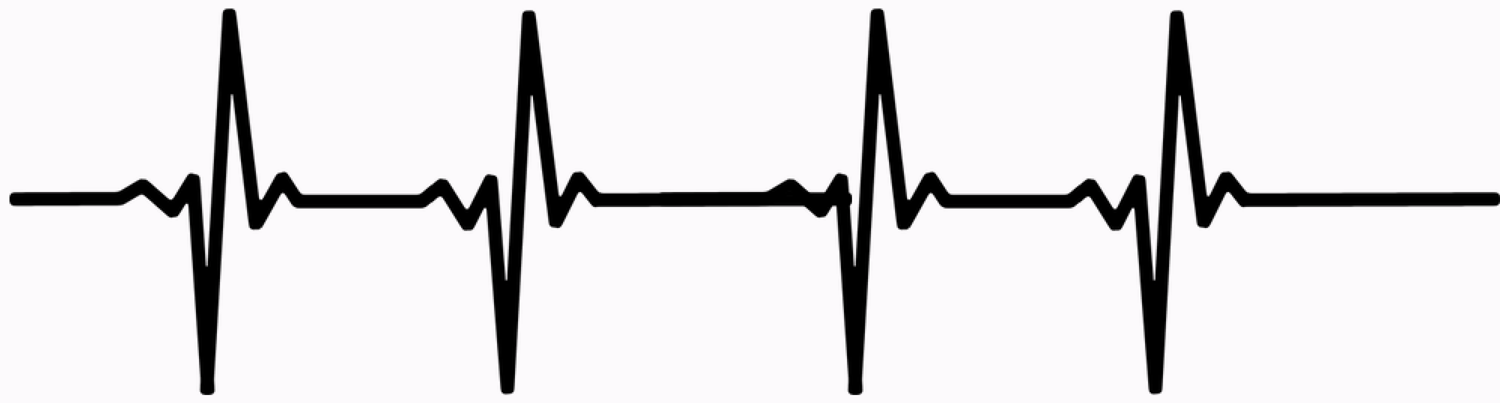
$$F(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{+\infty} f(t)\, \psi^*\left(\frac{t-\tau}{s}\right) dt$$



A wavelet optimization approach for ECG signal classification

BM4152 Biosignal Processing - Paper Implementation



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Paper:

Daamouche, Abdelhamid, et al. "A Wavelet Optimization Approach for ECG Signal Classification." Biomedical Signal Processing and Control, vol. 7, no. 4, July 2012, pp. 342–349, https://doi.org/10.1016/j.bspc.2011.07.001. Accessed 14 July 2020.

A wavelet optimization approach for ECG signal classification

Obtaining a custom designed optimum wavelet for a given classification task

Using that optimum wavelet classify ECG Beats in to 6 classes

- Normal
- Left Bundle Branch Block
- Right Bundle Branch Block
- Premature Atrial Contraction
- Premature Ventricular contraction
- Paced Beats

Method Description - Wavelet Design

Generate the filter bank using Sherlock-Monro Algorithm

Low pass filter coefficients - Scaling function

formulae for the even-numbered filter coefficients:

$$\begin{cases} h_0^{(k+1)} = c_k h_0^{(k)} \\ h_{2i}^{(k+1)} = c_k h_{2i}^{(k)} - s_k h_{2i-1}^{(k)} \quad \text{for} \quad i = 1, 2, \ldots, k-1 \\ h_{2k}^{(k+1)} = -s_k h_{2k-1}^{(k)} \end{cases}$$

with $h_0^{(1)} = c_0$ and $h_1^{(1)} = s_0$.

The formulae for the odd coefficients are given by:

$$\begin{cases} h_1^{(k+1)} = s_k h_1^{(k)} \\ h_{2i+1}^{(k+1)} = s_k h_{2i}^{(k)} + c_k h_{2i-1}^{(k)} \quad \text{for} \quad i = 1, 2, \ldots, k-1 \\ h_{2k+1}^{(k+1)} = c_k h_{2k-1}^{(k)} \end{cases}$$

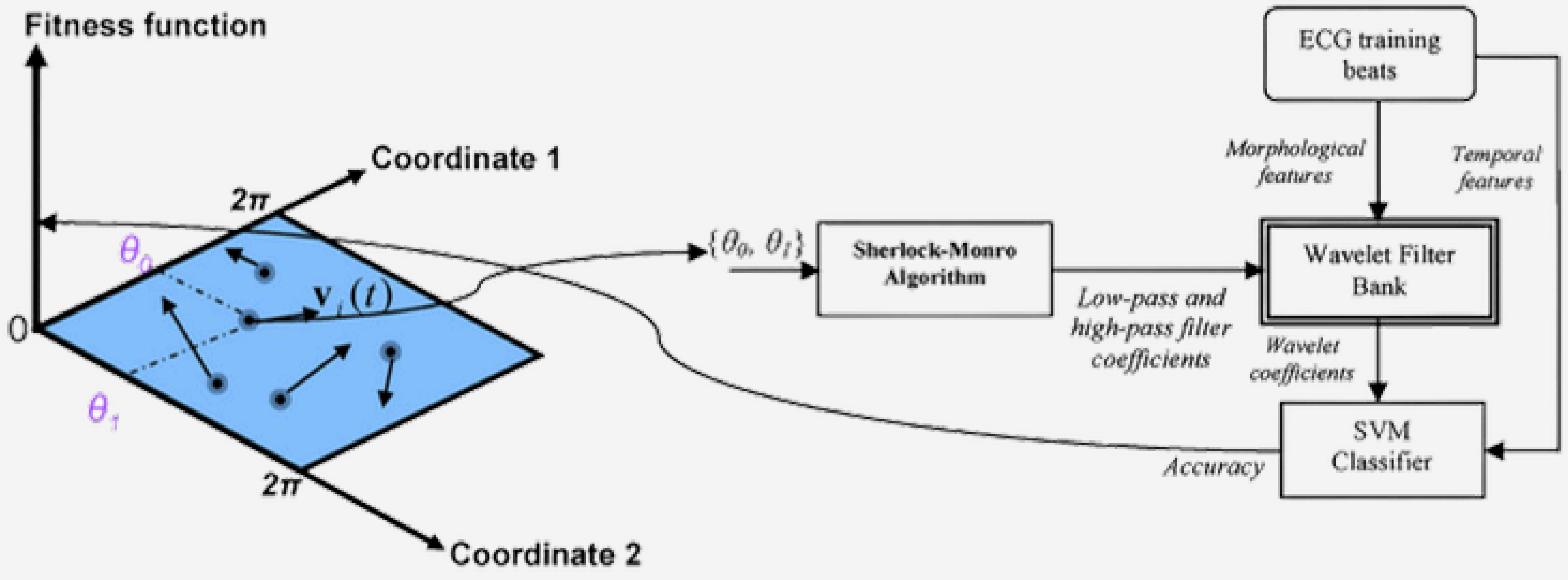
High pass filter coefficients $g_i = (-1)^{i+1} h_{2N-1-i}$

We can generate a Mother wavelet and a Scaling function with 2N length using N angular parameters $c_i = \cos(\theta_i)$ $s_i = \sin(\theta_i)$

All we have to do is find those N angular parameters which will give maximum accuracy

Method Description - PSO

Particle swarm optimization



Iterative Algorithm

1. Select S number of $\{\theta_0, \theta_i\}$ pairs, called **particles**.
2. Each particle has a position **Pi(t)** at each iteration (t), which is initially assigned to $\{\theta_0, \theta_i\}$ and they refer to the candidate solution of the algorithm using **velocity Vi(t).**
3. In addition to that each particle has a memory of **best local position** at iteration t called **Pbi(t)** and a **best global position** at iteration t **Pg(t)**.
4. Then the values are updated according to the following algorithm at each iteration after calculating the fitness function using **SVM**.
5. $\mathbf{v}_i(t+1) = w\mathbf{v}_i(t) + c_1 \cdot \mathbf{r}_1(t)(\mathbf{p}_{bi}(t) - \mathbf{p}_i(t)) + c_2 \cdot \mathbf{r}_2(t)(\mathbf{p}_g(t) - \mathbf{p}_i(t))$
6. $\mathbf{p}_i(t+1) = \mathbf{p}_i(t) + \mathbf{v}_i(t)$
7. Finally the algorithm terminates after a certain conditions are satisfied.

Method Description - Few more things about identifying the optimum wavelet -

Training Beats

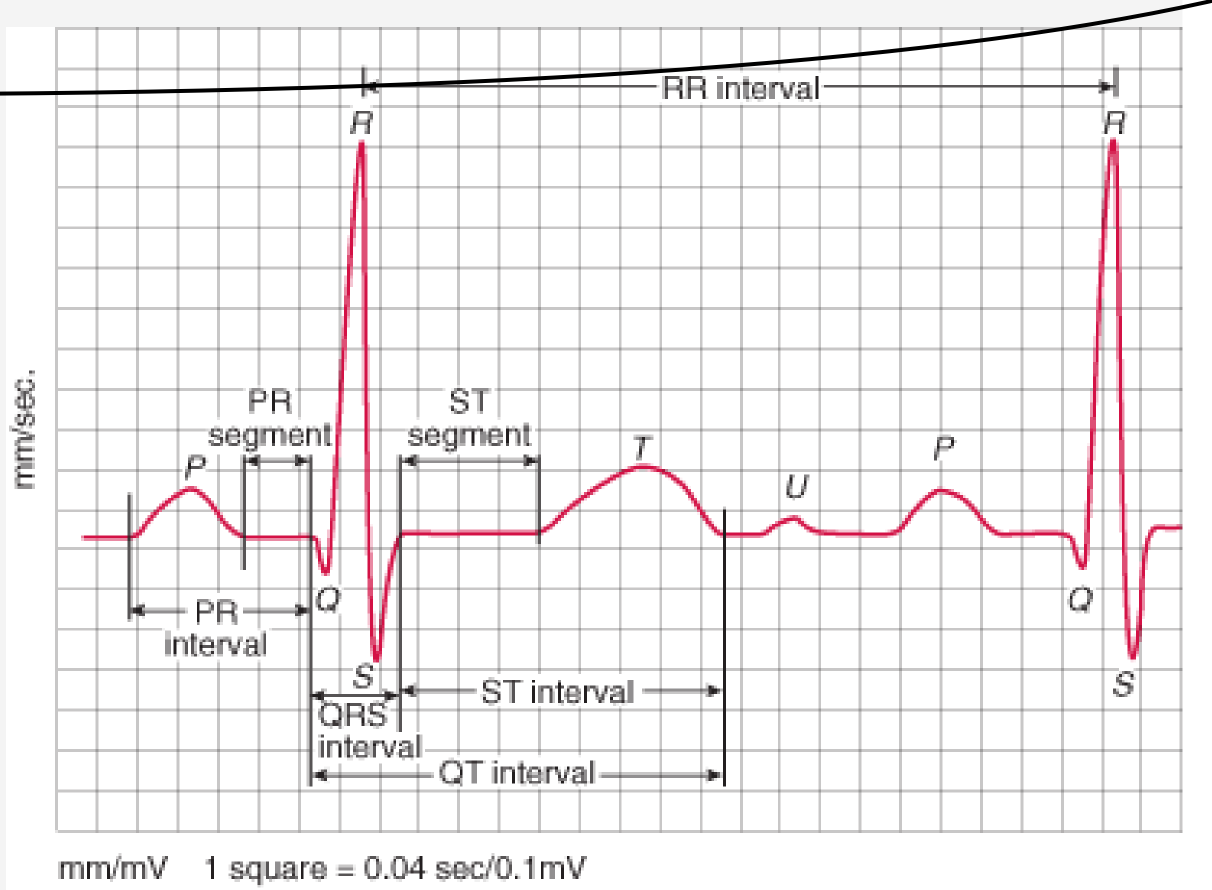
Class	N	A	V	RB	/	LB	Total
Training beats	37	24	25	13	13	13	125
Test beats	24,000	238	3939	3739	6771	1751	40,438

Morphological ECG Features

1. An extracted single ECG beat, each ECG beat should have 300 samples.
2. If the segmented beat doesn't have 300 samples it is over sampled or under sampled to 300 samples.

Temporal Features: 3 temporal features

1. QRS complex duration
2. The RR interval (the time span between two consecutive R points representing the distance between the QRS peaks of the present and previous beats),
3. RR interval averaged over the ten last beats [30].



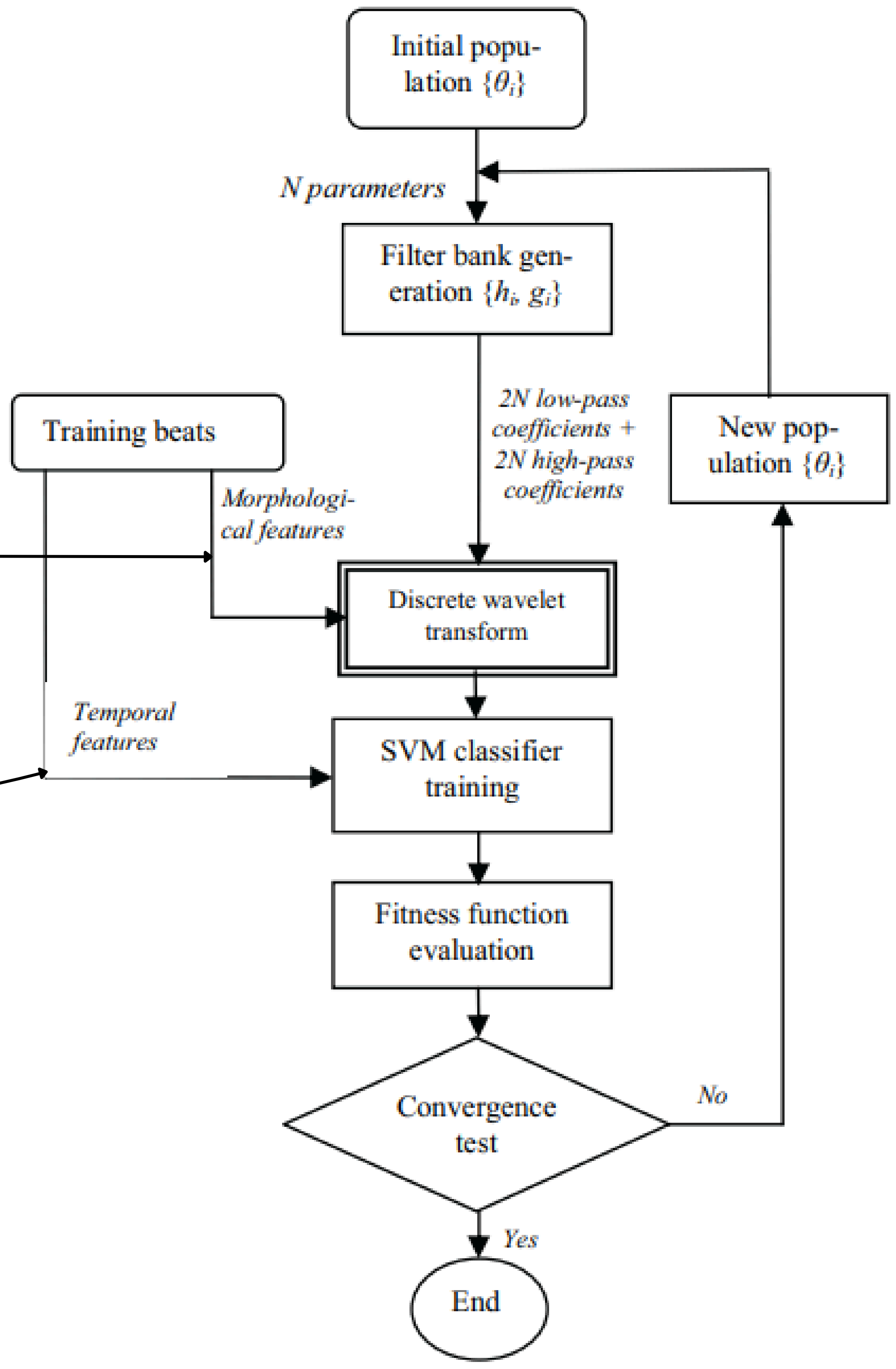
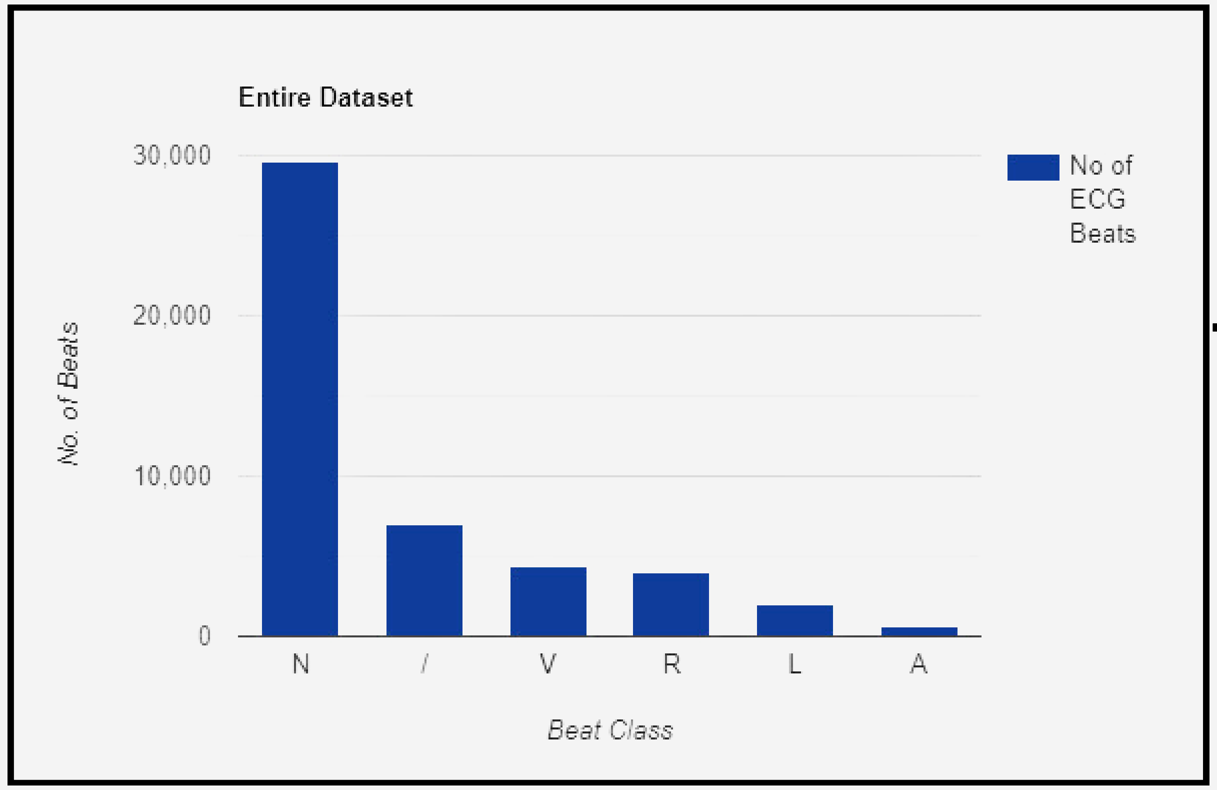


Fig. 2. Block diagram of the PSO search process.

Implementation Details

- **Preparing the Dataset - 47643 ECG Beats related to - N, A, V, /, R, L Classes**



Training Data
125

Testing Data
47518

N

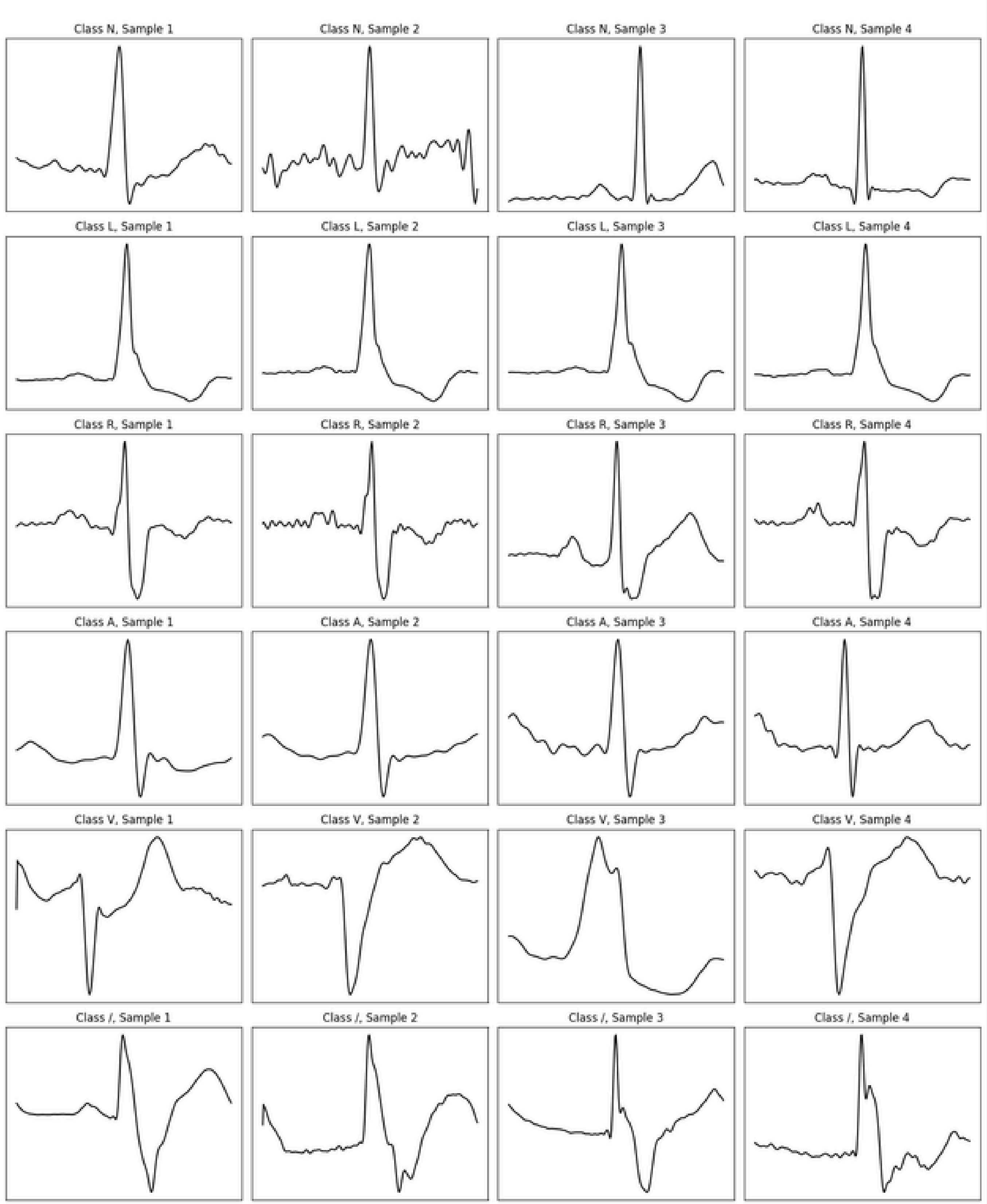
L

R

A

V

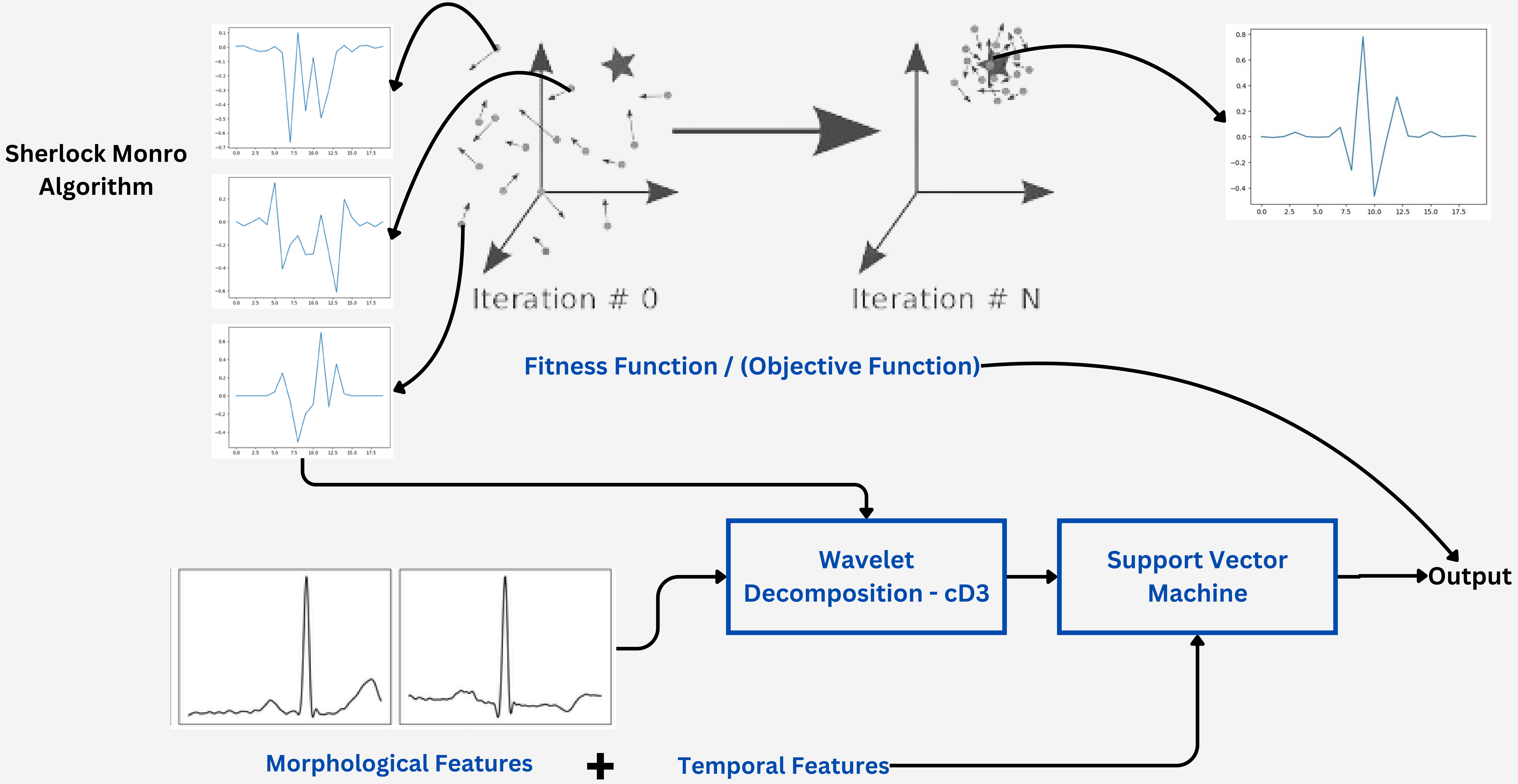
/



Training Data - 125

N	L	R	A	V	/
37	25	24	13	13	13

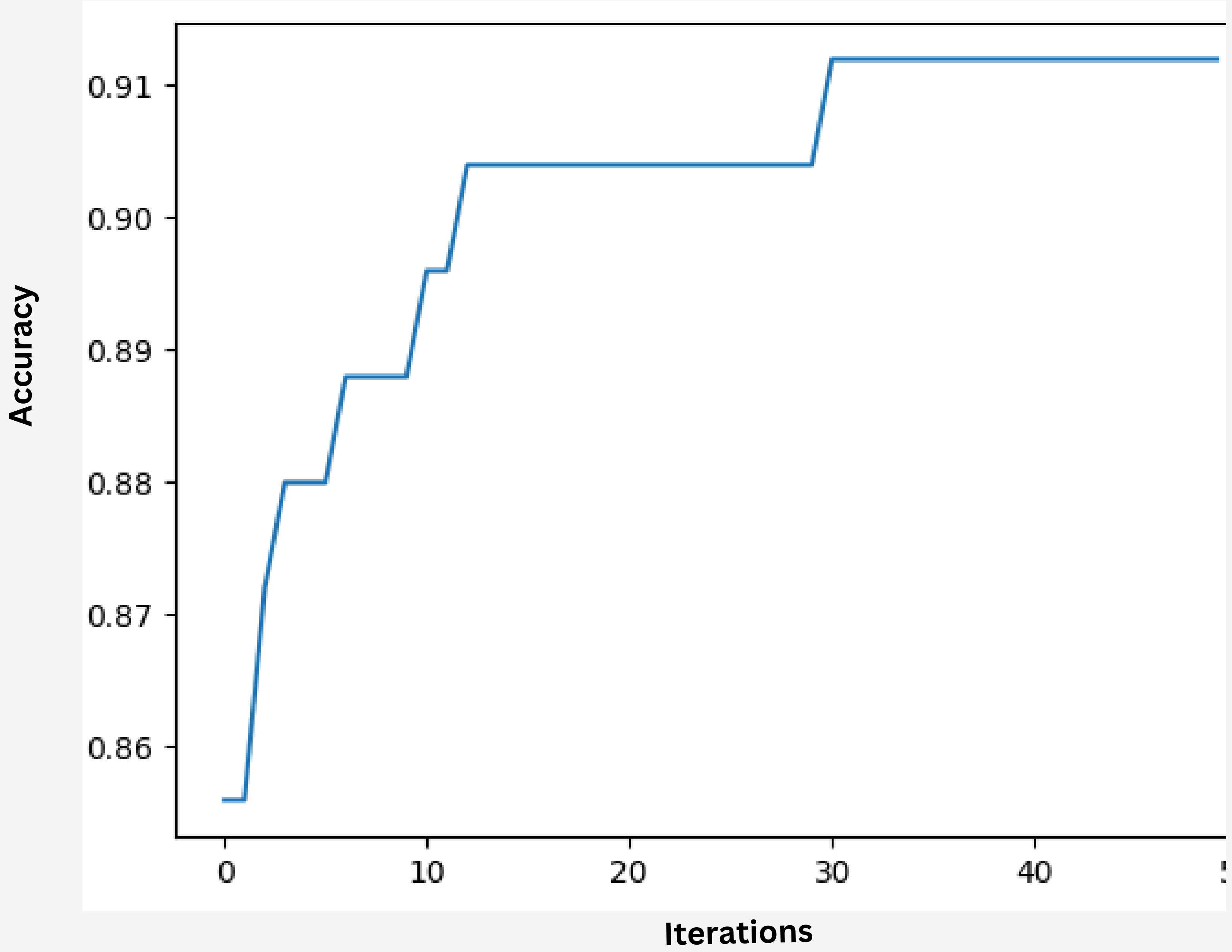
Implementation Details - Obtaining the Optimum Wavelet

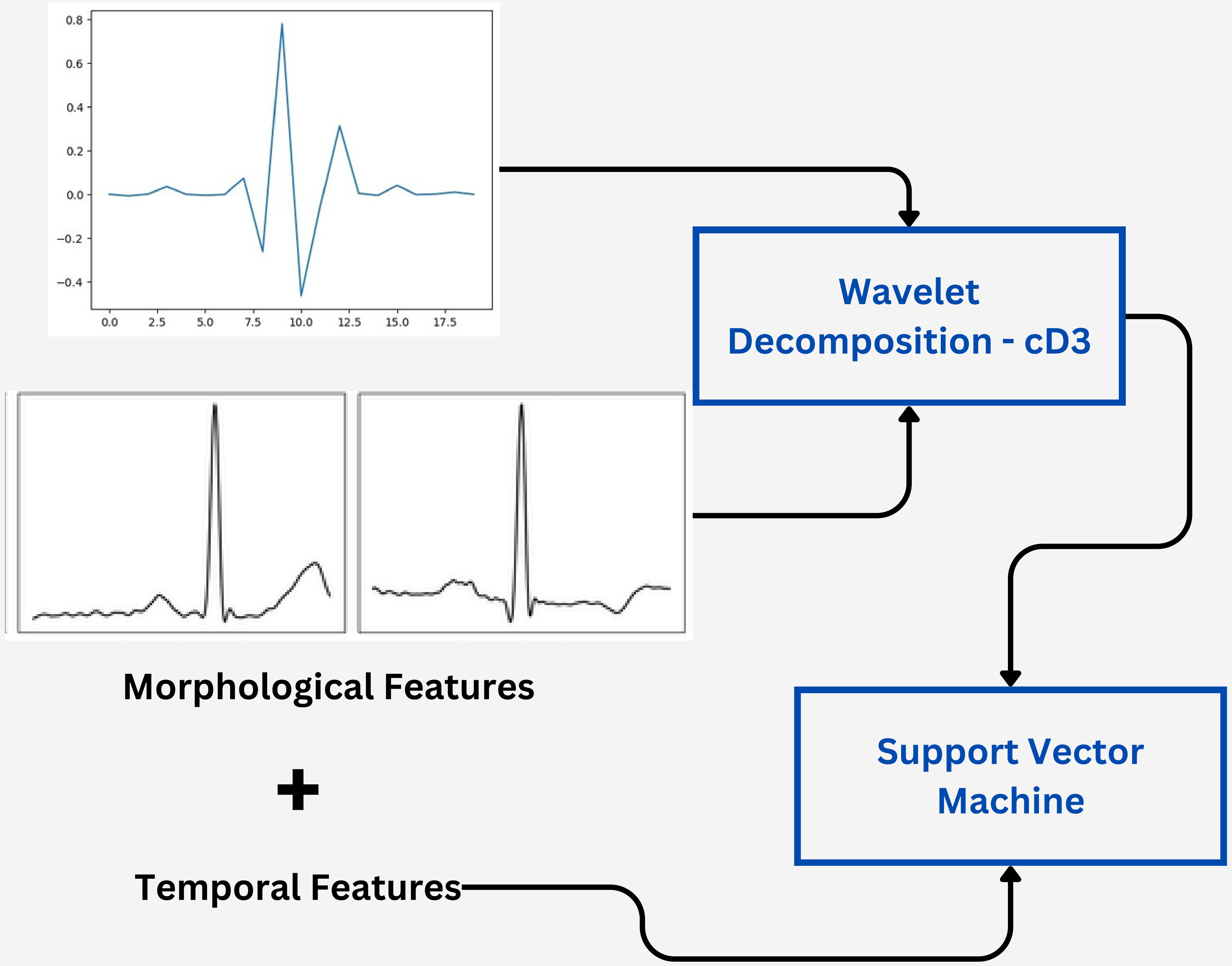


Implementation Details - Testing

```
Low pass filter ennergy: 1.0
High pass filter ennergy: 0.9999999999999998
Orthogonality of the filters: 4.7657014498098505e-18
```

Overall Accuracy change with the number of iterations during the training process

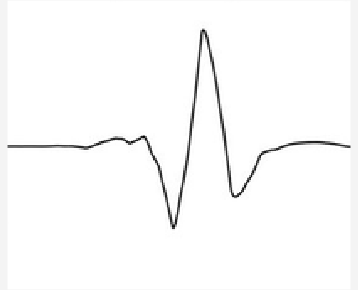




Testing Data - 47518 x 0.1

for training the SVM2

Implementation Results - Optimized Filters



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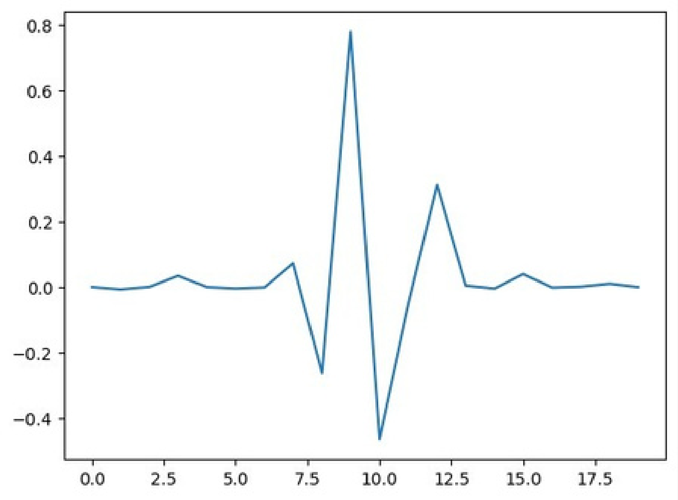
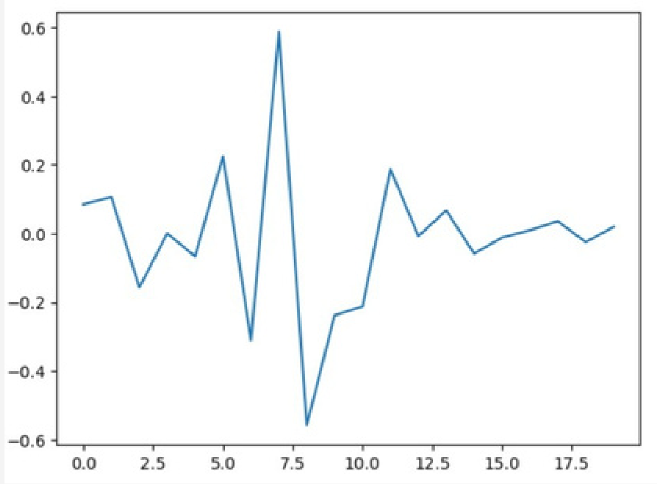
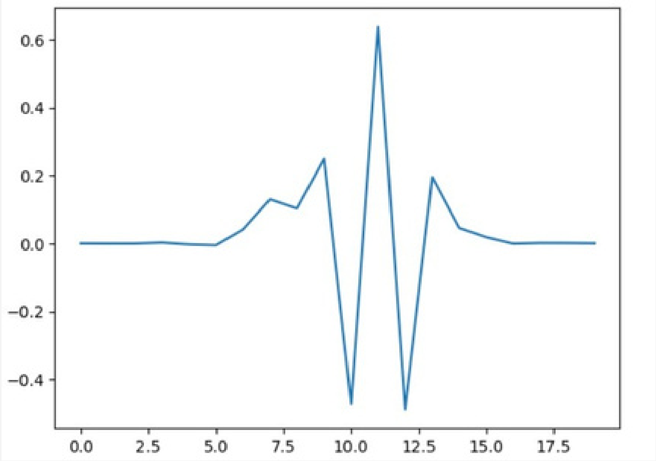
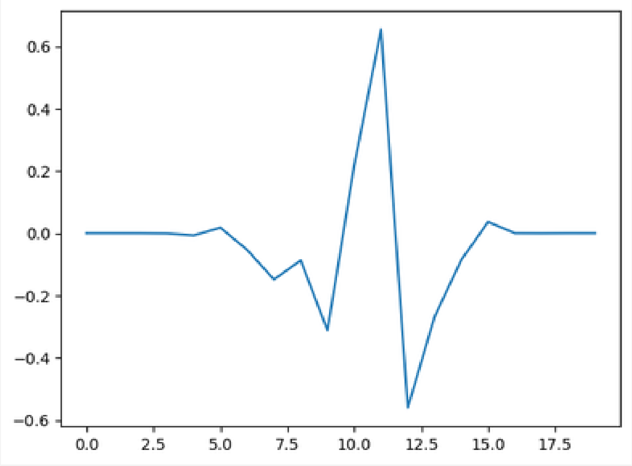
Low Pass Filters - Scaling Functions

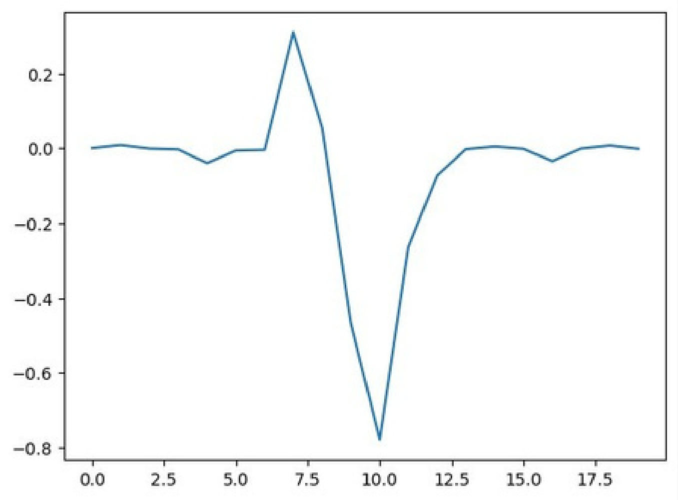


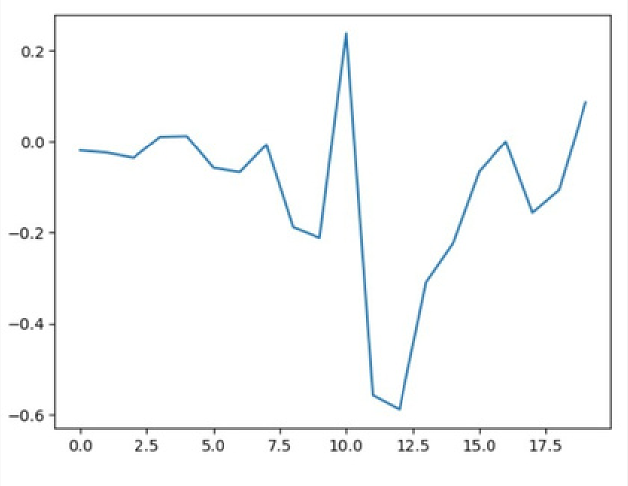


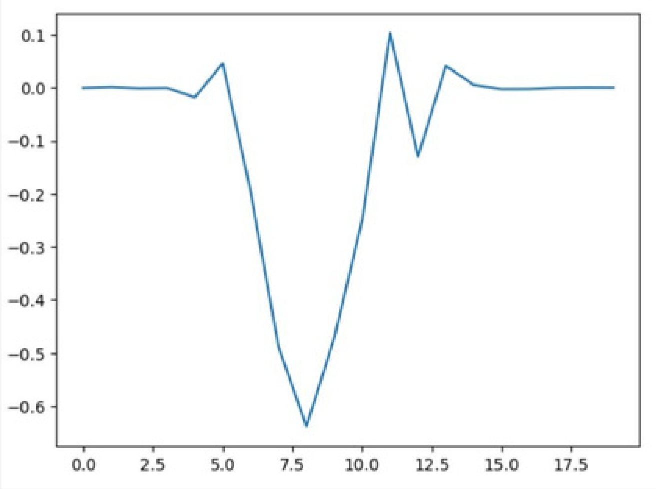


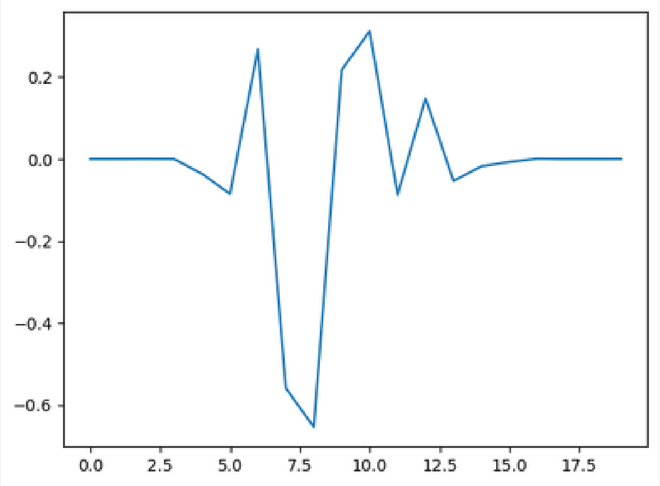


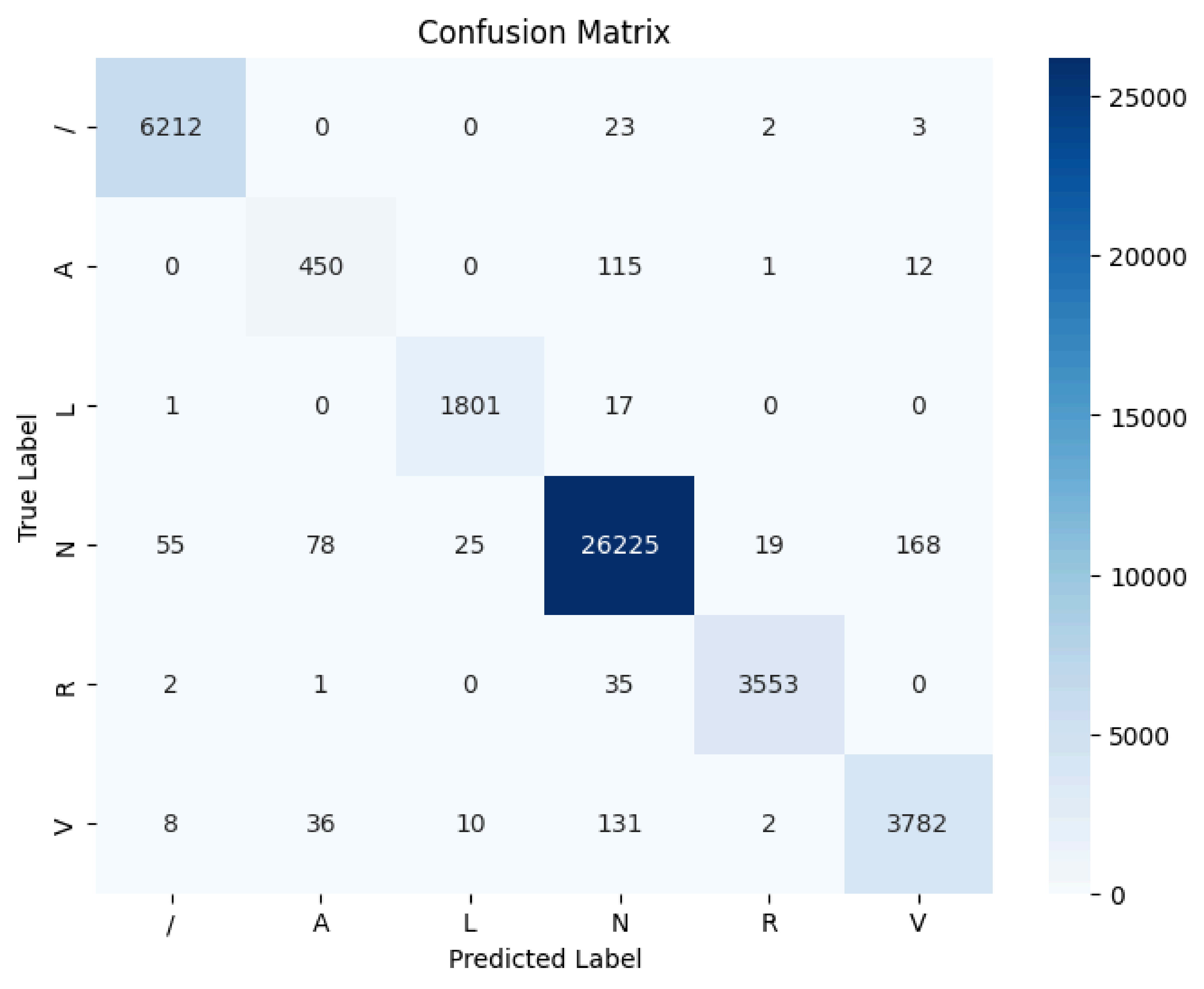
High Pass Filters - Wavelets

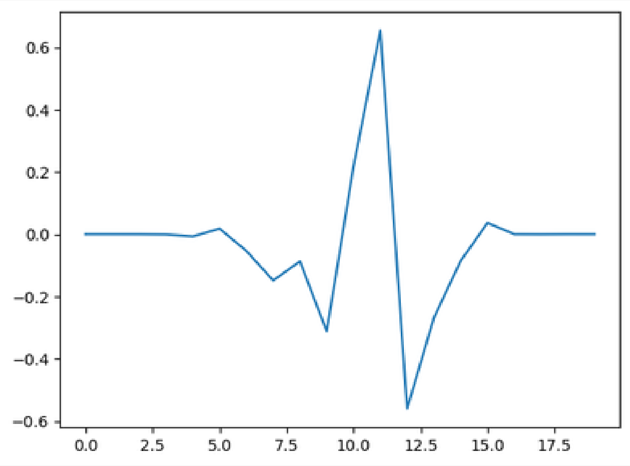


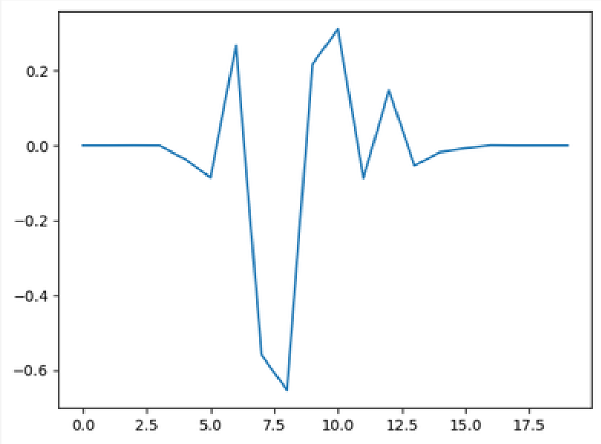










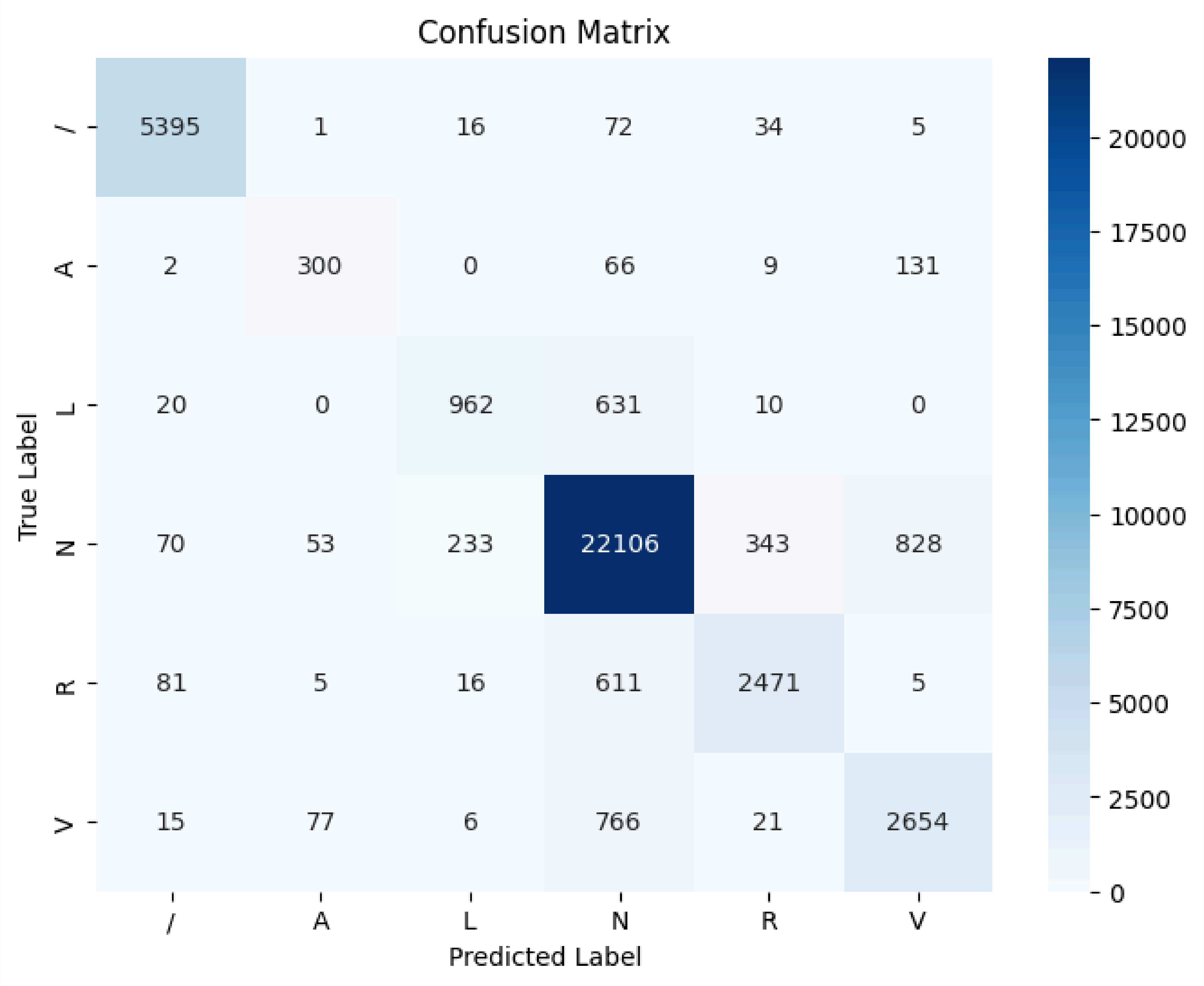


Implementation Results

Accuracy Values for Optimized Wavelet

N	L	R	A	V	/
98.70	99.01	98.94	77.86	95.29	99.55

OA = 98.26%



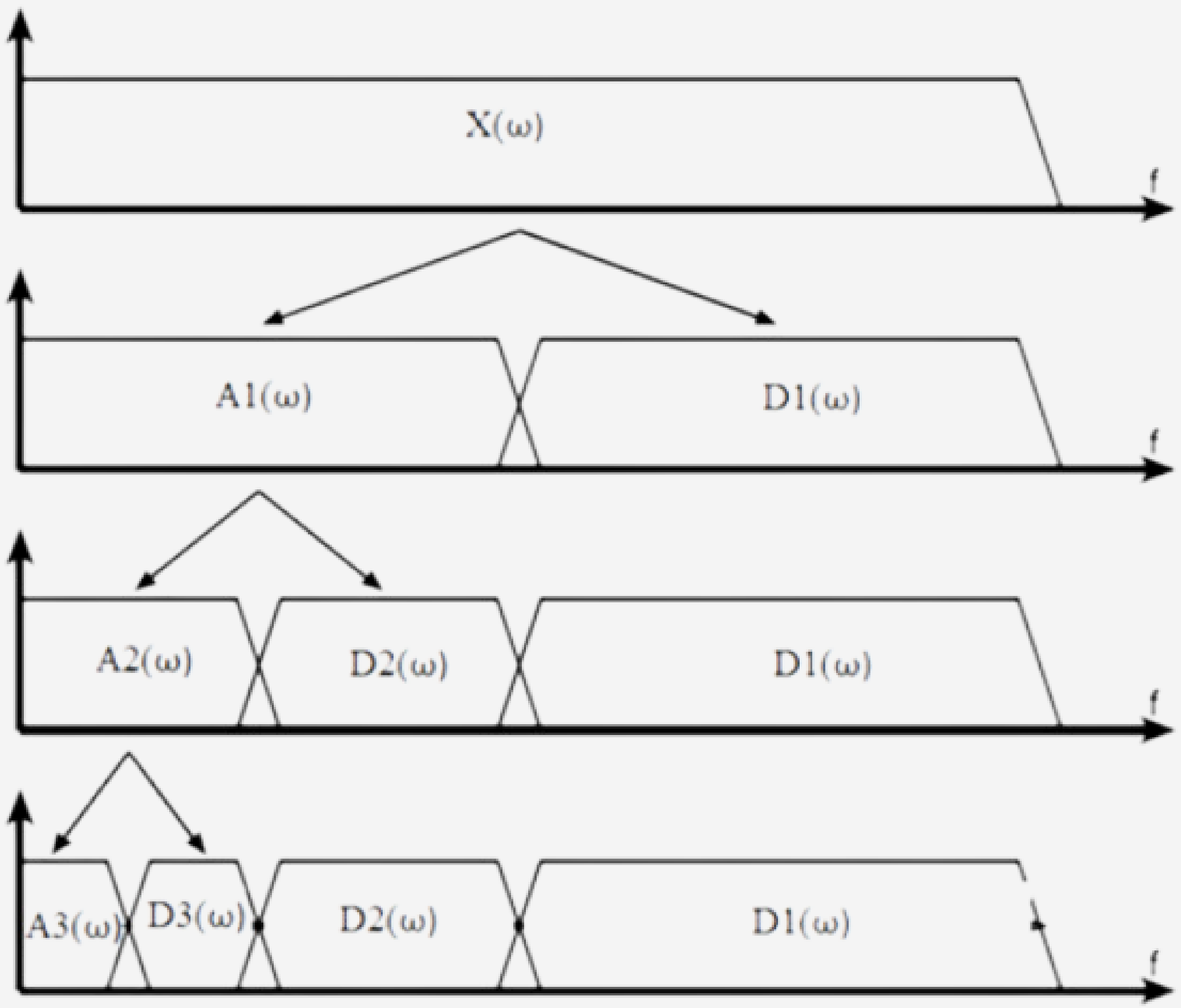
Implementation Results

Accuracy Values for db10 Wavelet

N	L	R	A	V	/
93.54	59.27	77.49	59.06	74.99	97.68

OA = 89.14%

Learnings and Challenges



Learnings

- How to use a wavelet as a feature extractor.
- What is the impact of using features (e.g., cD1, cD2, cD3, cA3, etc.) that belong to different frequency bands?
- Relationship between the optimal wavelet and the signal being analyzed.
- How to derive a custom wavelet while preserving the properties of the wavelet.
- Optimization techniques and SVM classifier.

Challenges

- Requires significant processing time to reach convergence, especially with large training datasets.

Conclusion

- When we use a custom wavelet optimized which is optimized for a given classification task which may give good results than using the conventional well defined wavelets.

Possible Improvements

- Training the classification algorithm using alternative methods
    - Neural networks
- Testing with **multiple lengths of the wavelets (N)** and with **multiple layers of decomposition.**
- Interpretation of the wavelets using characterization of ECG waveform.
- Train for classify more number of cardiac arrhythmias.
- Training with a **better optimization algorithm** rather than PSO.

Thank You !