ADAPTIVE FILTERING COMBINED WITH DEEP ENSEMBLES FOR BETTER ARRHYTHMIA DETECTION

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1. ABSTRACT

- PROBLEM: Heart rate problems are common and serious, they account for 1 out of 4 deaths worldwide.
- TASK: Reliable automated solution is required in order to improve early detection and relieve medical staff.
- OUR APPROACH: Combine different ML models to improve disease detection and increase the number of detectable problems.
- EVALUATION: Use well known MIT-BIH dataset for arrhythmia classification.

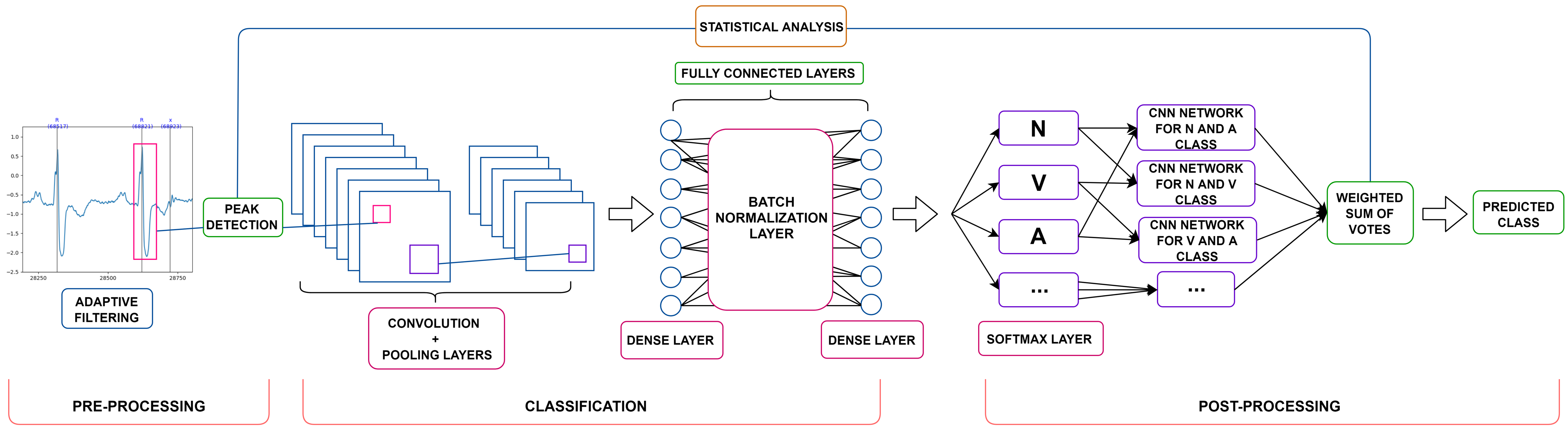
2. ARCHITECTURE

Problem is two fold - 1. QRS peak detection and 2. QRS peak classification. The system is divided into 3 parts: PRE-PROCESSING, CLASSIFICATION and POST-PROCESSING.

1. PRE-PROCESSING STEP
To improve results low pass filter (α=0.2) and drift correction is used. An envelope is calculated over the derivative of the signal. Peaks are detected with use of different moving thresholds based on average and median of signal and envelope.

2. CLASSIFICATION STEP
Most of the heart conditions can be recognized by malformed shape of the signal. Convolutional deep neural network (7 layers deep) performs best for classification of most heart problems. However, CNN is unable to capture time dependencies in data (example: irregular heart beat).
POSSIBLE SOLUTION: 1. LSTM, 2. Statistical analysis of peak recurrences.

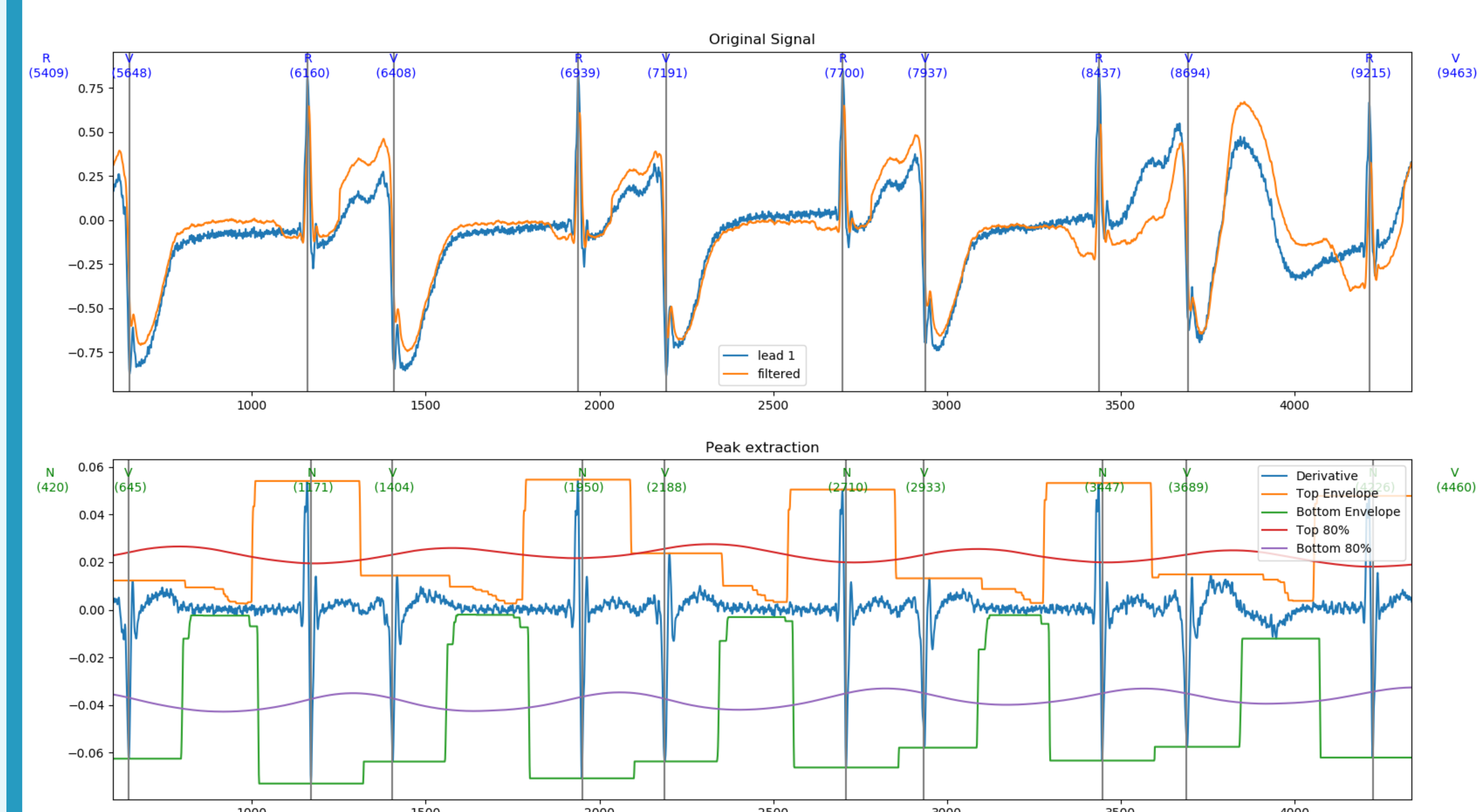
3. POST-PROCESSING STEP
Original CNN has problems distinguishing between certain classes.
IDEA; use ensemble of networks to classify between combinations of 2 classes ($\binom{10}{2} = 45$). Improve results by weighted voting (calculate weights by the models reliability for each class).



3. EVALUATION

Subset of MIT-BIH: 10 classes (use only classes with at least 450 samples), 11k labels.

QRS PEAK DETECTION



LSTM performs poorly, CNN achieves 99.92% accuracy and requires large amounts of data for training. Statistical model achieves 99.99% accuracy and adapts to the signal in real time - no pre-training is required.

QRS PEAK CLASSIFICATION

	+	N	A	V	/	f	F	L	R	!	F1
+	834.6	5.2	1.6	4.6	0.2	6.4	0.2	0.6	0	13.6	0.96
N	3	302.4	33.4	7.6	0.2	16.2	11	2.8	0.8	0	0.77
A	0.4	43	335.2	0.8	0.2	1.8	3.6	2.4	11.6	0	0.85
V	4.4	8.8	3.6	340.4	0	5	23.2	4.6	4	3.6	0.87
/	0	0.4	0	2	478.2	0.4	0	0	0	0	0.98
f	0.8	14.8	0.8	2.6	14	414	1.6	7.4	1.2	2	0.91
F	3.6	30.4	0.2	17.6	0.4	3.8	403.2	0.6	0.6	0	0.89
L	1.2	3.6	1.2	7	0	2.6	3.2	458	0	0	0.96
R	0	2.4	17.4	0	0	0.4	0	1.2	441.2	0	0.96
!	22	0	0	2.4	1.4	0.2	0	0	0.2	72.4	0.76

The model performs good, achieving 91.05% classification accuracy (majority class is 20%). The presented architecture improves results by 6% compared to simple CNN.

4. CONCLUSION

- Due to the complexity of the problem (time dependency, complex signal shapes, noisy data) simple deep architecture is not enough.
- Steps combining advanced pre-processing, statistical model and ensemble of deep neural networks significantly improve overall accuracy and achieve 91.05% accuracy for 10 classes in dataset MIT-BIH.