5.2 Component Detection

As *ADDHard* relies on extracted features of the signal from the detected components, it is non-trivial to evaluate the component detection performance as a first step. Hence, we compare the utilized discrete wavelet transform based component detection with the widely used Pan-Tompkins algorithm. The annotations that are required to derive the conclusions are taken from the MIT-BIH database. Both techniques are run on MATLAB for component detection. Table 1 presents the comparison results in terms of false positive and false negatives. One can observe that both of the techniques perform similarly good, but employed DWT technique slightly outperforms the Pan-Tompkins algorithm based component detection.

Table 1: Component Detection Performance

Parameter	DWT	Pan-Tompkins
False negative (%)	0.75	1.40
False positive (%)	0.47	0.47

5.3 Arrhythmia Detection

The arrhythmia detection performance of the proposed *ADDHard* is summarized in Table 2. *ADDHard* has an accuracy of 97.28%, specificity of 98.25% and sensitivity of 78.70%. Sensitivity indicates the percentage of sick people who are correctly identified as having arrhythmia and specificity indicates the percentage of healthy people who are identified as healthy. A low sensitivity is achieved due to more number of false negatives resulting from the existence of fusion beats (which resembles QRS complex), bigeminy and trigeminy ventricular rhythms. However, critical arrhythmias like Atrial and Ventricular premature contractions are efficiently detected.

Table 2: Arrhythmia detection performance of *ADDHard*

Accuracy	Specificity	Sensitivity
97.28%	98.25%	78.70%

5.4 Comparison

Table 3 compares our results (Accuracy and Specificity) with respect to several published works.

Table 3: Arrhythmia detection performance

	Acc.	Spec.	Note
ADDHard	97.28%	98.25%	Extracted features based analysis
[4]	70.00%	-	Bayesian classifier
[11]	98.10%	99.78%	Probabilistic ANN
[14]	99.00%	-	Beat-filtering and matching
[3]	98.60%	-	3-layer Feedforward NN
[19]	98.80%	99.96%	BPNN
[16]	97.35%	98.8%	Evolvable BbNN
[7]	93.20-99%	-	FCM-PCA-NN

One can observe that our method performs on par with some of the existing works, but neural network implementations are superior in terms of accuracy. However, the difference is limited to 2.5%, and our method does not need training in a clinical environment. Further, *ADDHard* extracts the features from the detected components, and does not require training with patient specific data. Hence, it is more generic. The number of operations involved are less complex and smaller in number compared to a neural network implementation, at the cost of slight reduction in accuracy. Some wearable devices for arrhythmia detection are proposed in [10, 13]. They sense the ECG signal and transmit the partially processed data to a remote end for further processing, which implies higher overhead in terms of power consumption due to more communication. In case of *ADDHard*, the circuit can off-load the communication load of the wearable device by avoiding continuous transmission of the data. Instead, it can be configured to transmit only when an arrhythmia is detected and at periodic instants (considerably less frequent than in traditional devices) for verification by the physician or analyst. This will bring additional power savings due to significantly lower communication needs.

6 CONCLUSION

In this work, a digital implementation for arrhythmia detection, *ADDHard* is proposed. *ADDHard* makes use of the extracted features to perform the arrhythmia detection. The extracted features are also updated to cope with changes. The benefits of *ADDHard* comes from its lightweight hardware footprint, less complex computations and no need of explicit training. As such it is a more generic ECG signal analyzer. *ADDHard* was tested on MIT-BIH Arrhythmia database and achieved an accuracy of of 97.28%. *ADDHard* occupies an area of 158.04 μm^2 and consumes 18.68 μW power in a 65 nm GF process CMOS node (excluding pre-processing).

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