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ORIGINAL RESEARCH

Real-Time Arrhythmia Detection Using Hybrid Convolutional Neural Networks

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BACKGROUND: Accurate detection of arrhythmic events in the intensive care units (ICU) is of paramount significance in providing timely care. However, traditional ICU monitors generate a high rate of false alarms causing alarm fatigue. In this work, we develop an algorithm to improve life threatening arrhythmia detection in the ICUs using a deep learning approach.

METHODS AND RESULTS: This study involves a total of 953 independent life-threatening arrhythmia alarms generated from the ICU bedside monitors of 410 patients. Specifically, we used the ECG (4 channels), arterial blood pressure, and photoplethysmograph signals to accurately detect the onset and offset of various arrhythmias, without prior knowledge of the alarm type. We used a hybrid convolutional neural network based classifier that fuses traditional handcrafted features with features automatically learned using convolutional neural networks. Further, the proposed architecture remains flexible to be adapted to various arrhythmic conditions as well as multiple physiological signals. Our hybrid- convolutional neural network approach achieved superior performance compared with methods which only used convolutional neural network. We evaluated our algorithm using 5-fold cross-validation for 5 times and obtained an accuracy of 87.5%±0.5%, and a score of 81%±0.9%. Independent evaluation of our algorithm on the publicly available PhysioNet 2015 Challenge database resulted in overall classification accuracy and score of 93.9% and 84.3%, respectively, indicating its efficacy and generalizability.

CONCLUSIONS: Our method accurately detects multiple arrhythmic conditions. Suitable translation of our algorithm may significantly improve the quality of care in ICUs by reducing the burden of false alarms.

Key Words: convolutional neural networks ■ false alarms ■ intensive care unit monitors ■ machine learning ■ multi-class classification

Intensive care units (ICUs) are generally equipped with physiological monitoring systems to alert the caregivers about the onset of an adverse condition. However, the majority of such alarms are triggered because of innocuous conditions such as motion artifacts and electrode problems. Although such a system generally does not miss many true alarms, it generates false alarms (FAs) at rates as high as 88.8%.[1,2] Frequent FAs can cause delirium in patients and also gradually impact the responsiveness of the staff to alarms. Indeed, reducing the harm associated with clinical alarm systems has been consistently listed as a National Patient Safety Goal from 2012 to 2020.[3]

Various algorithms have been developed to address FAs in ICUs. Early attempts used only ECG signals to alert the onset of an arrhythmic condition.[4,5] Recent algorithms that included the arterial blood pressure (BP) signal with the ECG signals have reported significant reduction in FA burden.[6–9] Algorithms based on wavelet transform, data mining, and machine learning approaches have been reported to further reduce FAs.[10–13] To foster the development of such algorithms, the "PhysioNet/Computing in Cardiology Challenge 2015: Reducing False Arrhythmia Alarms in the ICU" was introduced, especially for the scenario where prior knowledge of the alarm event is available. In response

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CLINICAL PERSPECTIVE

What Is New?

- We proposed a novel arrhythmia detection algorithm that uses handcrafted features along with features learned from a machine learning algorithm.
- While conventional intensive care unit monitors use single physiological signals to raise an alarm, our algorithm uses information from multiple physiological signals simultaneously to reduce the incidence of false alarms in the intensive care unit.

What Are the Clinical Implications?

- Deployment of the proposed method could reduce the number of false intensive care unit alarms, making the organization, integration, and interpretation of the enormous amount of intensive care unit data less time-consuming and more efficient.

Nonstandard Abbreviations and Acronyms

CNN	convolutional neural network
EB	extreme bradycardia
ET	extreme tachycardia
FA	false alarm
SR	sinus rhythm

to the challenge, many time domain and frequency domain techniques were proposed.[14–18] Although such methods achieve impressive performance when the alarm type is known, detecting the presence of an unknown arrhythmia remains challenging. Consequently, such methods remain as an add-on to existing monitoring systems to filter FAs. However, it has been observed that the alarm type on the monitor and the underlying arrhythmia may sometimes mismatch and hence alarm suppression based on a mismatched arrhythmia type can result in catastrophic consequences.

In the same vein, the "China Physiological Signal Challenge 2018"[19] and the recent "PhysioNet/Computing in Cardiology Challenge 2020: Classification of 12-lead ECGs", provided a large repository of 12-lead ECG recordings from various databases, with the goal of identifying the clinical diagnosis. In such databases, although an annotation is provided for the entire record, the actual onset and offset of the arrhythmia remain unavailable. Furthermore, the aforementioned databases include only the ECG signals for analysis. It is important to note that certain life-threatening conditions including ventricular tachycardia/ventricular fibrillation (VT/VF) can be better diagnosed if other vital-sign signals such as arterial BP and photoplethysmogram are included.

To date, most reported methods have relied in processing handpicked features that are tailored to the signals and the arrhythmia at hand. Recently developed algorithms have reported significant improvement in performance by using automated feature learning with deep learning methods.[20–22] A method proposed by Hannun et al[23] used a deep convolutional neural network (CNN) architecture to detect twelve arrhythmia types from a single ECG recorded from an ambulatory device. Methods that combine CNNs with recurrent neural networks have been reported to achieve improved performance on ECG classification.[24–26] However, these methods do not classify certain life-threatening arrhythmias including extreme bradycardia (EB), extreme tachycardia (ET), asystole and VF.

Given that deep learning methods, in particular CNNs have been proven effective and the preferred tools for various classification tasks,[27] in this study we propose to use a hybrid-CNN technique that fuses conventional handcrafted features with the features learned from CNN. Such a network, when appropriately trained, is expected to enjoy the benefits of automated learning as well as traditional features. Furthermore, the proposed approach is expected to be suitable for different arrhythmias, without requiring major architectural changes.

METHODS

Data Availability

The training data set will be available to any investigator upon request.

Code Availability

The code will be available to any investigator upon request.

Ethical Approval and Consent to Participate

The study was approved by the Institutional Review Board of Massachusetts General Hospital. We also used data from the "PhysioNet/Computing in Cardiology Challenge 2015: Reducing False Arrhythmia Alarms in the ICU". The data used are open source and are available at https://physionet.org/content/challenge-2015/1.0.0/.

Data Set

The study was approved by the Institutional Review Board of Massachusetts General Hospital. Adhering to

Table 1. Definitions of the 7 Classes

Class	Definition
Aystole	No heartbeats at all for a period of 4 s or more
EB	Heart rate is lower than 40 beats per minute; fewer than 5 beats occur within a period of 6 s
ET	Heart rate is higher than 140 beats per min; more than 17 beats occur within a period of 6.85 s
VF	A rapid fibrillatory, flutter, or oscillatory waveform for at least 4 s
VT	Five or more consecutive ventricular beats within a period of 2.4 s (a heart rate of 100 beats per min)
SR	Heart rate between 40 and 100 beats per min, for 8 s
AF	Tachyarrhythmia characterized by predominantly uncoordinated atrial activation with consequent deterioration of atrial mechanical function

AF indicates atrial fibrillation; EB, extreme bradycardia; ET, extreme tachycardia; SR, sinus rhythm; VF, ventricular fibrillation; and VT, ventricular tachycardia.

the institutional review board guidelines, we obtained de-identified data from the bedside monitors of the ICUs of Massachusetts General Hospital. The data consist of the ECG (4 channels), arterial BP, and photoplethysmogram waveforms recorded using 2 different device manufacturers. We used streaming data with the information corresponding to the time and type of the alarm recorded by the monitoring system.

The Association for the Advancement of Medical Instrumentation standards require that the alarm be raised within 10 seconds from the start of the event. Accordingly, we created a running 5-second window buffer for the 15 seconds of data before the onset of the alarm. We considered only alarms corresponding to asystole, extreme tachycardia (ET), extreme bradycardia (EB), ventricular tachycardia (VT), ventricular fibrillation (VF). and atrial fibrillation (AF). The definitions/criteria for each arrhythmia were taken from the PhysioNet 2015 challenge,[16] and are listed in Table 1. Further, we used the open source data from the "PhysioNet/Computing in Cardiology Challenge 2015: Reducing False Arrhythmia Alarms in the ICU",[16] as an independent data set to evaluate the proposed algorithm. The data are available at https://physionet.org/content/challenge-2015/1.0.0/. The data consist of 300 seconds long records of 2-lead ECG, BP, and photoplethysmogram signals before an alarm, as acquired by the bedside ICU monitors. The data also contain the corresponding annotations for each alarm, namely the alarm type and whether the alarm is true or false. We considered ≥15 second windows from each record and annotated it to mark the onset and offset of each arrhythmia (please, see Data S1 for details).

Human Annotations: Ground Truth and Arrhythmia Onset and Offset

We built a custom-made user interface to mark the onset and offset of noise portions and those of arrhythmia, corresponding to aystole, EB, ET, VF, and VT in each channel of ECG, BP, and photoplethysmogram signals. Based on the arrhythmia definitions/criteria listed in Table 1, the onset and offset of each arrhythmia record has been manually annotated by 2 experts. For complex cases, a third expert independently reviewed the record, and the majority view was used as the final annotation. Finally, we annotated noise and sinus rhythm (SR) portions in each of the channels of ECG, BP, and photoplethysmogram waveforms for further training and validations of our algorithms. Specifically, we annotated 953 independent alarms from 410 critical care subjects with diverse medical conditions. It has been observed that the alarm type indicated by the monitor may not correspond with the true alarm type. Table 2 provides the number of alarms raised for each event and their correspondence to the true underlying condition. About 50% of VF alarms that required immediate attention corresponded with a different arrhythmia type. Favorably, 80% of these mismatched alarms corresponded with VT. However, surprisingly, 22.6% of the EB alarms that require immediate attention corresponded with ET. Therefore, it becomes imperative to develop standalone arrhythmia detectors without considering the monitor alarm type.

Table 2. Number of Records in Each Alarm Type and Their Correspondence to the Gold Standard

		Alarm annotation by clinicians							Total records	PPV	% of mismatched true alarms
		Aystole	EB	ET	VF	VT	AF	SR			
Alarm type from monitor	Aystole	19	2	2	0	4	18	123	168	11.31	29.63
	EB	0	60	7	0	0	66	132	265	22.64	10.45
	ET	0	1	39	0	3	96	89	228	17.11	9.3
	VF	0	0	2	10	8	5	21	46	21.74	50
	VT	0	1	5	3	132	26	79	246	53.66	6.38
Total records		19	64	55	13	147	211	444	953		

AF indicates atrial fibrillation; EB, extreme bradycardia; ET, extreme tachycardia; PPV, positive predictive value; SR, sinus rhythm; VF, ventricular fibrillation; and VT, ventricular tachycardia.

Based on the gold standard annotations indicating the onset and offset of each arrhythmia, we derived the ground truth labels of the 4- and 8-second windows, as follows: A 4-second window is marked as VT if there are at least 5 beats meeting the VT criteria. In particular, the onset of VT is determined by the approximate midpoint between the first ventricular beat and the previous sinus beat. In the same vein, the offset is determined by the approximate midpoint between the last ventricular beat and the next sinus beat or the offset is considered as the end of the record if the arrhythmia persists until the end of the record. Similarly, the window is marked as VF only if the entire 4-second duration is marked as VF by the clinician. An 8-second window is considered as EB if the heart rate is <40 beats per minute in the given window. While the window is considered as ET, if at least 17 beats occur in the window with heart rate >140 beats per minute. Finally the window is considered as AF or SR if the entire window falls under the AF and SR criteria, respectively.

Performance Metrics

To report the performance of the classifier, along with the overall accuracy, we report the percent score (inspired from PhysioNet/Computing in Cardiology 2015 challenge) that heavily penalizes false negatives, to reduce or eliminate the lack of emergency care during a life-threatening event. The classifier's accuracy and score values are calculated as:

$$\text{Accuracy} = \frac{|TP| + |TN|}{|TP| + |TN| + |FP| + |FN|},$$
$$\text{Score} = \frac{|TP| + |TN|}{|TP| + |TN| + |FP| + 5 * |FN|}$$

where, |TP|, |TN|, |FP|, and |FN| refer to the counts of true positives, true negatives, false positives, and false negatives, respectively. Contrary to accuracy, the score value weighs the FNs, 5 times more than the FPs. We also report the classifier's sensitivity $\left(\text{Se} = \frac{|TP|}{|TP| + |FN|}\right)$ and positive predictive value $\left(\text{PPV} = \frac{|TP|}{|TP| + |FP|}\right)$, in each window (4 or 8 seconds), respectively.

To estimate the performance of the proposed method on unseen data, we performed k-fold cross-validation (with stratified random sampling) on the available data. We assessed the 5-fold cross-validation performance of our method, and then took the sum performance across all the folds to represent the classifier performance on the entire data. Further, to account for the randomness associated with model training and stochastic selection of k-folds, we repeated the 5-fold cross validation, 5 times, and reported the mean and SD of the classifier performance.

Data Preprocessing

Baseline-wander was corrected using median filters of window sizes 200 and 600 milliseconds, respectively.[28] Next, R-wave peak locations were identified using an R-wave detector that fuses information from multiple channels of ECG.[12] We excluded, across all channels, portions of records of ECG signals with amplitude <0.5 mV as being of low quality (normally, an alarm should be raised that would require lead repositioning to improve contact), resulting to a total of 1262.2 seconds of data being removed from the analysis. After data exclusion, the remaining 13032.8 seconds of data were used in the analysis. The proportion of data within each class were, SR=44.82%, AF=23.27%, VT=16.57%, VF=1.63%, EB=6.2%, ET=6.57%, and asystole=0.93%.

Block Schematic for Arrhythmia Detectors

In general, the majority of false alarms are attributed to noise, artifacts, or connection problems in ≥1 channels/signals. Accordingly, the first step is to identify such conditions. To this end, we first pass each signal through a noise detector and identify the signals that are corrupted with noise.

Next, depending on the arrhythmia type, we use either a window length of 4 or 8 seconds, respectively. Specifically, arrhythmias such as asystole, VT, and VF can be detected based only on 4 seconds of data, while EB, ET, AF, and SR require 8 seconds of data. As shown in Figure 1, we use a multi-tiered approach for arrhythmia detection. In particular, noise in each channel of ECG, BP, and photoplethysmogram is identified in Tier-0, and only those channels that are non-noisy are passed to the later stages. VT and VF are identified in Tier-1, ET and EB are identified in Tier-2, and finally Tier-3 distinguishes between AF and SR signals. At each tier, we use a classifier that is specific to the arrhythmia under consideration. In general, such classifiers are usually based on the handpicked arrhythmia dependent futures. As suggested earlier, we propose a hybrid-CNN based generalizable building block that can be trained to serve as a classifier at different tiers.

Hybrid Architecture as a Building Block

We consider a hybrid-CNN architecture comprising multiple convolutional layers and a fully connected layer with handcrafted features augmented before the output layer, as shown in Figure 2.

Handcrafted Features

We extracted a set of signal specific features from each ECG channel, as well as the BP and photoplethysmogram signals, to determine if the corresponding signal is noisy. Furthermore, a set of arrhythmia-specific features, which characterize each arrhythmia class, were also

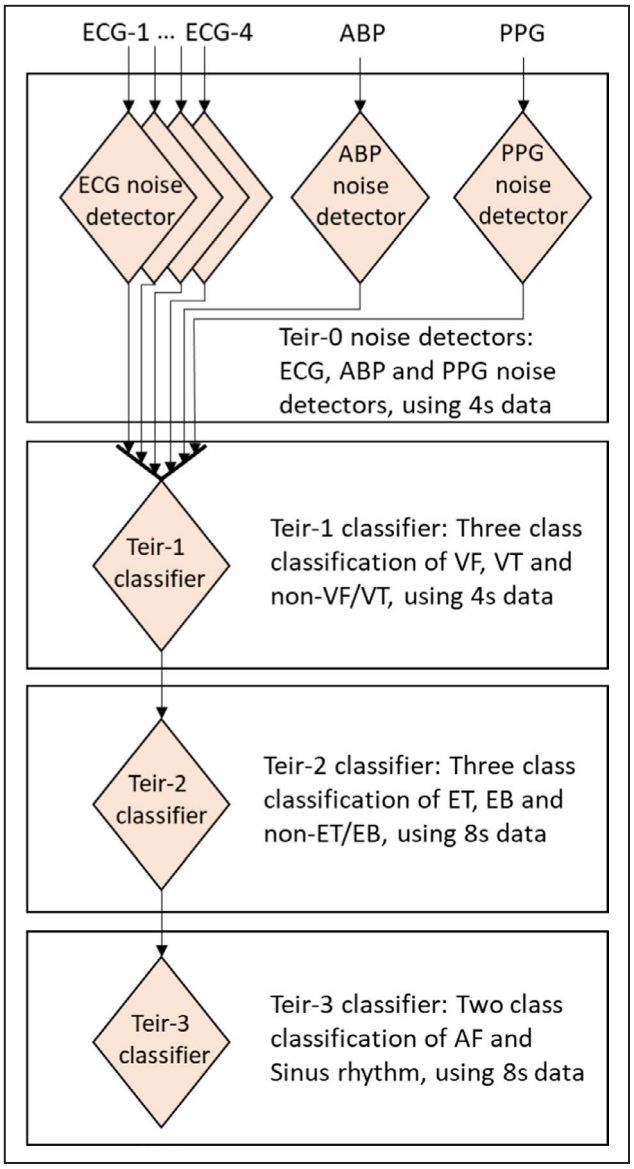

Figure 1. Block schematic of the proposed classifier.
ABP indicates arterial blood pressure; AF, atrial fibrillation; EB, extreme bradycardia; ET, extreme tachycardia; PPG, photoplethysmogram; VF, ventricular fibrillation; and VT, ventricular tachycardia.

extracted.[12] Details of these features are made available in the Data S1 (Tables S1 through S4). Missing ECG feature values were replaced with the average feature value from non-noisy channels of ECG. Whereas for BP and photoplethysmogram features, NaN values in the training and test set are replaced with the median value of the corresponding non-NaN feature values in the training set.

Hybrid-CNN Architecture

The input consists of a convolution layer with a single filter for all ECG channels and a different filter for each of the photoplethysmogram and BP channels. Each filter operates on the corresponding signal and an output is obtained by convolving the signal with the filter weights. Further, each filter component is assumed to have the same length. The convolved output is passed through a rectified linear unit and is pooled to reduce the dimension by a factor of 2. Next the output from the ECG, BP, and photoplethysmogram filters are concatenated and passed to the later stages. The filters of the subsequent layer fuse the information from all the channels into a single vector followed by rectified linear unit activation and pooling. The convolution, non-linear activation and pooling are treated as a single layer, which is repeated until penultimate layer (the second to last layer). The handcrafted features are augmented to the flattened convolution features, before fully connecting to the output layer.

Choice of Network Parameters

We used CNNs as building blocks to achieve the desired classification at each tier of the overall classifier. While training the CNNs, we used the binary cross entropy and the categorical cross entropy cost functions for binary and multi class classification tasks respectively. We also optimized the classifier performance by varying the number of filters, filter length, and pooling operations, to determine the effect of the convolution filter length as well as the network capacity, in terms of the number of trainable parameters.

RESULTS

Noise Detector Performance Evaluation

Before proceeding to the evaluation of the overall algorithm performance, we first evaluated the performance of the noise detector using 5-fold cross-validation. Based on the manual annotations corresponding with the onset and offset of the noise segment, we extracted 4 seconds of clean and noisy data windows from each record in the training and test folds. We developed signal specific noise detectors for ECG, BP, and photoplethysmogram signals using (1) a fully connected network with handcrafted features, (2) only CNN and (3) hybrid-CNN.

Using each classifier, we obtained the probability of determining whether the test window is a clean or noisy signal. Using this approach, we compared various classifiers using mean receiver operating characteristic curves, over 5-fold. The overall optimal operating point is provided by the hybrid-CNN classifier with a sensitivity and specificity of 94.0% and 91.9%, respectively.

The performance of the ECG noise classifier is shown in Figure S1. The desired operating point is obtained by computing the point on the receiver operating characteristic curve that is closest to the ideal classifier, ie, sensitivity=1 and specificity=1. The area under

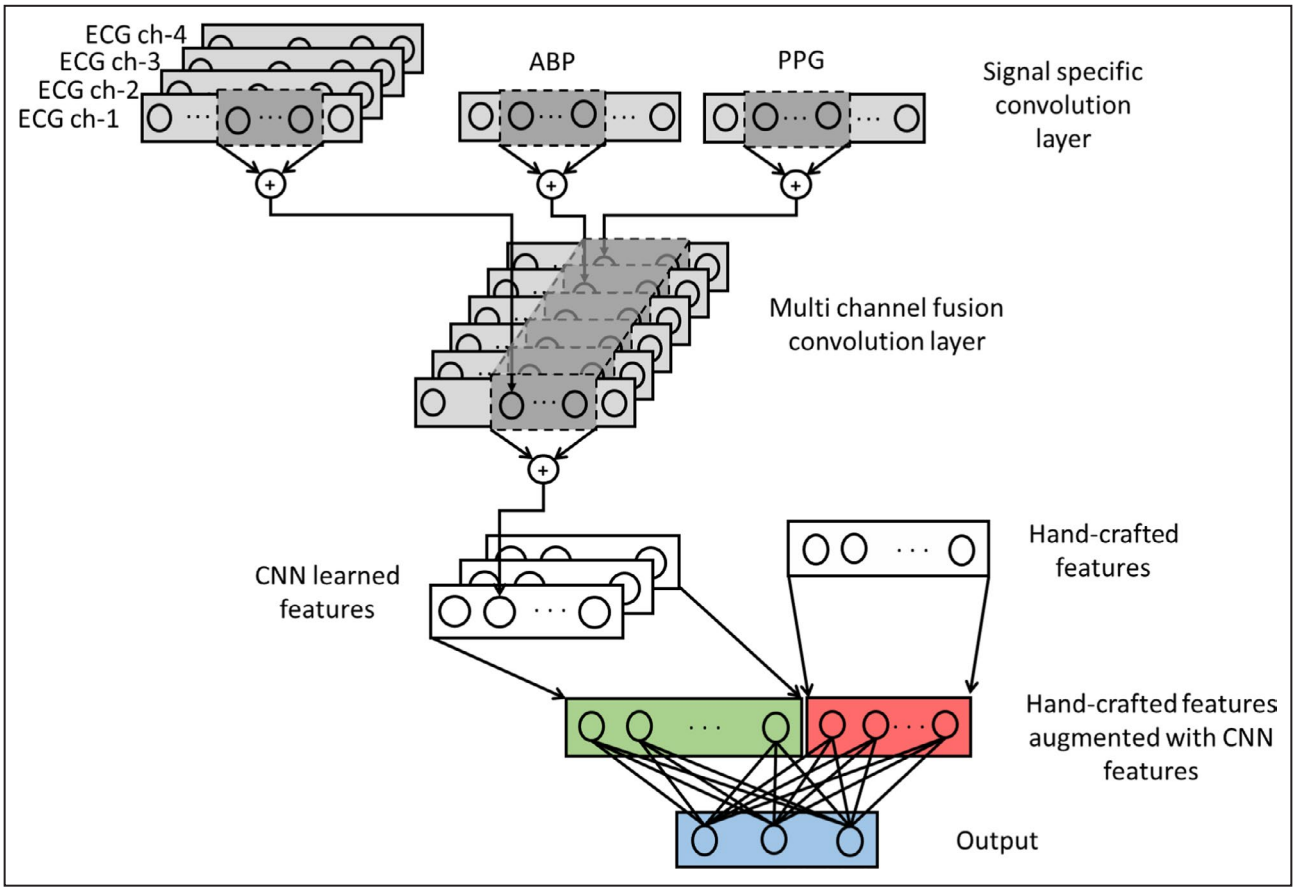

Figure 2. Hybrid- convolutional neural network architecture that fuses the information from learned and handcrafted features.
ABP indicates arterial blood pressure; CNN, convolutional neural network; and PPG, photoplethysmogram.

the curve of the ECG noise classifier for feature-based, only CNN, and hybrid CNN classifiers were 93.56%, 96.97%, and 97.17%, respectively. While the hybrid CNN and only CNN classifiers achieved similar performance, both classifiers achieved significant performance improvement compared with the only feature-based noise detector, perhaps because the features extracted from a short (4 seconds) window may not adequately capture the noise characteristics. The hybrid-CNN BP noise classifier provided a sensitivity and specificity of 88.6% and 90.9% respectively, and the hybrid-CNN photoplethysmogram noise classifier provided a sensitivity and specificity of 98.5% and 94.9%, respectively.

The proposed noise detectors appeared to be robust to the morphological changes in the signals during arrhythmic events, and have not classified any arrhythmia records as noise.

Algorithm Performance Evaluation

The data are processed sequentially in windows of 4 and 8 seconds while striding with 0.5-second steps. Next, each 4-second window of data is passed through the noise detector, and the noisy channels of ECG, BP, and photoplethysmogram signals are masked with zeros. If all ECG channels are noisy, the corresponding 4-second window is considered noisy, and disregarded. Otherwise, the window is passed through Tier-1 classifier to detect the presence of VT or VF. An 8-second window that does not contain a 4-second window of either noise, VT or VF, is passed on to the Tier-2 classifier to detect EB or ET; if EB/ET arrhythmias are not found, the 8-second window is marked as AF or SR based on the Tier-3 classifier output.

We developed 3 classifiers, with: (1) handcrafted features alone, (2) CNN, and (3) hybrid-CNN. We optimized the performance of only CNN and hybrid-CNN by varying the number of filters and the filter length. The performance for each hyper-parameter configuration is presented in Table 3. In terms of network capacity, for a Tier-1 classifier, the minimum and maximum number of trainable parameters in a hybrid-CNN were 15 457 (filter size=5, number of filters=4) and 3 134 669 (filter size=500, number of filters=32), respectively. Similarly,

Table 3. Performance of Various Network Architectures

Filter size	No. of filters	Pooling	Hybrid-CNN classifier		Only-CNN classifier	
			Overall accuracy (%)	Score (%)	Overall accuracy (%)	Score (%)
5	4	Max pooling	83.71	79.05	72.81	61.39
5	8	Max pooling	86.37	81.11	82.45	68.10
25	8	Max pooling	86.93	80.14	85.75	72.92
50	8	Max pooling	87.64	81.44	81.40	64.81
75	8	Max pooling	87.53	81.40	79.91	64.33
50	8	Average pooling	77.14	57.20	72.67	52.00
50	32	Max pooling	69.33	56.46	84.25	66.86
100	8	Max pooling	76.82	62.39	78.23	64.33
500	8	Max pooling	62.33	56.41	74.16	61.98
500	32	Max pooling	52.83	52.83	76.09	60.80
Only feature-based classifier			86.72	80.48		

CNN indicates convolutional neural network.

for only CNN classifier the minimum and maximum number of trainable parameters were 1015 (filter size=5, number of filters=4) and 3 120 227 (filter size=500, number of filters=32), respectively. It should be noted that the network capacity is increased with the filter size and the number of filters; also, the capacity of the hybrid network is greater than the equivalent only CNN classifier, because of the inclusion of the handcrafted features.

Interestingly, an increased network capacity does not translate to improved performance. It is observed that the hybrid-CNN achieved a slightly improved performance over only CNN classifier. Also, the performance increased with filter size, reached a peak, and then decreased. Intuitively, a small convolution filter operates on a short temporal window within the signal, and may not fully exploit the temporal dependency efficiently. On the other hand, a long filter also achieves low performance because, while observing for a significant duration, CNN filters might fuse and encode the information from the entire beat into few filter outputs. A similar observation is reported in earlier work,[26] and the choice of filter dimension plays a crucial role in determining the classifier performance. For hybrid-CNN, a filter dimension of 50, 8 filters, and maximum pooling operation, among all classifiers, achieved the highest accuracy and score, of 87.6% and 81.4%, respectively.

To account for the stochasticity in model convergence as well as the randomness in the choice of data in each fold, we performed 5 times 5-fold cross-validation and reported the mean and SD of the classifier performance, for optimal hyper-parameters. Our hybrid-CNN model, only-CNN model, and only feature-based classifiers achieved a mean (±SD) accuracy of 87.5% (±0.48), 81.2% (±0.94) and 84.3% (±1.35) and a score of 81.0% (±0.89), 64.6% (±4.1) and 80.7% (±0.48), respectively. Favorably, the low SD indicates that our method generalizes well to new data. Further, we verified the statistical similarity between hybrid-CNN and only feature-based classifier using McNemar test,[29,30] and we observed that the Tier-1, Tier-2, and Tier-3 classifiers are significantly different ($P<0.001$). The classification performance in terms of sensitivity, PPV, and accuracy, specific to each rhythm are presented in Table 4 and Table S5. For asystole classification, the SD is zero as it gets detected through a deterministic process, before passing through the classifier. The majority of EB and ET misclassifications are borderline cases in which the heart rate is close to 40 and 140 beats per minute, respectively. Such misclassifications can be corrected setting a hard-threshold on the heart rate, although such minor misclassifications are unlikely to have a meaningful clinical impact. Finally, although the present work appears to have a poor sensitivity for VF detection, all the misclassified VF signals are assigned as VT and in practice, alarms will be raised for 100% of the VF signals. Furthermore, clinical differentiation of VT from VF is somewhat arbitrary and therefore, binning the alarms together serves to maximize clinical utility.

Next, we attempted to understand the improvement in the performance of hybrid CNN compared with only CNN approach and feature-based approach. To this end, we used a Gradient-Weighted Class Activation Map[31] to visualize the discriminatory parts of the signal that generated the output of a CNN-based classifier (please, see Figure S2). Also, we used permutation-importance[32] to depict the importance of handcrafted features in a feature-based classifier (please, see Figures S3A through S3C). It appears, that since each arrhythmia is characterized by an associated morphology and well defined features, capturing these features using a hand engineered feature extraction approach

Table 4. Sensitivity, PPV, Accuracy and Score for Each Rhythm Following 5-Times 5-fold Cross-Validation (Highlighted in Grey), as Well as the Positive Predictive Value Observed by Bedside Monitors

Rhythm	Sensitivity (%)	PPV (%)	Accuracy (%)	Score (%)	PPV (%) Current study (clinical annotations)	PPV (%) Physionet 2015 Challenge	PPV (%) MIMIC II study	PPV (%) UCSF study
Aystole	100.00±0.00	61.58±0.00	99.42±0.00	99.42±0.00	11.31	16.67	9.33	32.83
EB	99.29±0.78	82.64±3.04	98.65±0.27	98.65±0.26	22.64	50	70.71	NA
ET	91.55±0.85	96.11±0.96	99.20±0.02	98.64±0.11	17.11	94.92	76.93	NA
VF	79.45±9.84	78.83±12.51	99.29±0.33	99.29±0.33	21.74	10.34	20.33	67.72
VT	97.33±0.60	95.13±0.99	98.73±0.21	98.22±0.27	53.66	26.23	53.42	13.00
AF	89.99±1.13	74.41±1.44	90.48±0.42	84.61±0.89	NA	NA	NA	NA
SR	80.33±1.41	94.74±0.81	89.16±0.45	NA	NA	NA	NA	NA

AF indicates atrial fibrillation; EB, extreme bradycardia; ET, extreme tachycardia; MIMIC, Medical Information Mart for Intensive Care; NA, not applicable; PPV, positive predictive value; SR, sinus rhythm; USCF, University of California, San Francisco; VF, ventricular fibrillation; and VT, ventricular tachycardia.

helps in classification; although CNNs attempt to characterize these features, a hybrid approach would combine the benefits of both approaches.

Algorithm Performance Comparison

Thereafter, we compared the performance of the present method with the existing bedside monitoring systems (Table 4). Although the existing monitors continuously process data to detect arrhythmias, the exact onset and offset locations of arrhythmias remain unavailable. In this setting, assuming that the existing systems do not miss any arrhythmic events, we compared the PPV of our proposed system to those of the bedside monitors used in the PhysioNet 2015 challenge,[16] MIMIC (Medical Information Mart for Intensive Care) II study,[8] and the alarm fatigue study from University of California, San Francisco[1] (Table 4). Specifically, we computed the PPV as the ratio of the reported true alarms to the total alarms raised corresponding to that particular arrhythmia. We aim to maximize the PPV while maintaining high sensitivity.

For 5 life-threatening arrhythmias, our method achieved an average PPV and sensitivity of 82.9% and 93.5%, respectively. The monitor-based average PPV of the current study (based on clinician's annotations), PhysioNet 2015 challenge and MIMIC II study are 25.29, 39.63, and 46.14, respectively. Among the common arrhythmias used in the present and the University of California, San Francisco studies (asystole, VT, and VF), we achieved a PPV of 78.57 with a sensitivity of 92.2% while the University of California, San Francisco study exhibited a PPV of 37.9%.

Independent Data Set Validation

We used data from PhysioNet 2015 challenge,[16] as an independent data set to validate the proposed algorithm. Record-wise annotations indicating signal quality, rhythm type, and the onset and offset of each arrhythmia are presented in Table S6. In particular, we used 2-channel ECG, BP, and photoplethysmogram signals as input and processed 4- and 8-second long data, while striding with 0.5-second steps. Although the proposed network is trained with 4-channel ECG, BP, and photoplethysmogram, it remains adaptable and effective even with 2 missing channels of ECG. In Table 5, we report the confusion matrix of the proposed classifier with an overall accuracy and score of 93.93% and 84.32%, respectively. While VF arrhythmia achieved a lesser sensitivity and PPV, all the VF misclassifications correspond to VT and in practice an alarm would have been raised for each VF incidence. The score of the proposed hybrid CNN is close to the

Table 5. Performance of Hybrid CNN Classifier on an Independent Validation Data Set From the PhysioNet 2015 Challenge

	Aystole	EB	ET	VF	VT	SR	Sensitivity (%)
Aystole	28	0	0	0	0	0	100
EB	0	227	0	0	0	15	93.80
ET	0	0	932	0	35	186	80.83
VF	0	0	0	10	12	0	45.45
VT	0	0	0	17	142	9	84.52
SR	17	25	69	0	62	5584	96.99
PPV (%)	62.22	90.08	93.11	37.04	56.57	96.38	Accuracy = 93.93% Score = 84.32%

CNN indicates convolutional neural network; EB, extreme bradycardia; ET, extreme tachycardia; PPV, positive predictive value; SR, sinus rhythm; VF, ventricular fibrillation; and VT, ventricular tachycardia.

Table 6. Performance of Only CNN Classifier on an Independent Validation Data Set From the PhysioNet 2015 Challenge

	Aystole	EB	ET	VF	VT	SR	Sensitivity (%)
Aystole	28	0	0	0	0	0	100.00
EB	0	184	0	0	0	51	78.30
ET	0	0	675	23	11	409	60.38
VF	0	0	0	18	2	2	81.82
VT	0	0	0	12	100	40	65.79
SR	4	68	64	55	110	5346	94.67
PPV (%)	87.50	73.02	91.34	55.56	11.92	91.42	Accuracy = 88.18% Score = 68.96%

CNN indicates convolutional neural network; EB, extreme bradycardia; ET, extreme tachycardia; PPV, positive predictive value; SR, sinus rhythm; VF, ventricular fibrillation; and VT, ventricular tachycardia.

top scoring entry of the challenge,[33] with a score of 85.04%. Favorably, the proposed algorithm in this article is trained to detect AF in addition to the arrhythmia considered in the challenge and is flexible to be extended to other arrhythmias. Only CNN based classifier achieved an overall accuracy and score of 88.18% and 68.96% (please, see the confusion matrix in the Table 6), respectively, and only feature based classifier achieved an overall accuracy and score of 88.4% and 72.48%, respectively (please, see the confusion matrix in the Table 7).

DISCUSSION

The majority of ICU abnormal heart rhythm triggered monitor alarms are found to be false,[1] primarily attributable to noise and artifacts in the physiological signals, which often result from patient motion or loose electrodes. Excessive numbers of false alarms create a noisy environment and cause alarm desensitization among caregivers. In the present study, we observed that about 74.7% of the critical ECG arrhythmia alerts are false alarms. In particular, individual arrhythmia rates vary between 46.3% and 88.6%, which are observations consistent with the reported ICU FA rates ranging between 40% and 90%.[5,8]

Various attempts have been made to address the issue of FAs. Recent algorithms that used machine learning techniques and prior information with respect to the alarm type have reported significant improvement in FA suppression.[17,18,34,35] However in practice it has been observed that, although some of the critical arrhythmia alarms are true, the condition indicated on the monitor may not indicate the true underlying arrhythmia. For instance, in our database, 22.6% of EB alarms that require attention correspond to ET. Therefore, it is imperative to develop arrhythmia detectors without prior knowledge of the alarm type. In this report, we present a standalone arrhythmia alerting system that identified life-threatening arrhythmias without prior knowledge of the arrhythmia type. Several conclusions can be drawn from this study: *first*, a hybrid-CNN approach performs better than either only CNN or only feature-based approaches; *second*, the proposed method can be adapted to use multiple modules such as signal-specific noise detectors and arrhythmia detectors; *third*, our algorithm is flexible to operate on different duration signals and can be extended to other arrhythmias with suitable training; *fourth*, the proposed hybrid-CNN algorithm would have suppressed 77.05% of the FA generated by an existing monitoring system, without prior knowledge of the underlying alarm, which

Table 7. Performance of Only Feature-Based Classifier on an Independent Validation Data Set from the PhysioNet 2015 Challenge

	Aystole	EB	ET	VF	VT	SR	Sensitivity (%)
Aystole	28	0	0	0	0	0	100.00
EB	0	203	0	0	0	32	86.38
ET	0	0	572	2	149	316	55.05
VF	0	0	0	15	5	2	68.18
VT	0	0	0	18	107	44	63.31
SR	4	62	54	14	130	5418	95.35
PPV (%)	87.50	76.60	91.37	30.61	27.37	93.22	Accuracy = 88.40% Score = 72.48

EB indicates extreme bradycardia; ET, extreme tachycardia; PPV, positive predictive value; SR, sinus rhythm; VF, ventricular fibrillation; and VT, ventricular tachycardia.

is superior to any other algorithm[8,9,36]; *fifth*, our classifier generalizes well with an excellent performance when validated in an independent data set.

Early attempts in heart rhythm classification have extensively analyzed the signal morphology in single and multiple channels of ECG signals.[4,5] Recent algorithms have determined that BP and photoplethysmogram improve the arrhythmia detection performance,[6–9] considering, for example, that arrhythmias such as VT and VF are accompanied with a drop in BP. Although various algorithms consider the information from BP and photoplethysmogram signals, features from each physiological signal are extracted independently. In contrast, our proposed solution fuses the information from multiple physiological signals through convolution filters and learns suitable features to achieve the desired classification goals. In addition, we also augment the learned features with handcrafted features to fully exploit the benefits of feature engineering and feature learning. Further, the proposed algorithm is flexible and effective when independently validated using PhysioNet 2015 challenge data, even when 2 ECG channels are missing. For 5 life-threatening arrhythmias (asystole, ET, EB, VT, and VF) recorded from the bedside monitors, the monitor-based average PPV (based on clinician's annotations) was 25.29%, resulting in 74.71% of false alarms. Using the same data, the proposed method achieved an average PPV of 82.9% resulting in 17.1% of false alarms. In practice, our proposal would have suppressed 77.05% of the false alarms generated by an existing monitoring system. Further, the proposed method facilitates real-time operation by raising an alarm as soon as the arrhythmia criteria are met.

AF is the most frequent arrhythmia in the ICU across all populations, with an incidence ranging from 47.4% to 61%.[37] Although the majority of ICU physiologic monitors (ie, the GE EK-Pro), are capable of detecting and alarming when AF is present (albeit they do not include classification of atrial flutter or atrioventricular block), the AF alarm is often kept inaudible, because AF is considered a non-critical alarm. However, because of the high incidence of AF in the ICU and its impact on electrocardiographic features, it is imperative to include AF within an arrhythmia detection algorithm.

With the ever-increasing use of wearable and mobile-based devices for ambulatory patient monitoring, multiple physiological signals including ECG, BP, and photoplethysmogram can be monitored from the comfort of the home, thus providing abundant information for the accurate detection of abnormal heart rhythms such as those described in this study.

CONCLUSIONS

In this study, we proposed a method for detecting critical arrhythmias encountered in ICUs using a hybrid-CNN based approach. In particular, we sought to accurately identify different life-threatening arrhythmias and reduce the burden of FA fatigue. In the process, we developed a generalizable hybrid-CNN architecture that fuses the hand-picked features with those learned by the CNN. Although only CNN based classifiers learn suitable features from the data to optimize the classification performance, CNNs augmented by hand engineered features that characterize various arrhythmic conditions resulted in improved overall arrhythmia detection accuracy. The hybrid approach gave superior performance to both traditional handcrafted feature-based methods and CNN based methods. While the proposed method is developed to process 4 and 8 seconds of data, the method remains generic to a variable processing window duration. Further, our method also retains the flexibility of including new arrhythmia detectors and novel handcrafted arrhythmia specific features, if needed, by simply reconfiguring and training the hybrid-CNN modules appropriately.

Study Limitations

ICUs encompass patient groups with diverse medical conditions and a wide variety of abnormal heart rhythms and generated alarms. Ideally all monitor alarms should be considered for analysis, however, because of the resource-intensive nature of the manual data annotations, this study was confined to the presented critical alarms. In addition, similarly to other studies, because of the limited available labeled data, the trained models are prone to overfit to the training data. To this end, we have used early stopping of classifier training based on the validation accuracy and, evaluated the model's generalizability on an external database. In summary, while the proposed method is developed to suppress only false critical alarms, the framework remains generic and can be extended to other conditions via suitable training and network modifications.

ARTICLE INFORMATION

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Disclosures

None.

Supplementary Material

Data S1
Tables S1–S6
Figures S1–S3

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SUPPLEMENTAL MATERIAL

Data S1

Feature Extraction

We extracted hand crafted features from the electrocardiogram (ECG), blood pressure (BP), and photoplethysmogram (PPG) signals to be used in the noise, tier-1, tier-2 and tier-3 classifiers. The majority of these features have been used in a recent study aiming to reducing false ICU alarms with prior knowledge of the alarm type[12].

In addition to those features, we considered arrhythmia specific features based on the heart rate (HR) as well as a set of features related to atrial fibrillation (AF) based on heart beat intervals and P-wave morphology. List of all the features used in the present work are described below.

Electrocardiographic Features

Periodicity Measure ECG signals generally follow a periodic rhythm in normal cases and in most arrhythmic cases except asystole and ventricular fibrillation (VF). One of the strongest markers of good signal quality for ECG is the degree of periodicity. Once R peaks are identified we obtain all peak-to-peak time periods and put them in an array $I = [I_1, I_2, \dots I_n]$. For highly periodic signals the standard deviation would be small for this array of time periods. We calculate the periodicity measure by equation (1):

$$Periodicity\ measure = \ 1 - s_I/\bar{I} \qquad (1)$$

where, s_I is the standard deviation of the array I and $\bar{I}$ is the mean value of the array I. Periodicity measure is close to zero for highly aperiodic signal and close to unity for highly periodic signals.

Sharpness Measure A good quality ECG has sharp QRS complexes except in the cases of VF and VT. We quantify the sharpness, S_i, of the i_{th} QRS complex by measuring the minimum absolute slope around the QRS complex. We calculate the sharpness for each QRS within the window of analysis and put it in an array $S = [S_1, S_2, \dots, S_n]$. The sharpness measure for an ECG signal within a window of analysis is given by equation (2):

$$Sharpness\ measure = \left(\frac{2}{\pi}\right) * \tan^{-1}(\bar{S}) \quad (2)$$

where, $\bar{S}$ is the mean of the array S. Sharpness measure can take values between 0 and 1. An ECG signal with highly sharp QRS complexes has values close to 1.

Correlation Measure As a QRS complex is a repeating pattern in the ECG, it generally has a high beat-to-beat correlation. We calculate the correlation between n successive QRS complex detection and store them in an array $C = [C_1, C_2, \dots, C_{n-1}]$. Correlation measure is given by equation (3):

$$Correlation\ measure\ (\bar{C}) = \frac{1}{n-1}\sum_{i=1}^{i=n-1} C_i \quad (3)$$

Correlation measure can take a value between 0 and 1. If two QRS complexes are identical then correlation measure is 1, while it is low for QRS complexes with different morphologies.

Peak Height Stability Measure Stable peak heights would often indicate high signal quality. Therefore, we invented the peak height stability measure. Each peak height is found by subtracting the amplitude of the ECG signal at the R peak detection by the mean amplitude of the ECG signal. All the peak heights within the window of analysis are stored in an array $\delta P = [\delta P_1, \delta P_2, \dots, \delta P_n]$. We find the peak height stability measure by equation (4):

$$Peak\ height\ stability\ measure = 1 - s_{\delta P}/\overline{\delta P} \quad (4)$$

where, $s_{\delta P}$ is the standard deviation of δP and $\overline{\delta P}$ is the mean of the array δP.

Complexity Measure Complexity measure is derived from the viewpoint of dynamical systems. The complexity measure was calculated by comparison and accumulation operations from a string of zeros and ones, which is a reconstruction of the original ECG data for a specific window length and an appropriate threshold. This complexity measure has been shown to effectively detect sinus rhythm, VT and VF.

Dominant Frequency Dominant frequency is the frequency at which the power spectrum has its highest power.[18] For VF, the dominant frequency should be in the range of 2.5-8Hz.

Maximum Power to Total Power Ratio We hypothesized that during VF the ECG would have most of its power in a single frequency. Therefore, we invented this feature which is the maximum power to total power ratio in the frequency domain to examine how concentrated the power is in a single frequency. ECGs during VF would have a higher maximum power to total power ratio than normal ECGs.

Co-dominant Frequencies This refers to the number of significant frequency components besides the dominant frequency. These frequency components have minimum peak heights of 0.2 in the normalized power spectrum.[35] This is another measure that describe how concentrated the power is at the dominant frequency.

Low Frequency Power Dominant After applying the method of amplitude envelope, one can conclude which frequency power band is the most dominant at a certain point in time. During VF, the low frequency power band should be the most dominant as VF resembles a signal of frequency 2.5-8Hz.[18] Therefore, we invented a binary feature, Low Frequency Power Dominant, to indicate whether low frequency power was dominant for 4 seconds continuously for VF alarms.

Bandwidth Here we define the bandwidth of the ECG signal as the difference between the last and first frequencies in the normalized power spectrum that exceeds power of 0.5. During VF, the bandwidth of the ECG signal would decrease significantly.

Mean Frequency The frequency spectrum is characterized by its mean frequency which is the sum of the product of the spectrum intensity and its respective frequency, divided by the total sum of spectrum intensity. This is shown in equation (5):

$$f_{mean} = \frac{\sum I*f}{\sum I} \qquad (5)$$

where, f is the frequency and I is the spectrum intensity.

Median frequency The frequency spectrum is also characterized by its median frequency. To find the median frequency, one has to calculate the total power of the whole spectrum first.

Then, the median frequency is the frequency at which the cumulative power (sum of all the power for lower frequencies) first exceeds half of the total power.

Ratio of maximum power to total power ratio We hypothesized that during VF the ECG would have most of its power in a single frequency. Therefore, we invented this feature which is the maximum power to total power ratio in the frequency domain to examine how concentrated the power is in a single frequency. ECGs during VF would have a higher maximum power to total power ratio than normal ECGs.

Ratio of Maximum power below 12Hz to average between 15Hz and 20Hz Is a frequency domain feature estimated by computing the ratio of maximum power below 12Hz to the average power between 15Hz and 20Hz.

Ratio of Maximum power below 12Hz to maximum power above 15Hz Is obtained by computing the ratio of maximum power below 12hz to the maximum power above 15Hz.

Five consecutive ventricular tachycardia beats We created a binary feature that indicated whether the ECG signals met the criteria of VT. If a sequence of five consecutive VT beats was found and these VT beats all occurred within 2.4 seconds, then this binary feature would be given the value of one. Otherwise, this binary feature would be given the value of zero.

Maximum heartrate over five beats Is the maximum heartrate estimated within a given window by considering five consecutive beats.

Maximum difference between low frequency sub peaks Is a frequency domain feature to identify the signature of VT and VT. It is obtained by taking the maximum difference between the low frequency sub peaks.

Not Enough Beats We created this binary feature to indicate whether there are enough heartbeats within the window of analysis for calculation of heart rate for classifying tachycardia alarms. The number of heartbeats required for calculation of heart rate for tachycardia is 17.

Heart Rate Heart rate is determined from the R peak detection. For exreme tachycardia, the fastest average heart rate from a sequence of 17 consecutive heart beats is extracted from the 8 second of the records. For extreme bradycardia, the slowest average heat rate from a sequence of 5 consecutive heart beats is extracted from 8 second of the records.

Minimum Heart rate Is the minimum heart rate within the given 8 second window estimated based on 5 consecutive heart beats.

Number of beats slower than 40 bpm Is the count of those heartbeats with heart rate lower than 40 beats per minute.

Number of heartbeats is the count of number of heartbeats within the given 8 second input data.

HR criterion of ventricular tachycardia (VT) We created a binary feature that indicated whether the HR met the criteria of VT. Specifically, if the HR is greater than 100 beats per minute and less than 140 beats per minute, then this binary feature would be set to one. Otherwise, this binary feature would be set to zero.

HR criterion of extreme bradycardia (EB) We created a binary feature that indicated whether the HR met the criteria of EB. Specifically, if the minimum HR for five consecutive beats is less than 40 beats per minute, then this binary feature would be set to one. Otherwise, this binary feature would be set to zero.

HR criterion of extreme tachycardia (ET) We created a binary feature that indicated whether the HR met the criteria of ET. Specifically, if the maximum HR for 17 consecutive beats is greater than 140 beats per minute, then this binary feature would be set to one. Otherwise, this binary feature would be set to zero.

P-waveMean: Mean P-wave peak amplitude of detected beats in the 8 s window.

P-waveStd Standard deviation of the P-wave peak amplitude of detected beats in the 8 s window.

P-waveAreaMean Mean of the P-wave area, between P-wave onset and P-wave offset of detected beats in the 8 s window.

P-waveAreaStd Standard deviation of the P-wave area, between P-wave onset and P-wave offset of detected beats in the 8 s window.

PR Mean Mean of the PR interval duration of detected beats in the 8 s window.

PR Std Standard deviation of the PR interval duration of detected beats in the 8 s window.

Blood Pressure and PPG Features

Decreasing δP During VT, blood pressure and PPG amplitude would often gradually decrease. Therefore, the binary feature, decreasing δP, was invented to indicate whether the amplitude of the BP signal or PPG signal keep on decreasing.

No peaks During VF, there should be no onsets of waveforms in BP and PPG signals because the heart is not pumping blood. Therefore, we created two binary features, absence of peaks, one for the BP signal and another one for the PPG signal, to indicate whether there are onsets of waveforms in the BP and PPG signals for VF alarms.

Maximum period We calculated the maximum gaps between consecutive onsets of waveforms in BP and PPG signals respectively and used them as features.

Maximum Amplitude before Onset This is the largest amplitude before the onset of the largest gap between consecutive valleys in the considered BP or PPG signal.

Maximum Amplitude after Onset This is the largest amplitude after the largest gap between consecutive valleys in the considered BP or PPG signal.

Minimum pressure at largest gap Minimum amplitude value before the occurrence of largest gap between consecutive onsets of waveforms is used as a feature.

PPG Amplitude Decrease This is a binary feature that indicates whether the signal amplitude decreases after the onset of the largest gap.

Periodicity Measure The periods between the onsets of n waveforms were calculated and stored in an array $I = [I_1, I_2, \dots, I_{n-1}]$. For highly periodic signals the standard deviation would be small for this array of time periods. The equation used for calculating periodicity measure for BP or PPG is the same as that for ECG as illustrated in equation (1).

δP Stability Measure When the signal quality is high, the value of the maximum amplitude minus the minimum amplitude for each waveform would be quite stable during sinus rhythm in BP and PPG signals. Such values were calculated for all detected waveforms within the window of analysis and stored in an array $\delta P = [\delta P_1, \delta P_2, \dots, \delta P_n]$. δP Stability Measure was calculated using equation (4).

Correlation Measure High-quality BP and PPG signals are often very regular. Therefore, we calculated the cross-correlation coefficients between n consecutive waveforms and put them

in an array $C = [C_1, C_2, \dots, C_{n-1}]$. The correlation measure for the BP or PPG signals within a window of analysis is the mean of these cross-correlation coefficients, and it can be obtained from equation (6).

Minimum heart rate Is the heart rate estimated from the corresponding BP and PPG signals using five consecutive beats within the given window of 8 seconds.

Number of beats slower than 40 bpm Is a count of number of beats with heart rate lower than 40 beats per minute.

Maximum heart rate Is the maximum heart rate with in a given window estimated by considering 16 consecutive beats.

Not enough beats to detect extreme tachycardia Is binary feature set to 1 if more than 16 beats are detected within the given window.

The specific set of features used in each classifier are listed in the Tables S1-S4.

PhysioNet Data Annotation

We used the open source training data from the "PhysioNet/Computing in Cardiology Challenge 2015: Reducing False Arrhythmia Alarms in the ICU[16]" as an independent dataset to evaluate the proposed algorithm. The database consists of 750 intensive care unit (ICU) records with two channels of electrocardiographic (ECG) signals and either one of the arterial blood pressure (BP) and photoplethysmogram (PPG) signals, or both.

Also, the time when the bed side monitor raised an alarm, and the annotation indicating whether the alarm is true or false are provided. We first re-annotated the data to identify the time instance at which the definition/criteria for the alarm are met. The rhythm of each record has been marked based on the consensus of two cardiologists, while remaining blind to each other, as well as to the annotations of the database. We considered 15 s of data (i) in sinus rhythm, (ii) prior to false alarms, and (iii) prior to the true alarm time and marked the onset and offset times, for each of the five life threatening arrhythmia corresponding to asystole, extreme bradycardia, extreme tachycardia, ventricular tachycardia (VT) and ventricular fibrillation (VF). Rhythms not belonging to any of the five aforementioned arrhythmias, were deemed inconclusive and not included in the analysis (Table 5). We also marked the signal quality for each

of the available physiological signals that was used for noise/artefact detection by our algorithm. Record-wise annotation details are provided in Table 5, below.

Explainability of Convolutional Neural Networks and Feature Based Classifiers

The ability to explain the decision of the classification algorithm enhances its significance in its clinical deployment. We used the gradient-weighted class activation mapping (grad-CAM) technique to explain the decision making process of the convolutional neural network (CNN) classifier. In particular, grad-CAM identifies those regions within the input data which result in its classification into a specific class, by using CNN layer feature maps and the gradient of a loss function with respect to the feature maps.

Specifically, let's assume that the output of a convolution layer L produces K feature maps, $A^k \in \mathbb{R}^{M\times 1}$, with each element indexed by i. So A_i^k refers to the activation at location i of the feature map A^k. Now for a given class c, a weight vector $W = [w_1, w_2 \dots w_k]$, is obtained from the mean of the gradient of the score (Y^c) with respect to the feature map as shown in equation (5):

$$w_k^c = \sum \frac{\partial Y^c}{\partial A_i^k} \qquad (5)$$

Finally, the weighted combination of all K feature maps at layer L, given by $\sum w_k A_k$ generates the grad-CAM heatmap, which is subsequently normalized and resampled to the original signal dimension to depict the regions of interest on the input signal. In Figure S2, we visualized the class activation map of the fourth convolutional layer of the Tier-3 classifier. Specifically, we plot the first ECG channel with the gray level proportional to the output of grad-CAM. Some of the important regions (in light grey) for classification correspond to a missing P-wave and a beat with irregular preceding and following RR intervals. Such features agree with the clinical diagnosis of AF.

To understand the feature based classifier, we used the permutation importance[32] technique to score the importance of each input feature. Specifically, each feature is randomly permuted within the original dataset to generate a permuted feature dataset. Now a feature weight is computed by taking the difference in the performance of the classifier on the original

data and on the permuted feature datasets. Finally, the feature importance score depicting the relative importance of each feature is obtained by normalizing the feature weights.

Feature importance scores for Tier-1, Tier-2 and Tier-3 classifiers are shown in the Figure S3A, Figure S3B and Figure S3C respectively. The two most important features for Tier-1 classification are the median frequency and the ratio of maximum power to total power. Both are frequency domain features that characterize the VT and VF signals that are classified in Tier-1 (Figure S3A).

Similarly important features for Tier-2 classification are ECG heart rate, ECG number of beats at a heart rate slower than 40 beats per minute and not enough ECG beats to detect extreme tachycardia. Such features are relevant in clinical practice for detecting extreme bradycardia and extreme tachycardia signals that are classified in Tier-2 (Figure S3B).

In the same vein, important features of Tier-3 classifier are the standard deviation of heart rate and P-waveAreaMean, that correlate with AF diagnosis. Indeed the feature importance scores are not surprising and most relevant clinical features are driving the classifier decisions, thus increasing the confidence in the classifier for practical deployment (Figure S3C).

To summarize, a CNN based classifier automatically extracts features from the signal to optimize the classifier performance. However, such features may not be intuitive to a clinician. In contrast, a feature based classifier clearly assigns high score to those features used in clinical practice, but may not achieve the highest classification performance. An optimal hybrid CNN approach that uses both automated feature learning along with handcrafted features achieves improved performance compared to only CNN and only feature based approaches.

Table S1. List of hand-crafted features used in noise classifier.

ECG	Periodicity measure
	Sharpness measure
	Correlation measure
	Peak height stability measure
	maxSignalEnergyBeyond_12Hz
BP	Periodicity measure
	δP Stability measure
	Correlation measure
PPG	Periodicity measure
	δP Stability measure
	Correlation measure

Features are extracted from 4 s of data from each channel of ECG, BP and PPG waveforms.

Table S2. List of hand-crafted features used in tier-1 classifier.

ECG	Heart rate criterion of ventricular tachycardia
	Heart rate
	Complexity measure
	Bandwidth
	Dominant frequency
	Mean frequency
	Median frequency
	Maximum amplitude
	Maximum power to total power ratio
	Co-dominant frequencies above 0.2
	Co-dominant frequencies above 0.5
	Low frequency power dominant
	Ratio of Maximum power to total power
	Ratio of Maximum power below 12Hz to average between 15Hz and 20Hz
	Ratio of Maximum power below 12Hz to maximum power above 15Hz.
	Five consecutive ventricular tachycardia beats
	Sharpness measure
	Correlation measure
	Maximum heartrate over five beats
	Maximum difference between low frequency sub peaks
BP	No peaks
	Decreasing δP
PPG	Decreasing δP

Features are extracted from 4 s of data from each channel of ECG, BP and PPG waveforms.

Table S3. List of hand-crafted features used in tier-2 classifier.

ECG	Heart rate
	Heart rate criterion of extreme bradycardia
	Heart rate criterion of extreme tachycardia
	Minimum Heart rate
	Number of beats slower than 40 bpm
	Periodicity measure
	Sharpness measure
	Correlation measure
	Peak height stability measure
	Maximum heart rate
	Not enough beats to detect extreme tachycardia
	Number of heartbeats
BP	Maximum period
	Maximum amplitude before onset
	Maximum amplitude after onset
	Minimum pressure at largest gap
	Amplitude decrease
	Periodicity measure
	δP Stability measure
	Correlation measure
	Minimum heart rate
	Number of beats slower than 40 bpm
	Maximum heart rate
	Not enough beats to detect extreme tachycardia
PPG	Maximum period
	Maximum amplitude before onset
	Maximum amplitude after onset
	Amplitude decrease

	Periodicity measure
	δP Stability measure
	Correlation measure
	Minimum heart rate
	Number of beats slower than 40 bpm
	Maximum heart rate
	Not enough beats to detect extreme tachycardia

Features are extracted from 8 s of data from each channel of ECG, BP and PPG waveforms.

Table S4. List of hand-crafted features used in tier-3 classifier.

ECG	Mean heart rate
	Standard deviation of heart rate
	P-waveMean
	P-waveStd
	P-waveAreaMean
	P-waveAreaStd
	PR_Mean
	PR_Std

Features are extracted from 8 s of data from each channel of ECG, BP and PPG waveforms.

Table S5. Sensitivity, positive predictive value (PPV) and accuracy for each rhythm following 5-times 5-fold cross-validation using only CNN and only feature based classifiers.

Rhythm	Only-CNN			Only features		
	Sensitivity (%)	PPV (%)	Accuracy (%)	Sensitivity (%)	PPV (%)	Accuracy (%)
AS	100.00+0.00	61.58+0.00	99.42+0.00	100.00+0.00	61.58+0.00	99.42+0.00
EB	95.41+1.65	79.7+5.4	98.17+0.53	99.7+0.30	79.58+3.48	98.38+0.31
ET	77.63+4.30	74.12+6.53	96.77+0.65	91.99+3.06	92.71+1.94	98.99+0.17
VF	82.05+6.94	84.46+17.3	99.38+0.4	66.04+2.67	66.15+2.56	98.89+0.06
VT	97.36+0.56	88.15+2.9	97.39+0.55	96.41+0.80	93.10+1.72	98.21+0.24
AF	89.99+1.13	71.08+1.85	86.36+1.04	93.63+1.93	68.11+2.80	88.23+1.02
SR	79.59+1.04	85.91+2.08	84.89+0.99	72.02+4.01	97.08+2.08	86.49+1.25

AS: asystole; EB: extreme bradycardia; ET: extreme tachycardia; VF: ventricular fibrillation; VT: ventricular tachycardia; AF: atrial fibrillation; SR: sinus rhythm.

Table S6. Record-wise annotation for "PhysioNet/Computing in Cardiology Challenge 2015: Reducing False Arrhythmia Alarms in the ICU" training data.

Record	Signal Quality				Rhythm	True alarm time (s)	Arrhythmia	
	ECG1	ECG2	ABP	PPG			Onset (s)	Offset (s)
a103l	Bad	Bad		Good	Noise/artifacts	300		
a104s	Bad	Bad		Good	Noise/artifacts	300		
a105l	Bad	Bad		Good	Noise/artifacts	300		
a109l	Good	Good	Good		Paced	300		
a123l	Bad	Bad	Bad	Bad	Noise/artifacts	300		
a134s	Bad	Bad	Good	Good	Noise/artifacts	300		
a142s	Good	Good	Bad	Bad	Asystole	300	295.5	300
a145l	Good	Bad		Bad	Inconclusive	300		
a152s	Bad	Bad		Good	Noise/artifacts	300		
a161l	Good	Good		Good	Asystole	299	294.3	299
a163l	Good	Good		Good	Normal Sinus Rhythm	300		
a165l	Good	Good		Good	Normal Sinus Rhythm	300		
a167l	Good	Good	Bad	Bad	Paced	298		
a170s	Bad	Bad	Bad	Bad	Noise/artifacts	300		
a171l	Good	Good	Good	Bad	Normal Sinus Rhythm	300		
a172s	Good	Good	Bad	Bad	Paced	294		
a178s	Bad	Bad	Good	Good	Noise/artifacts	300		
a185l	Good	Good		Bad	Asystole	299.5	295.1	299.5
a186s	Good	Bad		Bad	Paced	300		
a203l	Good	Good		Bad	Asystole	293	288.3	293
a219l	Good	Bad		Bad	PVCs	300		
a223l	Bad	Good	Good	Good	Bundle branch block	300		

a225l	Bad	Good	Good	Good	Bundle branch block	300		
a226s	Bad	Good	Good	Good	Bundle branch block	300		
a239l	Good	Good		Good	Normal Sinus Rhythm	300		
a266s	Bad	Bad		Bad	Noise/artifacts	300		
a267l	Bad	Bad		Good	Noise/artifacts	300		
a272s	Good	Good	Good	Good	Normal Sinus Rhythm	300		
a273l	Good	Bad	Good	Good	Normal Sinus Rhythm	300		
a278s	Good	Good		Good	Normal Sinus Rhythm	300		
a279l	Bad	Bad		Good	Noise/artifacts	300		
a287l	Good	Bad	Good		Normal Sinus Rhythm	300		
a288s	Good	Bad	Good		Normal Sinus Rhythm	300		
a297l	Bad	Bad	Good	Good	Noise/artifacts	300		
a301l	Good	Good		Good	Normal Sinus Rhythm	300		
a302s	Good	Good		Good	Normal Sinus Rhythm	300		
a306s	Bad	Bad		Good	Noise/artifacts	300		
a310s	Good	Good	Good	Good	Bundle branch block	300		
a311l	Good	Good	Good	Good	Bundle branch block	300		
a315l	Good	Good		Good	Bundle branch block	300	287.2	300
a345l	Good	Good	Bad	Bad	Extreme bradycardia	296	281	296
a363l	Bad	Bad	Good	Good	Noise/artifacts	300		
a372s	Good	Good		Bad	Asystole	299	294.9	299
a376s	Bad	Bad		Bad	Noise/artifacts	300		
a377l	Bad	Bad		Good	Noise/artifacts	300		
a378s	Bad	Bad		Bad	Noise/artifacts	300		
a382s	Bad	Bad	Bad	Good	Inconclusive	300		
a385l	Good	Good		Bad	Cardiopulmonary resuscitation	15		
a386s	Bad	Bad		Bad	Inconclusive	300		

a391l	Bad	Bad		Bad	Noise/artifacts	300		
a396s	Bad	Bad		Good	Noise/artifacts	300		
a397l	Good	Good		Good	Normal Sinus Rhythm	300		
a420s	Good	Good		Good	PVCs	300		
a422s	Good	Good		Good	Bundle branch block	300		
a429l	Good	Good	Good		Paced	300		
a435l	Bad	Bad		Bad	Noise/artifacts	300		
a436s	Bad	Bad		Good	Noise/artifacts	300		
a439l	Bad	Bad		Good	Noise/artifacts	300		
a442s	Good	Good		Bad	Asystole	291	287	291
a443l	Good	Good		Bad	Paced	300		
a446s	Good	Good		Bad	Asystole	295.5	291.2	295.5
a449l	Good	Good		Bad	Asystole	300	295.2	300
a457l	Bad	Bad		Good	Noise/artifacts	300		
a461l	Bad	Bad	Good	Bad	Inconclusive	300		
a462s	Bad	Bad	Good	Good	Noise/artifacts	300		
a465l	Bad	Bad	Good	Good	Noise/artifacts	300		
a490s	Bad	Bad	Good	Bad	Noise/artifacts	300		
a512s	Good	Bad		Good	Bundle branch block	300		
a514s	Bad	Bad		Bad	Bundle branch block	300		
a526s	Bad	Bad	Good	Good	Noise/artifacts	300		
a527l	Bad	Bad	Good	Bad	Noise/artifacts	300		
a539l	Inconclusive	Inconclusive	Bad	Bad	Inconclusive	300		
a550s	Bad	Bad		Good	Noise/artifacts	300		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	300		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	135		

a555l	Good	Good	Good	Good	Normal Sinus Rhythm	120		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	150		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	165		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	180		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	195		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	90		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	105		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	210		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	255		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	285		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	225		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	240		
a555l	Good	Good	Good	Good	Normal Sinus Rhythm	270		
a556s	Good	Good	Good	Good	Normal Sinus Rhythm	300		
a558s	Good	Good	Good	Good	Normal Sinus Rhythm	300		
a582s	Bad	Bad		Bad	Noise/artifacts	300		
a584s	Good	Good	Good		Paced	300		
a591l	Bad	Bad		Bad	Noise/artifacts	300		
a599l	Bad	Bad		Good	Noise/artifacts	300		
a603l	Good	Good		Bad	Paced	300		
a604s	Good	Good		Good	Asystole	298	293.6	298
a606s	Bad	Bad		Bad	Noise/artifacts	300		
a608s	Bad	Bad		Good	Noise/artifacts	300		
a624s	Good	Bad		Good	Normal Sinus Rhythm	300		
a631l	Good	Bad		Good	Noise/artifacts	300		
a639l	Bad	Bad	Good		Paced	299.5		
a645l	Bad	Bad		Good	Noise/artifacts	300		
a650s	Bad	Bad		Good	Noise/artifacts	300		

a651l	Bad	Bad	Good	Good	Inconclusive	300		
a653l	Good	Good	Good		Asystole	301	296.6	301
a653l	Good	Good	Good		Bundle branch block	135		
a654s	Good	Good		Bad	Drop beat	300		
a661l	Bad	Bad		Bad	Noise/artifacts	300		
a667l	Bad	Bad		Bad	Noise/artifacts	300		
a668s	Bad	Bad		Bad	Noise/artifacts	300		
a670s	Good	Good	Good		Paced	300		
a673l	Bad	Bad		Bad	Noise/artifacts	300		
a675l	Bad	Bad	Good		Noise/artifacts	300		
a694s	Good	Good		Good	Normal Sinus Rhythm	300		
a699l	Bad	Bad		Bad	Noise/artifacts	300		
a705l	Good	Bad		Bad	Noise/artifacts	300		
a712s	Bad	Bad		Bad	Noise/artifacts	300		
a715l	Good	Good	Good		Paced	300		
a723l	Bad	Bad	Good		Noise/artifacts	300		
a735l	Bad	Bad	Bad	Good	Noise/artifacts	300		
a740s	Good	Bad		Good	Normal Sinus Rhythm	300		
a746s	Bad	Good		Good	Normal Sinus Rhythm	300		
a750s	Bad	Bad		Bad	Noise/artifacts	300		
a754s	Good	Good	Good		Paced	300		
a776s	Bad	Bad	Good		Paced	299.75		
a778s	Bad	Bad	Bad	Good	Noise/artifacts	300		
a780s	Bad	Good	Bad	Bad	Noise/artifacts	300		
a785l	Bad	Bad		Bad	Noise/artifacts	300		
a796s	Good	Good		Bad	Asystole	298	293.8	298
a798s	Bad	Good		Good	Noise/artifacts	300		
a802s	Good	Good		Bad	Normal Sinus Rhythm	300		

a807l	Good	Good	Bad		Paced	300		
a810s	Good	Good	Good	Good	VT	300	290	295
a810s	Good	Good	Good	Good	Normal Sinus Rhythm	135		
a810s	Good	Good	Good	Good	Normal Sinus Rhythm	15		
a810s	Good	Good	Good	Good	Normal Sinus Rhythm	120		
a810s	Good	Good	Good	Good	Normal Sinus Rhythm	135		
a810s	Good	Good	Good	Good	Normal Sinus Rhythm	30		
a810s	Good	Good	Good	Good	Normal Sinus Rhythm	45		
a810s	Good	Good	Good	Good	Normal Sinus Rhythm	60		
a810s	Good	Good	Good	Good	Normal Sinus Rhythm	75		
a810s	Good	Good	Good	Good	Normal Sinus Rhythm	90		
a819l	Bad	Bad		Good	Noise/artifacts	300		
a822s	Good	Good	Good		Paced	300		
a825l	Bad	Bad		Good	Noise/artifacts	300		
a847l	Good	Good	Good		Paced	300		
b124s	Good	Good		Good	Extreme bradycardia	299	290	299
b125l	Good	Good		Good	Normal Sinus Rhythm	299		
b126s	Good	Good		Good	Extreme bradycardia	300	291.5	300
b183l	Good	Good		Good	Extreme bradycardia	300	291.7	300
b183l	Good	Good		Good	Normal Sinus Rhythm	15		
b184s	Bad	Bad		Good	Noise/artifacts	300		
b187l	Bad	Bad		Good	Paced	300		
b215l	Bad	Bad	Bad	Good	Noise/artifacts	300		
b216s	Good	Bad	Bad	Good	Noise/artifacts	300		
b220s	Good	Good		Bad	Bundle branch block	300	290	300
b227l	Good	Good		Good	Extreme bradycardia	300	292.5	300
b228s	Good	Good		Good	Extreme bradycardia	300	292.6	300
b228s	Good	Good		Good	Normal Sinus Rhythm	15		

b229l	Good	Good		Good	Extreme bradycardia	300	292	300
b231l	Good	Bad	Bad	Good	Noise/artifacts	300		
b231l	Good	Good	Good	Good	Normal Sinus Rhythm	135		
b231l	Good	Good	Good	Good	Normal Sinus Rhythm	15		
b265l	Good	Good		Good	Extreme bradycardia	300	286	300
b265l	Good	Good		Good	Normal Sinus Rhythm	15		
b268s	Good	Good	Good		Paced	300		
b269l	Good	Good		Bad	Extreme bradycardia	300	289.5	300
b285l	Good	Good	Good		Paced	300		
b286s	Good	Good	Good		Paced	300		
b299l	Good	Good		Good	Extreme bradycardia	300	285	300
b308s	Bad	Bad		Good	Noise/artifacts	300		
b313l	Good	Good		Good	Normal Sinus Rhythm	300		
b313l	Good	Good		Good	Normal Sinus Rhythm	135		
b313l	Good	Good		Good	Normal Sinus Rhythm	15		
b314s	Bad	Bad		Bad	Noise/artifacts	300		
b330s	Bad	Bad	Good	Good	Noise/artifacts	300		
b331l	Bad	Bad	Good	Good	Noise/artifacts	300		
b332s	Bad	Bad	Good	Good	Noise/artifacts	300		
b339l	Good	Good	Bad	Good	Normal Sinus Rhythm	300		
b339l	Good	Good	Good	Good	Normal Sinus Rhythm	15		
b340s	Good	Good	Bad	Good	Normal Sinus Rhythm	300		
b340s	Good	Good	Good	Good	Normal Sinus Rhythm	135		
b340s	Good	Good	Good	Good	Normal Sinus Rhythm	15		
b341l	Good	Good		Good	Normal Sinus Rhythm	300		
b341l	Good	Good		Good	Normal Sinus Rhythm	15		
b349l	Good	Good	Good		Bundle branch block	300		
b349l	Good	Good	Good		Bundle branch block	135		

b349l	Good	Good	Good		Bundle branch block	15		
b379l	Good	Good		Good	Paced	300		
b387l	Good	Good	Good	Bad	Normal Sinus Rhythm	300		
b388s	Good	Good	Good	Good	Normal Sinus Rhythm	300		
b389l	Good	Good	Bad	Good	Normal Sinus Rhythm	300		
b428s	Bad	Good		Good	Paced	300		
b451l	Good	Bad		Good	PACs	300		
b455l	Good	Good	Good	Good	Extreme bradycardia	300	289.7	298.7
b456s	Good	Good	Good	Good	Extreme bradycardia	300	290.5	299
b484s	Good	Bad	Bad	Good	Normal Sinus Rhythm	300		
b485l	Good	Bad	Good	Good	Noise/artifacts	300		
b486s	Good	Bad	Bad	Bad	Normal Sinus Rhythm	300		
b486s	Good	Good	Good	Good	Normal Sinus Rhythm	15		
b487l	Good	Good		Bad	Normal Sinus Rhythm	300		
b488s	Good	Good		Good	Normal Sinus Rhythm	300		
b494s	Good	Good	Good		Paced	300		
b495l	Good	Good	Good		Paced	300		
b497l	Good	Good		Good	Paced	300		
b515l	Good	Good	Good	Good	Extreme bradycardia	300	286	298
b516s	Good	Good	Good	Good	Extreme bradycardia	300	285	300
b517l	Good	Good	Good	Good	Extreme bradycardia	300	286	298
b528s	Bad	Bad	Bad	Good	Noise/artifacts	300		
b537l	Good	Good		Good	Extreme bradycardia	300	290.4	297.5
b538s	Good	Good		Good	Extreme bradycardia	300	290.3	300
b553l	Good	Good		Bad	Paced	300		
b554s	Good	Good		Good	Paced	300		
b560s	Good	Good	Good	Good	Extreme bradycardia	300	286.5	300
b561l	Good	Good	Good	Good	Extreme bradycardia	300	285	300

b562s	Good	Good	Good	Good	Extreme bradycardia	300	286	300
b578s	Good	Good	Good		Paced	300		
b587l	Bad	Bad		Bad	Noise/artifacts	300		
b588s	Good	Good		Bad	Extreme bradycardia	300	293	299.9
b588s	Good	Good		Good	Normal Sinus Rhythm	135		
b588s	Good	Good		Good	Normal Sinus Rhythm	15		
b600s	Bad	Bad	Good	Good	Noise/artifacts	300		
b617l	Good	Good		Bad	Bundle branch block	300		
b656s	Good	Good		Good	Extreme bradycardia	300	291.2	300
b659l	Good	Good	Bad	Bad	Extreme bradycardia	300	289.5	300
b664s	Good	Good		Good	Extreme bradycardia	300	292.8	300
b669l	Bad	Bad		Good	Noise/artifacts	300		
b672s	Good	Good		Good	Paced	300		
b681l	Bad	Bad	Good	Good	Noise/artifacts	300		
b684s	Good	Good	Bad	Good	Normal Sinus Rhythm	300		
b685l	Good	Good		Good	Normal Sinus Rhythm	300		
b685l	Good	Good		Good	Normal Sinus Rhythm	15		
b695l	Bad	Bad	Good	Good	Noise/artifacts	300		
b703l	Good	Good		Bad	Normal Sinus Rhythm	300		
b706s	Bad	Bad	Bad	Good	Noise/artifacts	300		
b708s	Good	Good	Good		Paced	300		
b722s	Good	Good	Good		Paced	300		
b730s	Good	Good		Good	Normal Sinus Rhythm	300		
b734s	Good	Good		Good	Normal Sinus Rhythm	300		
b734s	Good	Good		Good	Normal Sinus Rhythm	15		
b753l	Good	Good		Bad	Normal Sinus Rhythm	300		
b757l	Good	Good	Good		Paced	300		
b764s	Good	Good		Good	Extreme bradycardia	300	285	300

b794s	Good	Good		Good	Extreme bradycardia	300	291.7	300
b794s	Good	Good		Good	Normal Sinus Rhythm	135		
b794s	Good	Good		Good	Normal Sinus Rhythm	15		
b820s	Good	Good		Good	Extreme bradycardia	300	287.4	300
b824s	Good	Good	Good		Paced	300		
b824s	Good	Good	Good		Normal Sinus Rhythm	135		
b824s	Good	Good	Good		Normal Sinus Rhythm	195		
b824s	Good	Good	Good		Normal Sinus Rhythm	210		
b824s	Good	Good	Good		Normal Sinus Rhythm	225		
b824s	Good	Good	Good		Normal Sinus Rhythm	240		
b824s	Good	Good	Good		Normal Sinus Rhythm	255		
b824s	Good	Good	Good		Normal Sinus Rhythm	270		
b824s	Good	Good	Good		Normal Sinus Rhythm	285		
b824s	Good	Good	Good		Normal Sinus Rhythm	15		
b832s	Good	Bad		Good	Noise/artifacts	300	291.3	300
b835l	Bad	Bad	Good	Good	Noise/artifacts	300		
b838s	Good	Good		Good	Extreme bradycardia	300	292.3	300
b839l	Good	Bad		Bad	Extreme bradycardia	300	290	300
b840s	Good	Good		Bad	Normal Sinus Rhythm	300		
b841l	Good	Good	Good		Paced	300		
b849l	Good	Bad		Good	Normal Sinus Rhythm	300		
f120s	Good	Good	Good	Good	VT	300	289	300
f121l	Good	Good	Good	Good	VT	300	291.8	298
f129l	Good	Good	Good	Bad	ST elevation	300		
f130s	Good	Good	Good	Bad	ST elevation	300		
f137l	Good	Bad		Good	Paced	300		
f138s	Bad	Bad		Bad	Paced	300		
f144s	Bad	Good		Bad	Normal Sinus Rhythm	300		

f189l	Bad	Bad		Good	Noise/artifacts	300		
f190s	Good	Bad		Bad	Paced	300		
f196s	Good	Good	Good		PVCs	300		
f196s	Good	Good	Good		PVCs	135		
f196s	Good	Good	Good		PVCs	15		
f196s	Good	Good	Good		PVCs	120		
f196s	Good	Good	Good		Normal Sinus Rhythm	30		
f196s	Good	Good	Good		Normal Sinus Rhythm	45		
f196s	Good	Good	Good		PVCs	60		
f196s	Good	Good	Good		PVCs	75		
f196s	Good	Good	Good		PVCs	90		
f196s	Good	Good	Good		PVCs	105		
f236s	Good	Bad	Good		Noise/artifacts	300		
f237l	Bad	Bad	Good		Noise/artifacts	300		
f260s	Bad	Bad		Bad	Noise/artifacts	300		
f261l	Bad	Bad		Good	Noise/artifacts	300		
f281l	Bad	Good		Good	Noise/artifacts	300		
f304s	Good	Bad		Good	Noise/artifacts	300		
f321l	Bad	Bad		Bad	Noise/artifacts	300		
f346s	Bad	Bad	Bad	Bad	Noise/artifacts	300		
f352s	Good	Bad	Good	Good	PVCs	300		
f362s	Bad	Bad	Good	Bad	Noise/artifacts	300		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	135		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	15		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	120		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	150		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	165		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	30		

f362s	Good	Good	Good	Good	Normal Sinus Rhythm	180		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	195		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	45		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	60		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	75		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	90		
f362s	Good	Good	Good	Good	Normal Sinus Rhythm	105		
f407l	Bad	Bad	Good	Good	Noise/artifacts	300		
f408s	Bad	Bad	Good	Good	Noise/artifacts	300		
f414s	Bad	Bad		Bad	Noise/artifacts	300		
f415l	Bad	Bad		Bad	Noise/artifacts	300		
f440s	Bad	Bad	Good		Noise/artifacts	300		
f441l	Bad	Bad	Good		Noise/artifacts	300		
f450s	Good	Good		Bad	VF	294	289.3	294
f474s	Bad	Bad		Bad	Noise/artifacts	300		
f493l	Good	Good	Good		Paced	300		
f499l	Good	Good		Good	VT	300	291.8	300
f500s	Good	Bad	Good	Good	Noise/artifacts	300		
f529l	Bad	Bad	Bad	Good	Noise/artifacts	300		
f530s	Bad	Bad	Bad		Noise/artifacts	300		
f543l	Good	Good	Bad	Bad	VF	214	207.8	214
f544s	Good	Good	Good	Bad	VF	298	293.9	298
f544s	Good	Good	Good	Good	Normal Sinus Rhythm	135		
f544s	Good	Good	Good	Good	Normal Sinus Rhythm	15		
f545l	Good	Good	Bad	Bad	VF	27	21.9	27
f563l	Good	Good	Good	Bad	VF	296	290	296
f572s	Bad	Bad	Good		Noise/artifacts	300		
f576s	Bad	Bad	Good		Noise/artifacts	300		

f586s	Bad	Good		Good	Noise/artifacts	300		
f592s	Good	Good	Good		Bundle branch block	300		
f593l	Bad	Good		Good	Normal Sinus Rhythm	300		
f602s	Bad	Bad		Bad	Noise/artifacts	300		
f605l	Good	Good		Good	Bundle branch block	300		
f605l	Good	Good		Good	Bundle branch block	15		
f610s	Bad	Bad		Bad	Noise/artifacts	300		
f613l	Good	Bad		Bad	Noise/artifacts	300		
f618s	Good	Bad		Good	Normal Sinus Rhythm	300		
f637l	Good	Bad		Good	Normal Sinus Rhythm	300		
f642s	Good	Bad		Good	Noise/artifacts	300		
f657l	Bad	Bad	Bad	Good	Noise/artifacts	300		
f691l	Bad	Bad		Bad	Noise/artifacts	300		
f697l	Good	Good	Good	Good	VF	92	87.5	92
f751l	Bad	Good	Good		PVCs	300		
f768s	Bad	Bad		Bad	Noise/artifacts	300		
f768s	Good	Good		Good	PVCs	210		
f768s	Good	Good		Good	PVCs	45		
f789l	Good	Bad		Good	Noise/artifacts	300		
f792s	Bad	Bad		Bad	Noise/artifacts	300		
f799l	Bad	Bad		Bad	Noise/artifacts	300		
f829l	Bad	Good		Bad	Inconclusive	300		
t106s	Good	Good		Bad	Extreme Tachycardia	300	290.8	300
t107l	Good	Good		Good	Extreme Tachycardia	300	285.5	300
t108s	Good	Good		Bad	Extreme Tachycardia	300	292.4	300
t110s	Good	Good	Good		Extreme Tachycardia	300	285	300
t112s	Bad	Good		Bad	Extreme Tachycardia	300	285	300
t114s	Good	Bad		Bad	Extreme Tachycardia	300	285.5	300

t116s	Bad	Bad	Good		Noise/artifacts	300		
t117l	Good	Good		Bad	Extreme Tachycardia	300	285	300
t118s	Good	Good		Bad	Extreme Tachycardia	300	290.5	300
t149l	Good	Good		Good	Extreme Tachycardia	300	285	300
t150s	Good	Good		Bad	Extreme Tachycardia	300	286.5	300
t151l	Good	Good		Bad	Extreme Tachycardia	300	287	300
t156s	Good	Good		Bad	Extreme Tachycardia	299	291	299
t157l	Good	Good		Good	Normal Sinus Rhythm	300		
t157l	Good	Good		Good	Normal Sinus Rhythm	135		
t157l	Good	Good		Good	Normal Sinus Rhythm	15		
t173l	Good	Good	Good	Good	Extreme Tachycardia	300	285	300
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	135		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	120		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	135		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	150		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	165		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	30		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	210		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	255		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	45		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	60		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	75		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	90		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	105		
t173l	Good	Good	Good	Good	Normal Sinus Rhythm	15		
t174s	Good	Good	Good	Good	Extreme Tachycardia	300	285	300
t175l	Good	Good	Good	Good	Extreme Tachycardia	300	285	300
t191l	Good	Good		Good	Extreme Tachycardia	300	292	300

t191l	Good	Good		Good	Normal Sinus Rhythm	180		
t191l	Good	Good		Good	Normal Sinus Rhythm	195		
t191l	Good	Good		Good	Normal Sinus Rhythm	210		
t191l	Good	Good		Good	Normal Sinus Rhythm	225		
t191l	Good	Good		Good	Normal Sinus Rhythm	240		
t191l	Bad	Good		Good	Noise/artifacts	255		
t191l	Good	Good		Good	Normal Sinus Rhythm	270		
t191l	Good	Good		Good	Normal Sinus Rhythm	285		
t192s	Good	Good		Good	Normal Sinus Rhythm	299.5		
t193l	Good	Good		Good	Extreme Tachycardia	300	293	300
t195l	Good	Good		Good	PVCs	300		
t208s	Bad	Good	Good		Extreme Tachycardia	299.5	292	299.5
t209l	Good	Good	Good		Normal Sinus Rhythm	299.5		
t213l	Good	Good	Good	Good	Extreme Tachycardia	300	289	300
t214s	Good	Good	Good	Good	Extreme Tachycardia	300	290	300
t214s	Good	Good	Good	Good	Normal Sinus Rhythm	135		
t214s	Good	Good	Good	Good	Normal Sinus Rhythm	15		
t214s	Good	Good	Good	Good	Extreme Tachycardia	120	110	120
t214s	Good	Good	Good	Good	Extreme Tachycardia	150	135.8	145.6
t214s	Good	Good	Good	Good	PVCs	165		
t214s	Good	Good	Good	Good	Normal Sinus Rhythm	30		
t214s	Good	Good	Good	Good	Normal Sinus Rhythm	180		
t214s	Good	Good	Good	Good	Normal Sinus Rhythm	45		
t214s	Good	Good	Good	Good	Normal Sinus Rhythm	60		
t214s	Good	Good	Good	Good	Normal Sinus Rhythm	75		
t214s	Good	Good	Good	Good	Normal Sinus Rhythm	90		
t214s	Good	Good	Good	Good	Extreme Tachycardia	105	90.9	99.33
t234s	Good	Good		Good	Extreme Tachycardia	300	290.5	300

t234s	Good	Good		Good	Normal Sinus Rhythm	135		
t234s	Good	Good		Good	Normal Sinus Rhythm	30		
t234s	Good	Good		Good	Normal Sinus Rhythm	45		
t234s	Good	Good		Good	Normal Sinus Rhythm	60		
t234s	Good	Good		Good	Normal Sinus Rhythm	75		
t234s	Good	Good		Good	Normal Sinus Rhythm	15		
t235l	Good	Good		Good	Extreme Tachycardia	300	292	300
t235l	Good	Good		Good	Normal Sinus Rhythm	135		
t235l	Good	Good		Good	Normal Sinus Rhythm	30		
t235l	Good	Good		Good	Normal Sinus Rhythm	45		
t235l	Good	Good		Good	Normal Sinus Rhythm	60		
t235l	Good	Good		Good	Normal Sinus Rhythm	75		
t238s	Good	Good		Good	Extreme Tachycardia	300	290.5	300
t240s	Good	Good		Good	Extreme Tachycardia	299	291	300
t240s	Good	Good		Good	Normal Sinus Rhythm	135		
t240s	Good	Good		Good	Normal Sinus Rhythm	30		
t240s	Good	Good		Good	Normal Sinus Rhythm	45		
t240s	Good	Good		Good	Normal Sinus Rhythm	60		
t240s	Good	Good		Good	Normal Sinus Rhythm	75		
t240s	Good	Good		Good	Normal Sinus Rhythm	90		
t240s	Good	Good		Good	Normal Sinus Rhythm	15		
t249l	Good	Good	Good	Good	Extreme Tachycardia	300	290	300
t251l	Good	Good	Good	Good	Extreme Tachycardia	300	291.5	300
t252s	Good	Good	Good	Good	Extreme Tachycardia	300	285.5	300
t263l	Bad	Bad		Bad	Noise/artifacts	300		
t264s	Good	Good		Good	Extreme Tachycardia	300	292	300
t270s	Good	Good		Good	Extreme Tachycardia	300	292.7	300
t276s	Good	Good	Good		Extreme Tachycardia	300	292	300

t277l	Good	Good	Good		Extreme Tachycardia	300	291.5	300
t277l	Good	Good	Good		Normal Sinus Rhythm	135		
t277l	Good	Good	Good		Extreme Tachycardia	30	18.6	26
t277l	Good	Good	Good		Normal Sinus Rhythm	45		
t277l	Good	Good	Good		Normal Sinus Rhythm	60		
t277l	Good	Good	Good		Normal Sinus Rhythm	75		
t277l	Good	Good	Good		Normal Sinus Rhythm	90		
t277l	Good	Good	Good		Normal Sinus Rhythm	15		
t284s	Good	Good	Bad		Extreme Tachycardia	300	291	300
t300s	Good	Good		Bad	Extreme Tachycardia	300	287.8	300
t305l	Good	Good	Bad		Extreme Tachycardia	300	291.2	300
t320s	Bad	Good		Bad	PVCs	300		
t333l	Good	Good	Good		Extreme Tachycardia	300	292.5	300
t333l	Good	Good	Good		Normal Sinus Rhythm	135	292	299
t335l	Good	Good	Good		Extreme Tachycardia	300	292.1	299.5
t342s	Good	Good		Good	Extreme Tachycardia	300	290.2	300
t342s	Good	Good		Good	Extreme Tachycardia	135	120.5	129.7
t343l	Good	Good		Bad	Extreme Tachycardia	300	292.3	300
t344s	Good	Good		Good	Extreme Tachycardia	300	289.7	300
t350s	Good	Good		Good	Extreme Tachycardia	300	292	300
t351l	Good	Good		Good	Extreme Tachycardia	300	292	300
t356s	Good	Good		Good	Extreme Tachycardia	300	292.5	300
t357l	Good	Good		Good	Normal Sinus Rhythm	300		
t358s	Good	Good		Bad	Extreme Tachycardia	300	289	300
t383l	Good	Good	Good		Paced	300		
t383l	Good	Good	Good		Normal Sinus Rhythm	135		
t383l	Good	Good	Good		Normal Sinus Rhythm	15		
t384s	Good	Good	Good		Paced	300		

t393l	Good	Good		Bad	Extreme Tachycardia	300	285	300
t394s	Good	Good		Good	Extreme Tachycardia	300	285	300
t406s	Good	Good	Good	Good	Extreme Tachycardia	300	285.5	300
t409l	Bad	Bad	Good	Good	Inconclusive	300		
t410s	Good	Good		Bad	Extreme Tachycardia	300	285	300
t411l	Good	Good		Bad	Extreme Tachycardia	300	285	300
t412s	Good	Good	Good		Extreme Tachycardia	300	290	298.5
t413l	Good	Good	Good		Extreme Tachycardia	300	288.2	300
t416s	Good	Good		Good	Normal Sinus Rhythm	300		
t417l	Good	Good	Good		Extreme Tachycardia	300	292	300
t417l	Good	Good	Good		Normal Sinus Rhythm	135		
t417l	Good	Good	Good		Normal Sinus Rhythm	15		
t418s	Good	Good	Good		Normal Sinus Rhythm	300		
t418s	Good	Good	Good		Normal Sinus Rhythm	135		
t424s	Good	Good	Good		Normal Sinus Rhythm	300		
t425l	Good	Good	Bad		Normal Sinus Rhythm	300		
t430s	Good	Good		Bad	Extreme Tachycardia	300	285	300
t434s	Good	Good		Good	Extreme Tachycardia	300	285	300
t444s	Good	Good		Good	Extreme Tachycardia	294	285	294
t445l	Good	Good		Bad	Extreme Tachycardia	296	285	296
t447l	Good	Good		Good	Extreme Tachycardia	298	285	298
t458s	Good	Good		Good	Extreme Tachycardia	298	289	298
t467l	Good	Bad		Bad	Noise/artifacts	300		
t468s	Good	Good		Good	Extreme Tachycardia	300	291.4	300
t469l	Good	Good		Good	Normal Sinus Rhythm	300		
t469l	Good	Good		Good	Normal Sinus Rhythm	135		
t477l	Good	Good		Bad	PVCs	300		
t478s	Good	Good		Good	Normal Sinus Rhythm	300		

t478s	Good	Good		Good	Normal Sinus Rhythm	135		
t478s	Good	Good		Good	Normal Sinus Rhythm	15		
t496s	Good	Good	Good		Paced	300		
t503l	Bad	Bad		Bad	Noise/artifacts	300		
t504s	Bad	Bad		Bad	Noise/artifacts	300		
t506s	Good	Bad		Bad	Noise/artifacts	300	291.7	300
t507l	Good	Bad		Bad	Normal Sinus Rhythm	292		
t508s	Good	Good		Bad	Extreme Tachycardia	300	290	300
t509l	Good	Good		Good	Extreme Tachycardia	300	291.5	300
t520s	Bad	Bad		Bad	Noise/artifacts	300		
t521l	Good	Good		Bad	Bundle branch block	300	285	300
t524s	Good	Good		Bad	PVCs	300	285	300
t546s	Bad	Good		Good	Noise/artifacts	300	285	300
t547l	Bad	Good		Good	Extreme Tachycardia	300	285	300
t565l	Good	Good		Good	Extreme Tachycardia	300	290.9	300
t565l	Good	Good		Good	Normal Sinus Rhythm	135		
t565l	Good	Good		Good	Normal Sinus Rhythm	15		
t567l	Good	Good		Good	Extreme Tachycardia	300	290.5	300
t577l	Good	Good		Good	Extreme Tachycardia	300	291.7	300
t577l	Good	Good		Good	Normal Sinus Rhythm	15		
t580s	Bad	Good		Bad	PVCs	300		
t589l	Good	Good		Good	PVCs	300	285	300
t594s	Good	Good	Good		Extreme Tachycardia	300	292.9	300
t594s	Good	Good	Good		Normal Sinus Rhythm	135		
t595l	Bad	Good		Bad	Extreme Tachycardia	300	292.6	300
t614s	Good	Good		Good	Normal Sinus Rhythm	300		
t622s	Good	Good		Bad	Extreme Tachycardia	300	291.2	300
t662s	Good	Good		Good	Extreme Tachycardia	300	287.6	300

t662s	Good	Good		Good	Normal Sinus Rhythm	135		
t662s	Good	Good		Good	PVCs	15		
t665l	Good	Good		Good	Extreme Tachycardia	300	285	300
t677l	Good	Good	Good		Extreme Tachycardia	300	292.1	300
t677l	Good	Good	Good		Normal Sinus Rhythm	135		
t678s	Bad	Good		Good	Noise/artifacts	300		
t679l	Good	Good		Good	Extreme Tachycardia	299	291.6	299
t680s	Good	Good	Good	Bad	Extreme Tachycardia	300	291.8	300
t683l	Good	Good		Bad	VT	300	293.4	300
t688s	Good	Good		Bad	Extreme Tachycardia	300	285	300
t689l	Good	Good		Good	Paced	300		
t690s	Good	Good	Good		Extreme Tachycardia	300	288.4	300
t693l	Good	Good		Good	Extreme Tachycardia	300	285.5	300
t698s	Good	Good		Good	Extreme Tachycardia	300	285	300
t700s	Good	Good		Good	PVCs	300		
t702s	Good	Good	Good		Extreme Tachycardia	298.5	290.8	298.5
t702s	Good	Good	Good		Normal Sinus Rhythm	15		
t707l	Good	Good	Good		Paced	299.5		
t709l	Good	Good	Good		Extreme Tachycardia	299.5	290.1	299.5
t716s	Good	Good		Good	Extreme Tachycardia	299.5	291.8	299.5
t717l	Bad	Good		Bad	Noise/artifacts	300		
t719l	Bad	Good	Good		Bundle branch block	300		
t731l	Good	Good	Good	Good	Normal Sinus Rhythm	300		
t737l	Good	Good		Good	Extreme Tachycardia	299.5	291.3	299.5
t739l	Good	Good	Good	Bad	PVCs	300		
t741l	Good	Good		Good	Extreme Tachycardia	299.5	292	299.5
t742s	Bad	Good		Bad	PVCs	294		
t744s	Good	Good		Good	Extreme Tachycardia	300	289.4	300

t745l	Bad	Good		Bad	Extreme Tachycardia	298.5	291	298.5
t747l	Good	Good		Good	Extreme Tachycardia	300	292.4	300
t752s	Good	Good		Good	Extreme Tachycardia	300	291.8	300
t752s	Good	Good		Good	Normal Sinus Rhythm	135		
t752s	Good	Good		Good	Normal Sinus Rhythm	15		
t755l	Good	Good		Bad	Extreme Tachycardia	299	288.9	299
t760s	Good	Good	Good	Good	Extreme Tachycardia	300	291.8	300
t762s	Good	Good		Bad	Extreme Tachycardia	300	292.6	300
t771l	Good	Good		Bad	Bundle branch block	300		
t777l	Good	Good	Good		ST elevation	299.5	291.3	300
t786s	Good	Good		Bad	Extreme Tachycardia	298.5	291.2	298.5
t787l	Good	Good		Good	Normal Sinus Rhythm	300		
t790s	Good	Good		Bad	Extreme Tachycardia	300	292.5	300
t800s	Good	Good		Good	Extreme Tachycardia	300	285	300
t801l	Good	Good		Bad	Extreme Tachycardia	300	290.8	298.3
t812s	Good	Good		Good	Extreme Tachycardia	300	289.9	300
t816s	Good	Good	Good	Bad	Extreme Tachycardia	300	285	300
t817l	Good	Good		Good	ST elevation	300		
t821l	Good	Good		Bad	Extreme Tachycardia	300	292.4	300
v100s	Good	Good		Bad	Normal Sinus Rhythm	300		
v101l	Good	Good		Bad	Normal Sinus Rhythm	300		
v102s	Good	Good		Bad	Normal Sinus Rhythm	300		
v111l	Good	Good		Good	Normal Sinus Rhythm	300		
v113l	Bad	Bad		Bad	Noise/artifacts	300		
v115l	Bad	Bad		Good	Noise/artifacts	300		
v119l	Good	Good	Bad	Bad	VT	300	296.2	300
v122s	Good	Good	Bad	Bad	VT	300	293.6	300
v127l	Bad	Bad		Bad	Noise/artifacts	300		

v128s	Bad	Bad		Bad	Noise/artifacts	300		
v131l	Good	Good	Good		VT	299	296.2	299
v132s	Good	Good		Good	VT	298.25	295.5	298.25
v133l	Good	Good	Good		VT	298.5	295.5	298.5
v133l	Good	Good	Good		Normal Sinus Rhythm	135		
v135l	Good	Good	Good	Bad	Normal Sinus Rhythm	300		
v136s	Good	Good	Good	Good	VT	300	296.5	300
v139l	Good	Good		Good	Paced	298		
v140s	Good	Good	Good	Good	Extreme Tachycardia	300	285	300
v141l	Bad	Bad	Bad	Bad	Noise/artifacts	300		
v143l	Good	Good		Bad	Inconclusive	300		
v146s	Good	Good		Good	VT	300	285	300
v147l	Bad	Bad	Bad	Good	Noise/artifacts	300		
v148s	Bad	Bad	Bad	Good	Noise/artifacts	300		
v153l	Good	Bad		Good	Normal Sinus Rhythm	300		
v154s	Good	Bad	Good	Good	Normal Sinus Rhythm	300		
v155l	Good	Bad		Good	Normal Sinus Rhythm	300		
v158s	Good	Good		Good	VT	300	296.1	300
v159l	Good	Good		Good	Bundle branch block	300	285	300
v160s	Good	Good	Good	Bad	PVCs	300	285	300
v162s	Good	Good	Good	Good	NSVT	300	285	300
v164s	Good	Good		Good	Normal Sinus Rhythm	300		
v166s	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v168s	Good	Good	Good	Bad	Bundle branch block	300		
v169l	Good	Bad	Bad	Good	Noise/artifacts	300		
v176s	Bad	Bad	Good	Good	Noise/artifacts	300		
v177l	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v179l	Good	Bad	Good	Good	Normal Sinus Rhythm	300		

v180s	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v181l	Bad	Good	Bad	Bad	Normal Sinus Rhythm	300		
v182s	Good	Good	Bad	Good	Normal Sinus Rhythm	300		
v188s	Good	Good		Good	CPR	300	285	300
v194s	Good	Good		Good	VT	298.5	296.5	298.5
v194s	Good	Good		Good	Normal Sinus Rhythm	135		
v197l	Good	Good	Good		VT	299	295.7	299
v197l	Good	Good	Good		Normal Sinus Rhythm	135		
v198s	Bad	Good		Good	Noise/artifacts	300		
v199l	Good	Good		Good	VT	298.5	295.5	298.3
v199l	Good	Good		Good	Normal Sinus Rhythm	135		
v200s	Bad	Bad	Good	Good	Noise/artifacts	300		
v201l	Good	Good	Good	Good	PVCs	300		
v201l	Good	Good	Good	Good	PVCs	15		
v202s	Bad	Bad	Good	Bad	Noise/artifacts	300		
v204s	Bad	Bad		Bad	Noise/artifacts	300		
v205l	Bad	Good	Good	Bad	Noise/artifacts	300		
v206s	Good	Good		Good	VT	289	286.7	289
v206s	Good	Good		Good	Normal Sinus Rhythm	135		
v207l	Bad	Bad		Good	Noise/artifacts	300		
v210s	Good	Good		Good	Normal Sinus Rhythm	300		
v210s	Good	Good		Good	Normal Sinus Rhythm	135		
v210s	Good	Good		Good	Normal Sinus Rhythm	15		
v210s	Good	Good		Good	Normal Sinus Rhythm	120		
v210s	Good	Good		Good	Normal Sinus Rhythm	135		
v210s	Good	Good		Good	Normal Sinus Rhythm	30		
v210s	Good	Good		Good	Normal Sinus Rhythm	285		
v210s	Good	Good		Good	Normal Sinus Rhythm	45		

v210s	Good	Good		Good	Normal Sinus Rhythm	60		
v210s	Good	Good		Good	Normal Sinus Rhythm	75		
v210s	Good	Good		Good	Normal Sinus Rhythm	90		
v210s	Good	Good		Good	Normal Sinus Rhythm	105		
v211l	Good	Good		Good	Normal Sinus Rhythm	300		
v212s	Bad	Good		Good	Noise/artifacts	300		
v217l	Bad	Bad	Good	Good	Noise/artifacts	300		
v218s	Bad	Bad	Bad	Good	Noise/artifacts	300		
v221l	Good	Good	Good	Good	VT	295.5	292.9	295.8
v222s	Bad	Good	Good	Good	PVCs	300		
v224s	Good	Good	Good	Good	PVCs	300		
v230s	Bad	Bad	Bad	Good	Noise/artifacts	300		
v232s	Bad	Bad	Bad	Bad	Noise/artifacts	300		
v233l	Bad	Bad	Bad	Good	Noise/artifacts	300		
v241l	Bad	Bad	Good	Good	Noise/artifacts	300		
v242s	Bad	Bad		Good	Noise/artifacts	300		
v243l	Bad	Bad		Bad	Noise/artifacts	300		
v244s	Bad	Good		Good	Normal Sinus Rhythm	300		
v245l	Bad	Bad		Good	Noise/artifacts	300		
v246s	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v247l	Bad	Bad	Good	Good	Noise/artifacts	300		
v248s	Bad	Bad	Good	Bad	Noise/artifacts	300		
v250s	Bad	Bad		Good	Noise/artifacts	300		
v253l	Good	Good	Good	Good	VT	294	291.3	293.8
v253l	Good	Good	Good	Good	PVCs	135		
v253l	Good	Good	Good	Good	PVCs	150		
v253l	Good	Good	Good	Good	PVCs	195		
v253l	Good	Good	Good	Good	PVCs	210		

v253l	Good	Good	Good	Good	PVCs	255		
v253l	Good	Good	Good	Good	PVCs	270		
v253l	Good	Good	Good	Good	PVCs	60		
v253l	Good	Good	Good	Good	PVCs	75		
v253l	Good	Good	Good	Good	PVCs	105		
v254s	Good	Good	Good	Good	VT	292	288.9	291.8
v254s	Good	Good	Good	Good	PVCs	135		
v254s	Good	Good	Good	Good	Normal Sinus Rhythm	15		
v254s	Good	Good	Good	Good	PVCs	135		
v254s	Good	Good	Good	Good	PVCs	150		
v254s	Good	Good	Good	Good	PVCs	30		
v254s	Good	Good	Good	Good	PVCs	45		
v254s	Good	Good	Good	Good	PVCs	60		
v254s	Good	Good	Good	Good	PVCs	105		
v255l	Good	Good	Good	Good	VT	296	291.5	296
v255l	Good	Good	Good	Good	PVCs	135		
v256s	Good	Good		Good	Normal Sinus Rhythm	300		
v257l	Good	Good		Good	Normal Sinus Rhythm	300		
v258s	Good	Good		Bad	Bundle branch block	300		
v259l	Good	Good		Bad	Bundle branch block	300		
v262s	Good	Bad		Bad	Noise/artifacts	300		
v271l	Good	Good		Good	Normal Sinus Rhythm	300		
v274s	Good	Bad		Good	Noise/artifacts	300		
v274s	Good	Good		Good	Normal Sinus Rhythm	135		
v275l	Good	Bad		Good	NSVT	295	291.8	295.2
v280s	Good	Good		Bad	PVCs	300		
v282s	Good	Good		Bad	Normal Sinus Rhythm	300		
v283l	Good	Bad	Good		Noise/artifacts	300		

v283l	Good	Good	Good		Normal Sinus Rhythm	135		
v283l	Good	Good	Good		Normal Sinus Rhythm	15		
v289l	Bad	Good	Good		Normal Sinus Rhythm	300		
v290s	Good	Good	Good		VT	300	296.2	300
v291l	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v292s	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v292s	Good	Good	Good	Good	Normal Sinus Rhythm	135		
v292s	Good	Good	Good	Good	Normal Sinus Rhythm	15		
v293l	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v294s	Bad	Bad	Good		Noise/artifacts	300		
v295l	Bad	Bad	Good		Noise/artifacts	300		
v296s	Bad	Bad	Good		Noise/artifacts	300		
v298s	Bad	Bad	Good	Good	Noise/artifacts	300		
v303l	Good	Good		Good	Extreme Tachycardia	300	285.7	297.8
v307l	Bad	Bad		Bad	Noise/artifacts	300		
v309l	Good	Good	Good	Bad	VT	297.5	294.5	297.5
v309l	Good	Good	Good	Good	Normal Sinus Rhythm	135		
v312s	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v316s	Good	Good		Good	Normal Sinus Rhythm	300		
v316s	Good	Good		Good	Normal Sinus Rhythm	135		
v316s	Good	Good		Good	Normal Sinus Rhythm	15		
v317l	Bad	Good		Good	Noise/artifacts	300		
v318s	Good	Good	Bad	Good	VT	295	291	295
v319l	Bad	Bad	Good	Good	Noise/artifacts	300		
v322s	Good	Good		Bad	PVCs	300		
v323l	Good	Good	Bad	Good	PVCs	300		
v323l	Good	Good	Good	Good	Normal Sinus Rhythm	135		
v324s	Good	Bad	Good	Good	Noise/artifacts	300		

v325l	Good	Bad	Good	Good	Noise/artifacts	300		
v326s	Good	Bad		Good	Normal Sinus Rhythm	300		
v327l	Good	Good		Good	PVCs	300		
v327l	Good	Good		Good	Normal Sinus Rhythm	135		
v327l	Good	Good		Good	PVCs	15		
v328s	Good	Good	Good		PVCs	300		
v329l	Good	Good	Good		Paced	298		
v334s	Good	Good	Good		VT	300	296	299.6
v334s	Good	Good	Good		Normal Sinus Rhythm	135		
v334s	Good	Good	Good		Normal Sinus Rhythm	15		
v336s	Good	Bad	Bad	Good	Noise/artifacts	300		
v337l	Good	Bad	Bad	Good	Noise/artifacts	300		
v338s	Good	Bad	Bad	Good	Noise/artifacts	300		
v338s	Good	Good	Good	Good	Normal Sinus Rhythm	15		
v347l	Good	Bad	Bad	Good	Noise/artifacts	300		
v348s	Good	Good		Bad	VT	300	294	300
v353l	Good	Bad	Good	Good	PVCs	300		
v354s	Good	Good		Good	Normal Sinus Rhythm	300		
v355l	Bad	Bad		Bad	Noise/artifacts	300		
v359l	Bad	Good	Good		Noise/artifacts	300		
v359l	Good	Good	Good		Normal Sinus Rhythm	135		
v359l	Good	Good	Good		Normal Sinus Rhythm	15		
v360s	Bad	Bad	Good		Noise/artifacts	300		
v361l	Bad	Bad	Good	Good	Noise/artifacts	300		
v364s	Bad	Bad	Good	Good	Noise/artifacts	300		
v365l	Good	Good	Bad	Good	Normal Sinus Rhythm	300		
v366s	Good	Bad		Good	Noise/artifacts	300		
v367l	Good	Bad		Bad	Noise/artifacts	300		

v368s	Good	Good		Good	VT	293	289.4	294
v369l	Good	Good		Good	VT	300	295.5	300
v370s	Good	Good	Bad	Bad	Normal Sinus Rhythm	300		
v371l	Bad	Bad	Good	Good	Noise/artifacts	300		
v373l	Good	Bad	Good	Good	Noise/artifacts	300		
v374s	Good	Bad	Good	Good	Noise/artifacts	300		
v375l	Good	Bad		Bad	Noise/artifacts	300		
v375l	Good	Good		Good	Normal Sinus Rhythm	135		
v375l	Good	Good		Good	Normal Sinus Rhythm	15		
v380s	Bad	Bad		Good	Noise/artifacts	300		
v381l	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v390s	Good	Bad	Bad	Good	Extreme Tachycardia	300	285	300
v392s	Good	Good	Good	Good	VT	300	285	289
v395l	Good	Good		Good	Normal Sinus Rhythm	300		
v398s	Bad	Bad	Good	Bad	Noise/artifacts	300		
v399l	Bad	Bad	Bad	Bad	Noise/artifacts	300		
v400s	Bad	Bad		Good	Noise/artifacts	300		
v401l	Bad	Bad		Bad	Noise/artifacts	300		
v402s	Good	Good		Bad	Normal Sinus Rhythm	300		
v403l	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v404s	Good	Good		Good	VT	300	292	300
v405l	Bad	Good	Good	Bad	Noise/artifacts	300		
v419l	Good	Good		Good	Normal Sinus Rhythm	300		
v421l	Good	Good		Good	PVCs	300		
v423l	Good	Bad		Bad	Normal Sinus Rhythm	300		
v426s	Good	Good		Good	Normal Sinus Rhythm	300		
v427l	Good	Bad		Good	Noise/artifacts	300		
v431l	Bad	Bad	Bad	Good	Noise/artifacts	300		

v432s	Bad	Bad	Bad	Good	Noise/artifacts	300		
v433l	Good	Good		Good	Normal Sinus Rhythm	300		
v437l	Good	Bad	Good	Bad	Noise/artifacts	300		
v438s	Good	Bad		Good	Noise/artifacts	300		
v448s	Bad	Bad		Bad	Noise/artifacts	298		
v452s	Bad	Bad		Good	Noise/artifacts	300		
v453l	Good	Bad		Good	Noise/artifacts	300		
v454s	Good	Bad		Good	Noise/artifacts	300		
v459l	Good	Bad	Good		Noise/artifacts	300		
v460s	Bad	Bad	Good	Bad	Noise/artifacts	300		
v463l	Bad	Bad	Bad		Noise/artifacts	300		
v464s	Good	Bad	Good	Good	PVCs	300		
v466s	Bad	Bad	Bad	Bad	Noise/artifacts	300		
v470s	Bad	Bad		Bad	Noise/artifacts	300		
v471l	Good	Good		Good	VT	300	297.8	300
v472s	Bad	Bad	Bad	Bad	Noise/artifacts	300		
v473l	Good	Good	Bad	Good	Normal Sinus Rhythm	300		
v475l	Bad	Bad		Bad	Noise/artifacts	300		
v476s	Bad	Bad		Good	Noise/artifacts	300		
v479l	Bad	Bad	Good		Noise/artifacts	300		
v480s	Bad	Bad	Good		Noise/artifacts	300		
v481l	Good	Good	Good	Good	Bundle branch block	300		
v482s	Good	Good	Bad	Good	Bundle branch block	300		
v483l	Good	Good	Good	Good	Bundle branch block	300		
v489l	Bad	Bad	Good	Bad	Noise/artifacts	300		
v491l	Bad	Bad	Good	Bad	Noise/artifacts	300		
v492s	Bad	Bad	Bad	Bad	Noise/artifacts	300		
v498s	Good	Bad	Bad	Good	Noise/artifacts	300		

v501l	Good	Bad	Good	Good	Noise/artifacts	300		
v502s	Good	Bad	Good	Good	Noise/artifacts	300		
v505l	Good	Good		Bad	Normal Sinus Rhythm	300		
v510s	Bad	Good		Good	Normal Sinus Rhythm	300		
v511l	Bad	Bad		Good	Noise/artifacts	300		
v513l	Bad	Good		Good	Noise/artifacts	300		
v513l	Good	Good		Good	Normal Sinus Rhythm	135		
v513l	Good	Good		Good	Normal Sinus Rhythm	15		
v518s	Bad	Bad	Good	Good	Noise/artifacts	300		
v519l	Good	Bad	Good	Good	Noise/artifacts	300		
v522s	Good	Good	Good		VT	300	290.8	299.2
v522s	Good	Good	Good		Normal Sinus Rhythm	135		
v522s	Good	Good	Good		Normal Sinus Rhythm	15		
v523l	Good	Good	Good		VT	300	286.9	291.7
v525l	Good	Good		Good	VT	299	296.7	299
v531l	Bad	Bad	Bad	Bad	Noise/artifacts	300		
v532s	Good	Good		Good	PVCs	300		
v533l	Good	Good		Good	PVCs	300		
v534s	Good	Good		Good	Normal Sinus Rhythm	300		
v535l	Bad	Bad	Bad	Good	Noise/artifacts	300		
v536s	Bad	Bad	Bad	Good	Noise/artifacts	300		
v540s	Good	Good	Bad	Bad	VF	217	212	217
v541l	Good	Good	Good	Good	VF	300	295.9	300
v541l	Good	Good	Good	Good	Normal Sinus Rhythm	135		
v542s	Good	Good	Good	Good	VT	300	289.7	293
v548s	Good	Good		Good	Normal Sinus Rhythm	300		
v549l	Good	Good		Good	Normal Sinus Rhythm	300		
v551l	Bad	Bad	Good	Bad	Noise/artifacts	300		

v552s	Good	Bad	Good	Bad	Noise/artifacts	300		
v557l	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v557l	Good	Good	Good	Good	Normal Sinus Rhythm	135		
v557l	Good	Good	Good	Good	Normal Sinus Rhythm	15		
v559l	Good	Good	Good	Good	PVCs	300		
v564s	Good	Good	Good	Good	VT	300	296.5	300
v566s	Bad	Bad		Bad	Noise/artifacts	300		
v568s	Bad	Bad	Good	Good	Noise/artifacts	300		
v569l	Bad	Good	Good	Good	Noise/artifacts	300		
v570s	Bad	Bad	Bad	Bad	Noise/artifacts	300		
v571l	Good	Good	Good	Good	VT	298	295.8	298
v573l	Good	Good	Good	Good	VT	295.5	289.5	295.5
v573l	Good	Good	Good	Good	Normal Sinus Rhythm	135		
v573l	Good	Good	Good	Good	Normal Sinus Rhythm	15		
v574s	Good	Good		Good	VT	298.5	296.1	298.5
v574s	Good	Good		Good	Normal Sinus Rhythm	135		
v574s	Good	Good		Good	Normal Sinus Rhythm	15		
v575l	Good	Good		Good	Bundle branch block	300		
v579l	Good	Good	Good		VT	299.5	297	299.5
v579l	Good	Good	Good		Normal Sinus Rhythm	135		
v581l	Good	Good		Good	Normal Sinus Rhythm	300		
v583l	Good	Bad		Bad	Noise/artifacts	300		
v585l	Bad	Bad	Good		Paced	300		
v590s	Bad	Bad		Bad	Noise/artifacts	300		
v596s	Good	Good	Good		Paced	300		
v597l	Good	Good		Good	VT	298.5	295.4	298.5
v598s	Good	Good		Good	VT	300	293.5	297.3
v601l	Bad	Good		Good	Noise/artifacts	300		

v601l	Good	Good		Good	Normal Sinus Rhythm	135		
v601l	Good	Good		Good	Normal Sinus Rhythm	15		
v607l	Good	Good	Good		VT	298	294.4	298
v607l	Good	Good	Good		Normal Sinus Rhythm	135		
v607l	Good	Good	Good		Normal Sinus Rhythm	15		
v609l	Bad	Bad		Bad	Noise/artifacts	300		
v611l	Bad	Bad	Good		Noise/artifacts	300		
v612s	Bad	Bad	Good	Good	Noise/artifacts	300		
v615l	Good	Good	Good		Paced	300		
v616s	Good	Bad		Bad	PVCs	300		
v619l	Good	Good	Good		VT	300	295	300
v620s	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v621l	Bad	Bad		Bad	Noise/artifacts	300		
v623l	Bad	Bad		Good	Noise/artifacts	300		
v625l	Good	Good	Good		VT	298	295.4	298
v625l	Good	Good	Good		Normal Sinus Rhythm	135		
v626s	Good	Good	Good		VT	300	296.2	300
v627l	Bad	Bad		Bad	Noise/artifacts	300		
v628s	Good	Good		Good	VT	298	295.4	298
v629l	Good	Good	Good		PVCs	300		
v630s	Good	Good		Good	VT	300	296.4	300
v630s	Good	Good		Good	Normal Sinus Rhythm	135		
v630s	Good	Good		Good	Normal Sinus Rhythm	120		
v630s	Good	Good		Good	Normal Sinus Rhythm	150		
v630s	Good	Good		Good	Normal Sinus Rhythm	165		
v630s	Good	Good		Good	Normal Sinus Rhythm	30		
v630s	Good	Good		Good	Normal Sinus Rhythm	180		
v630s	Good	Good		Good	Normal Sinus Rhythm	195		

v630s	Good	Good		Good	Normal Sinus Rhythm	210		
v630s	Good	Good		Good	Normal Sinus Rhythm	225		
v630s	Good	Good		Good	Normal Sinus Rhythm	240		
v630s	Good	Good		Good	Normal Sinus Rhythm	255		
v630s	Good	Good		Good	Normal Sinus Rhythm	270		
v630s	Good	Good		Good	Normal Sinus Rhythm	285		
v630s	Good	Good		Good	Normal Sinus Rhythm	45		
v630s	Good	Good		Good	Normal Sinus Rhythm	60		
v630s	Good	Good		Good	Normal Sinus Rhythm	75		
v630s	Good	Good		Good	Normal Sinus Rhythm	90		
v630s	Good	Good		Good	Normal Sinus Rhythm	105		
v630s	Good	Good		Good	Normal Sinus Rhythm	15		
v632s	Good	Good		Good	VT	299	296.6	299
v633l	Bad	Good		Bad	Noise/artifacts	300		
v634s	Bad	Bad		Bad	Noise/artifacts	300		
v635l	Good	Good		Good	VT	300	296.5	299.9
v635l	Good	Good		Good	Normal Sinus Rhythm	135		
v635l	Good	Good		Good	Normal Sinus Rhythm	120		
v635l	Good	Good		Good	Normal Sinus Rhythm	150		
v635l	Good	Good		Good	Normal Sinus Rhythm	165		
v635l	Good	Good		Good	Normal Sinus Rhythm	30		
v635l	Good	Good		Good	Normal Sinus Rhythm	180		
v635l	Good	Good		Good	Normal Sinus Rhythm	195		
v635l	Good	Good		Good	Normal Sinus Rhythm	210		
v635l	Good	Good		Good	Normal Sinus Rhythm	225		
v635l	Good	Good		Good	Normal Sinus Rhythm	240		
v635l	Good	Good		Good	Normal Sinus Rhythm	255		
v635l	Good	Good		Good	Normal Sinus Rhythm	270		

v635l	Good	Good		Good	Normal Sinus Rhythm	285		
v635l	Good	Good		Good	Normal Sinus Rhythm	45		
v635l	Good	Good		Good	Normal Sinus Rhythm	60		
v635l	Good	Good		Good	Normal Sinus Rhythm	75		
v635l	Good	Good		Good	Normal Sinus Rhythm	90		
v635l	Good	Good		Good	Normal Sinus Rhythm	105		
v635l	Good	Good		Good	Normal Sinus Rhythm	15		
v636s	Good	Good		Good	Paced	300		
v638s	Good	Good		Good	PVCs	300		
v638s	Good	Good		Good	PVCs	135		
v638s	Good	Good		Good	PVCs	120		
v638s	Good	Good		Good	PVCs	150		
v638s	Good	Good		Good	Normal Sinus Rhythm	30		
v638s	Good	Good		Good	PVCs	180		
v638s	Good	Good		Good	PVCs	195		
v638s	Good	Good		Good	PVCs	210		
v638s	Good	Good		Good	PVCs	225		
v638s	Good	Good		Good	PVCs	240		
v638s	Good	Good		Good	PVCs	255		
v638s	Good	Good		Good	PVCs	270		
v638s	Good	Good		Good	PVCs	45		
v638s	Good	Good		Good	Normal Sinus Rhythm	60		
v638s	Good	Good		Good	Normal Sinus Rhythm	75		
v638s	Good	Good		Good	Normal Sinus Rhythm	90		
v638s	Good	Good		Good	Normal Sinus Rhythm	105		
v640s	Bad	Bad		Good	Noise/artifacts	300		
v641l	Good	Good		Good	Normal Sinus Rhythm	300		
v641l	Good	Good		Good	Normal Sinus Rhythm	135		

v641l	Good	Good		Good	Normal Sinus Rhythm	120		
v641l	Good	Good		Good	Normal Sinus Rhythm	30		
v641l	Good	Good		Good	Normal Sinus Rhythm	45		
v641l	Good	Good		Good	Normal Sinus Rhythm	60		
v641l	Good	Good		Good	Normal Sinus Rhythm	75		
v641l	Good	Good		Good	Normal Sinus Rhythm	90		
v641l	Good	Good		Good	Normal Sinus Rhythm	105		
v641l	Good	Good		Good	Normal Sinus Rhythm	15		
v643l	Bad	Good		Good	Noise/artifacts	300		
v644s	Good	Bad		Good	Noise/artifacts	300		
v644s	Good	Good		Good	Normal Sinus Rhythm	135		
v644s	Good	Good		Good	Normal Sinus Rhythm	30		
v644s	Good	Good		Good	Normal Sinus Rhythm	45		
v644s	Good	Good		Good	Normal Sinus Rhythm	60		
v644s	Good	Good		Good	Normal Sinus Rhythm	75		
v644s	Good	Good		Good	Normal Sinus Rhythm	90		
v646s	Good	Good	Good		Paced	300		
v646s	Good	Good	Good		Paced	135		
v646s	Good	Good	Good		Paced	30		
v646s	Good	Good	Good		Paced	45		
v646s	Good	Good	Good		Paced	60		
v646s	Good	Good	Good		Paced	75		
v646s	Good	Good	Good		Paced	90		
v647l	Good	Good		Bad	Normal Sinus Rhythm	300		
v647l	Good	Good		Good	Normal Sinus Rhythm	135		
v647l	Good	Good		Good	Normal Sinus Rhythm	30		
v647l	Good	Good		Good	Normal Sinus Rhythm	45		
v647l	Good	Good		Good	Normal Sinus Rhythm	60		

v647l	Good	Good		Good	Normal Sinus Rhythm	75		
v647l	Good	Good		Good	Normal Sinus Rhythm	15		
v648s	Good	Good	Good	Good	VT	300	296	300
v648s	Good	Good	Good	Good	Normal Sinus Rhythm	135		
v648s	Good	Good	Good	Good	Normal Sinus Rhythm	15		
v649l	Bad	Bad	Bad	Good	Noise/artifacts	300		
v652s	Good	Good		Good	VT	300	294.6	298.3
v655l	Bad	Bad		Good	Noise/artifacts	300		
v658s	Good	Good	Good		Normal Sinus Rhythm	300		
v658s	Good	Good	Good		Normal Sinus Rhythm	135		
v658s	Good	Good	Good		Normal Sinus Rhythm	15		
v660s	Good	Good	Good		Paced	300		
v663l	Bad	Bad	Good	Bad	Noise/artifacts	300		
v666s	Bad	Bad		Good	Noise/artifacts	300		
v671l	Good	Good		Good	Normal Sinus Rhythm	300		
v674s	Bad	Bad	Good		Noise/artifacts	300		
v676s	Bad	Good	Good		Normal Sinus Rhythm	300		
v676s	Good	Good	Good		Normal Sinus Rhythm	135		
v682s	Good	Bad	Bad	Bad	PVCs	300		
v686s	Bad	Bad		Bad	Noise/artifacts	300		
v687l	Bad	Bad		Good	Noise/artifacts	300		
v692s	Bad	Bad		Bad	Noise/artifacts	300		
v696s	Good	Good		Good	VT	300	296.5	300
v701l	Good	Good	Good		VT	297.5	295	297.5
v701l	Good	Good	Good		Normal Sinus Rhythm	135		
v701l	Good	Good	Good		Normal Sinus Rhythm	15		
v704s	Bad	Bad		Good	Noise/artifacts	300		
v710s	Bad	Bad		Bad	Noise/artifacts	300		

v711l	Bad	Bad		Good	Noise/artifacts	300		
v711l	Good	Good		Good	Normal Sinus Rhythm	135		
v711l	Good	Good		Good	Normal Sinus Rhythm	15		
v713l	Good	Good		Good	VT	300	285	300
v714s	Good	Good		Bad	VT	300	297	300
v718s	Bad	Bad	Good		Noise/artifacts	300		
v720s	Good	Good	Good	Bad	Normal Sinus Rhythm	300		
v721l	Bad	Bad	Bad	Good	Noise/artifacts	300		
v724s	Good	Good	Good		NSVT	300		
v724s	Good	Good	Good		PVC	135		
v725l	Bad	Bad		Bad	Noise/artifacts	300		
v726s	Good	Good	Good	Good	VT	299	290.6	294.1
v727l	Bad	Bad	Good	Bad	Noise/artifacts	300		
v728s	Good	Good		Good	VT	298.5	296.1	298.5
v729l	Good	Good	Good		VT	300	295.5	297.7
v732s	Good	Good		Good	Normal Sinus Rhythm	300		
v732s	Good	Good		Good	Normal Sinus Rhythm	15		
v733l	Good	Good		Good	VT	300	296.4	300
v736s	Bad	Good		Bad	Noise/artifacts	300		
v738s	Good	Good		Good	PVC	300		
v743l	Bad	Bad	Good	Good	Noise/artifacts	300		
v748s	Good	Good		Good	VT	300	296.5	300
v749l	Bad	Bad	Good		Noise/artifacts	300		
v756s	Good	Good	Good		Normal Sinus Rhythm	300		
v758s	Good	Good	Good	Good	VT	298	296.4	298
v759l	Good	Good	Good		NSVT	300		
v761l	Good	Good		Good	VT	300	296	298.7
v763l	Bad	Bad		Bad	Noise/artifacts	300		

v765l	Good	Good	Good		VT	300	297.4	300
v765l	Good	Good	Good		Normal Sinus Rhythm	135		
v765l	Good	Good	Good		Normal Sinus Rhythm	15		
v766s	Bad	Bad		Good	Noise/artifacts	300		
v767l	Bad	Good	Bad	Bad	PVC	300		
v769l	Good	Good		Good	VT	300	295.7	300
v769l	Good	Good		Good	Normal Sinus Rhythm	135		
v769l	Good	Good		Good	Normal Sinus Rhythm	15		
v770s	Bad	Bad		Bad	Noise/artifacts	300		
v772s	Good	Good	Good		VT	300	297	300
v772s	Good	Good	Good		Normal Sinus Rhythm	135		
v773l	Good	Good		Good	VT	299	296.6	299
v774s	Bad	Bad		Bad	Noise/artifacts	300		
v775l	Bad	Bad		Bad	Noise/artifacts	300		
v779l	Good	Good	Good		PVC	300		
v779l	Good	Good	Good		Normal Sinus Rhythm	135		
v781l	Good	Good		Good	Bundle branch block	300		
v782s	Bad	Bad		Bad	Noise/artifacts	300		
v783l	Good	Good		Good	NSVT	300		
v784s	Good	Bad		Good	Normal Sinus Rhythm	300		
v788s	Good	Good		Good	VT	292	289.8	292
v791l	Bad	Bad		Bad	Noise/artifacts	300		
v793l	Good	Good	Good		VT	299	296.5	299
v793l	Good	Good	Good		Normal Sinus Rhythm	135		
v793l	Good	Good	Good		Normal Sinus Rhythm	15		
v795l	Bad	Bad	Good		Noise/artifacts	300		
v795l	Good	Good	Good		Normal Sinus Rhythm	135		
v795l	Bad	Bad	Good		Noise/artifacts	15		

v797l	Good	Good	Good		VT	300	297.1	300
v803l	Good	Good	Good	Good	VT	294	290.7	294
v804s	Bad	Bad		Bad	Noise/artifacts	300		
v805l	Bad	Bad		Good	Noise/artifacts	300	294.8	300
v805l	Good	Good		Good	Normal Sinus Rhythm	135		
v805l	Good	Good		Good	Normal Sinus Rhythm	15		
v806s	Good	Good		Good	VT	297.5	295.4	297.5
v808s	Good	Good	Good		Paced	300		
v809l	Good	Good		Good	Normal Sinus Rhythm	300		
v811l	Bad	Bad	Good		Noise/artifacts	300		
v811l	Good	Good	Good		Normal Sinus Rhythm	135		
v811l	Good	Good	Good		Normal Sinus Rhythm	15		
v813l	Good	Good	Good		VT	299	296.5	299
v813l	Good	Good	Good		Normal Sinus Rhythm	135		
v814s	Bad	Bad		Bad	Noise/artifacts	300		
v815l	Good	Good	Good	Good	VT	300	285.6	300
v818s	Good	Good		Good	VT	300	297.1	300
v823l	Good	Good		Good	VT	297	294	297
v823l	Good	Good		Good	Normal Sinus Rhythm	135		
v826s	Bad	Good	Good	Good	Noise/artifacts	300		
v827l	Bad	Bad	Bad		Noise/artifacts	300		
v828s	Good	Good		Good	VT	294	291.4	294
v830s	Good	Good	Good		Paced	300		
v831l	Good	Good	Good	Good	VT	294	289.7	293.9
v831l	Good	Good	Good	Good	Normal Sinus Rhythm	135		
v831l	Good	Good	Good	Good	Normal Sinus Rhythm	15		
v833l	Good	Good	Good	Good	Normal Sinus Rhythm	300		
v834s	Good	Good		Bad	NSVT	300		

v836s	Good	Good	Good		Paced	300		
v837l	Good	Good	Good		VT	300	296.4	300
v837l	Good	Good	Good		PVC	135		
v842s	Good	Good	Good		Paced	298.25		
v843l	Bad	Bad		Good	Noise/artifacts	300		
v843l	Good	Good		Good	Normal Sinus Rhythm	15		
v844s	Good	Good	Good		Paced	300		
v845l	Good	Good	Good		Normal Sinus Rhythm	300		
v846s	Bad	Bad		Bad	Noise/artifacts	300		
v848s	Good	Good		Good	Normal Sinus Rhythm	300		

VF: ventricular fibrillation; VT: ventricular tachycardia; PVCs: premature ventricular contractions; PACs: premature atrial contractions, NSVT: non-sustained ventricular tachycardia.

Figure S1. ROC of ECG noise detector for classifiers based on (i) only features, (ii) only CNN approach and (iii) hybrid-CNN approach, with an AUC of 93.56%, 96.97% and 97.17% respectively.

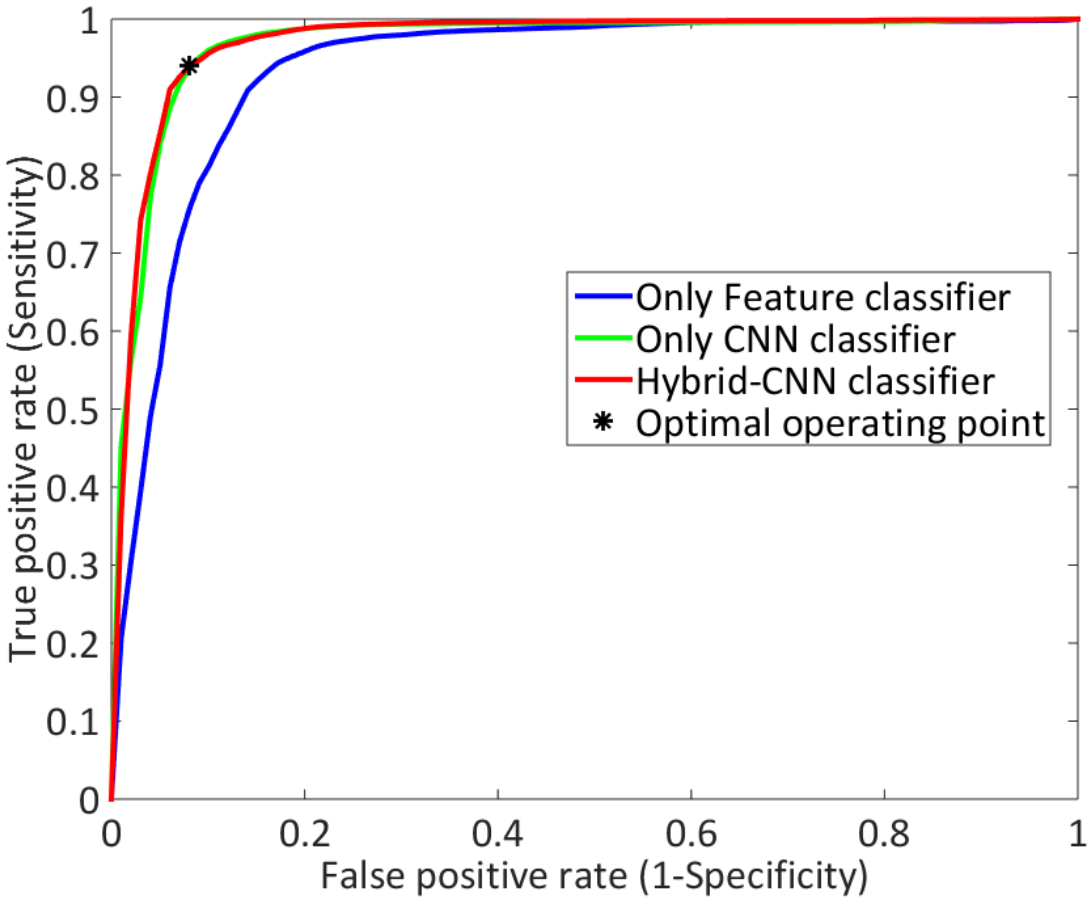
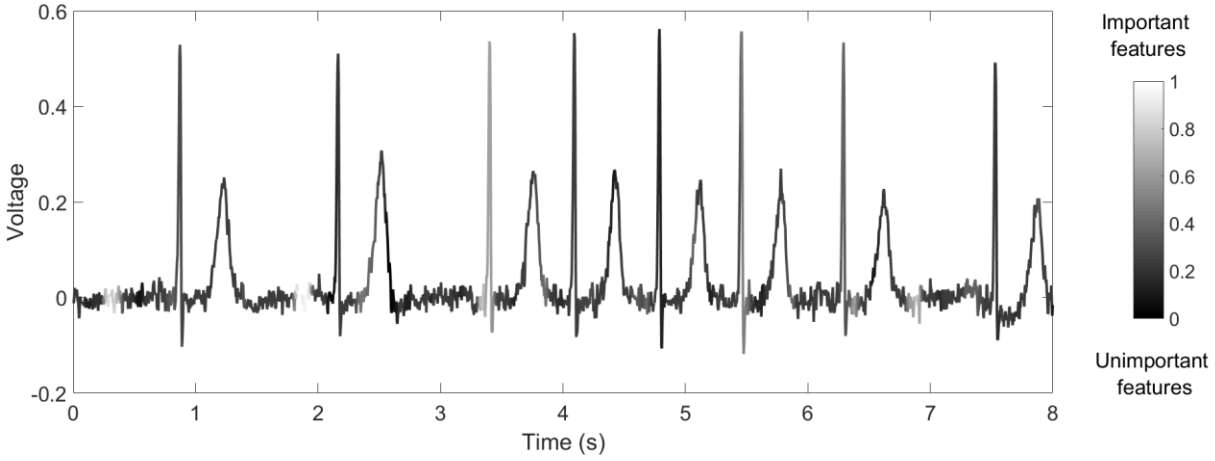
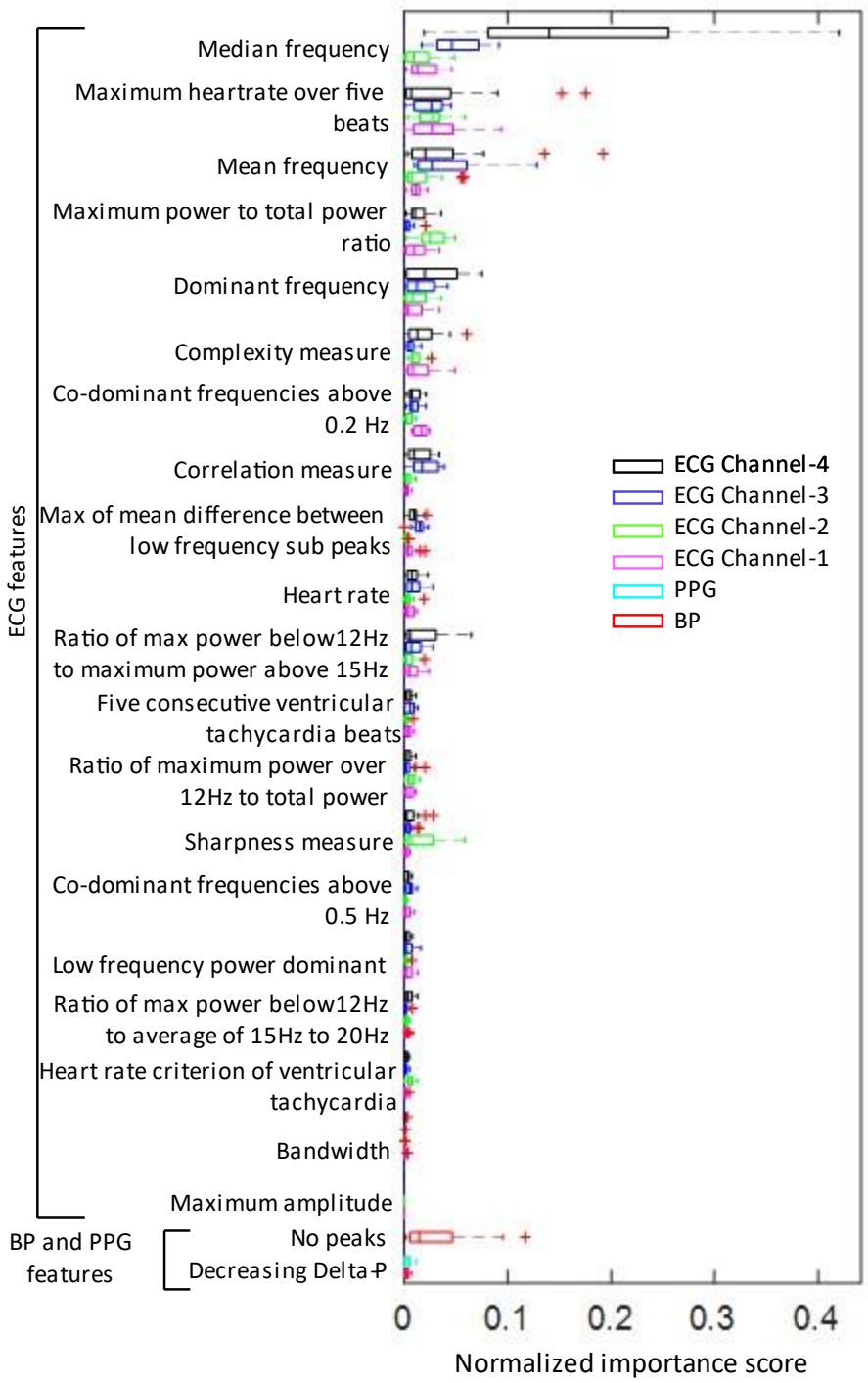


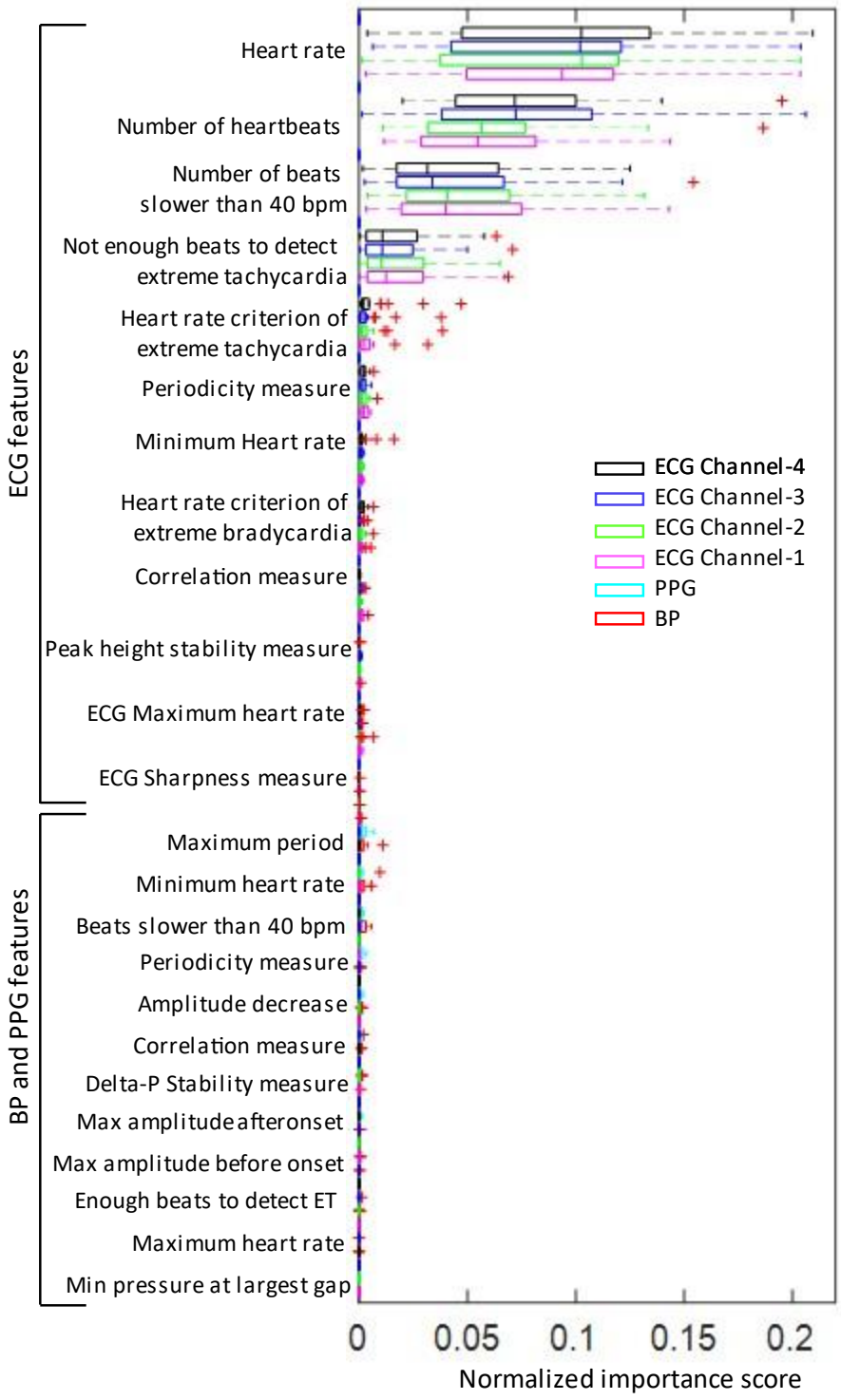
Figure S2. **Gradient-weighted class activation mapping (Grad-CAM) of trained convolutional neural network (CNN) corresponding to Tier-3 (normal vs atrial fibrillation) classifier.**

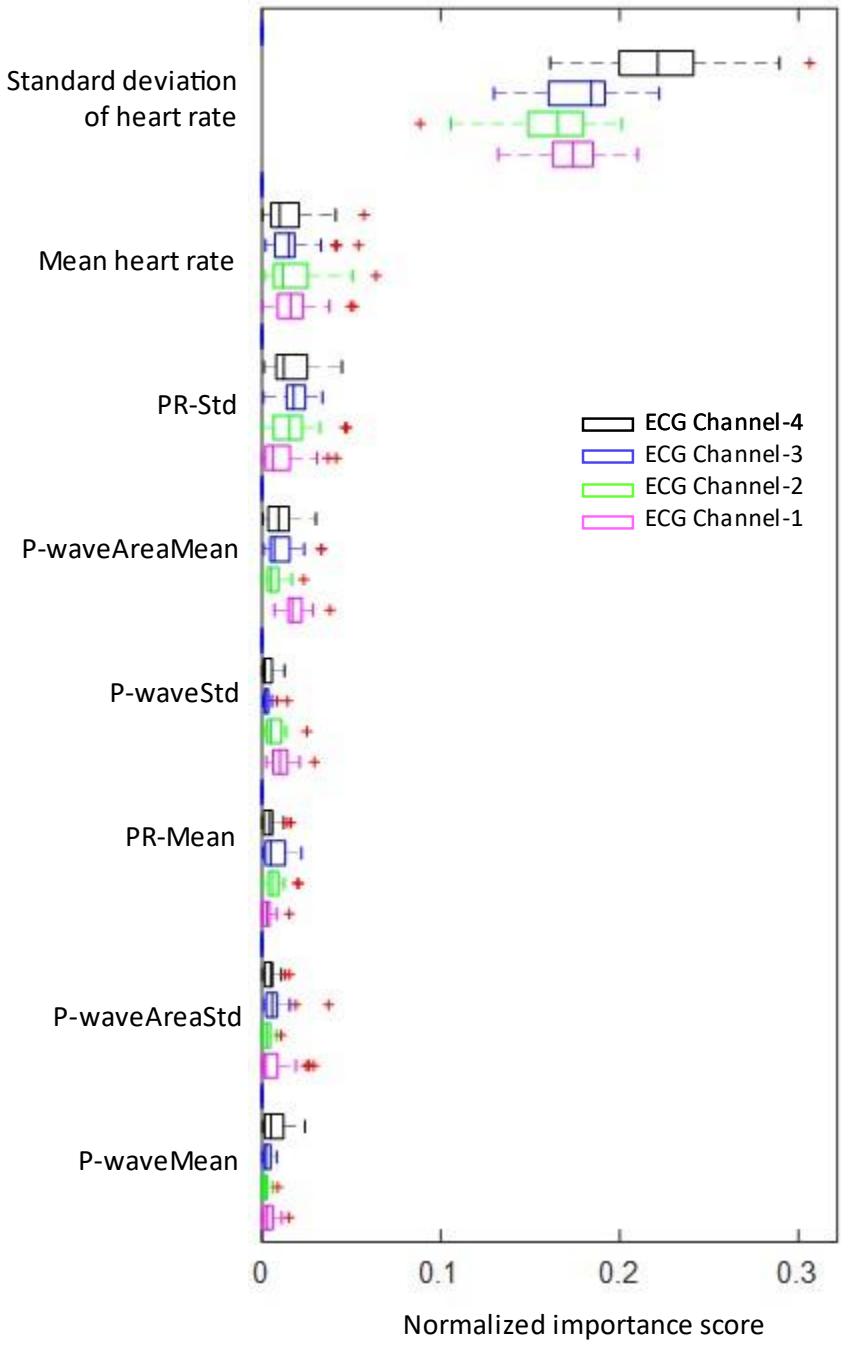


First channel of ECG signal is represented with the gray level proportional to CAM amplitude, which represents the regions of interest on the given signal that leads its classification into an AF class by CNN. The most important region within the signal correspond to a missing P-waves and an R-peak with irregular rhythm preceding and following RR intervals, which agrees with the characteristics of AF.

Figure S3. Feature importance scores of only feature based (A) Tier-1 classifier, the most important features for classification are median frequency and ratio of maximum power to total power, which are characteristics of VT and VF. (B) Tier-2 classifier, with high importance score for ECG heart rate, which distinguishes extreme bradycardia, extreme tachycardia and other conditions. (C) Tier-3 classifier, in which high importance is assigned to the standard deviation of heart rate and mean p-wave area, which are characteristics of atrial fibrillation.


ECG features
Median frequency
Maximum heartrate over five beats
Mean frequency
Maximum power to total power ratio
Dominant frequency
Complexity measure
Co-dominant frequencies above 0.2 Hz
Correlation measure
Max of mean difference between low frequency sub peaks
Heart rate
Ratio of max power below12Hz to maximum power above 15Hz
Five consecutive ventricular tachycardia beats
Ratio of maximum power over 12Hz to total power
Sharpness measure
Co-dominant frequencies above 0.5 Hz
Low frequency power dominant
Ratio of max power below12Hz to average of 15Hz to 20Hz
Heart rate criterion of ventricular tachycardia
Bandwidth
Maximum amplitude
BP and PPG features
No peaks
Decreasing Delta-P
ECG Channel-4
ECG Channel-3
ECG Channel-2
ECG Channel-1
PPG
BP
0
0.1
0.2
0.3
0.4
Normalized importance score


ECG features
BP and PPG features
Heart rate
Number of heartbeats
Number of beats slower than 40 bpm
Not enough beats to detect extreme tachycardia
Heart rate criterion of extreme tachycardia
Periodicity measure
Minimum Heart rate
Heart rate criterion of extreme bradycardia
Correlation measure
Peak height stability measure
ECG Maximum heart rate
ECG Sharpness measure
Maximum period
Minimum heart rate
Beats slower than 40 bpm
Periodicity measure
Amplitude decrease
Correlation measure
Delta-P Stability measure
Max amplitude afteronset
Max amplitude before onset
Enough beats to detect ET
Maximum heart rate
Min pressure at largest gap
ECG Channel-4
ECG Channel-3
ECG Channel-2
ECG Channel-1
PPG
BP
0
0.05
0.1
0.15
0.2
Normalized importance score


Standard deviation of heart rate
Mean heart rate
PR-Std
P-waveAreaMean
P-waveStd
PR-Mean
P-waveAreaStd
P-waveMean
ECG Channel-4
ECG Channel-3
ECG Channel-2
ECG Channel-1
0
0.1
0.2
0.3
Normalized importance score