Simultaneous Multiple Features Tracking of Beats: A Representation Learning Approach to Reduce False Alarm Rate in ICUs

Behzad Ghazanfari, Sixian Zhang, Fatemeh Afghah, Nathan Payton- McCauslin
School of Informatics, Computing and Cyber Systems
Northern Arizona University, Flagstaff, AZ 86011

***Abstract*—The high rate of false alarms is a key challenge related to patient care in intensive care units (ICUs) that can result in delayed responses of the medical staff. Several rule-based and machine learning-based techniques have been developed to address this problem. However, the majority of these methods rely on the availability of different physiological signals such as different electrocardiogram (ECG) leads, arterial blood pressure (ABP), and photoplethysmogram (PPG), where each signal is analyzed by an independent processing unit and the results are fed to an algorithm to determine an alarm. That calls for novel methods that can accurately detect the cardiac events by only accessing one signal (e.g., ECG) with a low level of computation and sensors requirement. We propose a novel and robust representation learning framework for ECG analysis that only rely on a single lead ECG signal and yet achieves considerably better performance compared to the state-of-the-art works in this domain, without relying on an expert knowledge. We evaluate the performance of this method using the *"2015 Physionet computing in cardiology challenge"* dataset. To the best of our knowledge, the best previously reported performance is based on both expert knowledge and machine learning where all available signals of ECG, ABP and PPG are utilized. Our proposed method reaches the performance of 97.3%, 95.5 %, and 90.8 % in terms of sensitivity, specificity, and the challenge's score, respectively for the detection of five arrhythmias when only one single ECG lead signals is used without any expert knowledge[1] [2].**

***Index Terms*—Simultaneous multiple feature tracking, representation Learning, cardiac event detection, false alarm, ECG.**

I. Introduction

False Alarms (FA) refers to the alarms that are falsely triggered by the patient monitoring systems. Medical monitoring systems generate audible alarms when the value of one or multiple monitoring sources reaches or goes beyond the predefined thresholds [6] [20]. Different sources of noise and signal distortion such as motion artifacts result in a high rate of false alarms in detecting different arrhythmia using the current techniques. The high rate of false alarm in ICUs can result in ignoring the true alarms by the medical staff [11]. The rate of ICU FA is reported between 65% to 95%, while between 6% and 40% of these alarms are true but clinically insignificant and do not require an immediate action [7, 8, 18]. Therefore, reducing the rate of false alarms is an important concern in hospitals.

Many works take steps to decrease the high rate of FA by different approaches from human knowledge [9, 21], and classical machine learning [12]. The methods based on human knowledge often lead to better results compared to machine learning ones [7, 20]. Several factors contribute to the weaker performance of ML-based methods including the problem of imbalanced datasets where there is a limited number of arrhythmia samples to train the ML model, and their impotence in dealing with long recordings of highly-noise contaminated signals with non-linear patterns.

In this paper, a novel framework based on simultaneous multiple feature tracking for representation learning is presented that considerably improves the state of the art results while it only utilizes the entire recording for one ECG lead. We like to note that the majority of the current methods achieve good performance when working with short recordings of signals. For instance, the best reported results for the false alarm reduction challenge take advantage of the fact that the alarm has occurred in the last 14 seconds of available recordings, therefore they only analyzed of a short window of the signals. However, these methods cannot offer the desired performance in online alarm detection when dealing with long recordings with no prior knowledge on when the arrhythmia is expected to happen. More importantly, the majority of current techniques take into account the general rules related to the arrhythmia type or extracted knowledge from the entire dataset rather than focusing on patient specific characteristics of the signal. In our proposed work, we develop a simultaneous multiple feature tracking method for periodic processing of time series signals. We segment the signal based on the periodic parts and map each segment to some simple features as a light weight feature extracting step. Then machine learning looks for the relationships between the entire signal recordings as the sequence of periodic parts through the time with labels. Since the method simultaneously learns the relation among the set of features that describe each segment through the time, the method is called *simultaneous multiple feature tracking.* In summary, the main contribution of the paper is to introduce a simultaneous multiple features tracking method for classification of semi-periodic time series signals using Bidirectional long short-term memory (Bi-LSTM) to track and learn non-linear patterns throughout the long signals. The proposed approach is applied on signals that last approximately between a range of 70 to 82 thousands time steps and learn even from a small number

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of instances without using human knowledge.

II. Related works

In this section, we review several reported works in the literature that achieved the best results in alarm detection on the 2015 PhysioNet Computing in Cardiology Challenge dataset [8].

The authors in [21] proposed a method that passes the pre-processed signals through multiple tests for each type of arrhythmia including regularity and arrhythmia tests. While this method shows a good performance, it highly relies on expert knowledge that limits its scalability to other arrhythmia. We like to note that this method was ranked the first place in the challenge and outperformed other methods that are based on classical machine learning or representation learning.

The presented method in [16] trains five SVM-based arrhythmia classifiers using different features according to the type of arrhythmia. A false-positive test is conducted after each classifier. A method based on signal quality index (SQI) for each channel was proposed in [9] that captures different lengths of the input signal based on different arrhythmia. Then, a trust assignment based on the SQI is applied after comparing the QRS annotation from a different channel, from which the final result is decided. The proposed method in [12] calculates the heart rate from ECG, ABP, and PPG, along with the spectral purity index from ECG. The veracity of the alarm is determined based on a set of decision rules on heart rate and the spectral purity index.

In [3], the authors proposed a false alarm suppression method that uses multiple models for beat detection. The detection results are verified and summarized into fused annotation results. Finally, the outputs of the previous step are used by a rule-based decision method that determined the accuracy of the alarm based on the type of arrhythmia. They use a combination of learning and expert knowledge in different phases of their approach. A method to suppress the false ventricular tachycardia alarm was proposed in [19]. After a beat detection step, the method selects a 3-second window that contains the beat with the highest ventricular probability from the last 25 seconds of the signal. Then a supervised denoising auto-encoder (SDAE) takes the FFT-transformed ECG features over the window and classify whether the alarm is true or not. It should be noted they uses the MIT-BIH database that includes annotated ECG recordings to train their ventricular beat classifier.

The proposed method in [15] used a deep neuroevolution method that utilizes genetic algorithms and [2] utilized neural networks for arrhythmia classification. The former utilizes handcraft features introduced in [4] which include morphological and frequency features extracted from ECG, ABP, and PPG. The latter one utilizes SQI, physiological features, and features used in obstructive sleep apnoea (OSA) detection.

We note that all of the aforementioned methods except [2] utilized all available signals for each patient and the methods with highest accuracy such as [3, 21] also utilize expert knowledge in their approaches, while the results of our method reported in Section V is only based on one lead ECG with no expert knowledege.

III. Database Description: PhysioNet Challenge 2015

The PhysioNet/Computing in Cardiology Challenge 2015 focuses on reducing the false arrhythmia alarm in the ICUs, which provides a publicly available database for training and a test database for evaluation that was not publicly released [8, 20].

The training set includes 5 minutes and 30 seconds or 5 minutes of one or some of the ECG, ABP, and PPG signals for each patient before the alarm is triggered, the type of arrhythmia that triggers the alarm, and a true or false label. The arrhythmia type includes asystole (no QRS for 4 seconds), extreme bradycardia (heart rate lower than 40 , beats Per minute, for 5 consecutive beats), extreme tachycardia (heart rate higher than 140 bpm for 17 consecutive beats), ventricular tachycardia (5 or more ventricular beats with heart rate higher than 100 bpm), and ventricular flutter/fibrillation (fibrillatory, flutter, or oscillatory waveform for at least 4 seconds). Each record, resampled at 250Hz, contains two ECG signals (from lead I, II, III, aVR, aVL, aVF, or MCL) and one or more pulsatile waveform, such as arterial blood pressure (ABP) or photoplethysmogram (PPG). The public training database contains 750 samples, whose arrhythmia types and labels are listed below in table I. The test database is not publicly available, hence the training dataset is used in this study for both training and testing.

IV. Representation Learning based on Matching Layer

In the proposed method, we first pre-process the signal by removing the noise, and the invalid parts of the signals. A segmentation approach is then applied on the pre-processed signal to extract the location of PQRST waves. Then, several morphological features are extracted from each segment as described in Table IV. The dataset is partitioned for K-fold cross-validation in which $k = 15$. k is selected as 15 since the number of instances in some classes are few. These features are then fed into the Bi-LSTM learning algorithm to classify the signals.

A. Pre-processing

We first choose one of two ECG leads for each record. The default choice is the lead II. If this lead is not available for a patient, we select another lead in the order of I, aVF, and V. If none of these leads are available, we use the first ECG channel. Out of 750 patients, there are 22 subjects which did not include lead II, and only one patient (patient ID: a675l) does not include any of the aforementioned four leads. Hence, we used the first provided ECG channel that was lead III. Table II presents the list of samples that any ECG leads beside the lead II was used.

The signal is first validated by detecting and removing unreadable parts that are caused by noise or interference. Some parts of the ECG signals could be unreadable due to the body movement of the patient or the electrodes falling off which creates sharp spikes, flat lines, and high-frequency noise signal. Thus, we remove those unreadable parts from the signal before further processing.

We used the method proposed in [21] to detect and remove invalid parts of the ECG signal. This method searches the

TABLE I
DATA SUMMARY OF PATIENTS PER ALARM AND ARRHYTHMIA.

Arrhythmia Type	Arrhythmia Definition	# of Patients	# of False Alarm	# of True Alarm
ASY	no QRS for 4 seconds	122	100	22
EBR	heart rate lower than 40 bpm for 5 consecutive beats	89	43	46
ETC	heart rate higher than 140 bpm for 17 consecutive beats	140	9	131
VFB	fibrillatory, flutter, or oscillatory waveform for at least 4 seconds	58	52	6
VTA	5 or more ventricular beats with heart rate higher than 100 bpm	341	252	89
Total		750	456	294

TABLE II
SUBJECTS THAT THE ECG LEAD II IS NOT AVAILABLE FOR THEM.

Patient ID	Lead	Total
b349l, b672s, b824s, t116s, t208s, t209l, v289l, v290s, v619l	I	9
t693l	aVF	1
t477l, t478s, t622s, t665l, a457l, a582s, a661l, t739l, v328s, v459l, v629l	V	11
a675l	III	1

TABLE III
DETAILS OF RECORDS THAT BECAUSE OF MANY INVALID PARTS ARE CONSIDERED AS FALSE ALARM.

Type	Name	Total
ASY	a382s, a391l, a608s, a668s	4
VFB	f530s	1
VTA	v244s, v400s, v405l, v433l, v491l, v623l, v774s	7

signal inside 2-second windows and detects high-frequency noise by looking at the amplitude envelope of the signal at the frequency range of 70-90 Hz. It also detects saturated areas including the aforementioned sharp spikes and flat lines, by analyzing the histogram of the 2-second windows. The marked invalid parts are removed before further processing. If a signal has more than 80% region marked as invalid, it will be treated as noise and labeled as false alarm. During the experiment, the ECG signals from 12 records are detected with more than 80% invalid regions and are removed from following process. All these records turn out to be false alarm according to their labels. Details of these records are listed in table III.

B. PQRST Detection and Signal Segmentation

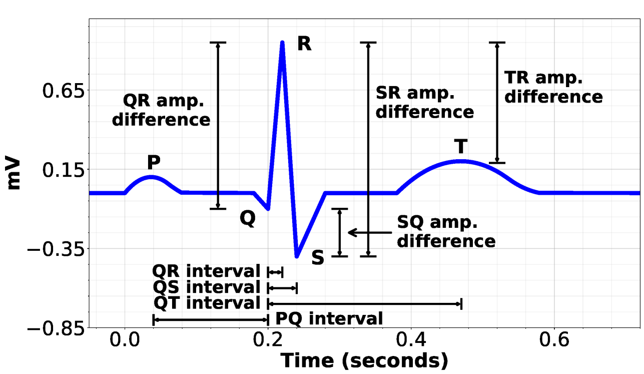

Fig. 1. An sample normal ECG beat.

Figure 1 shows an example of a normal ECG signal. We first search for the QRS complex locations using the proposed method in [21], which detects the R wave locations based on amplitude envelopes of the ECG signal. It detects local maxima by looking at the difference among three frequency ranges (1-8 Hz, 5-25 Hz, and 50-70 Hz) and using descriptive statistics to determine whether or not the maxima is an R wave location. Then, we refine the results and find PQST locations by searching for peaks and valleys within an interval around the R locations. If two segments are too close to each other, we compare their QRS complex amplitudes with the rest of the signal and remove the improper one. The signal is segmented by extracting PQRST waves of beats and then several morphological features are extracted from the aforementioned beats.

C. Morphological Feature Extraction

A proper low-level representation of the signal is vital for representation learning. Therefore, we extract several features from each beat as described in Table IV (using some of the introduced features in [10]). Extracting the proposed features only involves a low cost computation and yet our proposed method by only using these basic morphological features per segments offers significant performance using the simultaneous multiple feature tracking.

Morphological features describe the signal behavior in the time domain using the morphology of PQRST waves. These features (as described in Table IV) include PQRST amplitude, intervals, differential intervals, RR energy, the amplitude difference between SQ wave, the amplitude ratio of SR, SR (with respect to Q), TR, and QR waves, the width difference between QS, QR, QT, and PQ wave, and the slope between ST, QR, RS, Sx (slope of the period within 0.05 seconds after S wave) and PQ waves. We calculate different QT measurements using Bazett[5], Fridericia[13], and Sagie[22]'s QT formula. We also keep track of the negative ST slope and the zero-crossing point in the ST period. These features are fed into the matching layer learning and then to Bi-LSTM algorithm to determine the labels of arrhythmia.

D. Simultaneous Multiple Feature Tracking and Bi-LSTM

In this section, we introduce the proposed simultaneous multiple features tracking method to learn the relations among the multiple sets of morphological features extracted from different beats and with the labels. We first segment the ECG signal to its beats where each beat includes a complete beat (PQRST) and extract a set of d low-level morphological features from each beat, as depicted in Figure 2. The ECG signals is a pseudo-periodic signal since it consists of a sequence of beats with variable length (i.e., variable heart rate). Therefore, this method considers a variable-length window to extract a pre-determined number of initial features from the

TABLE IV
THE LIST OF MORPHOLOGICAL FEATURES THAT ARE EXTRACTED PER BEATS.

Feature Name	Number of Features
PQRST amplitude	5
PQRST interval	5
PQRST interval difference	5
RR energy	1
Amp difference of SQ	1
Amp ratio of SR, SR(wrt Q), TR, and QR	4
Width difference between QS, QR, QT, and PQ	4
Slope between ST, QR, RS, Sx, and PQ	5
ST neg slope, ST zero crossing point	2
Bazett, Fridericia, Sagie QT formula	3
RR cluster distance	3
PPRR ratio	1

ECG beats. The list of the features are shown in the IV with the total number of 39 features (i.e., $d = 39$). In order to learn the relationships among these low level features with each other and through the time with the labels. we need a machine learning approach that captures time relation among the sequence of features. Thereby, the features are fed to Bi-LSTM as a version of recurrent neural networks that have memories to capture time relation.

The extracted morphological low-level features from the signal's of each arrhythmia are normalized by z scores. We equal the number of each class of a arrhythmia by replicating randomly of each class as the amount of twice of instances in the largest class of that arrhythmia. Then, they are fed to the Bi-LSTM followed by a fully connected layer to obtain the classification label. A key difference of this method with existing works is that we consider the input layer as the number of features, d, per time steps for Bi-LSTM to track multiple features simultaneously and learn the relationships between them and thorough time. Bi-LSTM is a known machine learning method for sequence data and time series especially the long ones, but the input size of Bi-LSTM for time series is typically consider as 1 or 2 while in here we simultaneously track a set of features, d, of each beat. The architecture of the deep learning block is depicted in Figure 3. The learning of the network is based on adam [17]. The learning rate of the network is $5 * 10^{-6}$. We use L2 regularization and the rate is $1*10^{-7}$ and the number of epoch

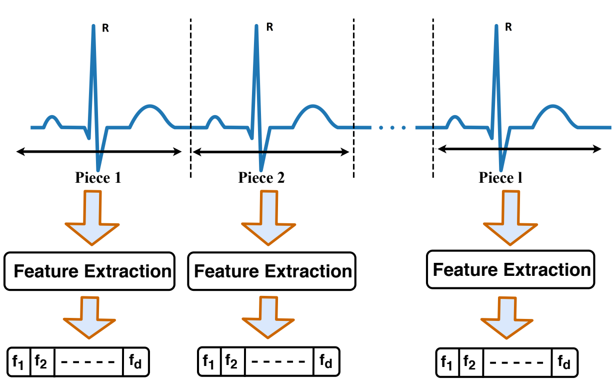

Fig. 2. A schematic description of the feature extraction step. The ECG signal is segmented to its beats, and then 39 low-level morphological features are extracted from each beat (d is 39).

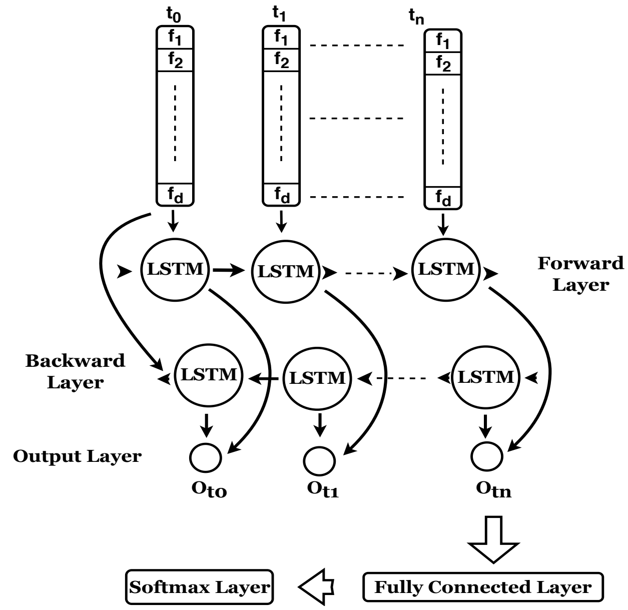

Fig. 3. The extracted morphological features per beat are fed as the features per time step to the Bi-LSTM.

is 700. The size of batch is 8.

V. Experimental Results

In this section, we evaluate the proposed method in comparison with the top-ranking entries from 2015 PhysioNet Challenge [8] and several other expert-based and machine learning-based methods. We also report the performance of several baseline classifiers applied on wavelet features. These wavelet features are obtained by using the discrete wavelet transform (DWT) applied on the entire ECG recording in which a 6-level Daubechies 8 (db8) wavelet is used. Since using all wavelet coefficients as features for classification methods can lead to over–fitting; we decrease the number of features by using 20 representative statistical and information–theoretic features of each level of the wavelet vectors as mentioned in [1, 14].

Since the test database of PhysioNet 2015 Challenge is not publicly available for evaluation, we re-implement most aforementioned approaches on the public training database for the sake of fairness in comparing the results. For example, the results of the top-ranked works for 2015 PhysioNet challenge were reported for the case that the model was trained on the training database and evaluated on the test database. Hence, we regenerated their results by evaluating their proposed algorithms on the training dataset with K-fold cross-validation ($k = 15$) to compare the results with our proposed approach. We replicate the data The results are compared based on the following three measures:

- True positive rate (TPR), also known as sensitivity, recall, and hit rate.
- True negative rate (TNR), also called as specificity, and selectivity.
- The challenge score calculated based on

$$Score = \frac{100 \cdot (TP + TN)}{(TP + TN + FP + 5 \cdot FN)} \tag{1}$$

TABLE V
COMPARISON OF TPR, TNR, AND THE CHALLENGE SCORE OF RECENT FALSE ALARM REDUCTION METHODS USING PHYSIONET 2015 CHALLENGE DATABASE.

Method	Features	Input Signal	TPR	TNR	Challenge Score
Rule-based Arrhythmia Test [21]	Hand crafted features	ECG, ABP, PPG	93.5	86.0	80.8
SVM-based Classifier [16]	Time and frequency features	ECG, ABP, PPG	85	93.2	72.9
Trust Assignment and Thresholding [9][1]	SQI and SPI	ECG, ABP, PPG	89.0	91.0	79.0
Feature-based Decision Making [12]	Heart rate and SPI	ECG, ABP, PPG	93.5	77.9	76.3
Decision Tree and Rule-based [3]	Detected beats	ECG, ABP, PPG	97.0	92.0	89.1
Deep Neuro-evolution [15][2]	Time and frequency features	ECG lead II, V, PPG	91.9		86.8
Neural Network [2]	SQI, physiological, and OSA features	ECG lead II	81.6	85.2	80.6
Unsupervised Feature Learning [14]	Morphological features	ECG lead II	81	83	–
Tree[3]	Wavelet features	ECG lead II	65.3	80.2	52.8
Linear Discriminant		ECG lead II	65.0	76.1	50.8
Logistic Regression		ECG lead II	55.4	67.8	41.3
Naive Bayes[4]		ECG lead II	52.7	76.1	43.0
SVM[5]		ECG lead II	55.1	89.0	49.6
KNN[6]		ECG lead II	68.0	71.1	50.8
Ensemble[7]		ECG lead II	76.2	82.9	62.7
PCA (Quadratic Discriminant)[8]		ECG lead II	98.6	9.0	43.2
Proposed representation learning based on simultaneous multiple feature tracking	Morphological features	ECG lead II	**97.3**	**95.5**	**90.8**

[1] The reported results in [9] are based on training on the public training dataset and testing on the private test database from PhysioNet 2015 Challenge.
[2] The reported results in [15] are not provided TPR and TNR, so the accuracy is reported instead. The result is based on a subset (572 records) of PhysioNet 2015 Challenge public database.
We experimented various methods for each baseline approach in MATLAB Classification Learner and reported the best results for that version. The specific name of the method we used are listed as follow: [3]Medium Tree. [4]Kernel Naive Bayes. [5]Fine Gaussian SVM. [6]Cubic KNN. [7]RUSBoosted Tree.
[8] The result scores of different classifiers utilizing principle component analysis (with 95, 98, and 99 percents explained variance) are far lower than those without it. Thus, we just report the best result of the baseline using PCA with 99 percents explained variance.

TABLE VI
COMPARISON OF TPR, TNR RESULT PER ARRHYTHMIA TYPE USING PHYSIONET 2015 CHALLENGE PUBLIC DATABASE.

Method	ASY1		EBR2		ETC3		VFB4		VTA5	
	TPR	TNR	TPR	TNR	TPR	TNR	TPR	TNR	TPR	TNR
Rule-based Arrhythmia Test[21]	95.5	92.0	97.8	74.4	99.2	88.9	83.3	100.0	83.1	82.5
SVM-based Classifier [16]	77.3	93.0	100.0	93.0	100.0	66.7	16.7	96.2	61.8	93.7
Trust Assignment and Thresholding [9][1]	78	94	95	66	100	80	89	96	69	95
Feature-based Decision Making[12]	100.0	88.0	97.8	62.8	96.9	33.3	83.3	84.6	85.4	76.6
Decision Tree and Rule-based [3]	95	86	98	88	98	67	50	100	97	94
Neural Network[2]	83	93	73	50	100	100	100	100	52	83
Supervised denoising autoencoder (SDAE)[19][2]	-	-		-	-	-	-	-training	89.0	86.0
Tree[3]	45.5	85.0	54.3	69.8	91.6	0	16.7	80.8	51.7	81.0
Linear Discriminant	72.7	63.0	69.6	58.1	77.9	22.2	83.3	80.8	48.3	73.4
Logistic Regression	68.2	58.0	58.7	48.8	79.4	22.2	33.3	69.2	50.6	68.7
Naive Bayes[4]	9.1	93.0	91.3	30.2	96.9	0	0	94.2	41.6	85.7
SVM[5]	13.6	99.0	87.0	34.9	100.0	0	0	100.0	23.6	96.0
KNN[6]	9.1	96.0	76.1	55.8	100.0	0	0	100.0	47.2	90.1
Ensemble[7]	72.7	73.0	67.4	51.2	70.2	33.3	50.0	73.1	69.7	77.8
Proposed representation Learning based on Simultaneous Multiple Feature Tracking	0.9897	0.875	100	0.9562	100	0.9924	100	100	0.957	0.9176

[1] This result comes from [9] and is based on the hidden database from PhysioNet 2015 Challenge.
[2] This result comes from [19] with the task of reducing false VTA alarm. It is based on two ECG leads of 562 VTA records from PhysioNet 2015 Challenge public and hidden databases.
We experimented various methods for each baseline category in MATLAB Classification Learner and reported the best results for that category. The specific name of the method we used are listed as follow: [3]Medium Tree. [4]Kernel Naive Bayes. [5]Fine Gaussian SVM. [6]Cubic KNN. [7]RUSBoosted Tree.

Table V and Table VI compare the performance of our proposed method with recent reported techniques for all alarm types and per alarm type, respectively.

As it can be seen in the first comparison table V, the proposed method with one ECG lead as the input and by learning from scratch without expert knowledge provides the best sensitivity, specificity, and challenge score even compared to other methods while they used more multiple signals of ECG, ABP and PPG. The best rank in the challenge [21] took into account the expert knowledge and processed only specific parts of the signals (the last potions of the signal?). Other methods such as [3] used several rule-based decision making based on expert knowledge and machine learning in different phases by using all the available signals to obtain the best result, while our proposed method is based on one ECG lead with a simple feature extraction method. Deep neuro-evolution [15] that involves much more processing and utilizes several input signals show weaker results related to our proposed method. The proposed approach in [14] is a light weight processing using a unsupervised representation learning to extract few features of the clustering of the beats, but the clustering step wipes out the temporal relation among the features. Table V also reports the results of several classifiers applied on wavelet features as generic approaches it can be seen in the most of them the scores much lower than other tuned methods.

VI. Conclusion

In this paper, a novel ECG analysis approach is proposed that provides unique abilities to process noisy and long time series recordings when the datasets are imbalanced. This method albeit uses one lead of ECG and completely stands on machine learning to learn from scratch and yet provides much better performance in comparison with the-state-of-the-art works that use several sensory information and processing units for each collected signal. The proposed framework offers significant performance for all arrhythmia types without any in advanced knowledge.

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