MEDINFO 2021: One World, One Health – Global Partnership for Digital Innovation
P. Otero et al. (Eds.)

doi:10.3233/SHTI220158

A Multi-Class Approach for the Automatic Detection of Congestive Heart Failure in Windowed ECG

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Abstract

Congestive heart failure (CHF) is a chronic heart disease that causes debilitating symptoms and leads to higher mortality and morbidity. In this paper, we present HARPER, a novel automatic detector of CHF episodes able to distinguish between Normal Sinus Rhythm (NSR), CHF, and no-CHF. The main advantages of HARPER are its reliability and its capability of providing an early diagnosis. Indeed, the method is based on evaluating real-time features and observing a brief segment of ECG signal. HARPER is an independent tool meaning that it does not need any ECG annotation or segmentation algorithms to provide detection. The approach was submitted to complete experimentation by involving both the intra- and inter-patient validation schemes. The results are comparable to the state-of-art methods, highlighting the suitability of HARPER to be used in modern IoMT systems as a multi-class, fast, and highly accurate detector of CHF. We also provide guidelines for configuring a temporal window to be used in the automatic detection of CHF episodes.

Keywords:
CHF, Machine Learning, DSS, Wearable, IoMT

Introduction

We are living in the era of wearable devices, which are important components of human health for the prevention of diseases or pathological conditions. These devices have become so widespread that they play an essential role in healthcare and telemedicine systems [1]. The key aim of incorporating technology into healthcare systems is to increase the quality and usability of medical devices and facilities by providing improved interfacing capability between patients and caregivers [2, 3]. In remote healthcare monitoring, the Internet of Medical Things (IoMT) played a critical role. The Internet of Medical Things is primarily used to collect remote data for patients via wearable sensors/devices and store it in cloud databases. These data are available to caregivers for real-time review and implementation and specific systems to provide automatic analysis [4, 5]. A recent example of a telemedicine system is ATTICUS [6, 7]. ATTICUS provides a bustier wearable [8] able to acquire at least 6-lead continuous electrocardiogram (ECG) signal and other vital parameters. A Decision Support System (DSS) [7] - structured as a distributed AI software - is in charge of providing the early diagnosis of several pathological conditions, which could require immediate attention by doctors.

One of such conditions is Congestive Heart Failure (CHF), a common pathophysiological condition common, with around 26 million adults diagnosed with the disease worldwide in 2014 [9].

Thus, much effort was undertaken by the scientific community to aim at automatically identify CHF. Most of the works propose a detector of CHF that provides a binary classification of a signal in CHF and Normal Sinus Rhythm (NSR) [10-13]. A minor part of the scientific community has modeled the CHF detection problem as a multi-class prediction problem to avoid that pathological signals different from CHF are erroneously classified as CHF [14]; in such cases, three classes are typically used: CHF, NSR, and no-CHF (i.e., pathology different from CHF). In both cases, a variety of temporal observations were adopted. For example, Xiong *et al.* [13] experimented with using an ECG segment with a fixed length in terms of samples, while Porumb *et al.* [12] relied on observations at heartbeat level. The main drawback of such approaches is that they provide only binary classifications [10-13] or depend on other safety-critical algorithms to obtain the ECG segmentation.

In this paper, we introduce HARPER (*detector of congestive **H**eart f**A**ilu**R**e e**P**isodes for m**E**dical suppo**R**t*), an automatic method to detect CHF in a single-lead digital ECG. *HARPER* is a near-real-time approach capable of multi-class identification of a given windowed ECG signal in CHF, NSR, and no-CHF (i.e., pathological rhythm, but different from CHF).

The main contributions of this paper are the following:

- we introduce *HARPER*, a reliable and independent detector because it is capable of providing a multi-class identification (instead of a binary one). It is not dependent on other algorithms (e.g., an R peak detector) for the ECG segmentation because it involves a fixed-length segmentation.
- Since CHF is a chronic condition [5], we conducted a complete study to assess the duration of the best temporal window in which to observe CHF. This was done within two scenarios: (i) *intra-patient* intended as the case when no personal data is available for a new subject to be monitored in ATTICUS and (ii) *inter-patients* when personal data are available in the training set.

The rest of the paper is structured as follows: Section 2 describes the planning of our study, highlighting the

workflow of *HARPER* and the datasets used, the experimental procedure and the validation schemes. Then, in section 3 "Results", the results obtained in all the experimental settings are described. Finally, section 4 concludes the paper by reporting analysis on the various outcomes and highlighting the future works.

Methods

In this section, we present the high-level workflow of *HARPER*. Then we describe the performed ECG processing and the context of this study. Moreover, we describe the experimental procedure and the validation schemes.

HARPER Workflow

The high-level workflow of *HARPER* is described as follows. First, we consider w the length of an observation window (in seconds). Then, *HARPER* takes the ECG signal from the patient as input, having a length greater than or equal to $w \cdot f$, where f is the sampling frequency of the ECG signal. Next, the ECG signal is divided into several segments based on the segmentation window. On each segment, we perform a feature extraction step. Finally, the extracted features are submitted to a trained machine learning model which performs the signal classification. In this way, as the output of the last step, *HARPER* provides a label for the most probable classification among NSR, CHF, and no-CHF.

ECG Signal Processing and Features Extraction

The signal processing performed on the ECG starts with the detrend operation, where the average of the signal is computed and subtracted from the input signal. Then the following literature features [15] are extracted: (i) energy of Maximal Overlap Discrete Wavelet Transform (MODWT), using db2 as Daubechies wavelet transform and 15 levels of decomposition [16], Autoregressive (AR) Model of order 16 [17], Multifractal Wavelet Leader [18], using db3 as wavelet transform and Fast Fourier Transform (FFT).

2.3 Study Design

The final goal of this study is to assess the suitability of *HARPER* as a detector of Congestive Heart Failure.

To achieve this, we designed two research questions:

- *RQ_1: What is* the optimal value of the w parameter? With the first research question, we aim to tune the w parameter to understand how many seconds of observation are needed to perform the best prediction;
- RQ2: What is the classification effectiveness of HARPER? With this second research question, we want to evaluate the accuracy of HARPER in the detection of CHF episodes.

We also want to evaluate *HARPER* in different validation techniques such as intra-patient and inter-patient (where the data of a subject is not or partially considered in the training of the model, respectively) strategies.

Context of the Study

In our study, we used a dataset of 162 ECG recordings extracted from the PhysioNet database [19], provided by MathWorks[1]. In the final dataset, there are 36 recordings of subjects with NSR, 96 with no-CHF anomalous episodes (*i.e.,* arrhythmia), and 30 recordings from subjects affected by CHF. The reason behind the use of this dataset is that (i) it is composed of signals from different datasets, providing a more heterogeneous set of ECG recordings, and (ii) it contains not only CHF recordings but also that no-CHF. In this way, *HARPER* can distinguish abnormal recordings with CHF episodes from abnormal but contains no-CHF heart diseases.

Baseline approach

We selected a recent approach from the literature, *i.e.,* the approach proposed by Yang *et al.* [14] as a reference baseline for the evaluation of *HARPER*. Beyond the high accuracy, we chose this work because the authors perform a three-class identification of ECG in NSR, CHF, and Coronary Artery Disease (CAD). Their approach combines an ECG fragment alignment (EFA) with principal component analysis (PCA) and a convolutional network (EFAP-Net) to ensure heartbeats consistency between subjects eliminating heart rate differences. Finally, they use a linear SVM as a classifier. They also successfully applied intra-patient and inter-patient validation techniques.

Table 1 - Evaluation of the best temporal ECG window and classifiers in the intra-patients scenario.

Model	Sampling	Preprocess	5s				10s				15s				20s			
			Se %	Sp %	Pre %	F1 %	Se %	Sp %	Pre %	F1 %	Se %	Sp %	Pre %	F1 %	Se %	Sp %	Pre %	F1 %
RandomForestClassifier	SMOTE	MinMaxScaler	97.73	**98.76**	97.76	97.74	98.67	**99.35**	98.69	98.67	98.46	**99.39**	98.49	98.46	98.64	**99.51**	98.67	98.65
RandomForestClassifier	-	-	**97.94**	98.08	**97.95**	**97.94**	**98.85**	99.07	**98.85**	**98.85**	**99.18**	99.24	**99.19**	**99.18**	**99.01**	98.98	**99.01**	**99.01**
SVM_Classifier	SMOTE	StandardScaler	97.43	98.69	97.48	97.44	97.76	98.82	97.80	97.77	97.91	99.35	97.99	97.92	97.90	98.85	97.94	97.91
SVM_Classifier	-	StandardScaler	97.43	98.21	97.44	97.43	98.25	98.68	98.25	98.25	97.91	98.71	97.93	97.91	98.15	98.45	98.15	98.15
KNeighborsClassifier	SMOTE	-	49.74	71.66	55.50	51.39	57.11	76.33	63.04	58.86	51.81	73.89	57.85	53.50	54.20	73.41	59.33	55.64
KNeighborsClassifier	-	-	58.79	57.82	55.30	55.68	63.04	61.83	60.30	60.88	60.25	60.90	57.35	57.81	61.85	61.80	59.87	60.01
LogisticRegressionClassifier	-	StandardScaler	94.49	95.44	94.49	94.49	96.85	97.54	96.87	96.86	96.82	97.68	96.84	96.83	97.16	98.04	97.19	97.17

Model	Sampling	Preprocess	25s				30s				60s				120s			
			Se %	Sp %	Pre %	F1 %	Se %	Sp %	Pre %	F1 %	Se %	Sp %	Pre %	F1 %	Se %	Sp %	Pre %	F1 %
RandomForestClassifier	SMOTE	MinMaxScaler	99.54	**99.70**	99.54	99.54	**99.27**	**99.36**	**99.28**	**99.27**	98.08	98.40	98.09	98.07	96.15	98.88	96.40	96.19
RandomForestClassifier	-	-	**99.69**	99.55	**99.69**	**99.69**	98.73	98.28	98.74	98.73	**99.23**	**99.26**	**99.23**	**99.23**	96.92	98.45	96.93	96.92
SVM_Classifier	SMOTE	StandardScaler	97.38	98.03	97.39	97.38	98.91	99.03	98.91	98.91	96.92	98.17	97.00	96.94	95.38	96.73	95.38	95.38
SVM_Classifier	-	StandardScaler	97.99	98.37	98.00	97.99	98.37	98.19	98.38	98.35	98.08	98.44	98.10	98.09	93.85	94.94	93.86	93.83
KNeighborsClassifier	SMOTE	-	50.93	73.08	57.02	52.69	46.46	68.32	52.63	48.18	46.54	67.72	54.51	48.71	44.62	73.56	51.71	46.51
KNeighborsClassifier	-	-	60.34	60.55	57.43	57.92	56.08	52.83	51.02	52.31	58.46	55.84	56.17	56.89	54.62	64.81	51.29	52.21
LogisticRegressionClassifier	-	StandardScaler	96.91	97.53	96.92	96.91	97.82	97.83	97.84	97.82	97.69	98.30	97.74	97.69	**97.69**	**99.42**	**97.93**	**97.74**

[1] PhysioNet ECG data - https://github.com/mathworks/physionet_ECG_data/

The main drawback of such an approach is that it involves the ECG segmentation at the heartbeat level, which could be less suitable in real-time scenarios because of the high computational cost of a robust R peak detector. Due to the consideration that CHF is a chronic condition, in *HARPER*, we tried to avoid any dependence on external algorithms, and we only focused on a fixed-length observation of the ECG. Indeed, in the context of ATTICUS, we needed to design a highly reliable *near* real-time approach of CHF episodes in two scenarios: when personal data are available in the monitoring and when a new ATTICUS user has to be continuously monitored.

Experimental Procedure

For what concerns RQ1, as we want to evaluate the best ECG temporal window to provide an accurate multi-class detection (therefore a better observation of CHF episodes), we need to (i) split the ECG recordings into segments and (ii) assess the best classifier that is possible to define on the top of that data is. First, we defined a set of possible durations of time windows. Furthermore, we performed the ECG segmentation based on the defined temporal windows and the extraction of the previously described features. We selected a set of time windows ranging from 5 to 120 seconds. We extracted a total of 321 features, where 256 are resulted from FFT, 16 from MODWT, 16 from Multifractal Wavelets and 33 from the AR Model.

Next, for the intra-patients scenario, we built different machine learning pipelines, testing out different models in combination with pre-processing and sampling techniques. In this way, we aimed to assess which is the best temporal window and which could be the best model to use for the specific intra-patients scenario. For example, for RandomForest, we only applied a min-max scaling, but for SVM, we applied standardization. We also evaluated the impact of data balancing techniques, such as SMOTE [20]. In detail, we first removed highly correlated features, removing those having a Pearson correlation coefficient *r* greater than 0.95. Then, we applied a tree-based estimator feature selection technique, where the impurity-based feature importance is computed. The parameters used were 100 as the *n_estimators* and 1.25*median as the *threshold* for feature importance. In this way, we discarded the irrelevant features according to their importance. The resulting number of features could vary based on the temporal window used for the ECG segmentation. The final step of our classification pipeline consisted of a combination of a random split of training and test set (*i.e.,* 80-20), data sampling (*i.e.,* SMOTE), data pre-processing (*i.e.,* scaling, standardization), and a classification algorithm. We used the default parameters for each classification algorithm, as provided by the Python library scikit-learn[2]. Finally, we opted for using the best model obtained from the intra-patients scenario to assess the best window duration also in the inter-patient scenario. The pre-processing scheme used was the same.

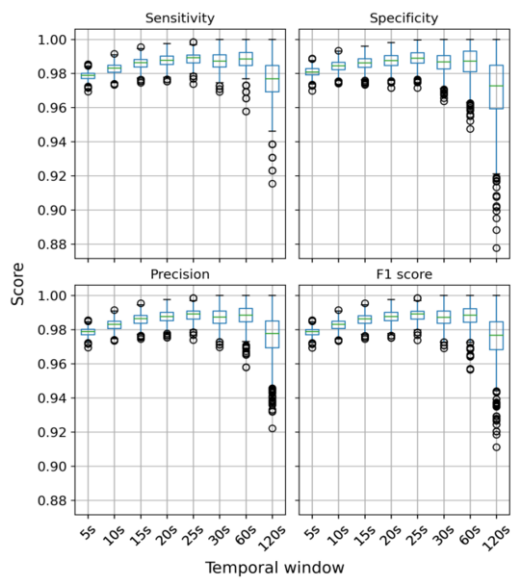
We evaluated the classification performance using widely-used metrics for classification tasks, namely *Sensitivity, Specificity, Precision, F1 score.*

Table 2 - Dataset overview after ECG segmentation

Temporal window (seconds)	ARR	NSR	CHF	Total
5	9792	3672	3060	16524
10	4896	1836	1530	8262
15	3264	1224	1020	5508
20	2400	900	750	4050
25	1920	720	600	3240
30	1632	612	510	2754
60	768	288	240	1296
120	384	144	120	648

With respect to RQ2, taking into account the results of RQ_1 and to assess the classification performance of *HARPER*, we conducted its validation considering the best ECG time window combined with the best performing classification pipeline. Moreover, we compared our approach with the selected baseline [14] to assess if *HARPER* has comparable performance to a state-of-the-art approach for CHF detection. As we used the random split technique to split the dataset into training and test set, we decided to perform 1000 executions to reduce a possible bias due to the randomness. On the other hand, for the intra-patient protocol, we performed *n* executions where *n* corresponds to the number of patients in our dataset (*i.e.,* 162). A specific patient is selected for each execution as the test set, and the remaining are used as the training set. In this way, the model observes a brand-new set of ECG recordings not evaluated before. We used the same classification metrics in RQ_1 (*i.e., Sensitivity, Specificity, Precision, F1 score.*), taking the average value across all patients.

Figure 1 - Metrics distribution for the intra-patient scheme.



[2] scikit-learn - https://scikit-learn.org/

Results

In the following sub-section, we describe the results achieved to answer our research questions.

RQ1: ECG Segmentation

In Table 1, the results of our experiment in the intra-patients scenario are reported. The percentage scores are displayed for each time window related to the classification metrics corresponding to each classification pipeline, where we described the used model and the data pre-processing techniques.

The primary outcome of this experimentation is that an observation of 25 seconds allowed to obtain the best overall metrics with a pipeline composed only of a RandomForest model. In this case, the results exceeded 0.99 on all the evaluated classification metrics. In Figure 1, the boxplots of the classification metrics are obtained by experimenting with each time window. In particular, from this distribution of data, it is also possible to derive how the time observation with the highest median of the classification performances is the 25 seconds window. However, the 20 and 25 time windows are the best in terms of robustness because even the outliers are approximately above 0.96. On the contrary, this happens for the 120s time window. For example, the Specificity score is below 0.88, considering the outliers below the first quartile.

The results of the intra-patient validation protocol showed that in this specific condition, the best time window is defined by 60 s and not 25 s as previously obtained in the other scenario (93.13 vs. 91.64 in terms of F1 score).

The reason behind this could be that in the case of a patient that is never examined before, a larger time window (i.e., a longer ECG buffering) is needed to achieve an accurate classification.

RQ2: HARPER Classification and Validation

Considering the results from RQ1, we used a reference time window of 25 seconds and the raw RandomForest as a reference classification pipeline. We also executed the validation on the other temporal windows to compare and verify if the previously selected time window is the best also in an inter-patient scenario. In Table 3, the average percentage classification metrics of the validation protocol are reported for the inter-patient scheme. We achieved a score slightly worse than the one achieved in RQ1 (where we reported the results of a single execution), but we aimed to preserve the repeatability of our experiment by avoiding the contribution of randomness.

Table 3 – Classification metrics of HARPER using a window of 25 seconds and inter-patient validation.

Class	Se (%)	Sp (%)	Pre (%)	F1 (%)
NSR	98.74	98.30	99.23	98.98
CHF	97.63	99.67	98.55	98.08
ARR	99.31	99.78	98.83	99.07
Avg.	**98.88**	**98.87**	**98.88**	**98.87**

We compared our two validation results with the baseline approach where we only considered the NSR and CHF classes from the multi-class detection because one of our classes (ARR) differs from the one proposed by Yang et al. [14] (CAD). In Table 4, we reported the results compared to the baseline approach. On the left side, there are the results of the intra-patient validation where the baseline approach slightly outperforms *HARPER* for a few percentage points. This could be due to their perfectly balanced dataset. For the inter-patient validation (right side), in some cases HARPER outperforms the baseline on both the NSR and CHF classes. Mainly for the CHF class, we have better Sensitivity and Specificity values but a lower Precision value. This means that our approach has more false positives than the baseline.

Threats to validity

The best procedure would have involved the tuning of all design parameters on one dataset and their validation on a completely different dataset of patients. To mitigate this limitation and work on the only available dataset, we opted to introduce robust validation schemes: L1SO and x1000 80-20 Cross Validation.

Table 4 - Classification performance compared with the baseline approach [14] of intra-patient validation (left) and inter-patient validation (right).

Class NSR

Metric	Our approach	Yang *et. al* [14]	Delta
Se (%)	98.74	99.82	-1.08
Sp (%)	98.30	99.93	-1.63
Pre (%)	99.23	99.86	-0.63
F1 (%)	98.98	99.84	-0.86

Class CHF

Metric	Our approach	Yang *et. al* [14]	Delta
Se (%)	97.63	99.82	-2.19
Sp (%)	99.67	99.90	-0.23
Pre (%)	98.55	99.81	-1.26
F1 (%)	98.08	99.81	-1.73

Class NSR

Metric	Our approach	Yang *et. al* [14]	Delta
Se (%)	98.95	92.44	**6.51**
Sp (%)	99.60	99.26	**0.34**
Pre (%)	98.61	98.79	-0.18
F1 (%)	98.78	94.46	**4.32**

Class CHF

Metric	Our approach	Yang *et. al* [14]	Delta
Se (%)	91.94	83.85	**8.09**
Sp (%)	93.78	89.36	**4.42**
Pre (%)	71.25	73.04	-1.79
F1 (%)	80.28	77.41	**2.87**

Conclusions

The results of this work clearly highlight that a longer (60 s) observation of the ECG is needed to best detect CHF episodes when monitoring in real-time a new user of an IoMT system. The duration can be reduced (25 s) once enough data points are made available to the ML pipeline.

HARPER is highly accurate, and it showed great potential to be embedded in scenarios of continuous monitoring due to its high accuracy in detection and technological independence. Indeed, no other algorithms are needed to obtain the ECG segmentation.

HARPER can be considered reliable because it also concerns the classification of pathological rhythm different from CHF.

As part of our future agenda, we plan to validate the accuracy of HARPER (i) when common ECG noises (electrode movement or motion artifact) are spread in the signal and (ii) within the signals directly acquired by the ATTICUS smart vest.

Acknowledgments

This work is supported by the project PON-ARS01_00860 titled *Ambient-intelligent Tele-monitoring and Telemetry for Incepting and Catering over hUman Sustainability - ATTICUS* funded by the Italian Ministry of Education and Research - RNA/COR 576347.

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