Early Detection of Decompensation Conditions in Heart Failure Patients by Knowledge Discovery: The HEARTFAID Approaches

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Abstract

For the clinical management of chronic heart failure (CHF) patient, a crucial mid-long term goal is the early detection of new acute decompensation events, for improving quality of outcomes while reducing costs on the healthcare system. Within the relevant clinical protocols and guidelines, a general consensus has not been reached about the prediction of further decompensations, even though many different evidence-based indications are known.

Under this respect we adopted Knowledge Discovery (KD) approaches as a practical and effective solution to extract new potentially useful facts from repositories of pertinent clinical data. In fact, we present the KD task which has been implemented into the EU FP6 Project HEARTFAID (www.heartfaid.org), aiming at developing an innovative knowledge based platform of services for more effective and efficient clinical management of heart failure within elderly population. 49 CHF patients were recurrently visited by cardiologist, measuring clinical parameters taken from clinical guidelines and evidence-based knowledge. Also general information about each patient was taken into account for the analysis. Several KD algorithms were applied on collected data, obtaining different binary classifiers performing the early detection of new acute decompensation events. Some of these models are "easy-to-understand" and their consistency was directly evaluated by the cardiologists. Moreover, high percentage of correct classifications (above 87%) was obtained by using suitable validation approaches.

1. Introduction

Chronic Heart Failure (CHF) is a complex clinical syndrome which impairs the ability of the heart to pump sufficient blood to cover the body's metabolic needs. This can severely affect people's ability in their normal daily activities, and it is a leading cause of hospital admissions and deaths, a strong impact in terms of social and economic effects[1,2]. CHF prevalence increases rapidly with age[3], with a mean age of 74 years, and the increase in the proportion of elderly population concurs in rising prevalence of heart failure. In particular, according to the European Society of Cardiology, there are at least 10 millions of patients with heart failure in the European countries.

Although heart failure is a chronic syndrome, it does not evolve gradually. Periods of relative stability alternate with acute destabilizations. During a stable phase the crucial mid-long term goal should be to predict and, hopefully prevent, destabilizations and death of the CHF patient, reducing the burden of heart failure on the healthcare system while improving the quality of life of affected patients.

Although a system of frequent monitoring could be useful for clinicians to recurrently evaluate the patient condition and eventually provide intervention before CHF patient becomes as severely ill as require re-hospitalization[4], symptoms and signs of HF remain often difficult to identify. Moreover, within the relevant clinical protocols and guidelines, a general consensus has not been reached about the definition and assessment of criteria on how to predict when a patient will further decompensate, even though many different evidence-based indications are known.

For such reasons, Knowledge Discovery techniques may be a practical and effective solution for generating and proving new hypothesis, mining and generalizing new medical knowledge directly from pertinent real examples. We present a KD task for the extraction of new decision models able to early detect new decompensation events. The KD task was performed within the EU FP6 Project HEARTFAID (www.heartfaid.org), aiming at developing an innovative knowledge based platform for more effective and efficient clinical management of heart failure within elderly population. Decision models extracted through KD task were embedded into the Clinical Decision Support System (CDSS) of HEARTFAID, integrating the platform's knowledge base. We used different Data Mining approaches, such as Decision Trees, Decision Lists, Support Vector Machines and Radial Basis Function Networks. As main result, in this paper we present a Decision Tree able to predict in a plausibly way a CHF patient destabilization.

2. Methods

2.1. Patient recruitment

A group of 49 patients with established CHF diagnosis was recruited and visited frequently (every two weeks) at the Cardiovascular Diseases Division, Department of Experimental and Clinical Medicine, Faculty of Medicine, University "Magna Graecia" of Catanzaro, Italy. During each visit medical doctor measured and stored values of a set of different clinical parameters, selected from guidelines and clinical evidence-based knowledge: Systolic Blood Pressure (SBP), Heart Rate (HR), Respiratory Rate (RR), Body Weight (weight), Body Temperature (BT) and Total Body Water (TBW). Furthermore, the patient condition evaluated by the cardiologist during the visit, was stored too. Patients recruitment started on February 2007 and subjects were recruited in different periods during the survey campaign. For each patient general information was stored too, such as gender, age, NYHA class, alcohol use and smoking. Moreover, monitored parameters are easy to be acquired at home setting in respect to the HEARTFAID project's goals.

2.2. Knowledge discovery task design and dataset construction

We defined the KD analysis as a "prediction task", in which every instance is represented by the general patient information and by the value of the aforementioned clinical parameters measured during a visit. The class label for each instance was defined on the base of the clinical condition assessed by the medical doctor "at the successive visit" (two weeks later). Starting from the available data we built a suitable dataset on which we applied several classification learning techniques.

Under respect to our formulation, only visits in which the patient was in a stable condition were useful to carry out the designed prediction task. In this way we had to perform a preliminary case-selection so that the final dataset was relative to 43 patients, for 301 valuable visits (instances). General descriptive about the dataset is reported in table 1.

Table 1 –Descriptive about dataset

	All	Male	Female
Patients	43	9	34
NYHA class (I, II, III, IV)	0, 28, 15, 0	0, 4, 5, 0	0, 24, 10, 0
Age	71.19±10.03	69.44±11.08	71.65±9.86
Smoking	7	0	7
Alcohol use			
No	18	8	10
Mild	12	1	11
Moderate	8	0	8
Severe	5	0	5
At least 1 new decompensation	9	4	5

2.3. KD methodologies

In a first step we used KD methodologies able to extract knowledge in a form easy to understand by the clinical domain experts, as Decision Trees[5-7] and Decision Lists (a set of rules[8] to be strictly interpreted in sequence: the first satisfied rule suggests the class of the instance).

The information extracted from the data was initially evaluated through suitable validation techniques, then the plausibility of the most performing classifiers were evaluated by the medical doctors.

In the next step other computational KD approaches, which extract models in an intrinsic form, were used, such as Support Vectors Machines[9] and Radial Basis Function Networks[10].

Unfortunately, our dataset showed a highly skewed class distribution, a common situation in many medical real-world data mining problems[11]. The dataset has only 11 new decompensation events (positive class) and 290 cases of stability persistence (negative class), but in our work the class of primary interest is the minority one, so it has a much higher misclassification cost than the majority class. Under this respect, when possible, we combined classical classification learning algorithms to a cost sensitive classification approach.

To evaluate the performance of extracted models we implemented a validation technique similar to leave-one-out validation, that we named "leave-patient-out validation". This approach works leaving apart (as test set) all the instances into the dataset which are relative to a patient, while all the remaining instances are used as training set. This procedure was repeated for each patient and the classification performances were averaged on all the folds.

3. Results

A first indication was obtained by a classical statistical approach: Respiratory Rate measured at current visit is potentially useful for preventing a new decompensation event. In fact, two weeks before a new assessed decompensation, value of RR is higher than during a visit relative to a stability persistence (Mann-Whiteny test: U=740 p-value= 0.002). This difference is showed in figure 1 (stability persistence: RR=20.21±3.48 min=12 Max=32; successive decompensation: RR=24.27±4.34 min=16 Max=29).

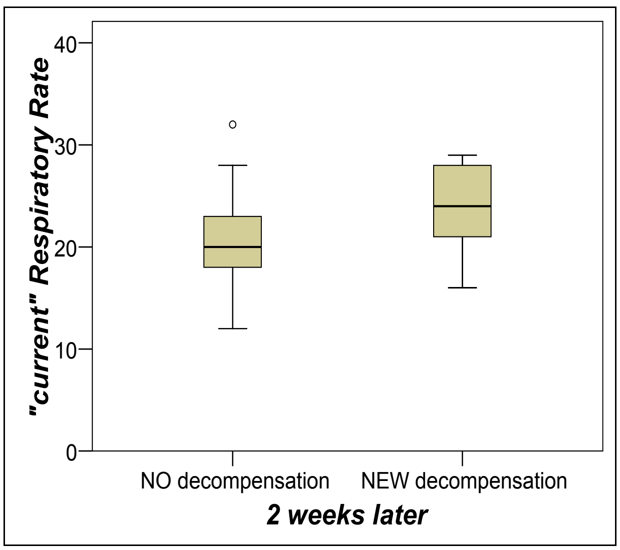

Figure 1 – current Respiratory Rate and condition at 2 weeks later

The difference on RR is significant for women (Mann-Whitney test: U=128.5 p-value<0.001) but not for men (Mann-Whitney test: U=106.5 p-value=0.497). It is showed in figure 2 and in table 2.

No other significant differences were founded for the other clinical parameters.

Table 2 – current RR and condition at 2 weeks later in men and women

	"current" Respiratory Rate	
	Male	Female
Successive decompensation	21.60 ± 4.56 (16-28)	26.50 ± 2.81 (22-29)
Stability	20.31 ± 3.20 (16-28)	20.19 ± 3.55 (12-32)

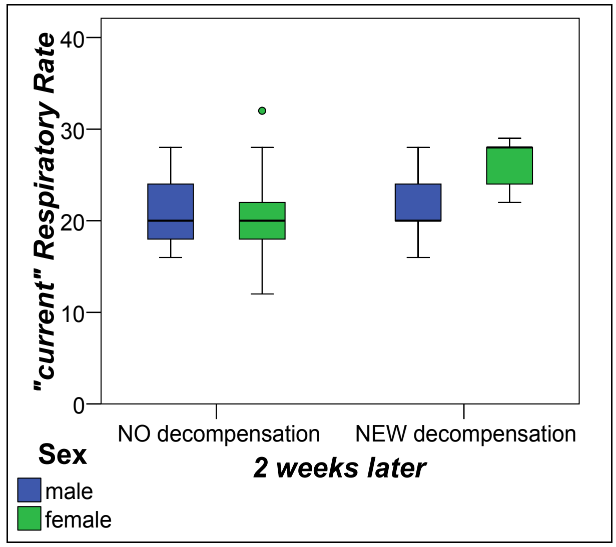

Figure 2 – current RR and condition at 2 weeks in men and women

For KD analysis all the available information was initially taken into account: value of clinical parameters at current and next visit, simple and relative variations of such values, and all general information about the patient.

However, the best result, which we present in this paper, is relative to a Decision Tree able to predict the patient condition at 2 weeks later, based only on a subset of the clinical parameters measured <u>at current</u> visit and on gender of patient (figure 3).

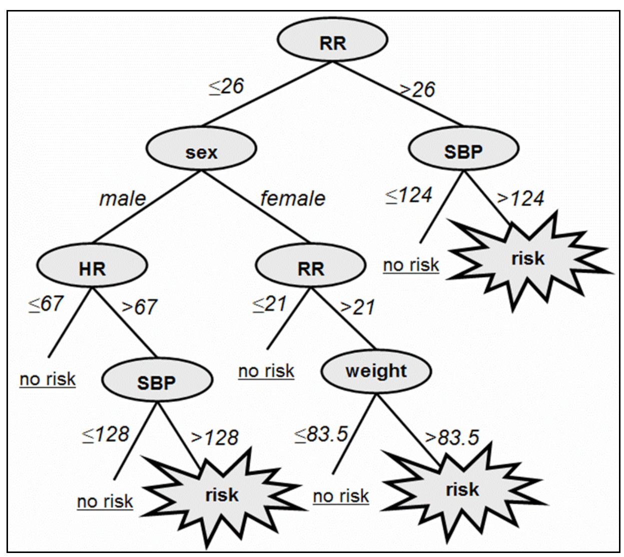

Figure 3 – Decision Tree form KD analysis

The tree presents a really simple structure and it is very easy to understand. The root node of the tree is a test on RR, identifying this parameter as the most relevant one in order to predict a new decompensation (according to the results from statistical analysis). In particular, a CHF patient with RR greater than 26 acts-per-minute (apm) and SBP greater than 124 mmHg, may decompensate in 2 weeks. This rule is associated to 5 of the 11 positive cases in our dataset but it covers also 5 false positive examples. Another rule that suggests a new decompensation in 2 weeks is relative to male patients with RR less or equal than 26 apm, HR garter than 67 bpm and SBP greater than 128 mmHg. This rule is associated to 4 of the 11 positive cases into dataset but it covers also 10 false positive cases. Finally, female patients with RR between 21 and 26 apm, and weight greater than 83.5 Kg may decompensate in 2 weeks. This rule covers only 2 positive cases in our dataset and 14 false positive examples. Female patients with RR less than 21 apm present the condition with higher probability to maintain stability: 172 negative cases in our dataset are covered by this rule and no false negative ones.

Generalization performances were evaluated through leave-patient-out validation technique, obtaining the best result for the learned tree (Accuracy: 92.03%, Sensitivity: 63.64%, False Positive Rate: 6.90%). Although the sensitivity is relative low, this is best obtained over all the adopted KD approaches. Another good performing model is a decision list (Accuracy: 88.04% Sensitivity: 63.64% False Positive Rate: 11.03%), but it showed a more high false positive rate. We also obtained computational models (SVM classifiers) with a high accuracy on validation (89.70%) but with very low sensitivity. For such reasons, presented decision tree is the only extracted model which may be adopted to perform an early detection of possible new decompensation events.

4. Discussion and conclusions

We presented a KD task which was implemented in HEARTFAID project with the goal to obtain predictive models able to early detect if a CHF patient in stable phase will further decompensate. The study was performed on a group of CHF patients recurrently visited by cardiologists, every two weeks. We presented a decision tree which was evaluated in terms of predictive performance (accuracy and sensitivity) through a suitable validation technique and which was checked by clinical experts in terms of plausibility.

In some tree's rules, clinical experts recognize earlier physic-pathological mechanisms of decompensation.

According to the tree learned from data and to results from statistical approach, they confirmed that RR may be a predictive factor for a new destabilization. From a clinical point of view, the possible physic-pathological explanation could be that when the heart becomes unable to pump, an increase in left ventricular telediastolic pressure could occur. This shows an increase in pulmonary pressure and a consequent reduction of gaseous exchanges, which causes an increase of RR as compensation. These changes could occur before than an evident impaired cardiac function, which is characterized by a decrease of SBP and an increase of HR, and it is the cause of the acute and severe symptoms afterwards referred by the patient.

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