A System to Improve Continuity of Care in Heart Failure Patients

G. Guidi[1], P. Melillo[2], M.C. Pettenati[3], M. Milli[4], and E. Iadanza[1]

[1] University of Florence, Dept. of Information Engineering, Italy
[2] University of Bologna, Dept. of Electrical Energy and Information Engineering, Italy
[3] ICON Foundation, Florence, Italy
[4] Azienda Sanitaria Fiorentina Dept. of Cardiology, Italy

Abstract— **In this paper we expose the design of a system for the remote monitoring of Heart Failure (HF) patients, complemented by an Artificial Intelligence (AI) engine to perform a classification of patients severity on a three levels scale: mild, moderate and severe. The system allows multiple care regimes: a scheme called IHC (Integrated Home Care) and a scheme called CIHC (Continuous Integrated Home Care). The first needs that a health care worker is traveling periodically to the patient's home to perform various measurements of physiological parameters, the second is fully automatic but requires that a kit for the automatic acquisition of the parameters is provided to the patient. In results section we show performances of AI, trained using our clinical partner database, in assessing HF severity and HF type that are respectively 89% and 86% hold out accuracy. This system would facilitate the application of the principles of the Chronic Care Model, in our case regarding the assistance for Heart Failure, but the system is scalable to many other chronic diseases. Due to the amount of input parameters and the fact that HF involves the whole body, we believe that it can be the right disease for the prototype of a disease-specialized system that allows structured communications between hospital and territory.**

Keywords— **Heart Failure, Telecare, Automatic diagnosis, Artificial Intelligence, Chronic Care Model.**

I. INTRODUCTION

Telemonitoring of Heart Failure (HF) is an issue of increasing interest, as alternative strategies of care to patient hospitalization could be affordable methods to maintain and improve the quality of care for HF [1]. This is crucial since the increased prevalence of HF (due to the ageing of populations) makes it difficult to maintain the quality of care with limited use of resources. For that reason, a recently published systematic review [1] compared the effectiveness of management delivered via structured telephone support or telemonitoring with usual post-discharge care in patients with HF, living within the community. This review showed that the alternative programs of care had a positive effect in reducing death and re-hospitalization rates, especially for strategy of care based on more advanced technologies. This evidence has motivated the development of an HF system whose main objective is to enable telemonitoring at patient's home or other point of care by non-specialist staff equipped with devices for automatic detection of vital signs, in order to improve the collaboration with specialist staff. This scheme can be represented by a "triangle of HF" (See Fig. 1) whose vertices are the cardiologists, the general practitioner (or other care staff) and the patient. In fact, according to the Chronic Care Model (CCM) [2] we paid a particular attention in designing the system so that the patient is able to actively participate and collaborate with care process and physicians and nurses. We thought that such a system should have three components: a multiparametric device to easily perform measurement at patient's home, a web-based platform to manage patients data and allow communication between care actors (patient included) and a Computer Decision Support System (CDSS) to assess the severity of HF and to provide other smart functionalities understandable also to non-experts.

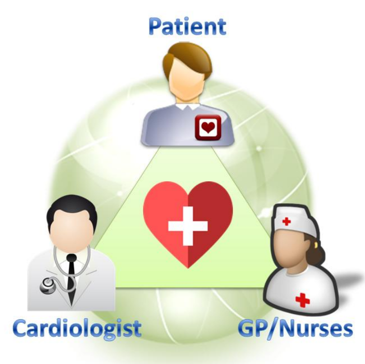

Fig. 1: Heart Failure Triangle.

II. MATHERIALS AND METHOD

In this section we described the whole system parts:

- web architecture (and the whole system design), including various scenarios;
- Artificial Intelligence (AI);
- home measurements devices kit and data transfer.

A. Whole System Design and Protocols

The system is suitable for use in two telemonitoring application scenarios, corresponding to two different care schemes. The choice of appropriate care scheme depends on patient's age and HF severity.

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Care schemes are:

- IHC (Integrated Home Care): a trained but non-specialist team (nurses) goes regularly to the patient's home provided with a parameters acquisition kit. Using a tablet PC the acquired data are immediately sent to a server and analyzed by the Artificial Intelligence that calculates HF severity and eventually generates a warning (Fig. 2).
- CIHC (Continuous Integrated Home Care): The patient is equipped with a device that automatically guides him in measuring the parameters and then sends the data to the central server (see section C. Device Kit). The data are then analyzed by the AI in a slightly different way from the IHC scheme. This automation makes it possible to obtain a daily update of patient conditions, together with some more outputs by the AI (Fig.3). The system can be profitably linked to some system for the automated tracking of the patient's position (e.g. using radiofrequency identification), in order to achieve a full context aware patient management [3].

Fig. 2: IHC monitoring schema.

In principle, a patient is more serious is the most appropriate to the CIHC. So for elderly patients would be more appropriate a CIHC schema in order to ensure a more continuous monitoring, however, is to be evaluated case by case the patient's compliance to the technological necessary devices. In collaboration with Dep. of Cardiology of S. Maria Nuova Hospital, Florence, Italy, we developed a clinical protocol suitable for our project. In this protocol we decided which parameters are more related with HF and how often they should be measured, consistently with the monitoring scenario. The measured parameters and their acquisition rates are listed below.

Comprehensive framework (hospital discharge - outpatient):

- Registry, etiology, comorbidity, symptomatology
- Weight
- BIVA (Bioelectrical Impedance Vector Analysis)

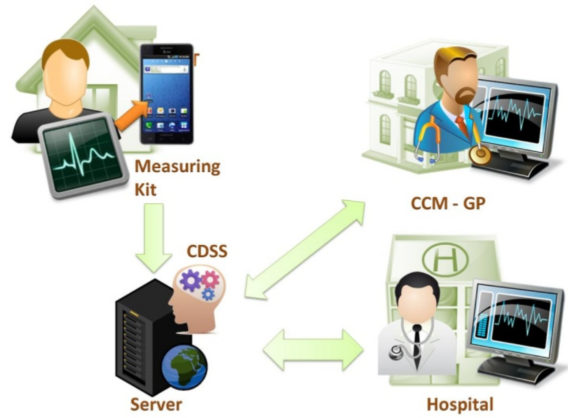

Fig. 3: CIHC monitoring schema.

- Ejection Fraction (EF)
- Brain Natriuretic Peptide (BNP)
- Systolic and Diastolic Blood Pressure (SBP, DBP)
- SpO_2
- Heart Rate (HR)
- Complete ECG (signal + medical report)
- Therapy

Once a day, measured by the patient himself (CIHC case)

- BIVA (at point of care)
- Weight
- Pressure
- SpO_2
- 2-leads ECG and HRV (Heart Rate Variability) parameters

Once a week by nurses (IHC case)

- BIVA
- Weight
- Pressure
- SpO_2
- Automatic ECG (signal + automatic medical report)
- Symptomatology
- Therapy

Once a month by nurses (IHC and CIHC):

- In addition to the weekly standard parameters, every 4 weeks the team will also detect the BNP using a handheld device.

Una Tantum (3-6 months depending on the patient condition)

- In-hospital cardiology visit (including EF measurement)

B. The Artificial Intelligence

To facilitate the choice of a non-expert and also to help experienced staff in decision-making, the system is equipped with an artificial intelligence that provides different outputs, depending on whether the patient is under the IHC or CIHC care scheme. See Table 1.

We have compared various machine learning algorithms in order to choose the best and we finally used the one that best deals with the typical HF data. [4]

Table 1: System's AI Outputs.

Output name	Output Values	Care Schema
HF Severity	Mild/Moderate/Severe	Both
HF Type	Stable, Ex1 (<2 exacerbation/year), Ex2 (>=2 exacerbation/year)	Both
Worsening Prediction	Alert, incoming exacerbation in next few days.	Only CIHC
Score Based Prognosis	Survival score automatically calculated with 4 literature models*	Both

* Models are [5], [6], [7], [8].

The compared algorithms are a Neural Network [9], a Support Vector Machine (SVM) [10] tree (the tree is due to the 3 levels outputs, since SVM is a binary classifier), a Fuzzy Expert system whose rules are genetically produced using Pittsburgh approach [11], a Classification and Regression Tree (CART) [12] and its natural evolution that is the Random Forest algorithm [13]. The best performing algorithm is Random Forest [14], which provides slightly better results than CART. Compared to CART the weakness of Random Forests is a lack of readability of the process that drives to the outputs. CART is a very often used algorithm in Heart Failure field. [15] In addition, the system provides other indications coming from the comparison among the various follow-up parameters. Possible examples are patients improvement and its correlation to changes in therapy. The Random Forest is trained using an anonymized database, provided by our clinical partner, containing the input data of 136 patients. Unfortunately, we still lack sufficient follow-up data in order to properly train the system to give the "Worsening Prediction" output. The whole system is supported by a management graphical interface developed with .NET framework. Such interface is also used by our clinical partner to collect data during his cardiology outpatient visits. These data are useful for a continuous machine training. We need the training target to be stored in the database, since our machine uses a supervised training. So, at the time of the data collection, the specialist physician provided an HF severity assessment using the three levels scale showed in Table 1. Moreover, after 12-24 months from the data collection, the status of each patient in terms of HF type was assessed and associated to the corresponding record. This made possible to train all the implemented machine learning techniques.

C. Devices Kit

Two kits of multiparametric acquisition are needed. Regarding the IHC scheme the kit, called nurse-kit, is simply composed of portable instrumentation for the various measurements together with a tablet that allows the transmission and storage of the immediate data using a custom application. The CIHC scheme requires that the patient is self-sufficient in measuring the needed parameters. A kit suitable for this project could be the one proposed by Evolvo [16], which consists of a smartphone connected to multiple devices via Bluetooth. One app reminds the patient when it is time to take measurements and guides him through the necessary operations. After the acquisition phase, all data are then transmitted to the central server via 3G.

III. RESULTS

The showed results are related to the Artificial Intelligence performances. We completed hold-out and cross-validation tests. Table 2 shows results of Random Forest algorithm in assessing HF severity and HF type. We defined an error as "critical" when a patient with Mild HF is classified as Severe and vice versa. Accuracy is calculated using multiclass formula as recommended in [17]. Performances of various AI techniques are accurately compared in [18].

$$Accuracy = \frac{\sum_{i=1}^{N^\circ\,class} \frac{TP_i+TN_i}{TP_i+TN_i+FP_i+FN_i}}{N}$$

Table 2: Random Forest results in HF severity and HF type assessing.

Valid. Method	Average Accuracy	N° of Critical Errors*
HF Severity - Hold Out	89.39%	0/35
HF Severity - Cross Validation	83.30%	1/99
HF Type - Hold Out	86.36%	4/39
HF Type - Cross Validation	85.68%	5/122

*Number of possible Critical Errors varies with the considered dataset.

IV. DISCUSSION AND CONCLUSIONS

In this article has been presented a telemonitoring system for patients suffering from Heart Failure, that aims to make it easier to apply the principles of the Wagner's Chronic Care Model on this pathology. The system is easily applicable to other chronic diseases. Particular attention was paid to patient self-care, by giving him the right tools for a constant easy self-monitoring and continuous connection with the physicians. The other presented solution (IHC scheme) is thought for all those cases when there is a lack of available technologies and infrastructures and for those patients that are not confident with advanced technological tools. This solution is not fully automatic but does not require specialized personnel to make periodic measurements at the patient's home. To achieve this and to automate the process, it has been necessary to train an artificial intelligence engine in order to recognize the severity of Heart Failure. In the results section we showed the performance of this AI. We were able to train most features through outpatients data, achieving an accuracy higher than 83% which is a good result for a 3 levels classifier. This system will help in decreasing the hospital overload caused by chronic diseases, reflecting and facilitating the principles of the CCM. Using the telematics infrastructure on which the system is based, the structured communications between General Practitioner and Specialist Cardiologist are empowered and facilitated. The existence of medical devices at patient's home requires an appropriate system design and management from the hospital's clinical engineering department, both for the correct maintenance and for electromagnetic interferences issues [19], [20]. A detailed description of the custom desktop tool currently used by our clinical partner (Dept. of Cardiology of S. Maria Nuova Hospital, Florence, Italy) can be found in [21]. The system as a whole instead is still in a development phase and it's not in operation.

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