Advanced Medical Expert Support Tool (A-MEST): EHR-based Integration of Multiple Risk Assessment Solutions for Congestive Heart Failure Patients

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Abstract— **More and more the continuum of care is replacing the traditional way of treating the subjects of care putting people in the centre of the healthcare process. Currently clinicians start treatment after a problem occurs due to the low adoption of Clinical Decision Support Systems (CDSS) integrated with standardised Electronic Health Record (EHR) systems; The volume to value revolution in the healthcare (from stakeholder-centric to patient-centric) will allow doctors to follow the evolution of the individual before a medical episode happens, treating the patient based on statistical trends to forecast the future. The CDSS techniques applied on tele-monitoring tools permit the doctors to predict forthcoming events, improve the diagnosis and avoid continuous visits to the hospital, therefore saving costs. Advanced Medical Expert Support Tool is a step towards achieving the patient-centric approach by incorporating the health information into the EHR using European standards (ISO/EN 13606) to provide semantic interoperability by means of the dual model approach (reference model and archetypes). Three different CDSS modules have been implemented and contextualised publications are provided to the cardiologist to facilitate their daily work. A person-centric Graphical User Interface (GUI) facilitates the visualization of the health status of the patients providing meaningful information to the cardiologists. The use of archetypes allows scalability, transparency and efficiency to the hospital environment.**

Keywords— **Risk assessment, EHR, Congestive Heart Failure, Clinical Decision Support System, Person-centric**

I. INTRODUCTION

A. Clinical problem

High interest and intense research can be observed on developing effective tools to assess impending risks in Congestive Heart Failure (CHF) patients, including home and/or ambulatory tele-monitoring [1]. However, apart from few studies with implanted materials and less than optimal results [2][3], most work up to date concentrated on ECG and blood pressure changes [4]. Multi-parametric time-domain integration was not considered, nor were parameters such as ambient or skin temperature and humidity or the amount of exercise [5]. Risk modeling was classically evaluated at relatively medium- or long-term so that predictability was frequently diluted into a long list of relatively unspecific elements without a constant relevance consensus among experts. By contrast, short- and very short-term risk parameters and their multiple interactions were not deeply assessed [6].

B. Technical solution

EHR standards must be considered in CDSS in order to facilitate the exchange of information in a machine-readable format [7]. The adoption of standardised EHR allows processing the information more effectively across multiple Hospital Information Systems (HIS) and care settings. Standards need to clearly represent (i) Terminologies and information models and (ii) Clinical knowledge [8].

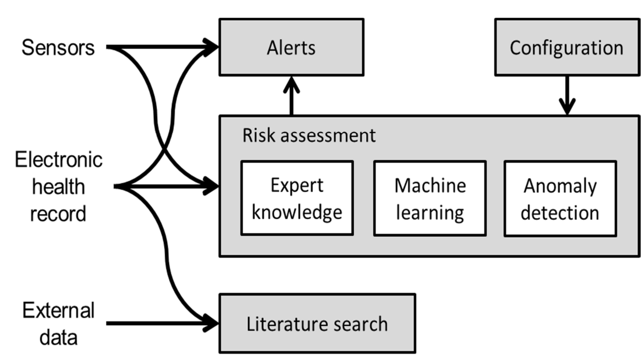

Fig. 1 – The architecture of the CDSS

Three different CDSS modules have been implemented and an intelligent search tool to recommend external content from the literature, contextualised to the specific patients. All the information is stored using archetypes and each component can operate independently from each other.

The modules are seamlessly integrated in the Advanced Medical Expert Support Tool (A-MEST), which also has the following features:

- **Scalability and transparency**
- **Openness**, by means of standards
- **Robustness**, integrity and confidentiality
- **User-friendliness**, through rich visualization

The use of archetypes permits the EHR integration fully compliant with the European standard EN13606 [9].

II. ARCHETYPES FOR EHR INTEROPERABILITY

The semantic interoperability (SIOp) addresses the issue of how to seamlessly exchange the information between health services providers and patients [10]. The openEHR and ISO/EN 13606 standard follow the two-level modeling approach which separates out the clinical knowledge from the information model. The former are the clinical concepts which are modeled using archetypes and the latter remains static and it is composed by a few immutable classes leaving the technical solution unaltered.

For the presented research several archetypes have been created or reused to (i) store the parameters considered relevant for CHF and (ii) store the risk assessment data using evaluation archetypes. The CHIRON data are collected from sensors and stored using the archetypes included as entries inside one composition of the patient EHR.

III. RISK ASSESSMENT

A. Configuration of the system

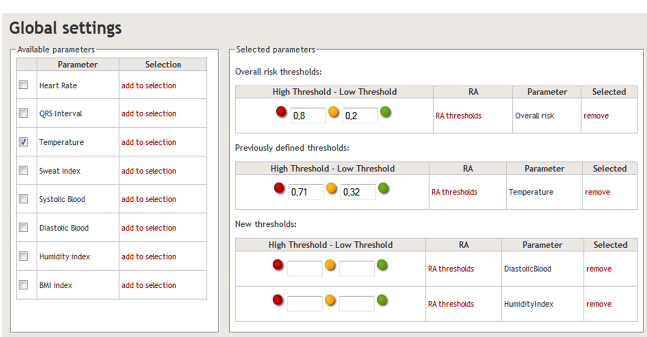

Fig. 2 – Global Monitoring Settings

Monitored parameters used by the risk assessment module are set for each patient, since the risk to different patients' health may depend on different parameters. Furthermore, green/yellow/red risk areas are defined by terms of customizable thresholds doctors may modify if they judge different values to suit their patients better.

B. Expert System

The first module for risk assessment relies on expert knowledge. It is thus able to leverage the existing experience in the field of cardiology. The construction of the expert system started with an extensive search of the medical literature, which yielded over 60 parameters considered potential risk factors for CHF. To estimate the importance, a survey was conducted among the European opinion leaders in cardiology. Based on 32 responses, each parameter was assigned low, medium or high importance [6].

Three risk assessment models were constructed for different time horizons: long-, medium- and short-term. The following information was required on each parameter:

- The relation between the parameter value and the risk.
- The minimum and the maximum parameter value.
- Two parameter values representing thresholds.
- The importance: low, medium or high.
- The frequency at which the parameter changes.

Each parameter value was first transformed into a risk value by linearly scaling the parameter value to the (0, 1) interval. The same transformation was used to obtain the thresholds between the low-, medium-, and high-risk areas. The risk values of individual parameters were combined into an overall risk value by a weighted sum. Each weight in the overall-risk was the product of the importance and a model-specific weight related to the time horizon.

C. Machine Learning

The second module is an artificial neural network (ANN) which is a tool able to give response almost in real time, in order to support clinical decision in the detection of CHF class 2 to 3 alert problems. ANN consists of simple elements massively interconnected in parallel, denoted as neurons, with a hierarchical organization similar to biological nervous systems. Drawing an analogy between the synaptic activity and the ANN, we can set the following concepts [11]:

- Signals arriving at the synapses are the neuron entries.
- Entries are weighted through a parameter denoted weight, which is associated with a specific synapse.
- Signals can excite or inhibit the neurons.
- The effect on the neuron results from the addition of all the entries.

Structure of ANN consists of three levels or neuron layers: input level, hidden layers level, with 16 hidden neurons, and the output level. The network adapts the different weights during its learning process. After building an ANN for the risk assessment, the validation of the results is crucial [12]. Pre-processing transformations were applied to the input data using simple linear rescaling of the data. Mean and standard deviation of the training set were normalized. This process forced input variables to have similar ranges for easier training. Due to the amount of available data, the input was reduced to 12 variables giving 3 levels of risk (low, medium and high). In order to obtain the best performance on new data, 35 different ANNs were compared. The Levenberg-Marquardt back-propagation algorithm was chosen. Performance validation [12,13] of the network was performed with cross-validation, on a data set that is independent of the training data; practically mean error value of 0.003503% was obtained.

D. Anomaly detection

The final module for risk assessment requires neither knowledge nor data weighted with the risk, but only some data considered normal. The parameters describing the patient's normal condition tend to follow recurrent patterns. Such patterns can be learned, and when a new potentially anomalous pattern is detected, the module raises an alert that medical professionals can confirm or not.

Local Outlier Factor (LOF) algorithm [14] is used to detect anomalies. The algorithm compares the density of data instances around a given instance X with the density around X's neighbors. If the former is low compared to the latter, it means that X is relatively isolated – that it is an outlier and thus considered anomalous. The LOF algorithm assigns a value to each instance that indicates the degree of its anomalousness, which we consider to correspond to the risk. To also compute the degree of anomalousness of individual parameters, which corresponds to their contributions to the risk, an extension was made to the algorithm.

The anomaly detection was tested on a dataset of five healthy test subjects performing a range of activities, and a subset of the parameters relevant to CHF [15]. These data were used to set the parameters of the LOF algorithm and thresholds between the low- medium- and high-risk areas. To set the thresholds, anomalous data was generated by randomly replacing some parameter values during one activity with those during another.

IV. LITERATURE SEARCH

Questions and Answers (Q&A) systems attempt to extract direct answers from large data sets, regardless of the complexity or ambiguity of the question and size and amount of data sources. To date, few Q&A systems have focused on designing effective interfaces and avoiding long lists of retrieved documents.

Clinical Q&A system approach is founded on Evidence-Based Medicine (EBM). It works on plain text, extracting the relevance of certain medical paper using Medical Subject Heading (MeSH) codes and summarizes the publication's content into a few annotated sentences using Natural Language Processing (NLP) techniques. Firstly, the system is implemented creating rules manually to discover new semantic information, in order to enrich the user's questions with inferred new conclusions. The module is contextualised with information coming from the EHR using an ontological semantic system[1], which permits to run rules over the patient information and extract new diagnoses to enrich the queries.

The system automatically reads, identifies and extracts binary relations from whole publications texts extracting the relevant information by means of triples (subject, object, predicate). The CHF ontology used is constantly updated and filled automatically with the information received from the medical sources. This brings two response levels: direct answers from the knowledge database and complex responses using reasoning. The first one includes as knowledge data a system with a SVM classifier (Support Vector Machine) over a tokenized input (clinical terms) coming from the user questions. If the confidence is not enough (85%) ontology classifier looks for inferences over questions terms also included in the working memory referenced to the query to provide complex responses. Finally, the conclusions are presented to the user in a natural language sentence.

V. GRAPHICAL USER INTERFACE

A-MEST provides a full support to clinical risk management process with a simple set of GUIs, whose design followed a person-centric approach, based on interviewing medical professionals. The process, driven by medical experts, starts from risk evaluation; it goes iteratively exploring its causes and finishes with actions whose purpose is to mitigate the current values of risk [16].

The first component, the Monitoring Settings, provides a mean to pre-configure the system (Fig. 2. Section III. A); the second component is the Risk Assessment (Fig. 3. Sec-

[1] Ontology used was developed by the Laboratory for Information Systems; RBI Zagreb Croatia, Dragan Gamberger, Rudjer Boskovic Institute.

tion III. B, C, D), where the medical experts are allowed to review the clinical status of their patients. Risk level source is set by a toggle selector.

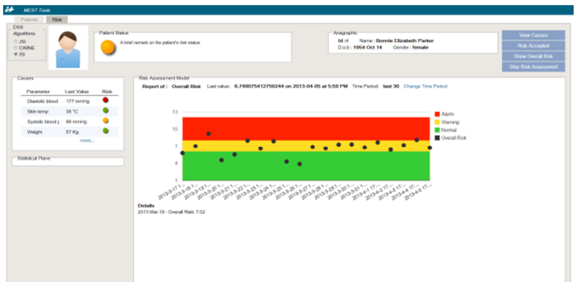

Fig. 3 – A-MEST Graphical User Interface – Risk Assessment activity

Upon patient selection, the system shows a more detailed view including recent-past evaluations of the patient's risk presented in a graphical way that highlights the overall trend. If the clinician starts a new Risk Assessment procedure, he/she can access a broad spectrum of information regarding the patient together with literature search module. The relevant publications (Section IV) are shown below the parameters. The system also raises alerts if the risk values exceed the thresholds defined.

VI. CONCLUSIONS

In this paper the Advanced Medical Expert Support Tool has been presented, which permits the doctors to evaluate the health risk of a CHF patient and get the relevant publications contextualised to specific cases.

Three different Decision Support Systems are used to assess the risk to the patient from different viewpoints. The seamless integration is fulfilled by means of standards, concretely the European norm EN13606. Health data and the automatic risk assessment calculation are incorporated in the Electronic Health Record providing a common solution to store and use the data.

Predicting the future has been pursued during centuries of history, but right now the technology makes it possible to do this accurately in the healthcare environment. The proposed tools will facilitate the daily monitoring of the CHF patients, and reduce the visits to hospitals because the doctor will know in advance the possible problems instead of treating them when they have already happened.

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