Home-based Multi-parameter Analysis for Early Risk Detection and Management of a Chronic Disease

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Abstract. Proactive support of patients with chronic diseases such as Congestive Heart Failure is vital since the recovery from a critical condition usually presents complications and it is not always possible. Although emergency situations may occur without prior warning, still in the majority of emergency cases, there are "signals" that precede their appearance. By capitalizing on technology developments that are changing the way how healthcare services are provided, we propose a multi-parameter and multi-level data analysis approach in order to detect possible alarms which can then trigger proper preventive medical interventions. The main contribution of the presented approach is a methodology that combines selected health parameters that can be measured in a home environment using ambient assisted living technologies, with clinical history, in order to design a risk detection system for a chronic disease based on a Bayesian reasoning network. The added value of the proposed approach is that the system not only collects, processes and transmits vital measurements to the healthcare experts but also detects risks within the collected data. The system developed is discussed in detail as well as the validation process performed both on a technical and a medical level.

Keywords: Risk Prevention, Bayesian Network, Chronic Diseases, Medical Knowledge Modelling, Remote Healthcare, Multi-layered Architecture, Sensors, Pervasive Computing, Ambient Assisted Living.

1 Introduction

World population aging is accompanied by a significant increase of chronic diseases, such as Congestive Heart Failure (CHF) and Diabetes Mellitus (DM). The cost of managing chronic diseases is huge representing 48% of global GDP (Gross Domestic Product) in 2010 and estimated to approach at a global level 30 trillion US$ in the next two decades [1]. At a national level, treatment expenses can be high and the loss of labor due to chronic diseases can make a substantial dent in a country's productive capacity.

Additionally heavy burdens are put in the care system for the management of patients devoting resources directly or indirectly to prevention, screening, treatment and care. These difficulties render the management of such medical problems at home as an extremely attractive solution.

However, the management and treatment of chronic diseases at home presents many challenges for patients, their caregivers and health professionals, particularly with respect to the prevention and treatment of dangerous situations and complications such as deregulation-hospitalization in patients with CHF or hypoglycemia in patients with DM. Telemedicine monitoring of patients with chronic conditions has been proposed as an alternative for patient monitoring and early risk detection, however the plethora of parameters that accompany their remote monitoring, create challenges in the management of telemedicine services [2].

The development of information and communications technology systems that integrate modeling of medical knowledge and using of advanced processing techniques on medical and other data can assist the physicians in a diagnostic level, and contribute effectively to the prevention of health risks for the patients. In this perspective we present here the development of a home-based system for supporting CHF patients and addressing the early detection and management of health risks. At the heart of the system lies a multi-parameter analysis process for the early detection of critical medical conditions in CHF patients using artificial intelligence methods for modeling the medical knowledge and algorithmic data processing techniques to extract diagnostic features.

The main contribution of our approach is a methodology that combines health measurements that can be taken in a home environment using ambient assisted living technologies, with clinical history, in order to design a risk detection system for CHF that uses a Bayesian reasoning network. The added value of the proposed approach is that the system not only collects, processes and transmits vital measurements to the healthcare experts but also detects CHF risks within the collected data.

The rest of the text is structured as follows. In Section 2 we elaborate on the Bayesian Network model we have used to represent the domain knowledge and build a probabilistic reasoning method. Furthermore, related work is discussed and compared to our approach. Section 3 introduces the multi-parameter and multi-level data analysis approach that is followed in order to detect possible alarms which can then trigger proper preventive medical interventions. In Section 4 we discuss details of system development in terms of the logical layers found at the endpoints of the client-server architecture followed and the tools used for measurement scenario management and for system implementation. Section 5 gives information on the validation process performed both on a technical and a medical level. Finally, Section 6 gives our conclusions and suggestions for future work.

2 Background

In the domain of disease diagnosis many approaches have been proposed using Artificial Intelligence techniques, however, because on the one hand the expert knowledge in the medical domain is very important and on the other hand the experts want to clearly distinguish the way a diagnostic algorithm reaches a conclusion, Bayesian Networks (BNs) and in particular a variation for continuous data, called dynamic BNs, have been popular and at the same time a powerful approach [3, 4].

A BN is a graphical model, in particular a directed acyclic graph (DAG), which can express probabilistic relationships among a set of nodes or variables whereas arcs represent causal relations among the variables [5]. BNs have been used, for example, to model domain knowledge with a perception of causal effects for asthma case finding [6], for pneumonia [7], for hyper-kinetic disorder [8] and for early detection of hyperglycemia in patients with diabetes [9]. BN-based diagnostic systems for heart failure have been also developed [10] while the typical approach for BN construction is the use of clinical data [11].

BN model construction requires the specification of Conditional Probability Tables (CPTs) which denote the statistical dependence of the corresponding variables. However, for a specific variable, the number of parameters in the CPT is exponential to the number of parent nodes in the BN and thus can be prohibitive for the BN building. An approximation that considers a causal independence among the parent nodes that model causes related to the child node that model the effect can significantly reduce the dimensions of a CPT. This assumption is known as the Noisy-OR model [12] giving a logarithmic complexity on the number of parameters required for the CPT.

A critical question that arises when using the Noisy-OR model to build a BN is whether the performance of the network's reasoning is affected. There have been many studies that examined the effects of using this approximation for specifying the CPTs of a BN. For heart failure diagnosis the Noisy-OR model was successfully used to alleviate the difficulties involved in providing statistical data for all possible combinations of predecessor variables that, all or some combination of them, may cause heart disease [11]. For asthma case finding, an empirical study compared the original BN which was constructed from clinical data taken from a large medical database, with a BN that constructed using the leaky Noisy-OR formalism [6]. Comparison of the two methods concluded that the causes of asthma are independent and therefore both BNs had similar results, proving that the Noisy-OR approach is a strong assumption and a valid construction method for Bayesian reasoning networks. In a similar comparative study related to the early detection of classical swine fever original probabilities of the BN were replaced by Noisy-OR calculated probabilities with the involvement of the domain expert without affecting the sensitivity of the reasoning network [13]. The consistency of the outcomes reported by the above and similar studies led us also to use the Noisy-OR model in our approach for the early detection of CHF risks.

Focusing on heart failure risk detection many approaches have been proposed. An example is an early warning system for CHF using a BN which combined weight and blood pressure data with the location of the user and context-specific health questions in order to calculate a risk probability [14]. In another case researchers proposed a prediction rule to detect low-risk patients with heart failure by analyzing through classification trees a large data set including parameters such as demographics, clinical, laboratory, electrocardiographic and radiographic results [15]. The same clinical data sets and variables were also used to develop algorithms that perform Bayesian model averaging over a set of models using the characteristics of a specific patient to provide heart failure prediction [16]. Such approaches represent research efforts to develop decision making systems at a laboratory environment and not home-based systems to support early CHF risk detection by using ambient assisted living technologies.

Finally, a number of home-based wearable real-time monitoring systems have been proposed by researchers for continuous medical care of patients [17-19]. However, most of such systems collect, process and transmit vital measurements to healthcare experts in order to remotely monitor their patients, but they generally don't detect CHF risks within the collected data. This is the main difference compared to our system.

3 Multi-parameter Analysis

A risk detection algorithm that performs multi-parameter and multi-level data analysis in order to detect dangerous situations for patients with chronic heart failure is the core of the proposed system. Fig. 1 depicts the overall structure of the risk detection algorithm for CHF patients. Multi-parameter data analysis involves a combination of medical measurements and clinical history. Medical measurements include systolic/diastolic blood pressure, heart rate, blood oxygen saturation and electrocardiograph. The clinical history includes clinical measurements specified in the European System for Cardiac Operative Risk Evaluation (EuroSCORE) model that are used in order to calculate the patient risk according to the logistic formula given by EuroSCORE II [20].

The data processing is performed at multiple levels including: i) medical analysis of measurements based on decision rules which use threshold values specified by medicine science; ii) statistical analysis of biological data to detect considerable variations between the current measurements and the corresponding medical history data of the same patient; iii) clinical history data processing which uses EuroSCORE II risk calculation as a method to assess the health risk status for patients that have been operated for heart failure; and iv) a Bayesian reasoning network which gets as evidence variables the output of the medical analysis and the EuroSCORE II risk calculation to assess an overall risk level. On the output pre-alarm indicates initial evidence which is not considered critical but should be taken into account for further assessing patient's health state. Alarm indicates evidence that is considered as an emergency for patient's health and requires immediate intervention.

In the following sections we briefly present the various levels of data analysis. A more elaborated description given by the authors can be found in [21].

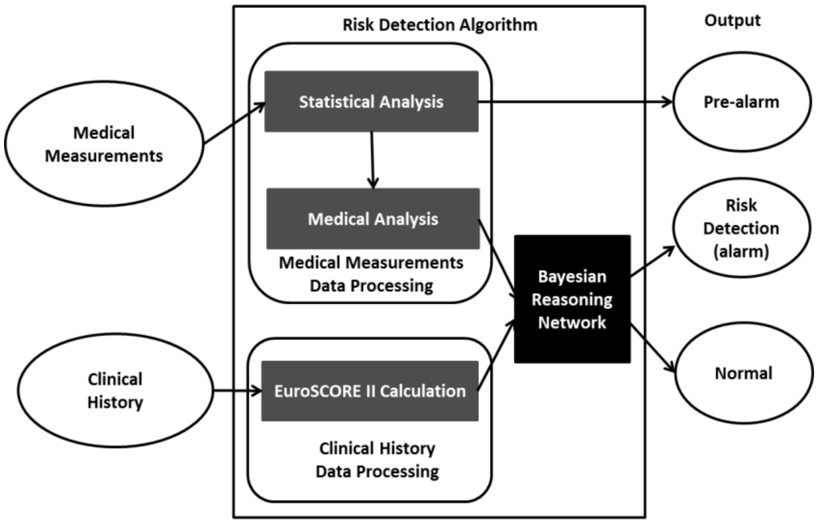


Fig. 1. Multi-parameter, multi-level data analysis for CHF risk detection

3.1 Medical Data Processing

In this category of data processing medical measurements are taken regularly at home. As shown in Fig. 2, there are two data processing steps applied by the risk detection algorithm on the medical measurements before outcomes are provided as evidence variables in the Bayesian reasoning network: statistical and medical analysis.

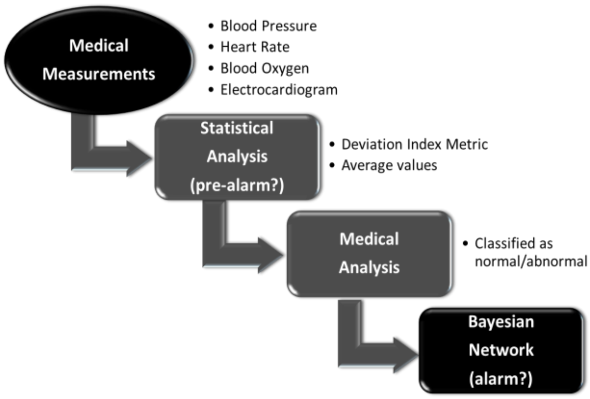


Fig. 2. The medical data processing flow.

The statistical analysis step of the risk detection algorithm uses the deviation index (DI) metric, which is the z-statistic quantity of Statistical Theory measuring the deviation of the measured value of a variable x, from the average value μ of the same variable in standard deviation σ units of its distribution [22]:

$$\mathrm{DI} = \frac{x - \mu}{\sigma} \tag{1}$$

A high value of instant DI corresponds to a significantly differentiated measurement in relation to the history of the measurements and thus this is assessed as a component of the pre-alarm status for a patient. The deviation index value for a variable x is then categorized based on medical expert empirical knowledge according to the formula [21]:

$$\mathrm{CDI}_x = \begin{Bmatrix} 0 & \mathrm{DI} \leq 1.5 \\ 1 & 1.5 < \mathrm{DI} \leq 3 \\ 2 & \mathrm{DI} > 3 \end{Bmatrix} \tag{2}$$

For DI > 3 the observed value occurs with probability less than 0.3% and this signifies a strong pre-alarm. For 1.5 < DI ≤ 3 the observed value occurs with probability approximately 13% and signifies a moderate pre-alarm. For DI ≤ 1.5 the observed value occurs with probability approximately 87% and signifies a normal state. The output values of the statistical analysis are fed to the medical analysis component for further processing.

The medical analysis step of the risk detection algorithm examines whether medical variable measurements are exceeding normal value ranges in order to be classified as normal or abnormal based on criteria related to the patient profile (Table 1).

Table 1. Medical parameters and their normal value ranges [21].

Parameter	Normal Range
ECG QRS width/amplitude	60-110msec/≤1mV
ECG P-wave width/amplitude	80-110ms/≤0.1mV
ECG T-wave width/amplitude	160-200ms/≤0.25mV
heart rate	60-100bpm
systolic pressure	100-130mmHg
diastolic pressure	60-85mmHg
blood oxygen saturation	96%-100%
temperature	36.1ºC-37.4ºC

The Electrocardiogram (ECG) signal is a basic parameter giving evidence of the electrical activity of the heart. Fig. 3 shows a typical ECG signal with its constituent segments identified as the P wave, the QRS complex and the T wave referring to depolarization or repolarization of the heart [23]. The R-R interval variable denotes the time between two consecutive R waves and a time series of this variable is used to calculate heart rate in beats per minute (bpm).

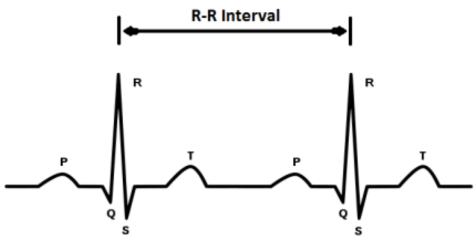


Fig. 3. ECG waveform.

3.2 Clinical History Data Processing

Clinical history is classified into three data categories: risk factors related to the patient, to the heart health and finally to the heart operation, as defined in EuroSCORE II model [20]. As shown in Fig. 4, the risk detection algorithm in this data processing component calculates the EuroSCORE II risk and then categorizes it as low, medium or high before feeding it as evidence variable in the Bayesian reasoning network.

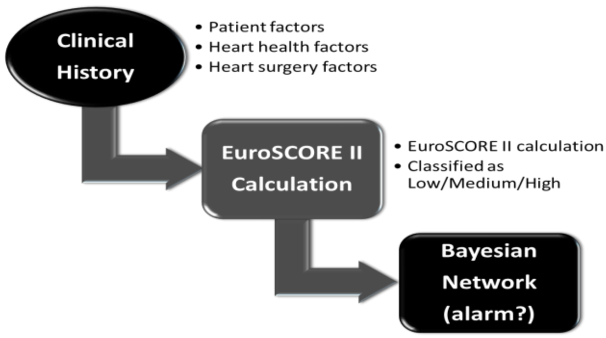


Fig. 4. The clinical history data processing flow.

The following formula calculates the patient risk as defined by the EuroSCORE II model [20]:

$$eSCORE = \frac{e^{(\beta_0 + \Sigma\, \beta_i + x_i)}}{1 + e^{(\beta_0 + \Sigma\, \beta_i + x_i)}} \tag{3}$$

where e the natural logarithm base, β_0 equals to −5.324537, x_i is a binary variable representing a specific risk factor and β_i is the variable's corresponding coefficient as defined in [20]. The calculated value is then categorized according to the following formula suggested by the euroSCORE model and is fed to the BN [21]:

$$eSCORE' = \begin{cases} LOW & if\ eSCORE < 0.03 \\ MEDIUM & if\ 0.03 \leq eSCORE \leq 0.07 \\ HIGH & if\ eSCORE > 0.07 \end{cases} \tag{4}$$

3.3 Bayesian Reasoning Network

The basic concept in BNs is that probabilities can be assigned to variable values and by applying the Bayes laws these probabilities can be updated given new measurements [12]. There are two main methods for constructing BNs when trying to model a particular situation (Fig. 5). The first is the knowledge representation approach, in which the domain knowledge is captured into a BN with the assistance of the domain expert. The second method is based on learning from data, where the structure, the probabilities or both can be learned from a given database.

The lack of adequate clinical data as well as the need of having less computational demands and smaller model in size guided us to construct the BN by surveying the relevant literature and consulting the domain experts. Moreover, with this approach we can have a significant amount of discrete binary variables, allowing us to benefit from computational techniques.

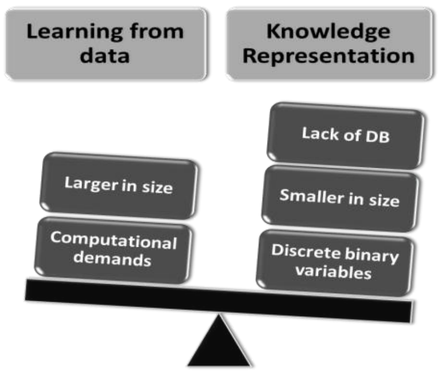


Fig. 5. Bayesian network design options.

Given a problem domain one needs to define the BN model structure. CHF disease, in our case, is related to many causes and effects [24]. Relevant literature was explored to determine parameter dependencies and the original conditional probabilities employed in the BN model [11, 26, 27]. For instance, we found that the prognostic importance of systolic and diastolic blood pressure is well known [28]. Moreover the heart rate parameter is also considered as a predictive factor of CHF risk for seniors whereas the ECG parameter establishes a diagnostic factor. Besides the knowledge extracted by surveying medical studies, in-depth discussions with medical experts provided the proper guidance in order to streamline the network with only the variables that are appropriate in the specific problem domain, to fine-tune conditional probabilities in specific edges of the BN model and to specify validation rules for detecting a CHF risk.

Nevertheless, an important factor for choosing the basic BN variables was their appropriateness with respect to gathering the relevant medical measurements in a home environment.

So, in our constructed model there are five evidence variables. Four of them represent categorical medical variables provided by the medical analysis phase, which can take one out of two values abnormal/high or normal. The fifth is the categorized EuroSCORE II risk value derived by Eq. (4), which can take one of three values low, medium, high. For the calculation of conditional probabilities and because both parent and child nodes in the BN model are binary variables we can assume a causal independence among the modeled causes and their common effect and therefore we can apply the Noisy-OR model. According to this model each of the parent variables γ_i is considered as a possible cause of the child variable π, which can cause the effect by itself, with a certain probability p_i. Then the probability that the child variable is TRUE is given by the following equation [21]:

$$p(\pi = \{T\}|\gamma_i) = 1 - \prod_{\gamma_\iota \in \Gamma_T}(1 - p_i) \qquad (5)$$

where the product contains only the factors corresponding to parent variables that are TRUE ($\gamma_\iota \in \Gamma_T$).

In our case we use a variant of the Noisy-OR model called the *leaky Noisy-OR* approach which attempts to solve the practical problem that not all causes of an effect can be modeled in a BN [29]. This model uses the notion of p_{leak}, which is the total probability of the causes that have not been modeled and can be regarded as one of the causes which may cause the result. In this case Eq. (5) is updated as follows [21]:

$$p(\pi = \{T\}|\gamma_i) = 1 - (1 - p_{leak}) \prod_{\gamma_\iota \in \Gamma_T}(1 - p_i) \qquad (6)$$

Fig. 6 shows the probabilities of each variable in the case when no evidence is provided, i.e. the risk probability calculated by the model reflects only the input probabilities of the variables.

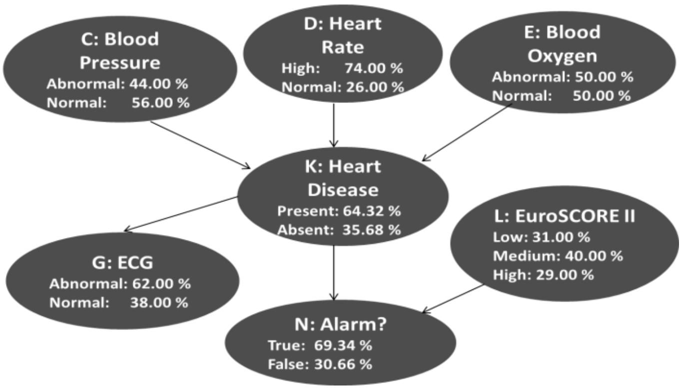


Fig. 6. Bayesian network structure for CHF risk detection when no evidence is given.

Conditional Probabilities

Prior probabilities of nodes in the BN model representing the medical variables “Blood pressure”, “Heart rate” and “ECG” were defined according to the study of Ghosh and Valtorta [11]. Table 2 summarizes the Normal value probability for these nodes.

Table 2. Prior probabilities of medical variables based on literature [21].

BN node	Variable	Probability
C	Blood pressure	0.56
D	Heart rate	0.26
G	ECG	0.38

Blood oxygen is associated with other diseases so there are equal chances of influence. For this reason the prior probability of node (E) was set to 0.5.

Prior probabilities of node “EuroSCORE II”, were defined based on EuroSCORE model data as follows: p(L={LOW}) = 0.31, p(L={$MEDIUM$}) = 0.40 and p(L={$HIGH$}) = 0.29.

The CPT of node K “Heart Disease” given nodes C, D and E was defined using the leaky Noisy-OR formalism. Table 3 gives the contents of the CPT using p_{leak}=1−0.93=0.07, where 0.93 is the probability of state “Present” in node K when all parent nodes are in “Abnormal” state. The conditional probability of node G given node K is defined as: p(G|K={$PRESENT$}) = 0.95

Table 3. CPT of node K “Heart Disease” [21].

C	D	E	K
Abnormal	Abnormal	Abnormal	0.93
Abnormal	Abnormal	Normal	0.86
Abnormal	Normal	Abnormal	0.74
Abnormal	Normal	Normal	0.48
Normal	Abnormal	Abnormal	0.88
Normal	Abnormal	Normal	0.76
Normal	Normal	Abnormal	0.54
Normal	Normal	Normal	0.07

The CTP of node N “Alarm” given nodes K and L (Table 4) was defined using the Total Probability Theorem as described by the following equation:

$$p(N|K,L) = p(K)p(N|K) + p(L)p(N|L) \tag{7}$$

Typically the alarm outcome given that the heart disease is present can be set to 0.99.

Also based on the EuroSCORE model data from the 698 deaths, 36 were low risk patients, 182 were medium risk patients and 480 were high risk. So we have the following probabilities per category: p(N|L={LOW}) = 0.05, p(N|L ={$MEDIUM$}) = 0.26 and p(N|L ={$HIGH$}) = 0.69.

Table 4. CPT of node N "Alarm" [21].

K	L	N
Present	Low	0.71
Present	Medium	0.80
Present	High	0.89
Absent	Low	0.02
Absent	Medium	0.11
Absent	High	0.20

4 System Development

In this section we discuss the development of an integrated telemedicine system for supporting CHF patients at home by addressing the early detection and management of health risks. The system developed follows a multi-tier client/server architecture. The advantages of this model refer to the scalability, reusability and maintenance capabilities provided. The system architecture diagram is given in Fig. 7 and its structure consists of six separate layers, three in the client-side and three in the server-side. In the client-side the system collects biomedical measurements using devices and sensors in the user's home space under the supervision of the Local Subsystem Manager (LSM) which after performing local filtering and formatting of the gathered information forwards it to the remote server that can make assessments about the patient's health status. This multi-layer scheme makes integration of new devices and sensors easier and also facilitates the integration of different technologies that may be used between the layers.

To demonstrate the usage of such a system an indicative scenario is given. A CHF patient following the doctor's instructions takes regularly specific measurements (e.g., blood pressure). The data is collected by the LSM through the device's communication protocol (e.g. Bluetooth). LSM packages the data into a secure JSON envelope and sends it to the server. The server combines the data with past measurements (e.g., taken during the past week/month) and analyses the patient's health status by applying the risk detection algorithm described in Section 3. The system may assess that there is a possibility of health risk, and as a response sends a message back to the LSM for a pre-alarm warning and communicates with the local administrator. When the local system receives the pre-alarm message, warns the user to communicate with the doctor because the measurements have been out of balance lately.

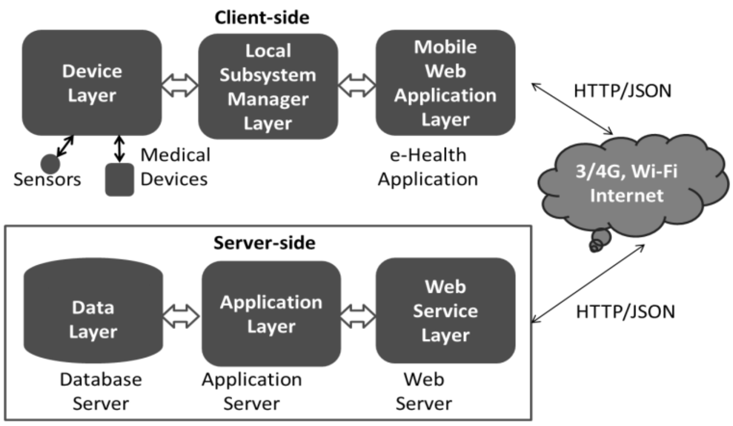


Fig. 7. Multi-tier client/server architecture.

4.1 Client-side

In this section we describe the layers of the system implemented in the client-side.

Device Layer: This layer includes all the devices and sensors measuring medical parameters (Table 5). These are mainly wireless devices (e.g. Bluetooth) that transmit the data to the LSM through which it can be transmitted with web connectivity to the remote server for storage and processing with the algorithms for medical diagnosis. The basic selection criteria for the devices are:

a) Openness (i.e. the device has to provide an Application Programming Interface (API) for direct downloading of data without the mediation of some cloud server).

b) Reliability via proper certifications (e.g. MED CERT ISO 13485) and

c) Interoperability (e.g. Continua Product Certification).

Table 5. Medical devices characteristics.

Device	Parameter	Certified	Link
EMB1	ECG	MED CERT ISO 13485	https://www.corscience.com/emb
UC-355PBT-Ci	Weight	Continua-certi-fied	http://www.andonline.com/
CorScience Pulse Oximetry	Blood oxygen saturation	MED CERT ISO 13485	https://www.corscience.com/chip ox
AnD Medical UA-767PBT-Ci	Blood pressure	Continua-certi-fied	http://www.andonline.com/

The API of the devices provide raw measurements that can be subsequently be processed by algorithmic techniques in order to extract useful diagnostic features. For example, the Pan-Tompkins algorithm [30] is used to recognize the QRS-complexes in the ECG signal and then the amplitude and duration can be measured in rode to assess the normal or abnormal classification by checking the threshold values defined in Table 1.

Local Subsystem Manager Layer: This layer includes key processes in the client-side of the system which implement the following operations:

- User notification to start a periodic measurement scenario.
- Data gathering from the medical sensors and devices.
- Temporary storage of data in case of network problems in the communication with the server.
- Data validity checking based on the normal value ranges defined in Table 1.
- Data forwarding to the server.
- Receiving commands and processed responses (pre-alarms, alarms) from server.
- User notification management through warning messages.

To initiate a regular medical measurement, the LSM creates the proper low level messages to trigger the relevant devices for starting measurements and prepares the appropriate data structures to store the data collected from the devices. Moreover, the LSM updates the graphical user interface to display a set of guidelines to the user for using the devices (Fig. 8).

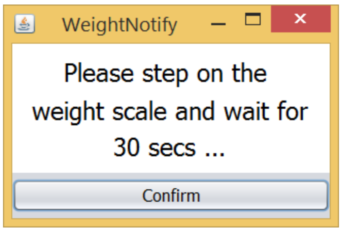


Fig. 8. A typical interaction message with the patient.

Mobile Web Application Layer: This layer provides access to the user profile and stored data. It also provides a personalized view of data as well as access levels depending on whether the user is a patient, medical staff or administrator. Fig. 9 shows the main screen of the Web Application.

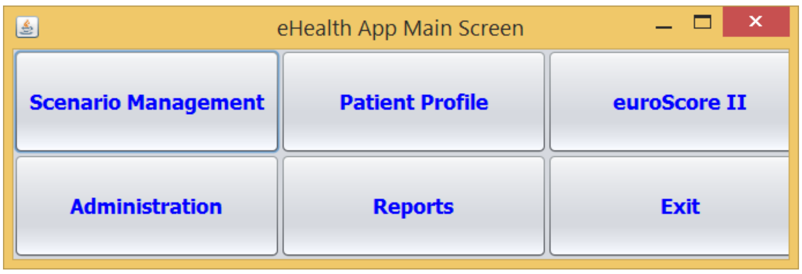


Fig. 9. Main screen of the Web Application.

In summary the following functionality is provided:

- An interface to create a new medical measurement protocol/scenario;
- A personal profile interface where the user can enter patients' personal information as well as relevant chronic diseases;
- A GUI to simulate sensor measurements for debugging purposes;
- An interface where the history measured data can be displayed in graphs;
- An interface to manage reports;
- An interface to provide notification to the user;
- An interface to create new users and to define new time periods for measurements and new thresholds for the medical analysis process.

4.2 Server-side

The remote server provides the ability to interface with one or more clients for monitoring one or more patients and accepting HTTP type requests for storing measurements via a web application. In addition it supports the recording of each patient's profile into the database, decision-making by using a risk detection algorithm that performs multi-parameter and multi-level data analysis to identify emergencies and generate alarms and pre-alarms and finally the generation of suitable reports based on the information stored in the database. Fig. 10 illustrates the component diagram of the server.

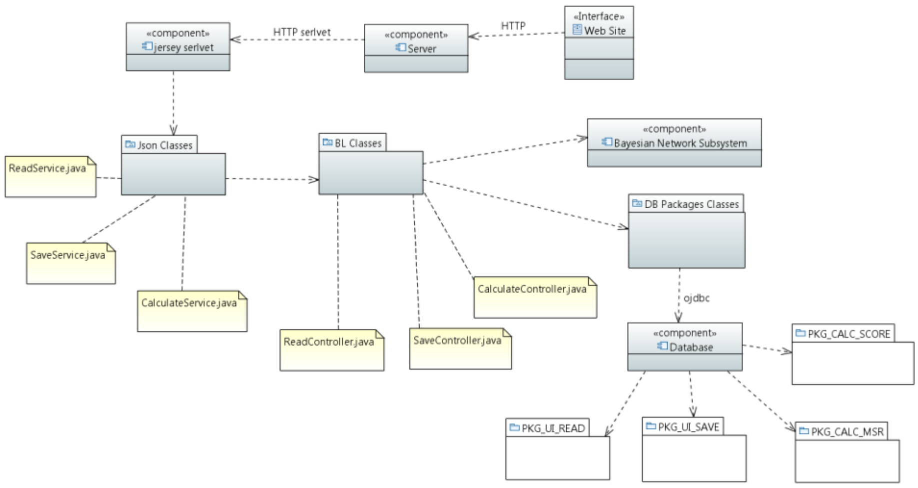


Fig. 10. Server-side system component diagram.

The server is divided into the following logical layers:

Web Service Layer: The components in this layer are responsible for receiving and sending messages from/to the client and also authenticating and validating the http calls and initiating measurement data recording. The communication mechanism is based on sending messages through the HTTP protocol, using the representational state transfer (REST) model.

Application Layer: The main purpose of this layer is to run the health risk assessment algorithm, which may generate pre-alarm or alarm states. More precisely, the received JSON message with the measurements from the client is checked initially for integrity and then the data are stored using the corresponding database package procedures. The EuroSCORE II model procedures are called to perform the calculation of the model result. The risk detection algorithm can then be initiated to check for an alarm or a pre-alarm. In case of abnormality the system either notifies its administrator to contact the patient or sends back to the corresponding client LSM the appropriate notification messages in order to be presented to the user.

Therefore, the application layer contains in the implemented Java classes the business logic of the server-side. In particular, it encompasses the Bayesian reasoning network component and components that interact with the data layer for storing measurements and EuroSCORE values. The application layer performs the following four basic tasks: data retrieval, data storage, patient's EuroSCORE II model calculation and risk detection estimation using the BN.

Data Layer: The data layer contains a relational database which was designed and implemented in Oracle platform. It also includes all the necessary procedures for storing, retrieving, updating and maintenance of data, as well as the necessary mechanisms for ensuring data integrity. The database scheme includes 14 tables with 92 fields in total and 14 relationships between the tables (Fig. 11).

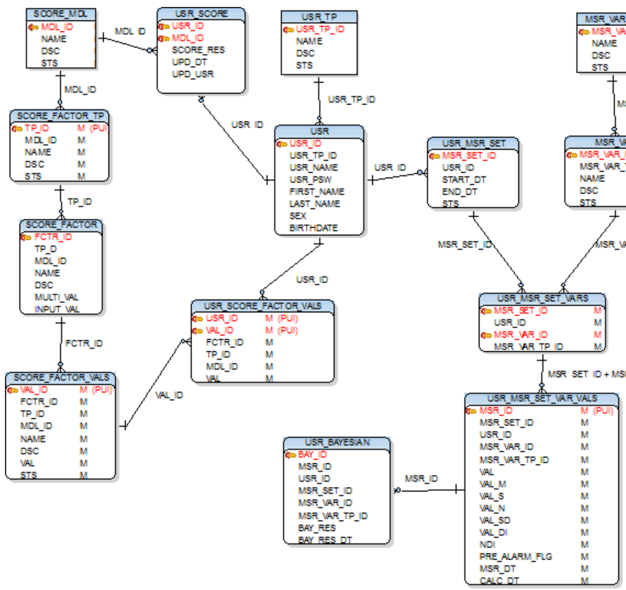


Fig. 11. Database entity-relationship diagram.

The tables are classified into three categories:

EuroSCORE Model Tables. Tables in this category are containing information describing the EuroSCORE related models. The risk detection algorithm uses, in particular, the EuroSCORE II model to determine the degree of patient's health risk. In fact, the corresponding tables in the database have been designed in a general way so that additional risk assessment models related to patient's health can be also supported. Tables in this category are the following:

- SCORE_MDL: This table contains records for all three EuroSCORE models, i.e., additive EuroSCORE, logistic EuroSCORE and EuroSCORE II which is the latest version used by the system.
- SCORE_FACTOR_TP: This table contains records regarding the different data categories per model. For example, EuroSCORE II model has three such categories, namely risk factors related to the patient, risk factors related to heart health and risk factors related to heart operation.
- SCORE_FACTOR: This table contains records with the names and the descriptions of risk factors per category and per model. For example, a risk factor related to the patient in the EuroSCORE II model is the "Extracardiac arteriopathy".
- SCORE_FACTOR_VALS: This table contains the coefficient for each risk factor that is used in Eq. (3). For example the risk factor "Extracardiac arteriopathy" has a single record with the value 0.5360268.

Medical Measurement Tables. Tables in this category are containing information describing medical protocols for which the system collects measurements. The design of the tables takes into account that these tables may have to store measurements from various sources in the future so that the system can be expandable. The tables in this category are the following:

- MSR_VAR_TP: This table contains records for all types of sensors and devices that may be used for medical measurements. For example, biometric measurements from a Bluetooth oximeter.
- MSR_VAR: This table contains records for all the medical measurements supported by the system per device type.

Users Tables. Tables in this category are containing user-related information such as the medical history and stored measurements. The tables in this category are the following:

- USR_TP: Defining user types (patient, doctor, and administrator).
- USR: Containing users' profile.
- USR_SCORE: Containing EuroSCORE II model results that have been calculated.
- USR_SCORE_FACTOR_VARS: Containing values of risk factors that have been recorded for each patient.
- USR_MSR_SET: Containing time periods sets for measurements of each patient.
- USR_MSR_SET_VARS: Measurements per time period of each patient.
- USR_MSR_SET_VAR_VALS: Containing detailed measurements of medical parameters collected by sensors as well as statistical values recorded by the system for each patient. Also it contains the number of measurements, the sum of squares, the average value, the standard deviation and Deviation Index which are calculated and recorded every time a measurement is added to the database.
- USR_BAYESIAN: Bayesian reasoning network results calculated for each patient.

Finally, the access to the data is performed through database procedure packages and not directly from table queries for transparency reasons and separation of concerns between the data layer and the application layer. The packages defined are the following:

- PKG_UI_READ: Procedures to retrieve data for the GUI.
- PKG_UI_SAVE: Procedures to update data.
- PKG_CALC_MSR: Procedures to calculate EuroSCORE model and statistical analysis results.
- PKG_BAYESIAN_NET: Procedures to update and store Bayesian network results.

4.3 Measurement Scenario Management

The system administrator can manage the creation/update/deletion of a measurement scenario using the main screen of the Web Application (Fig. 9). A scenario may consist of one or more MEASUREMENT activities and a number of interaction activities like the NOTIFY activity. A NOTIFY activity stores a message content which notifies the user when such activity is executed by displaying the corresponding message on a screen (an example is shown in Fig. 8) and/or by playing an audio message when a speech to voice conversion utility is available. The scenario creation process is assisted by a wizard tool through a number of interaction steps. The administrator has to define for example the basic properties of the scenario such as its name, type and patient risk level (Fig. 12, left screen). A periodic scenario indicates a measurement process that is taken place on a regular basis. Other types include “On demand” and “Test”. The former is initiated by the patient while in the latter case measurement values are not stored in the system database. A user interface is provided also to assist the definition of activities sequence in a scenario. Fig. 12 (right screen), depicts the summary of a simple scenario that involves a blood pressure measurement activity and notification activities.

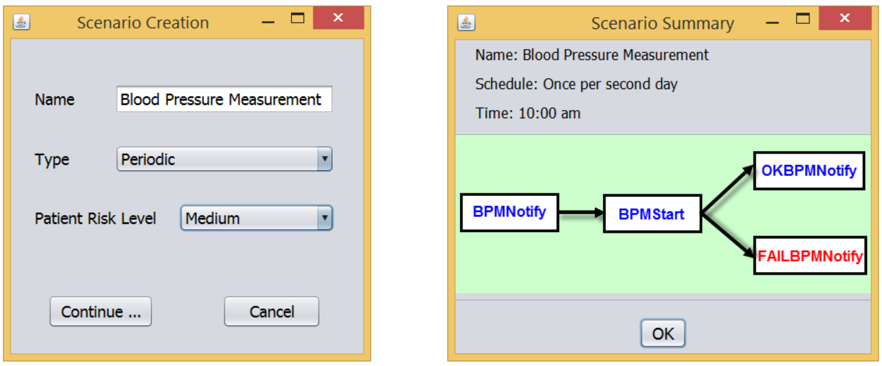
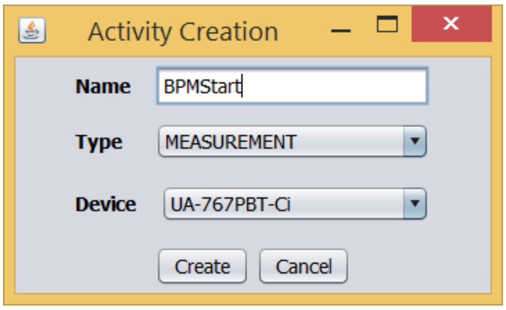


Fig. 12. Scenario creation and summary sample screens.

New activities as components of the scenarios can be defined by the administrator using the provided user interface. For example Fig. 13 shows activity creation for two different activity types.



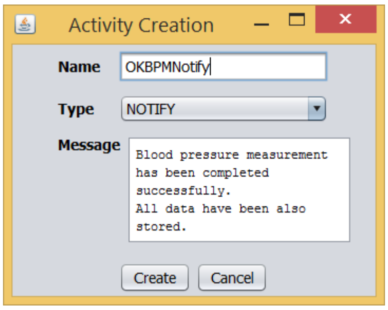


Fig. 13. Activity creation sample screens.

4.4 Implementation Tools

The overall system was implemented using several development technologies and tools. The Java programming language and the Eclipse Mars 2 Integrated Development Environment were used to implement the application layer and the LSM. The wireless communication with the medical devices was based on the Bluetooth stack of the operating system. HTML 5 in combination with the Bootstrap CSS framework were used to develop the web application providing cross-browser compatibility, whereas the jQuery JavaScript library was used to implement the asynchronous calls to the restful web services. Web services were implemented using HTTP and JSON data format for transferring messages between the client and the server.

The Bayesian reasoning component of the risk detection algorithm was designed and tested using a tool developed at University of California at Los Angeles for modeling and reasoning with BNs named Sensitivity Analysis Modeling Inference And More – SamIam [27]. For the development of the Bayesian reasoning component we employed the Jayes library [31].

Lastly, the Oracle database framework, Express Edition 11g Release 2, was used to implement the relational database.

5 Validation

5.1 System validation

From a technical perspective, the system validation process was performed in three levels: unit level, function-level and overall process level testing. At the unit level, all modules developed were tested regarding their proper operation including device management by the matching software driver depending on the communication interface employed (e.g. wireless LAN, Bluetooth). At the function-level, specific system functionality was tested like system login, user profile management, activity and scenario creation, data storage, recognition of pre-alarms and alarms, and communication of the client-side with the server-side and vice versa. At the overall process level, the system was tested with respect to cohesion and reliability of the provided functionality when combinations of operations are executed for a long period of time.

5.2 Medical inference validation

Medical inference validation was performed in two directions. First, the risk values of the EuroSCORE II model calculated by the system were compared to the values calculated by the on-line EuroSCORE calculator [32] and were found to be equal for the same inputs. Secondly, the predictive validity of the risk detection algorithm was checked. The accuracy of the BN reasoning was determined with the participation of medical experts due to the lack of reliable clinical data to compare with the system predictions. The BN model was also checked regarding the mechanism through which prediction is obtained. As suggested by Pitchforth and Mengersen there are seven dimensions of validity in a BN model that should be examined [33]. Fig. 14 summarizes how our BN model satisfied these validation tests.

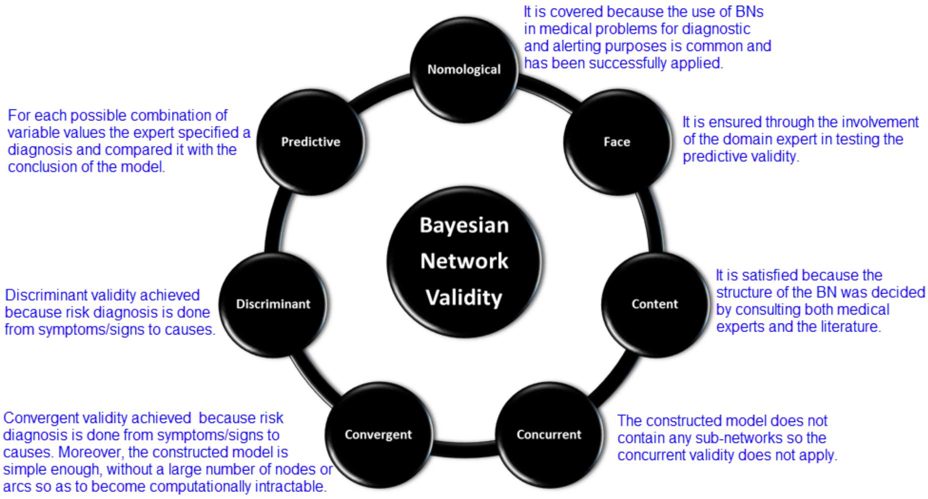


Fig. 14. BN validity tests performed.

In particular, for predictive validity the agreement between the reasoning of the model and the diagnosis made by the domain expert was checked for each possible combination of evidence variable values. In our model there are 48 possible evidence combinations generated from five variables. Four of them represent medical parameters that take one out of two values and the EuroSCORE variable with three values. The process was facilitated by using the SamIam tool to manage the testing of all possible combinations and automatically calculating the probability of the CHF risk. The expert assessed the conclusions of the model as reasonable and also specified the following validation rules for which the CHF risk should always be true:

- Patients with eSCORE risk Low must have all medical measurements Abnormal.

- Patients with eSCORE risk Medium must have at least two medical measurements Abnormal.
- Patients with eSCORE risk High and anyone medical measurement Abnormal.

A critical task was to locate a specific threshold for the probability of CHF risk that divides all the evidence combinations into alarm and no alarm in the same manner as the domain expert. As a result of the analysis, the alarm threshold was found to be sixty-five percent (0.65), in order to generate the alarm. Fig. 15 gives a comprehensive view of the BN conclusions according to the eSCORE risk category when different evidences are generated. As it can be observed the generation of an alarm is in accordance to the recommendations made by the expert. As an example, for patients with medium risk and two abnormal measurements, the model calculated an alarm probability of 65.52%, whereas with only one abnormal measurement the alarm probability was 56.54%, which is below the threshold as normally expected.

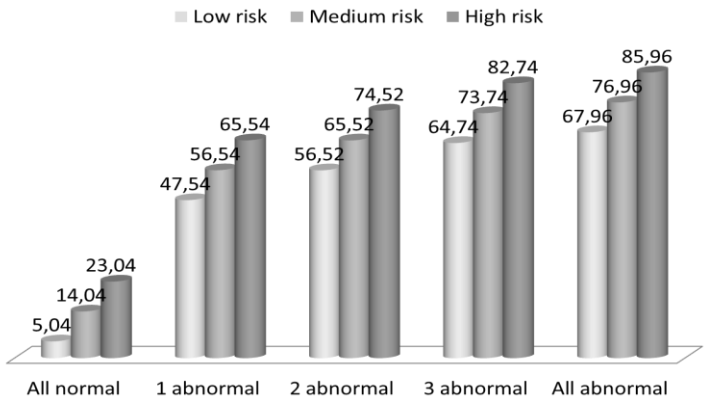


Fig. 15. Bayesian probability result by risk category and medical measurement result.

6 Conclusion and Future Work

Proactive support of CHF patients is vital since the recovery from a critical condition usually presents complications and it is not always possible. Although emergency situations may occur without prior warning, still in the majority of emergency cases, there are “signals” that precede their appearance. The regular monitoring of selected health variables followed by a multi-parameter and multi-level data analysis for the identification of abnormal health trends is the main contribution of the presented methodology.

Today, telecare systems typically incorporate the monitoring of patients’ vital signals which can be transmitted, wirelessly, to a public or private medical care center for the provision of healthcare services. Furthermore, many systems support the automatic generation of alarms when the measurements exceed a predetermined range. The presented system surpasses this functionality and provides risk inference capabilities for the specific chronic disease by combing biological signals with a validated risk model.

The system integrates additional mechanisms like the scenario creation tool which can facilitate system usage in different measurement situations.

The technical solution has been validated in several levels where as the medical inference component and the associated BN model defined were validated for prediction accuracy with the assistance of the domain expert with positive results.

Although the system presented addresses the problem of early prevention and management of health risks and complications in CHF patients, still with the proper enhancements in the BN modeling and health parameters monitoring the system could be used for risk management in other chronic diseases such as hypoglycemia in patients with Diabetes Mellitus. Our goal is the specification of a general methodological framework on the management of chronic diseases, as a result of the study of more use cases highlighting the perspective of the system to become a generic tool with built-in medical inference capabilities for various diseases. This aim needs to be validated in clinical trials using the integrated system with patients at their home.

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