A Home-based Early Risk Detection System for Congestive Heart Failure using a Bayesian Reasoning Network

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Abstract: Congestive heart failure (CHF) is a progressive condition in which the heart is no longer capable of supplying adequate oxygenated blood to the body. Since the incidence of CHF increases with age, mainly due to the development of heart failure risk factors the epidemic of CHF is expected to grow further in the coming decades and thus becoming an important public health problem. In this paper we present a risk detection system for CHF that uses a Bayesian Network (BN) combined with health measurements that can be taken in a home environment using ambient assisted living technologies. The algorithm is empowered by employing statistical and medical analysis of the stored biological data and the output can be used as a basis for triggering proper preventive interventions. The BN design was established by surveying the relevant literature and consulting the domain expert. The network content combines both biometric variables that are daily monitored and data from patient's clinical history as well as additional heart failure risk factors in terms of the EuroSCORE model. The predictive validity was tested with the involvement of the domain expert who specified proper validation rules in terms of criteria for detecting a CHF risk.

1 INTRODUCTION

According to the World Health Organization cardiovascular diseases (CVDs) are the prime cause of death worldwide (World Health Organization, 2016). In 2012, an estimated 17.5 million people died from CVDs, representing 31% of all global deaths. Preventive medicine and early risk detection are critical factors to reduce mortality and the associated healthcare system overheads.

Traditional heart disease treatment protocols are costly and require periodic visits at healthcare centers which are uncomfortable, especially for seniors suffering from chronic heart failure. ICT developments, however, in terms of wireless body sensor networks, ambient assisted living technologies, computational techniques and inference algorithms are changing the way how healthcare services are provided (Rashidi and Mihailidis, 2013). For instance, vital biological parameters such as Electrocardiogram (ECG), heart rate, systolic/diastolic pressure and temperature can be measured accurately and in real-time by wearable and mobile sensors and transmitted wirelessly to a gateway device (e.g. smartphone, tablet). The latter forwards the collected information through web connectivity to remote servers for storage and analysis by medical experts or algorithms in order to make the appropriate decisions.

In this paper we present a home-based early risk detection system for senior patients suffering from congestive heart failure (CHF). Patients can take medical measurements at the convenience of their home using wearable sensors avoiding visits to healthcare centers. Collected data are stored in a database and are processed in real time by a risk detection algorithm. This algorithm combines statistical and medical analysis of the stored biological data and a probabilistic reasoning approach using a Bayesian Network (BN) in order to detect possible alarms which can then trigger proper preventive medical interventions. The BN combines both biometric variables that are daily monitored (ECG, blood pressure, heart rate, blood oxygen saturation, temperature and weight) as well as data from patient's clinical history. The latter includes

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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 (Nashef et al., 2012).

The rest of this paper is organized as follows: Section 2 examines related work, Section 3 presents the proposed methodology in terms of the risk detection algorithm and the developed system while Section 4 discusses the validation of the developed BN. Finally, our conclusions and suggestions for future work are given.

2 RELATED WORK

Bayesian reasoning networks are often used in disease diagnosis (Lucas et al., 2004). BN-based prognostic systems for heart failure have been also proposed (Gatti et al., 2012). In the study of Ghosh and Valtorta (1999) a Bayesian decision network for heart disease was developed from clinical data. The constructed network was consisted of seventeen variables chosen after an extensive study of the relevant literature. The Noisy-OR approximation was 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. Some of the conclusions were that the ECG is a sensitive and specific diagnostic tool and blood pressure has significant role in the disease occurrence.

Su (2001) developed an early warning system for CHF using a BN. The network combined simulated biometric data (weight and blood pressure) and the location of the user to dynamically select context-specific health questions. Answers to questions and biometric data were then used by the BN to calculate a probability that the user is at risk for CHF.

Auble et al., (2005) developed a prediction rule to detect low-risk patients with heart failure by analyzing through classification trees a large data set. The variables used included demographic, clinical, laboratory, electrocardiographic and radiographic findings. The outcome was that an individual patient can be identified as low risk based on the presence of a few prognostic factors. Visweswaran et al., (2010) used the same clinical data sets and variables and developed algorithms that perform Bayesian model averaging over a set of models using the features of the patient case at hand to predict heart failure prognosis.

Most of the above approaches represent research efforts to develop BN models to support decision making at a clinical or laboratory environment and not systems that can be deployed in a home environment to support early detection of CHF risk by using medical sensors/devices in the context of an ambient assisted living setting.

A number of out of hospital wearable real-time monitoring systems have been proposed by researchers for continuous medical care of patients (Malan et al., 2004, Ko et al., 2010). In particular, Suh et al., (2010) developed an automated vital sign monitoring system for CHF patients. Through a weight and activity with blood pressure monitoring system, called WANDA, they could monitor patients' health status and behaviors in order to provide health reminders and patient feedback. The system has enabled patients to reduce or maintain weight, and to reduce the amount of blood pressure values which are out of the acceptable range.

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 METHODOLOGY

3.1 Risk Detection Algorithm

Figure 1 depicts the overall structure of the risk detection algorithm. There are four categories of data processing. Statistical analysis of biological data detects considerable variations between the current measurements and the corresponding history data of the same patient. Medical analysis of biological data is based on decision rules which use threshold values specified by medicine science. EuroSCORE risk calculation uses clinical history data and medical examination measurements (weight, pulmonary artery systolic pressure, etc.) as a method to assess the health risk status for patients that have been operated for heart failure. Finally, the Bayesian reasoning network is used as a diagnostic tool of possible medical risks based on multi-parameter information provided by both medical measurements and clinical history. The output of the data processing will be one of the following states: normal, pre-alarm and alarm. Normal indicates a healthy state. 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.

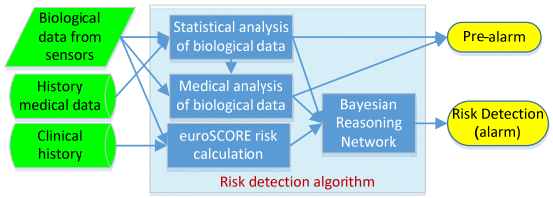

Figure 1: Structure of the risk detection algorithm.

3.1.1 Statistical Analysis

The statistical analysis module 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 (Altman, 1990):

$$\mathrm{DI} = \frac{\mathrm{x} - \mu}{\sigma} \quad (1)$$

The DI value is associated with the probability of a variable value and is used in the mechanism of the pre-alarm estimation. The larger the DI absolute value is, the more unlikely it is to observe such a value and therefore the more noticeable the difference from the normal.

Let $tw_{ij}=(t-\Delta t_{ij}, t)$ be a time window from the current point in time t until Δt_{ij} time points in the past, where index i denotes the variable under consideration and index j denotes the time window class. Different time window classes may be used referring to different time phases spread in the immediate past, e.g. tw_{i1} is the most recent time window of variable i, tw_{i2} is the immediately preceding time window of the same variable, etc.).

In the system database at time $t-\Delta t_{i1}$ the average values (M_i) of measurements are defined after dividing the sum of the values of each variable with their count (N_i). After the interval Δt_{i1}, L_{i1} new values are recorded (x_{ik}) and the following calculations are taking place in the context of the current time window:

Mean value:
$$M_{i1} = \frac{\sum_{k=1}^{L_{i1}} \mathrm{x}_{ik}}{\mathrm{L}_{i1}} \quad (2)$$

Sum of squares:
$$S_{i1} = \sum_{k=1}^{L_{i1}} \mathrm{x}_{ik}^2 \quad (3)$$

Standard dev:
$$SD_{i1} = \sqrt{\frac{S_{i1}}{L_{i1}} - M_{i1}^2} \quad (4)$$

Based on Eqs (2)-(4) the new mean value and standard deviation for all measurements of the variable i at time t are updated:

Mean value (total):
$$M_{i,new} = \frac{N_i \cdot M_i + L_{i1} \cdot M_{i1}}{N_i + \mathrm{L}_{i1}} \quad (5)$$

Sum of squares (total):
$$S_{i,new} = S_i + S_{i1} \quad (6)$$

Standard dev (total):
$$SD_{i,new} = \sqrt{\frac{S_{i,new}}{N_{i,new}} - M_{i1}^2} \quad (7)$$

where $N_{i,new} = N_i + L_{i1}$.

Based on Eqs (5)-(7) the following formulas can be used to calculate DI resulting in different sensitivity of the pre-alarm status estimation:

Instant DI:
$$DI = \frac{x_{ik} - M_{i,new}}{SD_{i,new}} \quad (8)$$

Time Window DI:
$$DI_{tw_{i1}} = \frac{M_{i1} - M_{i,new}}{\frac{SD_{i,new}}{\sqrt{L_{i1}}}} \quad (9)$$

ΔTW DI:
$$DI_{\Delta tw} = \frac{(M_{i1} - M_{i2}) - (M_{i,new1} - M_{i,new2})}{\sqrt{\frac{SD_{i,new1}^2}{L_{i1}} + \frac{SD_{i,new2}^2}{L_{i2}}}} \quad (10)$$

A high value of instant DI (Eq. (8)) 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. However, the transient deviation of a measurement from the total mean value, although important, is likely to appear due to noise factors. On the other hand, a high DI value featuring a whole time window, offers a more reliable indication for transition to the pre-alarm status (Eq. (9)). Finally, the detection of significant variations between time windows of different classes (on the same variable) can support the assessment that the patient undergoes a transition from a clinical state to another as described by Eq. (10). In this formula the tw index value 1 refers to the time window of first-class (most recent) and the value 2 to the time window of second order (preceding of the first). These time windows encapsulate the necessary

information regarding the classification of the patient's state at the current phase, and can have different durations depending on the variable under consideration. In our prototype the duration of tws is defined to 5-7 days based on the feedback provided by the medical experts.

The deviation index value for a variable x is then categorized based on medical expert empirical knowledge according to the formula:

$$\mathrm{CDI}_x = \begin{cases} 0 & \mathrm{DI} \leq 1.5 \\ 1 & 1.5 < \mathrm{DI} \leq 3 \\ 2 & \mathrm{DI} > 3 \end{cases} \qquad (11)$$

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.

3.1.2 Medical Analysis

The medical analysis component of the risk detection algorithm examines whether medical variable measurements (i.e. average values of the current time period) are exceeding normal value ranges in order to be classified as normal or abnormal based on criteria related to the patient profile. Table 1 gives normal value ranges in typical resting state for medical parameters as suggested by medical experts and literature for the target patients (Kucia and Quinn, 2013, Webster, 2014).

Table 1: Normal value ranges of medical parameters.

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	36.1°C-37.4°C

A basic parameter is the Electrocardiogram (ECG) signal which measures the electrical activity of the heart. Figure 2 depicts a typical ECG waveform which is composed of a series of positive and negative waves identified by the symbols P, Q, R, S, and T. A normal waveform combines three different segments identified as the P wave, the QRS complex and the T wave referring to depolarization or repolarization of some region in the heart (Dale, 2000). 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).

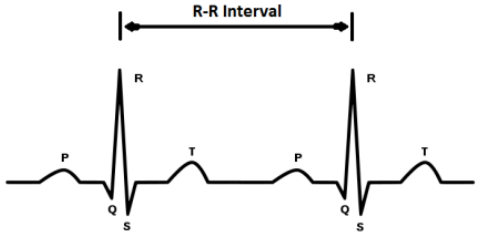

Figure 2: A typical ECG signal.

The output of medical analysis is fed to the Bayesian Reasoning Network as part of the model so that the system can estimate a dynamic risk evidence as an alarm for the patient.

3.1.3 EuroSCORE Risk Calculation

Various prediction models have been developed in the field of medicine for determining patient risk. Most of these are related to the field of cardiology, and one of them is the EuroSCORE, which was developed for predicting the mortality risk probability of a patient during or shortly after cardiac operation. Latest and most updated EuroSCORE model is the EuroSCORE II (Nashef et al., 2012), which uses the same logistic formula as the original EuroSCORE (Nashef et al., 1999), but encompasses extra risk factors and was validated by a highly accurate database with data collected from 22,381 patients at 154 hospitals in 44 countries. EuroSCORE II risk factors include factors relevant to patient, to heart health and to cardiac operation. In our approach, EuroSCORE II is used as one of the risk estimation factors for patients with CHF.

The formula that calculates the patient risk by EuroSCORE is given below:

$$eSCORE = \frac{e^{(\beta_0 + \sum \beta_i + x_i)}}{1 + e^{(\beta_0 + \sum \beta_i + x_i)}} \qquad (12)$$

where e is the base of the natural logarithm, β_0 is a constant (−5.324537), x_i is a categorical risk factor with value 1/0 if present/absent and β_i is the coefficient of the variable x_i as shown in Table 3 in the Appendix.

The value calculated by Eq. (12) is then categorized according to the following formula based on the application of the scoring system suggested by the euroSCORE model and is fed to the Bayesian Reasoning Network.

$$eSCORE' = \begin{cases} LOW & if\ eSCORE < 0.03 \\ MEDIUM & if\ 0.03 \leq eSCORE \leq 0.07 \\ HIGH & if\ eSCORE > 0.07 \end{cases} \quad (13)$$

3.1.4 Bayesian Reasoning Network

Bayesian Networks (BNs) belong to the category of Probabilistic Graphical Models, particularly in the specific category of Directed Acyclic Graphs, in which the nodes represent variables and arcs represent relationships between them. BNs are ideal for representing causal relations and offer the possibility of creating intelligent systems with automated reasoning. In fact, they are knowledge or model based systems, wherein the knowledge is the BN and the reasoning engine is based on the laws of Probability Theory (Pearl, 2014). 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.

The arcs connecting two nodes denote the statistical dependence of the corresponding variables and are quantified by Conditional Probability Tables (CPTs). CPTs contain all the conditional probability combinations expressed as $p(\pi_i/\gamma_j)$, where: π is a child variable, i.e. the node on which the arc is pointing; γ is a parent variable; i is a possible value of variable π; and j is a possible value of variable γ.

Parent nodes model causes and children nodes model effects. A node in a BN may have more than one parents. In this case the conditional probability is expressed as $p(\pi_i/\gamma_{1j}, \gamma_{2k}, \gamma_{3m}, \dots)$ which is interpreted as the probability of observing the value i for the variable π within the subpopulation of data given that the variable γ_1 has taken the value j, the variable γ_2 has taken the value k, and so on.

The calculation of this conditional probability based on the stored data and given the known structure of the BN may be performed as follows.

Conditional probability calculation algorithm:
Let a child variable π with m possible values and connected to k parent nodes each of which with $n_1, n_2, \dots n_k$ possible values.
For each value combination j of the total $n_1 \cdot n_2 \cdot \dots \cdot n_k$ combinations the parent nodes can take, repeat the steps:
1. Search and count the number of records that contain the combination j of the parent nodes: N_j
2. For each value i of the total m values the variable π can take repeat steps 3 & 4
3. Search and count the number of records that contain the combination j of the parent nodes and the value of the variable π is the *ith*: N_{ij}
4. Calculate the probability: $p(\pi_i/\gamma_j) = \frac{N_{ij}}{N_j}$

When all $p(\pi_i/\gamma_j)$ quantities have been calculated, i.e. the probability to observe an effect given the existence of a specific cause, the BN is updated, which is then ready to be used with the support of special software libraries for reasoning the quantities that we are interested in, i.e. the probability to exist a risk given that certain effect/symptom has been observed, $p(\gamma_i/\pi_j)$.

When a node has more than two parents the calculation of such probabilities is conceptually complex. Furthermore, the reliability of the calculated probability is small because the calculations are based on small sub-populations of the database. For this reason when both parent and child nodes are discrete binary variables (e.g., TRUE/FALSE or NORMAL/ABNORMAL) we can assume a causal independence among the modeled causes and their common effect which is known as the *Noisy-OR* model (Pearl, 2014). 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 Eq. (14).

$$p(\pi = \{T\}|\gamma_i) = 1 - \prod_{\gamma_i \in \Gamma_T} (1 - p_i) \quad (14)$$

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

An extension of the Noisy-OR model is 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. This solution 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. Eq. (14) is then updated as follows:

$$p(\pi = \{T\}|\gamma_i) = 1 - (1 - p_{leak}) \prod_{\gamma_i \in \Gamma_T} (1 - p_i) \quad (15)$$

CHF disease includes many causes and effects (Braunwald and Bristow, 2000). Medical studies were used to determine dependencies and the initial conditional probabilities employed in the network (Long et al., 1997, Ghosh and Valtorta, 1999, He et al., 2001). In particular, the predictive significance

of systolic and diastolic blood pressure is well known (Haider et al., 2003). Heart rate is also considered as a prognostic factor of CHF risk for seniors while ECG establishes a diagnostic factor. Discussions with medical experts provided insight in order to simplify the network using only the variables that are most relevant in the specific problem domain, to adjust conditional probabilities in specific arcs of the network and to specify validation rules as expressions of criteria for detecting a CHF risk. Finally, a significant factor for selecting the key BN variables was their suitability regarding the collection of the relevant medical data in a home setting.

Categorical medical variables provided by the medical analysis phase and the categorized EuroSCORE risk value derived by Eq. (13) were promoted to the BN as evidence variables. Figure 3 depicts the BN structure established for the risk detection of CHF. The prior probabilities of the categorical values for variables without parents were given. Conditional probabilities for variables with parents were also defined. Figure 3 shows also 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.

In the following we explain the conditional probabilities assigned in the BN model.

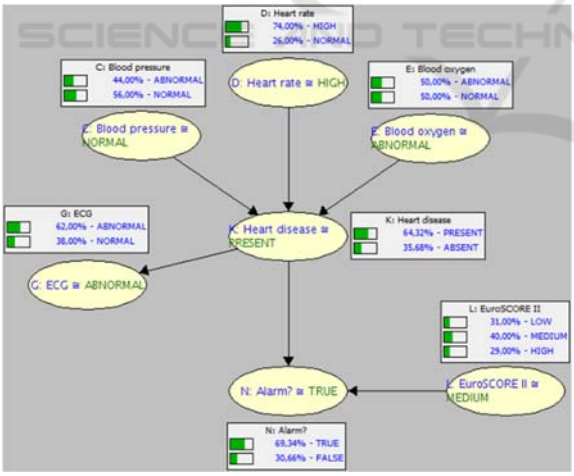

Figure 3: BN structure for risk detection of CHF when no evidence is given.

CPTs of nodes (C), (G), (D)

Prior probabilities of nodes representing the medical variables "Blood pressure" (C), "Heart rate" (D) and "ECG" (G) were defined according to the study of Ghosh and Valtorta (1999). Table 2 gives the NORMAL value probability for the specific nodes.

Table 2: Prior probabilities based on literature.

Node	Variable	Normal value probability
C	Blood pressure	0.56
D	Heart rate	0.26
G	ECG	0.38

CPT of node (E)

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.

CPT of node (L)

Prior probabilities of node "EuroSCORE II" (L), were defined based on EuroSCORE model data. In the EuroSCORE model from 14,799 patients, 4,529 had low risk, 5,977 had medium risk and 4,293 had high risk. So we defined the following prior probabilities of node (L):

$$\mathrm{p}(L = \{LOW\}) = 0.31 \quad (16)$$

$$p(L = \{MEDIUM\}) = 0.40 \quad (17)$$

$$\mathrm{p}(\mathrm{L} = \{HIGH\}) = 0.29 \quad (18)$$

CPT of node (K)

The CPT of node "Heart Disease" (K) given nodes C, D and E was defined using the leaky Noisy-OR formalism. Table 4 in Appendix gives the contents of this CPT using as 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:

$$p(G|K = \{PRESENT\}) = 0.95 \quad (19)$$

CPT of node (N)

The CTP of node "Alarm" (N) given nodes K and L was defined using the Total Probability Theorem as described by Eq. (20).

$$p(N|K, L) = p(K)p(N|K) + p(L)p(N|L) \quad (20)$$

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

$$p(N|K = \{PRESENT\}) = 0.99 \quad (21)$$

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:

$$\mathrm{p}(\mathrm{N}|\mathrm{L} = \{LOW\}) = 0.05 \quad (22)$$

$$\mathrm{p}(\mathrm{N}|\mathrm{L} = \{MEDIUM\}) = 0.26 \quad (23)$$

$$\mathrm{p}(\mathrm{N}|\mathrm{L} = \{HIGH\}) = 0.69 \quad (24)$$

Table 5 in Appendix gives the contents of this CPT.

3.2 System Architecture

The system follows a multi-tier client/server architecture. The specific model was chosen because of its scalability, reusability and maintenance capabilities. System architecture is given in Figure 4. The system gathers information using devices and sensors in the user's local space and filters this information in the Local Subsystem Manager (LSM) before forwarding the formatted information to the remote server that can take decisions about the patient's status. This multi-layer approach makes integration of new sensors and smart devices easier and hides the complexity of the system as well as the different technologies used between the layers.

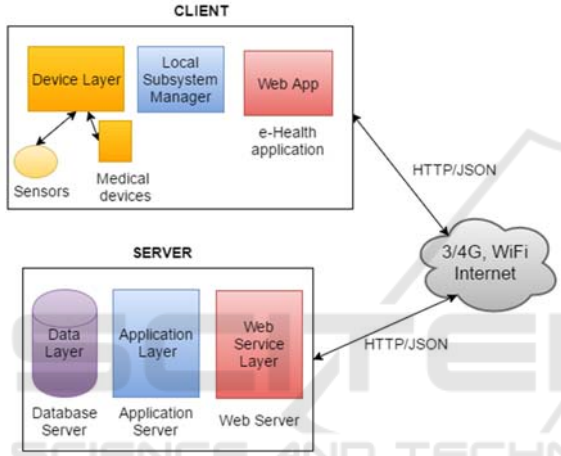

Figure 4: System architecture.

A simple usage scenario of the system goes as follows: The system notifies the patient to take a measurement (e.g., blood pressure). The data is collected by the LSM through the device's communication protocol. 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) and analyses the patient's current status by running the risk detection algorithm described in Section 3.1. The system may decide that there is a possibility of health risk, so it sends a message back to the local system for a pre-alarm warning and communicates with the local administrator. When the LSM receives the pre-alarm message, it sends it to a notification device which warns the user to communicate with the doctor because the readings aren't so good.

3.2.1 Device Layer

The device layer contains all the devices and services that are deployed in the user's local space. These are not used just for sensory input but they also provide actuation (such as displays or speakers for warning messages).

Figure 5 displays the medical sensors and devices required for the measurements. The Shimmer ECG sensor, the AnDMedical UA-767PBT blood pressure device and the Tanita BC-590BT weight scale use Bluetooth for wireless transmission of their measurements. The Avant 4000 Digital Pulse Oximetry System measures the blood oxygen saturation and transmits its data into a virtual serial port through a USB adaptor.

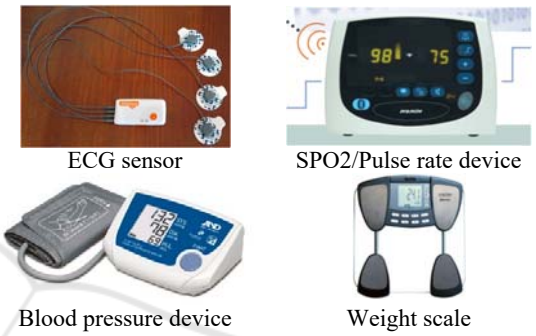

Figure 5: Sensors and devices.

For example, for measuring the ECG signal we have used Shimmer's wearable sensor board. The ECG sensor node is strapped to an elastic chest belt and three of the four electrodes are placed on the body to form lead II and lead III recording configurations according to the manual instructions. To gather the data the Multi Shimmer Sync for Windows application is used with a sampling rate of 100 Hz. The Pan-Tompkins algorithm (Pan and Tompkins, 1985) is used to detect the QRS-complexes in the ECG signal and then the duration and amplitude can be calculated so that the threshold values defined in Table 1 can be checked to decide the normal or abnormal classification.

3.2.2 Local Subsystem Manager

The LSM is a composite process in the client-side of the system and is responsible for the following operations:

- User notification to start a periodic measurement process
- Data gathering from the medical sensors and devices
- Temporary storage of data in case of network problems with the server

- Validity checking of the data based on the normal value ranges defined by domain experts (see Table 1)
- Data forwarding to the server
- Receiving commands and processed responses (pre-alarms, alarms) from the server
- User notification management through warning messages

When it's time to initiate a periodic measurement, the LSM creates the appropriate messages to enable the relevant devices for starting measurements and prepares the appropriate data structures to store the data from the devices. In addition the LSM updates the graphical user interface for the presentation of messages to the user with a set of instructions for using the devices.

3.2.3 Web App

The Web App provides the following main functionality:

- A personal profile interface where the user can enter patients' personal information as well as relevant chronic diseases (Figure 6);
- 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.

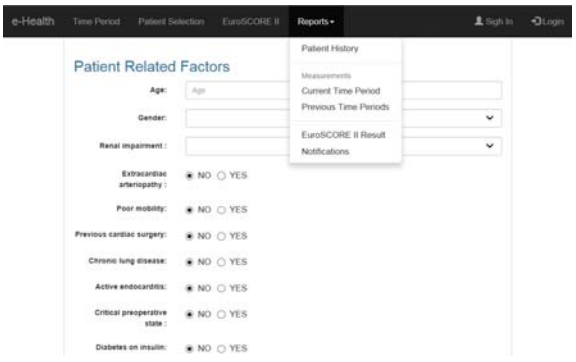

Figure 6: Web app GUI.

3.2.4 Web Service Layer

The web service layer receives and sends messages from/to the client and also communicates with the application layer. The communication mechanism is based on sending messages through the HTTP protocol, using the representational state transfer (REST) model. The header of the message should contain the data types of the measurement values and a key for authentication purposes. In case the client-side posts measurement data, instead of getting data, the HTTP message body will contain the measurement data with the types specified in the header. For example, the body of a measurement message will have the form given in Figure 7.

```
<MESSAGE>
    <HEADER>
        <SENDER>sender_IP</SENDER>
        <PATIENTID>patientID</PATIENTID>
    </HEADER>
    <DATA_ TRANSMIT >
        <TIMESTAMP>TIME</TIMESTAMP>
        <SUCCESS>{true/false}</SUCCESS>
        <MEASUREMENTS>
            <MEASUREMENT>
                <NAME>var_name</NAME>
                <DTYPE>var_type</DTYPE>
                <VALUE>value</VALUE>
            </MEASUREMENT>
        </MEASUREMENTS>
    </DATA_TRANSMIT>
</MESSAGE>
```

Figure 7: Measurement message structure.

3.2.5 Application Layer

The purpose of the application layer is to collect the data for each patient from each local subsystem and to run the health risk assessment algorithm, which may derive pre-alarm or alarm states. In such cases the system either notifies its administrator to contact the patient or sends back to the local subsystem the appropriate notification messages in order to be presented to the user using his local devices.

The application layer contains in the implemented Java classes the business logic of the system. In particular, it encompasses the Bayesian reasoning network component and interacts 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.

Initially the received JSON message with the measurements is checked 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. Figure 8 represents this process as an activity diagram.

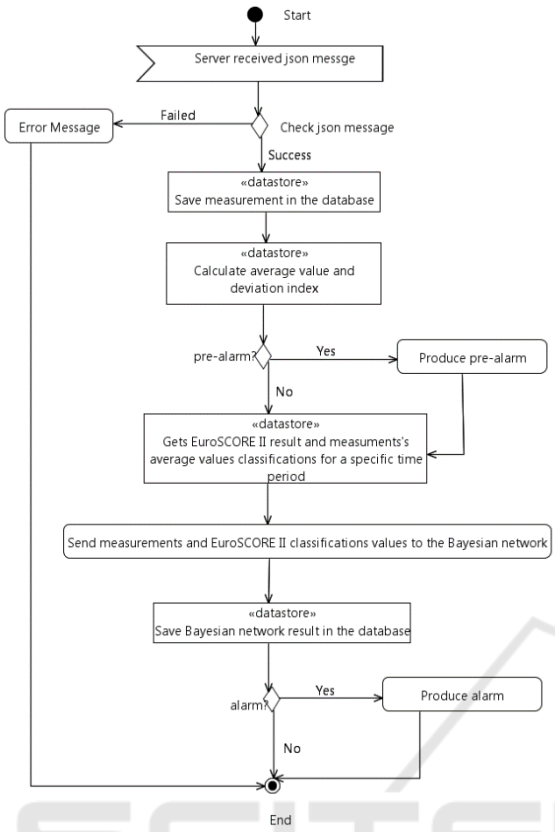

Figure 8: Activity diagram of the risk detection process.

3.2.6 Data Layer

The data layer was designed and implemented as a relational database in Oracle platform which provides all the necessary support for storing, retrieving, updating and maintenance of data, as well as the necessary mechanisms for ensuring data integrity. 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. Relational database tables are classified into three categories:

- Tables containing information describing the EuroSCORE model.
- Tables containing information describing medical examinations for which the system collects measurements.
- Tables related to the patients' medical history and stored measurements.

In total there are 14 tables with 92 fields and 14 relationships between the tables. For example, the entity-relationship diagram in Figure 9 depicts the tables for storing user-related information such as the user type (patient or doctor), user profile, EuroSCORE II model results, values of risk factors, time periods sets for measurements, measurements per time period, detailed measurements of medicals parameters collected by sensors as well as statistical values and Bayesian reasoning network results calculated by the system.

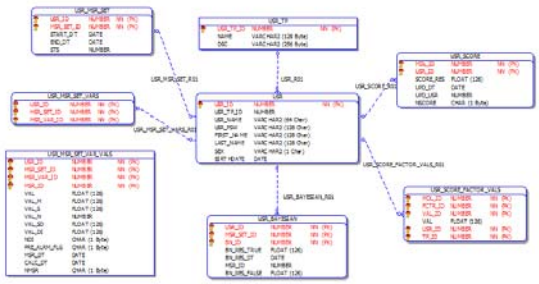

Figure 9: Entity relationship diagram for user tables.

3.3 Implementation Environment

The system was developed using several implementation technologies. The application layer and the LSM were developed in Java programming language with the Eclipse Mars 2 (version: 4.5.2). The Bluetooth stack of the operating system was used to support the communication with the sensors. The web app was develop in HTML 5 with Bootstrap CSS framework (version 3.3.6) for cross-browser compatibility, and with jQuery JavaScript library (version: 1.12.3) for the asynchronous calls to the restful web service. The latter was implemented using HTTP and JSON data format for transferring messages between the client and the server.

The Bayesian reasoning network for the system was designed and tested using Sensitivity Analysis Modeling Inference And More – SamIam, a tool developed at University of California at Los Angeles (UCLA) for modeling and reasoning with BNs (Darwiche, 2009). The Bayesian reasoning component of the application was implemented with the Jayes Java library.

Finally, the relational database was implemented with the Oracle database Express Edition 11g Release 2.

4 VALIDATION

System validation for good operation was performed in terms of the predictive validity of the risk detection algorithm. Due to the lack of reliable clinical data to compare with the system predictions, a domain expert (i.e. a cardiologist) was involved in

order to comment on the accuracy of the BN reasoning. For each possible combination of variable values the expert needs to specify a diagnosis and compare it with the conclusion of the model. In our model there are five evidence variables. Four of them represent medical parameters which can take one out of two values (abnormal/high, normal) and the EuroSCORE variable which can take one of three values (low, medium, high). So there are $2^4 * 3^1 = 48$ possible evidence combinations. All the combinations were tested automatically using the SamIam tool which calculates also the probability of CHF risk. The task then is 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.

For example, given the query "*What is the risk when declining health evidence is given, i.e, blood pressure, heart rate and ECG are high and the risk of the EuroSCORE II model is medium?*" the BN model gave a probability 0.77 to produce the risk alarm (Figure 10). Given that the alarm threshold was found to be 0.65, the alarm signal is enabled. The expert assessed the conclusions of the model as reasonable and also specified the following validation rules as expressions of criteria for which the CHF risk should always be true:

- Patients with LOW eSCORE risk must have all measurements Abnormal.
- Patients with MEDIUM eSCORE risk must have at least two measurements Abnormal.
- Patients with HIGH eSCORE risk and anyone measurement Abnormal.

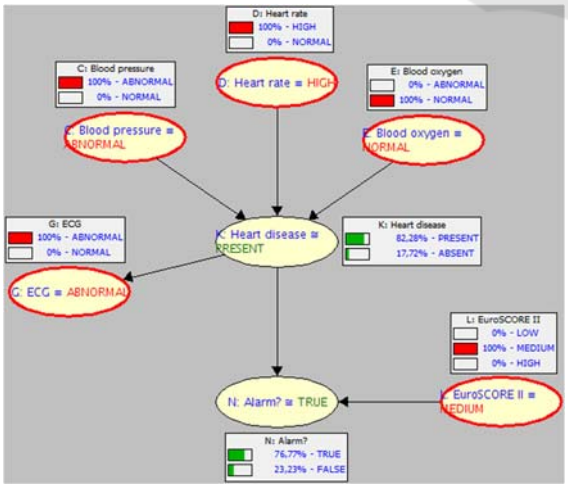

Figure 10: BN behaviour given certain measurements.

The graph in Figure 11 gives a comprehensive view of the BN conclusions according to the eSCORE risk category when different evidences were generated. For patients with LOW eSCORE risk and all four measurements Abnormal, the model calculated an alarm probability of 67.96%, whereas with three measurements Abnormal, the alarm probability was 64.74%, slightly below the threshold. For patients with MEDIUM eSCORE risk and two measurements Abnormal, the model calculated an alarm probability of 65.52%, whereas with only one Abnormal measurement the alarm probability was 56.54%. Finally, for patients with HIGH eSCORE risk and one measurement Abnormal, the model calculated an alarm probability of 65.54%, whereas with all measurement Normal the alarm probability was 23.04%, well below the threshold. Consequently, we observe that the BN fulfills the criteria recommended by the expert in order to generate an emergency alarm.

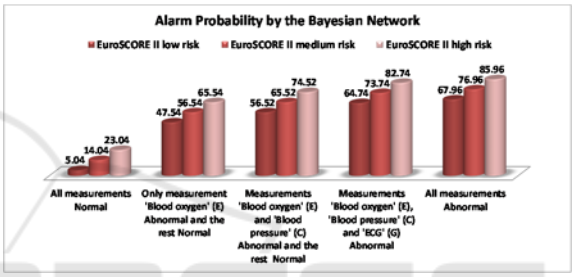

Figure 11: Bayesian result by risk category.

Beyond predictive validity a BN model should be also checked regarding the mechanism through which this prediction is obtained. Pitchforth andMengersen (2013) suggested that seven dimensions of validity in a BN model should be examined: nomological, face, content, concurrent, predictive, convergent and discriminant validity.

The use of BNs in medical problems for diagnostic and alerting purposes is common and it has been successfully applied thus covering the nomological validity. The involvement of the domain expert in testing the predictive validity ensures the face validity. The content validity is satisfied because the structure of the BN was decided by consulting both medical experts and the literature. Moreover, the constructed model is simple enough, without a large number of nodes or arcs so as to become computationally intractable. The constructed model does not contain any sub-networks so the concurrent validity does not apply. Convergent validity as well as discriminant validity are achieved because risk diagnosis is done from symptoms/signs to causes.

Finally, the risk values of the EuroSCORE II model calculated by the system were compared to the values calculated by the on-line EuroSCORE

calculator (http://www.euroscore.org/calc.html) for the same inputs and were found to be equal.

5 CONCLUSIONS

The main contribution of this paper is a methodology that combines biological parameters with heart failure risk factors to design a new early risk management system for seniors suffering from CHF. The core of the system is the risk detection algorithm whose functionality is not limited to monitoring health parameters and comparing the measured values with predefined thresholds. Through a combination of medical and statistical analysis of the measured health variables and the employment of probabilistic reasoning techniques health status decline can be effectively identified generating pre-alarm and alarm notifications which can be exploited for providing medical interventions.

Based on the validation performed, we argue that the use of a probabilistic reasoning approach using a BN can provide positive results on risk detection. We tested the prediction validity of the BN with the involvement of a medical expert in order to assess the usefulness of the system.

The methodology and the technical solution proposed could be applied to other health conditions (e.g. hyperglycemia linked to diabetes) with the proper extensions regarding health parameters and BN structure and thus it could provide a multi-disease health monitoring framework with integrated risk detection capabilities.

We are currently working on a deployment of the system to validate our experimental results in a pilot study with real users. In addition, we would like to investigate using sensor parameters from smart environments, like environmental parameters and activities of daily living (e.g., sleeping patterns), as additional evidence variables to the BN.

Another enhancement to this work would be to analyze the stored data in order to provide feedback to doctors on the diagnosis and specific treatment recommendations.

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APPENDIX

Table 3: EuroSCORE II model risk factors.

Risk factor	Coeffic.	Risk factor	Coeffic.
NYHA		LV function	
II	0.1070545	Moderate	0.3150652
III	0.2958358	Poor	0.8084096
IV	0.5597929	Very poor	0.9346919
CCS4	0.2226147	Recent MI	0.1528943
IDDM	0.3542749	PA systolic pressure	
Age	0.0285181	31–55mmHg	0.1788899
Female	0.2196434	≥55	0.3491475
ECA	0.5360268	Urgency	
CPD	0.1886564	Urgent	0.3174673
N/M mob	0.2407181	Emergency	0.7039121
Redo	01.118599	Salvage	1.362947
Renal dysfunction		Weight of procedure	
On dialysis	0.6421508	1 non-CABG	0.0062118
CC ≤ 50	0.8592256	2	0.5521478
CC 50−85	0.303553	3+	0.9724533
AE	0.6194522	Thoracic aorta	0.6527205
Critical	1.086517	Constant	−5.324537

For age, $x_i = 1$ if patient age ≤ 60; x_i increases by one point per year thereafter ($x_i = 2$ if age 61; $x_i = 3$ if age 62 etc.).

Table 4: CPT of node (K).

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

Table 5: CPT of node “Alarm?”(N).

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