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EVALUATION OF LIFESTYLE EFFECTS ON CHRONIC DISEASE MANAGEMENT

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ABSTRACT

In this study, we propose a model that helps to analyze the behavior of chronic disease patients with a focus on heart failure patients based on their lifestyle. We consider how living conditions affect signs and symptoms of chronic disease and, accordingly, how these signs and symptoms affect chronic disease stability. We use an agent-based model, a state machine, and a fuzzy logic system to develop the model. Specifically, we model the required “living condition” parameters that can influence required medical variables. These variables determine the stability class of chronic disease. The model allows creation of virtual patients with a given pathology and analysis of their impact on quality of the Emergency Department. Analysis of the Emergency Department’s quality based on modeling and simulation enables us to develop new planning strategies for efficient care systems.

1 INTRODUCTION

Healthcare systems try to reduce total expenses and time, as well as improve the efficient use of resources. An aging population, along with increasing rates of chronic disease, will detract from the quality of care (Liu et al. 2015).

Chronic patients often need to access healthcare systems and many of them need to be readmitted even though they are not in an emergency or a dangerous situations. However, many chronic diseases are preventable or predictable as many chronic conditions are a consequence of lifestyle choices that are under our control. Reducing unnecessary attendance of chronic patients to the healthcare system and controlling their time of visit could be an important solution to improving healthcare system efficiency. As most chronic patients are aged people, usually they have different behavior from non-chronic patient.

Considering the behavior of chronic patients individually and separately from other patients can help us to know how much time, resources and services will be occupied by the chronic patient and how reducing the number of the chronic patients can affect the efficiency of the healthcare system.

In order to be able to predict chronic patient behavior, we need to consider different parameters and conditions and see how they influence health variables.These parameters and conditions include the physical environment, lifestyle and other considerations. These parameters make each chronic patient behave differently from others.

Agent-based modeling and simulation (ABMS) allow us to model complex systems as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules (Bonabeau 2002). In an agent-based model, each agent has a set of attributes and behaviors. Each patient with the combinations of attributes such as age, gender, lifestyle, behavior and identify the agents.

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Usually, the living conditions of each chronic patient affect health variables and change the quantity of these health variables, so they can modify the stability situation of the chronic patient to instability and they can also go from unstable to stable. We classify each chronic patient into different classes based on their symptoms and signs, then we assume a state machine to present the movement between different states. As shown in Figure 1, each transition from one state to another presents the behavior of each patient and transition takes place when the health variables are changed, which means that the living condition of the patient is changed.

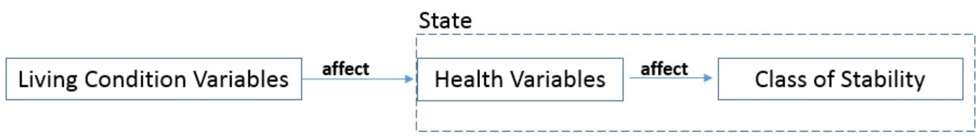

Figure 1: Influence of living condition on state.

The set of states show the patient's different level of stability which, is made up of the classes of chronic disease and medically related variables. Any transition from one class to another can be shown in a diagram to present the patient's behavior, which is shown in Figure 2 which, is the extended shape of Figure 1. It shows our inputs are life condition parameters in a specific time and these transitions happen between classes according to the quantity of state variables in a particular time, and all the modifications throughout time are displayed in diagram.

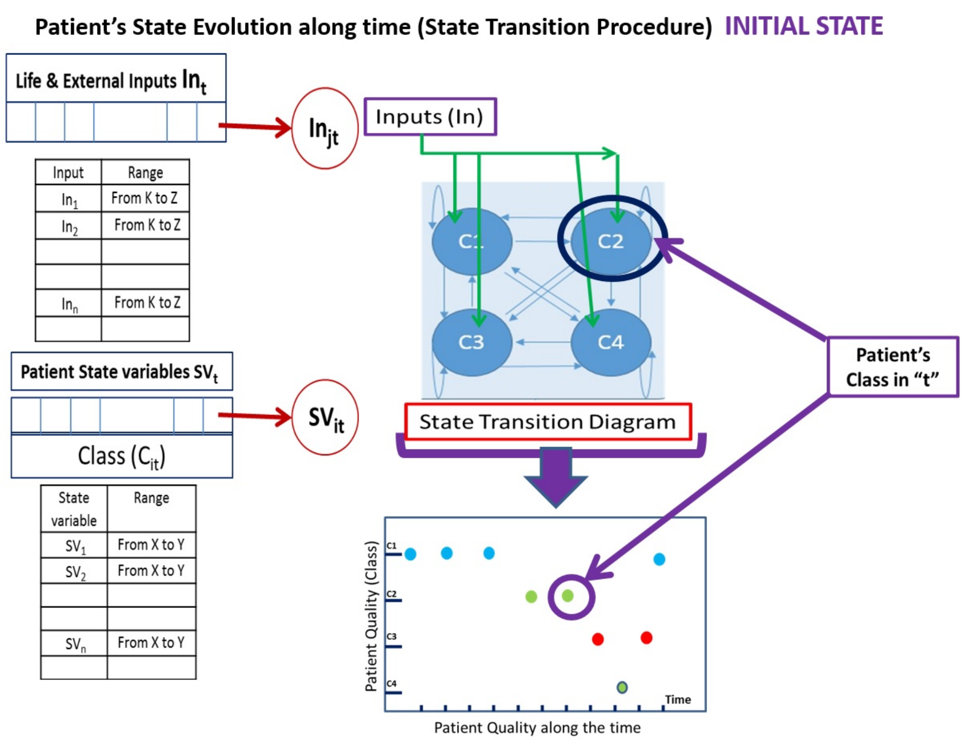

Figure 2: Extended shape of influence of living is shown condition on state.

Chronic disease variables are usually in natural language and computing based on the degree of truth rather than Boolean principle (binary truth). In the other words, it's not easy to translate this type of variable into an absolute term of one or zero. As our variables (Living condition Parameter and health variables (state variable)) are mostly in a vague language, we use the fuzzy logic system (Wang 2015).

We use fuzzy logic in this model twice. Firstly, for the classification of each medical health variable (state variable) where inputs are the living conditions parameters and, secondly, we classify the chronic disease quality (classes of stability), where the inputs are the medical health variables.

We have designed a model to consider how living conditions affect chronic disease clinical parameters, and how a change in clinical parameters can modify the stage of the health plus the quality of care system, then we simulate this model to evaluate and organize diverse visions and aspects of the structure model. So, simulation provide us with the possibility to qualify the proposed model more safely (Jacobson et al. 2006). This framework model can be simulated in Matlab and Netlogo. Simulation evaluates the framework which has this capability to consider all types of chronic diseases individually. We evaluate this simulated model by real data which is collected from hospital. Furthermore we can drive virtual data from this real data and predict the patient's behavior with different lifestyles. Simulation of the suggested model not only enables us to compare the behavior of heart failure patient with himself/herself at various time and in various conditions, but it also provide us with the possibility of comparing the behavior of a heart failure patient with others.

This study is carried out with the collaboration of healthcare staff at the Emergency Department of Hospital Universitari Parc Tauli (one of the biggest hospitals in Catalonia, Spain). This hospital provides care service to a catchment area of about 500,000 people, receiving over 160,000 patients annually in its ED (Liu et al. 2015). This research is a continuation of research work published in (Liu et al. 2015); (Liu et al. 2017). Their work contribution was simulation of ED classifying patients according to their acuity level. We present now how living conditions can affect heart disease and how this chronic disease influences on health care system efficiency. Then the framework developed is a step towards building a full model of an integrated care system.

We present how living conditions can affect heart disease and how this chronic disease influences on health care system efficiency. The remainder of this article is organized as follows: Related work in section2. Formal models and approach are detailed in Section 3. Section 4 talks about heart failure model. In Section 5 we discuss capabilities of the proposed simulation system. We have validation and transparency in Section 6 and in Section 7 we discuss future work and conclusions.

2 RELATED WORK

In the past three decades, interest in the use of simulation in health care has risen. Simulation is a 'bottom-up' tool that has been used to provide medical education, optimal treatment, as well as ensure patient safety and well-being. It also plays a role in modifying emergency department output and health care system performance. In medicine, an agent-based model is widely used in order to design and simulate a model for chronic disease progression and medical decision-making. The term fuzzy logic was introduced by Lotfi Zadeh in 1965 for many-valued data. Fuzzy Logic has been used in many fields such as engineering, social science, medical care, etc. One of the uses of fuzzy logic application in medical research is the classification of risk level of chronic diseases. The classification can be used for prediction, diagnoses, treatment, following-up and support of some chronic diseases. It has eased the modeling for health system designer as the medical data are presented in natural language. The simulated results of our proposed merged model simplify and identify how a person's lifestyle precisely affects risk factors and then compares the outcomes as it relates to overall health.

3 FORMAL MODELS AND APPROACH

In Figure 3, we can see how the algorithm for the proposed model works. At the beginning, it obtains the current state (the class of stability of the patient and its related health variables), then checks whether the living conditions of the patient are changed or not, if nothing is changed it means that the patient is in the same situation, then the state won't be changed. If the life condition is changed it means it could affect

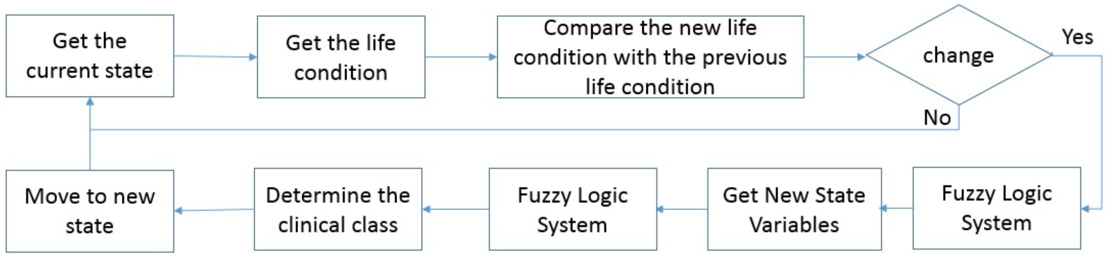

Figure 3: General model of chronic patient's behavior according to living condition.

state variables, so it goes to a Fuzzy logic system and gains the new health variables. Then by using new state variables it goes to the fuzzy logic system to find the new class, then it moves to a new state.

This main model is an agent-based model which is composed of two sub-models: a state machine model and a fuzzy logic model. As we mentioned before, each patient is counted as an agent. Then the state machine presents this agent action and movement according to some set of rules. These rules are defined and determined by the use of Fuzzy logic.

3.1 Fuzzy Logic

As predicting a chronic patient's behavior model is an uncertain, dynamic and sophisticated model and given that we will have a great amount of data in the health variables as well as life and medical conditions, then we should formulate this data by a fuzzy system and make an output, and for this reason we have decided to use fuzzy logic system (Wolkenhauer 1997). Each Fuzzy system design includes the determination of three steps: input variables, output variables and Fuzzy Inference, which is a primary application of fuzzy logic. The main approach of fuzzy inference is taking input variables through a mechanism which is comprised of parallel If-Then rules and fuzzy logical operations and then reaching the output (Wolkenhauer 1997).

3.1.1 Input and Output Variables

We apply fuzzy logic for two sub-models. Firstly, the inputs are living conditions in order to gain health variables as output and, secondly, we get health variables as input for classifying the chronic disease (patient quality) as output. By using these inputs and their range, we can design membership functions of input variables. With Equations (1), (2), and (3), for each language expression we can obtain its membership as follows. Figure 4 shows the chart of membership function of the variable (Adeli and Neshat 2010) and Allahverdi et al. (2007). In the first step in this system, the output variables are the state variables and then, in the next step, output is the class of chronic disease. These outputs also have to be defined with the formula 1, so we consider a different output variable which is divided into the fuzzy set (State1, State2, State3 and etc.).

$$\mu_{\text{Low}}(x) = \begin{cases} 1 & x < a \\ \frac{b-x}{b-a} & a \leq x < b \end{cases} \tag{1}$$

$$\mu_{\text{Normal}}(x) = \begin{cases} \frac{x-a}{b-a} & a \leq x < b \\ 1 & b \leq x \leq c \\ \frac{d-x}{d-c} & c \leq x < d \end{cases} \tag{2}$$

$$\mu_{\text{High}}(x) = \begin{cases} \frac{x-c}{d-c} & c \leq x < d \\ 1 & x \geq d \end{cases} \tag{3}$$

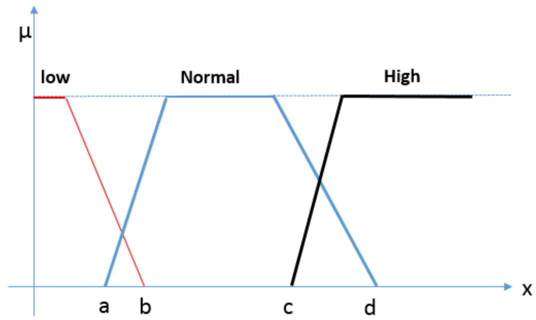

Figure 4: Membership graphic.

3.1.2 Fuzzy Rules Base

While the input and output variables and membership function are defined, we have to design the rule base composed of expert IF-THEN rules (Wang 2015). These rules transform the input variables to an output that in this study we use in three steps.

- First step: These are the rules that are based on living conditions inputs and give us the modification of the amount of state variables. In Figure 5, we can see a different combination of living conditions. This combination helps us to make the IF-THEN rules.
  In figure 6, the definition of rules based on a living conditions is shown. In this figure, we can see how we apply the fuzzy logic system to gain the state variables.

Living condition 1	Living condition 2	...	Living Condition n	State Variable1	State Variable2	....	State variable n
high	high	high	high	(↓/↑/=/≈...)			
high	high	high	moderate	(↓/↑/=/≈...)			
high	high	high	Low	(↓/↑/=/≈...)			
...	....	...	....	(↓/↑/=/≈...)			
low	low	low	low	(↓/↑/=/≈...)			

Figure 5: The different combination of living conditions.

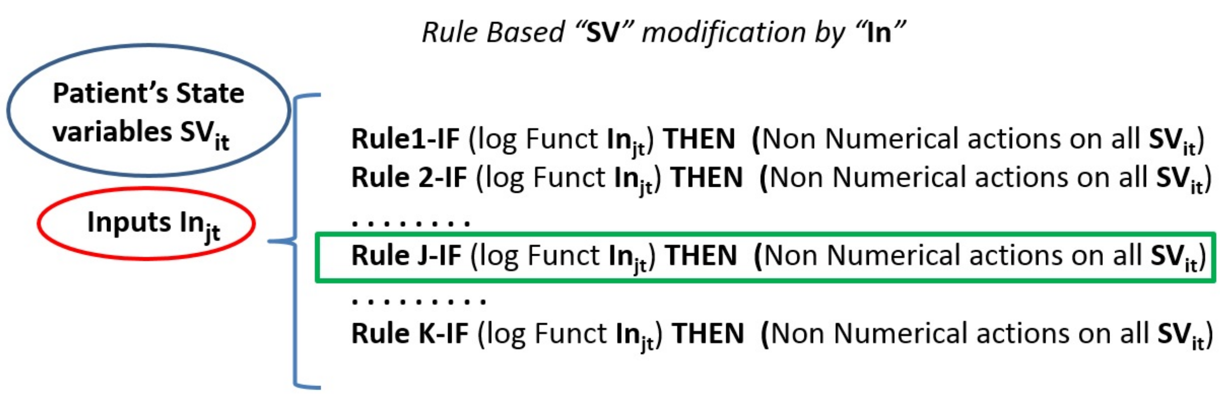

Figure 6: Obtaining state variable based on modification of living conditions.

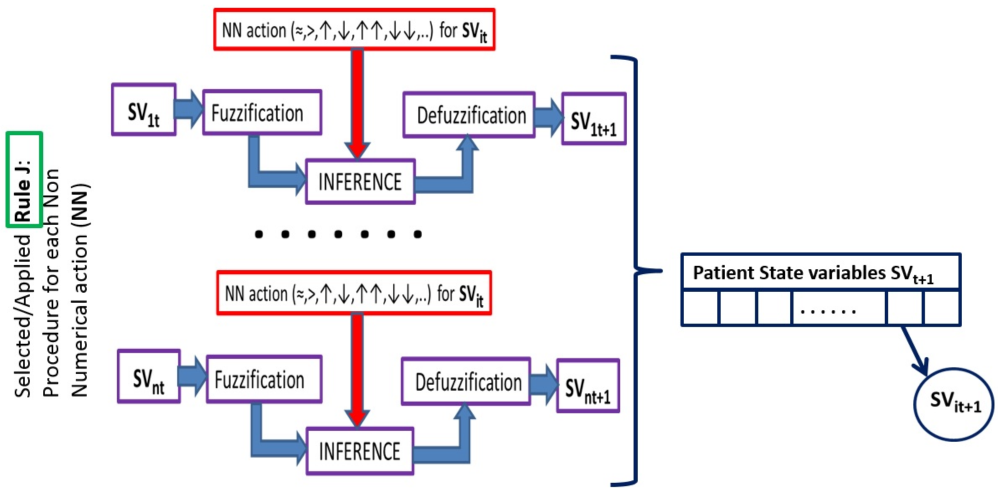

Figure 7: Obtaining state variable based on modification of living conditions for time t+1.

State Variable1	state variable2	....	State variable n	Class i	Class i+1
↑	↑	↑	↑	I	(I or II or III,....)
↑	↑	↑	↑	II	(I or II or III,....)
...	...	...	...	...	(I or II or III,....)
↑	↑	↑	↓	I	(I or II or III,....)
...	...	...	...	...	(I or II or III,....)
↓	↓	↓	↓	IV	(I or II or III,....)

Figure 8: Table of obtaining class for time i+1 based on modification of state variables and class in time i.

- Second step: Now the required rules are created, so we apply the rules to gain the future state variable in time $t+1$ from the current state variable in time t. This means SV_t is an input and SV_{t+1} is an output. This is displayed in Figure 7.
- Third step: A different combination of state variables make IF-THEN rules to gain a different classification of chronic disease (patient quality). Figure 8 shows a table that includes all possible combinations of state value, so we can select some of these combinations based on probability of occurrence to make the rules.
  Rule1:IF (Function SV_{t+1}) THEN Select $class(C_{it+1})$
  While rules are made, we can gain the chronic disease classifications based on state variables. This is shown in Figure 9.

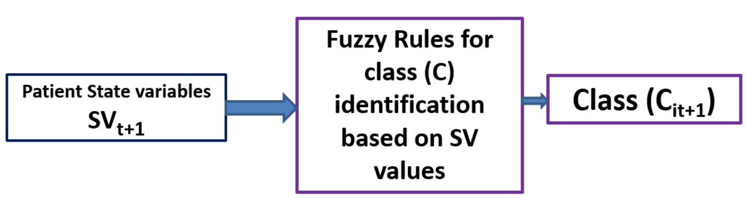

Figure 9: Obtaining state variable based on modification of living conditions for time t+1.

3.1.3 Defuzzification

This step is the process that maps a fuzzy set to a crisp set. The proposed model can use the inference system, whose output membership function is a fuzzy set. There are some different methods for defuzzification, whose center of gravity is most prevalent in defuzzification technique. This crisp set is an integer number. Equation (4) shows the method's center of gravity Saritas et al. (2003) and (Wang 2015) as follows:

$$D^* = \frac{\int D.\mu_M(D)dD}{\int \mu_M(D)dD} \tag{4}$$

3.2 Full Figure of Integrated Model

In Figure 10, we can see an integrated model that merges the state machine model and the fuzzy logic models. It shows everything we have mentioned in this section. The arrows on the figure show the steps of the integrated model.

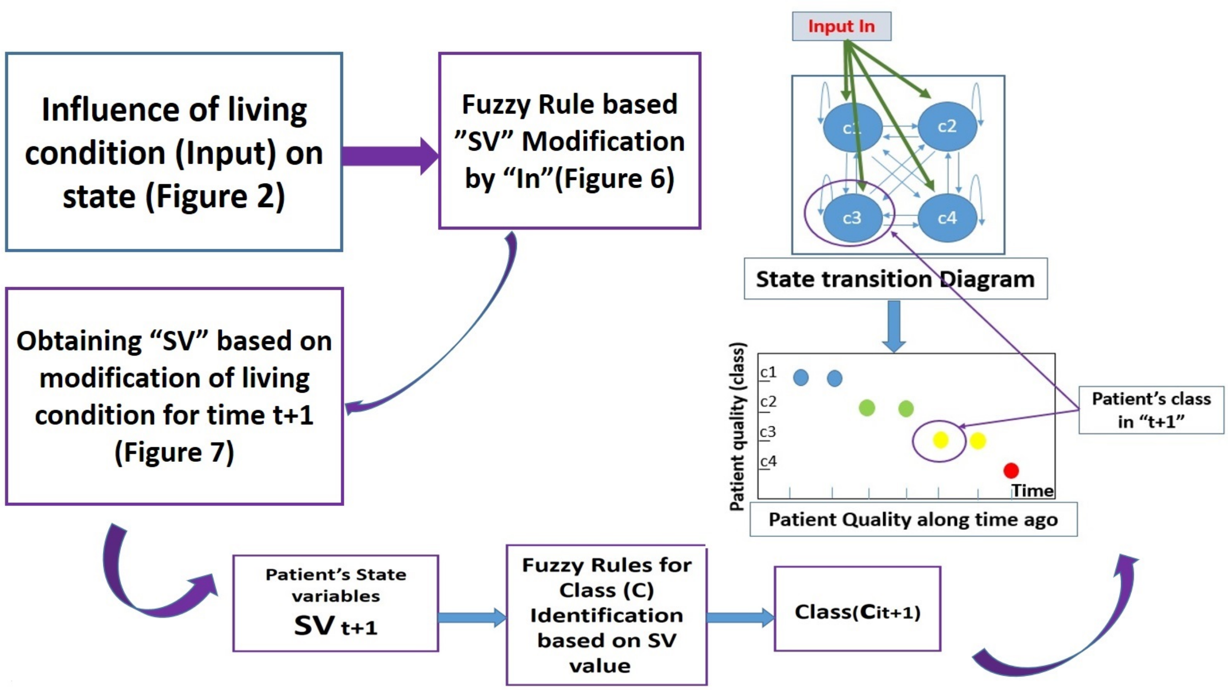

Figure 10: Integrated model.

4 CLASSIFICATION OF HEART FAILURE

Based on literature, in developed countries, the prevalence of heart failure in an adult is 1-2 percent whereas among the people over 70 years old, it around 10 percents (Savarese and Lund 2017). That is why we have selected heart failure disease as a first chronic disease to work on.

Doctors usually classify patients' heart failure according to the severity of their symptoms into four classesPonikowski et al. (2016). Figure 11 (right side) shows the progression of heart failure in the simulation. In the progression of acute heart failure in Figure 11 (left side), A shows a good recovery after the first acute episode followed by a stable period. B shows that the first episode is not survived.

C shows poor recovery followed by deterioration. D shows ongoing deterioration with intermittent acute episodes and an unpredictable death point (Network).

4.1 Heart Failure Signs and Symptoms

Some of the Important Heart Failure Signs and Symptoms are Oedema, obesity, heart rate, heart beat, blood pressure, saturation of Oxygen and body temperature. These items are considered as state variables. Any change in these signs and symptoms can have an effect on the heart failure categories and change it from one class to another one (Figure 11).

4.2 Living Condition of Heart Failure Patients

For heart failure disease all these parameters are binary, so in this step we don't need fuzzy logic for classifying state variables. These parameters are as follow Not following the adherence of the treatment, having infection, bad nutrition (amount of salt and if percentage of water in body has increased more than two kg per week), drinking alcohol, smoking.

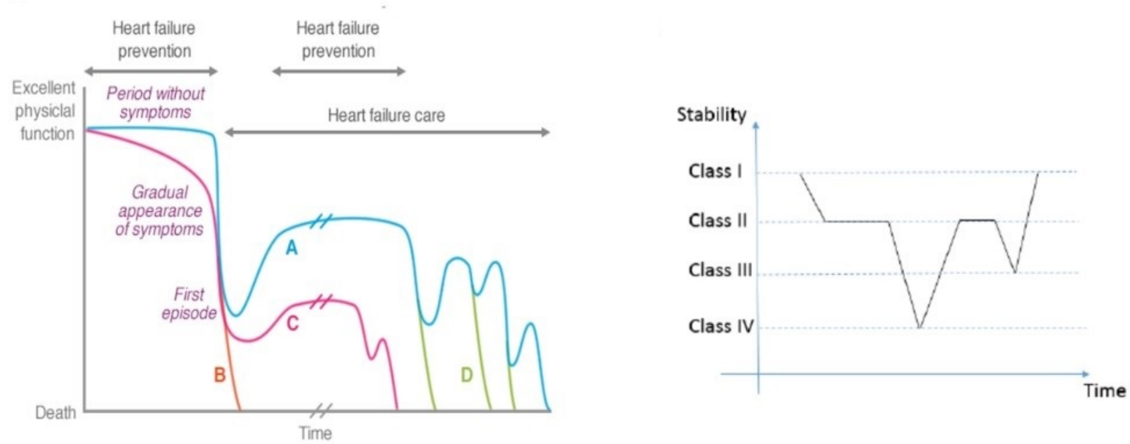

Figure 11: Progression of acute heart failure (left side). In simulation of progression of chronic heart failure (right side), we can see the graph that shows the transitions between classes.

4.2.1 Different Combinations of Living Conditions for Making Rules for Heart Failure Classification

The lifestyle of each person impacts on their health behavior. The significant conditions for heart failure patients include if they follow their adherence of treatment, if they have an infection, the amount of salt in their body, if the amount of water increases more than two kg per week, if they smoke and if they drink alcohol. Figure 13 shows some parts of the living and medical conditions composition and the effects of these on heart failure variables. We have six conditions where each condition is a binary variable, so in total we will have $2^6 = 64$ compositions of different living conditions. According to Figure 12, we can make the rule IF-THEN for heart failure symptom variables. IF Adherence=yes and infection=yes and salt=yes and water =yes and alcohol=yes and smoking=yes THEN oedema=increase.

4.2.2 Different Combinations of State Variables for Making Rules for Heart Failure Classification

After obtaining the range of the different living conditions variables, we can build the different combination of state variables in order to make the If-THEN rules for classification of heart failure. Some parts of these rules are shown in Figure 13. These rules are driven by a different combination of state variables.
Rule 1: IF OEDEMA = Yes and Obesity = Yes and Heart Rate = High and Blood Pressure = High and

Saturation of Oxygen = High and Temperature = High Then the State of Patient = CIV (Saritas, Allahverdi, and Sert 2003).

Adherence	Infection	Salt	Increasing water>2kg	Alcohol	Smoking	Edema	Obesity	Heart Rate	...
Yes	Yes	Yes	Yes	Yes	Yes				
Yes	Yes	Yes	Yes	Yes	No				
...	...	...	...	...	...				
No	No	No	No	No	Yes				
No	No	No	No	No	No				

Figure 12: The combinations of different living and medical conditions influence on heart failure variables.

Rule No	OEDEMA	Obesity	Heart Rate	Heart Beat	Blood Pressure	Saturation of Oxygen	Temperature
Rule1	Yes	Yes	High	Reg	High	High	High
...							
Rule38	Yes	Yes	Normal	Non-Reg	High	High	High
...							
Rule289	No	No	Low	Non-Reg	Low	Normal	Normal

Figure 13: Fuzzy rules to gain heart failure classes.

4.3 Heart failure State Variables Classification

Figure 15 shows a model where living conditions are our input and based on the rules in Figure 13, we receive the patient's state variables

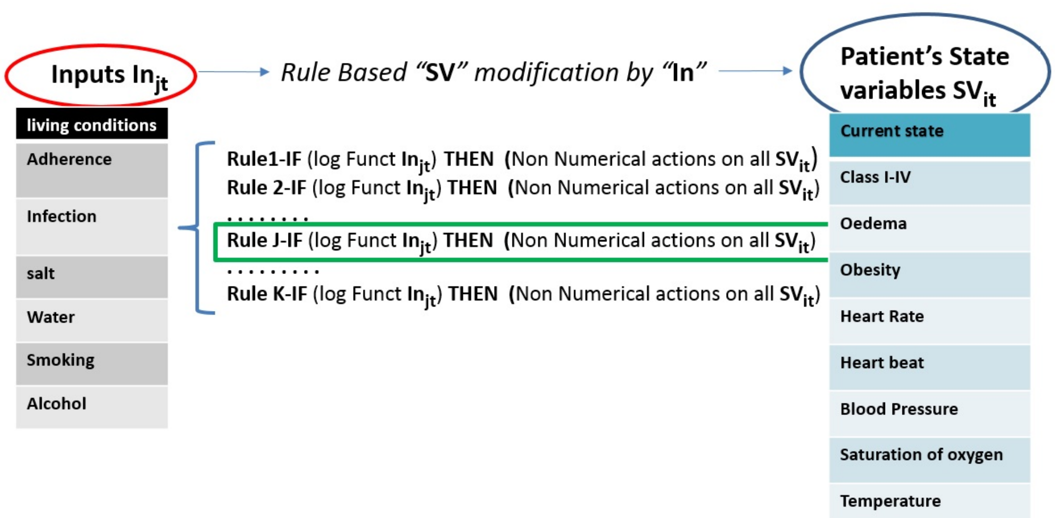

Figure 14: Making patient's state variable.

4.4 Fuzzy Model for Heart Failure Classification

In this part we use fuzzy logic, where health variables are our inputs and states of chronic disease are our outputs Hadianfard et al. (2015). This is shown in Figure 15. The Structure of heart failure state fuzzy model consists of three main parts, including inputs, inference engine and output (Figure 16) Hadianfard et al. (2015); (Adeli and Neshat 2010).

5 CAPABILITIES OF THE PROPOSED SIMULATION SYSTEM

Accessibility and applying advanced analytics to data enables the management of the healthcare system to predict the patient's behavior and improve insight into risk, resources, time and cost (IBM 2013). The proposed models enable us to predict the patient's level and situation because of this available knowledge.

If some people can receive remote recommendations, we can reduce the quantity of unnecessary attendance in the healthcare facilities. Also some patient who need to visit hospital but not in urgent time and have lower priority, can make an appointment for sensible time of care system. In addition, because of prediction model there is the possibility that staff will be aware of likely critical scheduling of the healthcare system. All this information will help to improve care management, decrease the related cost, assure better quality in health care system and finally deliver patient and staff satisfaction. taking a deep look at different aspects of the designed model and trying out divers assumptions within it is not easy achievable. Creating a successful system we first need to empower all the weak points of idea, in addition to implementing the proposed model directly and only basing on literature studies will be costly, time-consuming and quite risky. In order to make the idea affordable, we first need to use a tool to perform it in a virtual environment, simulation as a tool can investigate possibility and capability of the system before implementation, then it considers all viewpoints and sights, and at the end this proposed model can go for implementation in actual world.

6 VALIDATION AND TRANSPARENCY

The proposed model would have accessible technical and non-technical documentation with sufficient details for interested readers. It describes the structure of model, input, output, data resources and their relationships and results. The suggested model will be programmed and then evaluated through real data.

The results will be analyzed. The outcome of this simulation would be prediction of class of heart failure using the proposed model (agent-based modeling and fuzzy logic). Specifically, 80 percent of collected medical data would be used to train the model and 20 percent of the data would be used to verify the model (through comparing predicted versus measured class of heart failure).

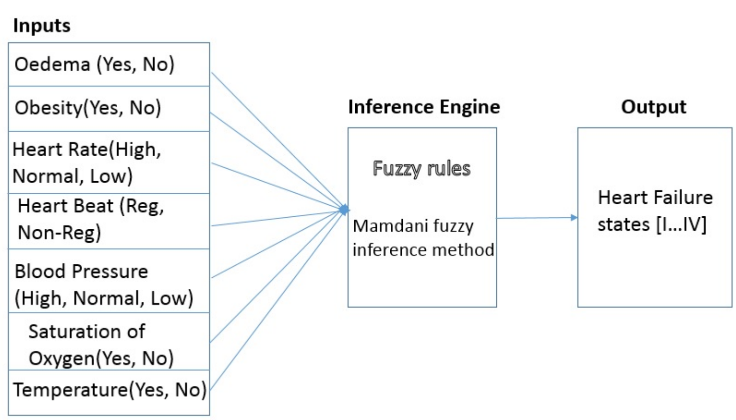

Figure 15: Heart Failure Fuzzy Model.

7 CONCLUSIONS AND FUTURE WORK

This paper describes the behavior of chronic disease patients in different conditions. Analyzing the simulation outputs can help the healthcare system to explore how chronic patients can cope with different living conditions and health situations. This proposed model is designed in a way that also can be used by the patient. Thus it can be beneficial for self-care management and patient quality of life. Furthermore, it is helpful for the healthcare system management to have the possibility of predicting the critical time and situation of the hospital. This proposed model has the potential of being extended to each type of chronic disease and it is also possible to extend to more health variables as well as living and medical conditions.

The designed model can be redesigned as long as the analysis of simulation outcome shows that the result is precise and rational enough for the real world.

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