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Intelligent e-Health System for Patient and Elderly People Monitoring Using Multi Agents System

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Abstract— In this paper, an intelligent e-Health system for patients and elderly people monitoring using multi agents system is designed and developed. The developed system is highly needed in rural areas because of the inadequate number of available specialized physicians or nurses. The proposed system will enhance the process of health condition monitoring compared with the existing system which relies on patients themselves. The proposed system can save patients life through continuous online monitoring of their medical conditions by specialized physicians not necessarily available in the same geographical areas. The monitoring system is based on a multi-agent system which consists of Physician Agents and Elderly Agents. Both agents are supported with a fuzzy decision mechanism that makes initial diagnosis regarding the medical condition of the patient/elderly. The issue of how physician and elderly agents, located in different places, are working collaboratively and proactively communicate with each other has been addressed in this paper. We have described the architecture, design and implementation of an elderly agent and a physician agent. To evaluate the performance of the system, we have implemented a four-agent system: two Elderly Agents and two Physician Agents. We also generated simulation results. We choose four agents because the size is representative enough while computing time is still reasonable. From the software standpoint, the four agents collaboratively worked one another as designed. Two physicians on our research team independently reviewed the fuzzy decision mechanism performance. Evaluation shows excellent agreement between physicians and the fuzzy decision mechanism. Having such e-health system will speed up and improve communication between different medical units in the health system and drive healthcare costs down for the benefit of patients.

Keywords— Confidence level, GSM, Fuzzy logic, Monitoring system, Multi-agent system, Patient, SMS.

I. INTRODUCTION

The Hashemite Kingdom of Jordan suffers from absence of electronic systems to monitor the sick and elderly in addition to the lack of specialist doctors in rural areas. Some elderly and patients need continuous monitoring. This monitoring in the current system is only available in hospitals but not in homes, clinics or medical centers. Some cases need long monitoring time though the cases are not severe. Admitting them to the hospital will cost the government, patient or insurance companies much money. In addition, patients in rural areas have to travel long distances in order to take consultation from a specialist doctor (i.e. 200km distance between rural areas of Tafila and Amman, the capital). This becomes an obstacle that may prevent some patients from going to the specialist, especially when they think that the medical issue is not that severe. This will contribute to making their medical condition worse. In addition, the current system does not provide an electronic system that combines the patient's data such as laboratory tests results, X-rays, treatment procedure made by physicians and medication taken by patients. Lack of such data complicates the job of physicians in diagnosing patients' cases; and this may lead to incorrect decisions. This can also prevent developing smart software that is used in diagnosing rare health conditions such as adverse drug reactions. Having intelligent software that is able to analyze patients' data and assist in diagnosis medical cases is very beneficial in the medical world.

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Monitoring the health condition of elderly people is a complex problem that involves different medical units and requires continuous monitoring [1]. Besides, there is the case if we realistically assume that a set of medical rules that is readily acceptable to all human experts (e.g., physicians and nurses) does not exist. Furthermore, the specifications of the medical decision rules vary according to the physician's experience. This will make it difficult to decide which physician is right or wrong. It should be obvious that these dynamic issues will pose challenges when different medical units work collectively to help one another to reach a common goal (e.g., monitoring health conditions). Current monitoring systems [2]-[5] are based on clinical judgments and traditional medical signs including heart rate, blood oxygen saturation, respiratory rate and blood pressure. One of the currently widely tool used for drug adverse events monitoring in practice is the “Modified Early Warning Score”. Drug adverse events monitoring and reporting system is one of the most important monitoring systems in the medical sector. The assessment of the MEWS scores is relatively subjective. Also, the range of sensitivities and specificities is dependent on the cutoff score used and the MEWS which requires some training to be accurate [6]. The most important source of severe medical event information to the FDA in U.S. is the MedWatch program. Other Spontaneous reporting systems such as Yellow Card [7] of the U.K. suffer from low reporting rates, typically less than 10%. Underreporting is a common problem in spontaneous surveillance programs which can delay medical event detection and underestimate the problem size [8]. Data mining algorithms are being used to explore spontaneous reporting databases. Paper [9] compares the findings of data mining algorithms with those from classical reporting methods. Most medical events identified by both methods were highlighted in product labeling. Classical reporting methods identified four potentially unexpected serious events which may lead to label changing and close monitoring. The other finding of that paper is that none of these medical events has been identified using the data mining algorithms. This makes the data mining algorithms not helpful since they could not detect or enhance classical reporting methods surveillance in this particular setting.

In this paper, we propose a multi-agent intelligent system that will be used in monitoring health conditions of the elderly people. Multi-agent system has been a hot topic in recent years [2], [10]. And it is still being researched and developed because it will have an important effect on our lives. Such monitoring must have autonomous interactions among different medical units in order to be effective. The proposed system which uses a multi-agent system is formed by a community of agents that exchange information and proactively help one another to achieve the goal of elderly and patient monitoring. Agents in the developed system will be equipped with an intelligent decision maker that arms them with the rule-based reasoning capability that can assist in making initial decisions regarding the medical condition of patients and elderly people.

Having such a system will speed up and improve communication between different units in the health system of Jordan. Hospitals and medical providers will also benefit from the proposed system in exchanging patients’ data and medical knowledge at a much faster rate. The proposed system will connect patients and their physicians beyond hospital doors regardless to their geographical area. Physicians will be able to seamlessly track patients and elderly people healthcare records in order to be monitored for unusual or sudden health issues. To this end, our system design enables physician agents to effectively interact and share their experiences by setting up an environment for the agents to learn from each other and work in a proactive way. The system allows the most important and insightful medical decision rules produced by the most experienced agent (i.e., the agent that has the largest amount of patients in its patient database) to bubble up for the benefit of the entire physician agents’ community.

The rules will be updated over time, leading to an improved patient monitoring performance. Decision rules are based on demographic data and laboratory test results of patients' data. Using such a system with the ability of making medical decisions will improve the quality of medical care. This will provide more accurate, effective, and reliable diagnoses and treatments especially if physicians have insufficient knowledge.

II. THE DEVELOPED PATIENT MONITORING SYSTEM ARCHITECTURE

A) The Proposed System Framework

In this research, we propose a multi-agent intelligent system that will be used for monitoring the health conditions of elderly people and patients. Multi-agent system methodology offers an implementation that fits the design needs. The agent is a special software working for its human client/clients to perform certain tasks that imitate human agents or systems; and it has the ability to be autonomous in its action. Monitoring health condition of elderly people is a complex medical problem since it involves different hospitals, departments and medical centers. The proposed system provides agents with the ability to share patients' information, make initial decisions regarding the medical case of the patient and exchange knowledge in a proactive way. There are five agents in the preliminary proposed MAS [10]. The highest medical authority unit is the Information Center Agent (ICA). It carries out necessary management and information collection tasks [14]. As seen in Fig. 1, the proposed system has many Physician Agents (PAs) and Elderly Agents (EAs) in different geographical areas. The PAs can belong to the same or different hospitals. Since PAs are connected to physicians with different specializations, each EA is being assigned to one or more PAs. Different PAs can communicate with each other in order to exchange knowledge (i.e. medical decision rules) [15]. Each hospital has its own database that is monitored and managed by ICA agents.

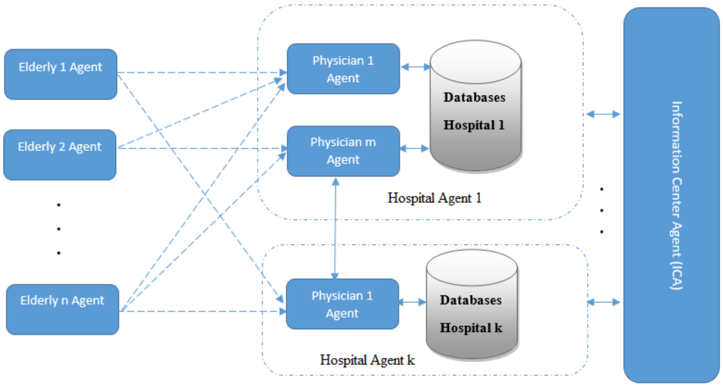

Fig. 1. The proposed Multi-Agent system for monitoring health conditions of the elderly people.

B) Agent Architecture

Functionally speaking, the PA's and EA's architecture consists of four main components (Fig. 2): Communicator and Manager, Decision Maker, Knowledge Updater, and Databases. Communication and Manager Module deals with high level communication details and manages all incoming and outgoing messages. Communicator and Manager are also responsible for sending requests to Knowledge Updater to update decision rules and confidence level. The decision maker contains the reasoning algorithm (Fuzzy Inference Engine), which is the agent's brain. It performs reasoning tasks and executes local events.

White Board enables a PAs and EAs to communicate with other PAs without prior knowledge about them. It contains information about agent service type, agent name, communication languages and ontologies. This information allows White Board to connect different agents located at different geographical areas. An agent can use White Board to search for other agents that can provide services to aid in fulfilling its particular goals. To do that, White Board will provide requesting agents with the name of other agents based on the nature of the request [14]. White Board collects decision rules and confidence levels from PAs in order for them to be used in the rule updating process described later. Updating occurs at programmed times. In this updating process, each PA will contribute by providing its decision rules, fuzzy sets and parameters of medical formulas to White Board. Knowledge Updater will use the collected rules in White Board to update its own medical decision rules and modify rules confidence levels. This can be done by selecting the rules that have the highest confidence level. The confidence level presents how much the agent is sure about a rule. Knowledge Updater will also update the associated fuzzy sets and the parameters of the decision rule. Databases contain patients' medical information and medical history.

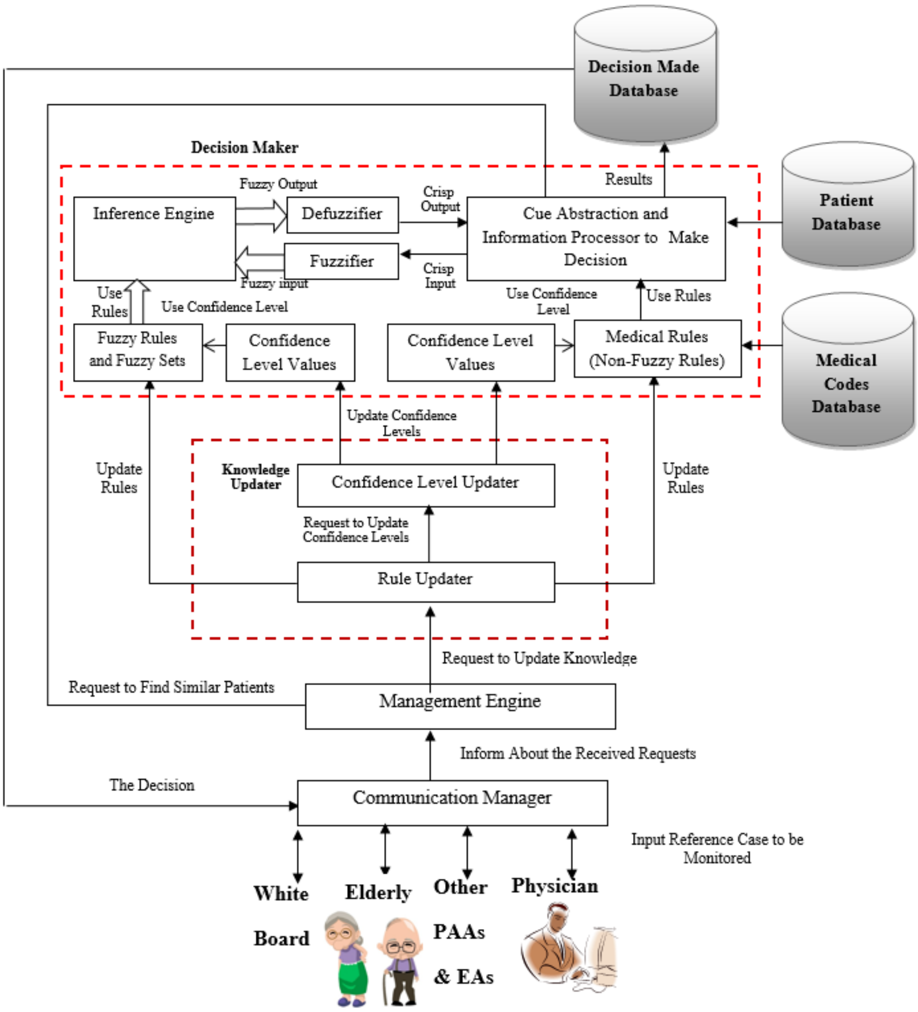

Fig. 2. Architecture of the PAs showing the four components

C) Decision Maker (Fuzzy Inference System)

PAs and EAs in the proposed system will be equipped with a Decision Maker as shown in Fig. 2, which will help get some medical cues that can be used in the early detection of a disease or medical problem [11], [12].The reasoning will be implemented using Fuzzy logic [16]. Fuzzy logic is used to represent, interpret and compute vague and/or subjective information of health condition factors [17]. A decision making in medical applications has a certain degree of uncertainty.

C.1. Fuzzy Implications

Fuzzy logic is a well-established methodology that is effective for systematic handling of a deterministic uncertainty and subjective information. Using Fuzzy rule based approach will enhance the monitoring performance of elderly people. Integrating a fuzzy decision mechanism into agents makes them more proactive and encourages closer agent-human collaboration [16]. The developed decision rules used by EAs and PAs are experience-based as experience plays a key role in the design of it; and it contains a set of fuzzy IF-THEN rules and a set of membership functions of fuzzy sets. Generally, a fuzzy system with *m* fuzzy rules has the form:

IF x_1 is A_1
and x_2 is A_2
... x_i is A
THEN y is B_j

Where x_i is the input variables; y is the output variable of the fuzzy system; and A_i and B_j are fuzzy sets characterized by fuzzy membership functions.
The Min-Max fuzzy reasoning is used to infer the correct decision. The first step is to take the crisp inputs, x_1 and y_1, and determine the degree to which these inputs belong to each of the appropriate fuzzy sets. Inputs are then applied to the antecedents of the fuzzy rules. To evaluate the disjunction of the rule antecedents, AND fuzzy operation is used to obtain a single number representing the result of the antecedent evaluation as shown in (1) [18].

$$\omega = \bigcap_k (\mu_X(A_i), \mu_Y(B_j)) \tag{1}$$

Where w is the weighting factor that measures the contribution of the i^{th} rules of the fuzzy inference system. This number is then applied to the consequent membership function as in (2) [16].

$$\varsigma_i = \bigcup_{i=1}^{n} (\omega_i \bigcap \mu_Z(C_i)) \tag{2}$$

The last step in the fuzzy inference process is defuzzification. The decision task is performed by the inference engine that evaluates all the rules in the rule base and combines the weighted consequents of all relevant rules into a single output fuzzy set. That set is then defuzzified to produce a crisp similarity value. Fuzziness helps us to evaluate the rules, but the final output of a fuzzy system has to be a crisp number. There are several defuzzification methods, but the most popular one is the centre of gravity (COG) technique. It finds the point where a vertical line would slice the aggregate set into two equal masses. Mathematically, this COG can be expressed as in (3) [16].

$$COG = \frac{\int_a^b (\mu_\varsigma(x).x)dx}{\int_a^b \mu_\varsigma(x)dx} \tag{3}$$

C.2. Fuzzy Sets Construction

The linguistic concepts, most of which are inherently vague, are represented and manipulated by fuzzy sets using the theoretical tools provided by the fuzzy set theory. They enable us to express and deal with various relations and functions that involve linguistic concepts. The construction of fuzzy sets involves a specific knowledge domain of interest, two experts in the adverse drug reaction domain and a knowledge engineer. The knowledge of interest is elicited from experts by the knowledge engineer. In the first stage, the knowledge engineer attempts to elicit the knowledge in terms of propositions expressed in natural languages. In the second stage, he attempts to determine the meaning of each linguistic term employed in these propositions. During the second stage, the functions representing fuzzy sets and operations are constructed. Direct method of construction has been used in this research. In direct methods, experts are expected to give answers to questions of various kinds that explicitly lead to the construction of membership function. The knowledge can be also extracted from other sources such as statistics of relevant database, literature, etc. [17].

C.3. Fuzzy Monitoring System Architecture

The developed fuzzy monitoring system is based on 5 cues as shown in Fig. 3: Blood Sugar Level, Triglycerides, High-density lipoproteins (HDL), Low-density lipoproteins (LDL) and Abnormality in Blood Pressure. The cues represent the higher-level information obtained from the patients' elementary data. As mentioned in section C.2., fuzzy sets used in Decision Maker Unit are constructed from expert's knowledge.

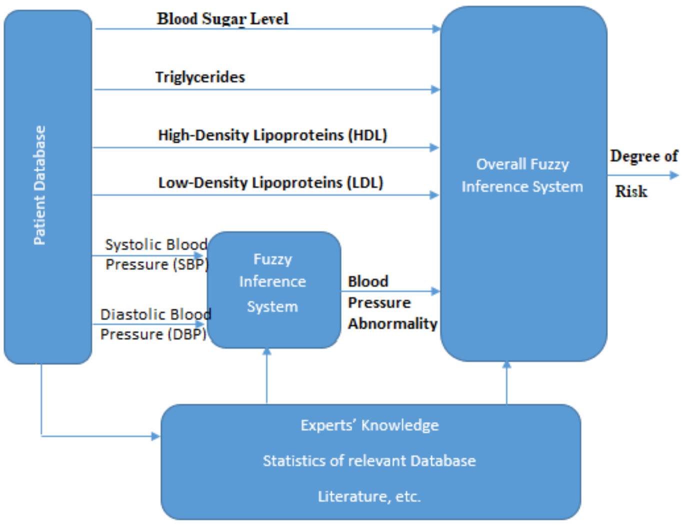

Fig. 3. Framework for fuzzy inference system

Diabetes is a major, complex chronic disease. Based on the Jordanian Center for Diabetes Endocrinology and Genetic [24], the percentage of people affected by diabetes has been raised from 16% in 1996 to 23% in 2007. The Jordan national study (conducted on 7000 randomly selected people) shows that 40% of the Jordanians above age 25 is being diagnosed with diabetes. It is an abnormal rise in the concentration of blood sugar. It is caused by the hormone insulin needs. Higher than normal blood glucose levels may be a sign of diabetes. If someone is diagnosed with diabetes, it means that it is not well controlled. For the Blood Sugar Level, there are three fuzzy sets as Low, Normal and High (Fig. 4).

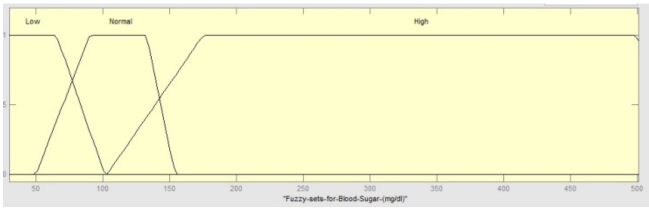

Fig. 4. Membership functions of blood sugar level

Triglycerides can also raise heart disease risk. In the same studies mentioned before [24], 50% of the Jordanian people were diagnosed with high triglyceride. This input field has four fuzzy sets (Normal, Borderline-High, High, and Very High). Fig. 5 shows membership functions of Triglycerides. Membership functions of these fuzzy sets are trapezoidal.

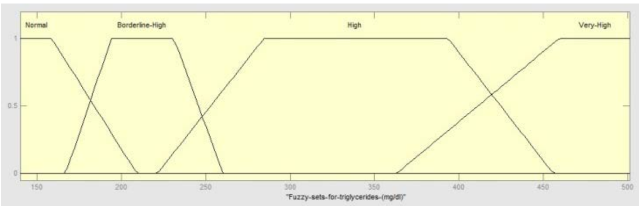

Fig. 5. Membership functions of triglycerides

The blood cholesterol level may cause a heart disease. Many people with high blood cholesterol are unaware that their cholesterol level is too high because it does not cause symptoms. High blood cholesterol is one of the major risks that leads to a heart attack [24]. There are two types: High-density lipoproteins and Low-density lipoproteins.

High-density lipoprotein (HDL- High Density Lipoproteins) helps keep cholesterol from building up in the arteries. Low-density lipoproteins (LDL- Low Density Lipoproteins) is the main source of cholesterol buildup and blockage in the arteries so-called some bad cholesterol or malignant. There is an inverse relationship between the level of LDL and HDL in the blood. Both the High-density lipoproteins (HDL) and the Low-density lipoproteins (LDL) are characterized in this paper as fuzzy variables. There are three fuzzy sets for the input High-density lipoproteins (HDL)- Low, Medium, and High (Fig. 6)- and four fuzzy sets for the other input variable Low-density lipoproteins (LDL)- Desirable, Near Desirable, Border High, High, Dangerous (Fig. 7).

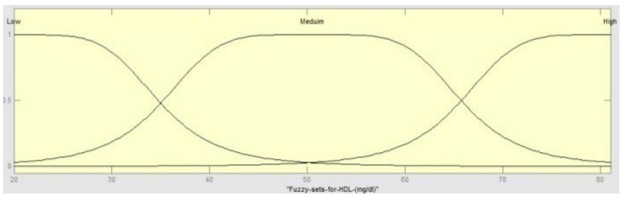

Fig. 6. Fuzzy sets for high-density lipoproteins (HDL)

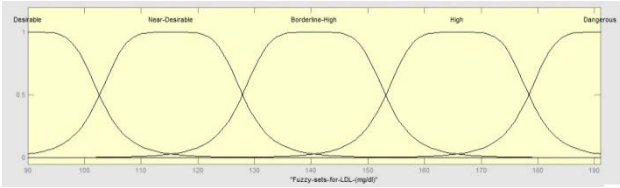

Fig. 7. Low-density lipoproteins (LDL)

Blood pressure is used in clinical environments to measure systolic and diastolic blood pressures which represent the force of blood which pushes the walls of the blood vessels through which it passes. Over one million people in Jordan suffer from blood pressure. The number is expected to go up to 1.5 million in 2020 [25]. In [26], the total of 14,310 Jordanian adults were selected randomly in various regions of Jordan. The study found that cases of undiagnosed hypertension, hypotension, and an increase or a decrease in heart rate were detected. The Systolic Blood Pressure (SBP) measure is the top number. It measures the pressure of the blood within the vessels when a heart contracts. The Diastolic Blood Pressure (DBP) measure is the bottom number. It is the pressure of the blood within the vessels when the heart is resting and then refilling.

The Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP) will be the input to the Fuzzy Inference System in Decision Maker Unit as shown in Fig. 3 while the abnormality value in blood pressure will be the output. Both inputs and outputs are fuzzy variables. There are three fuzzy sets for the input variable Systolic Blood Pressure (SBP)- Low, Medium, and High (Fig. 8)- three fuzzy sets for the input variable Diastolic Blood Pressure (DBP)- Low, Medium, and High (Fig. 9)- and three fuzzy sets for the output variable Abnormality in Blood Pressure- Low, Medium, and High (Fig. 10). Here are some of the rules:

- If Systolic Blood Pressure Value is Low and Diastolic Blood Pressure Value is Low, then Abnormality in Blood Pressure Test is Low.
- If Systolic Blood Pressure Value is Low and Diastolic Blood Pressure Value is High, then Abnormality in Blood Pressure Test is Medium.
- If Systolic Blood Pressure Value is High and Diastolic Blood Pressure Value is Low, then Abnormality in Blood Pressure Test is Medium.
- If Systolic Blood Pressure Value is High and Diastolic Blood Pressure Value is High, then Abnormality in Blood Pressure Test is High.

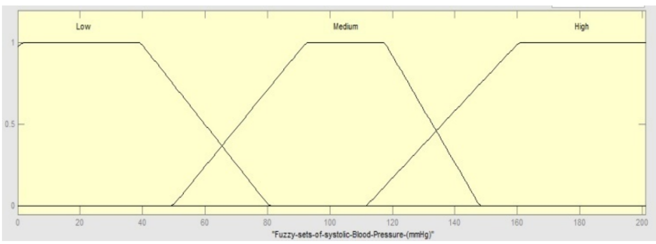

Fig. 8. Membership function of systolic blood pressure (SBP)

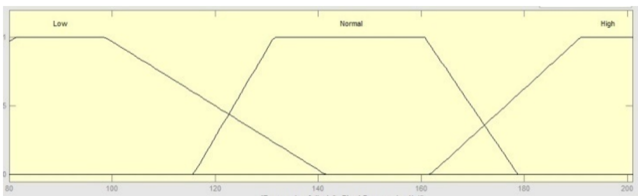

Fig. 9. Membership function of diastolic blood pressure (DBP)

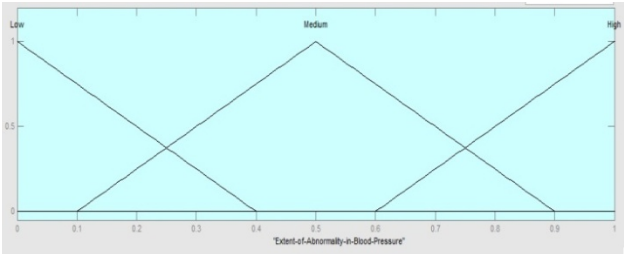

Fig. 10. Membership function of the abnormality in blood pressure

A risk factor is a value that shows the chance of getting a disease and/or the health risk of the patient. It is the output of the overall Fuzzy Inference system as shown in Fig.3. The strength of the risk is called "Degree of Risk". The Degree of Risk is a fuzzy variable whose values are represented by triangular fuzzy sets categorized as "Very High", "High", "Medium", "Low" and "Very Low" (Fig. 11).

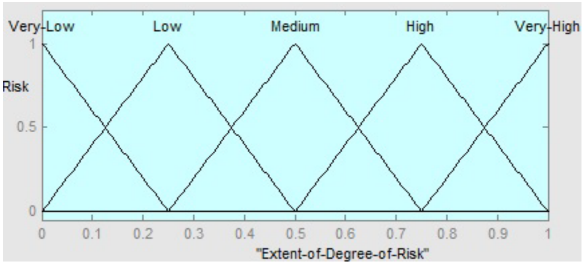

Fig. 11. Membership of degree of risk

Based on the experience of the two physicians working with the team, we define the fuzzy rules to link Blood Sugar Level, Triglycerides, High-density lipoproteins (HDL), Low-density lipoproteins (LDL) Abnormality in Blood Pressure and Degree of Risk. A sample of the rules used to determine Degree of Risk:

- If Abnormality in Blood Pressure is Low, Blood Sugar Level is low, Triglycerides is Normal, LDL is Desirable, HDL is High, then Degree of Risk is Low
- If Abnormality in Blood Pressure is Low, Blood Sugar Level is low, Triglycerides is Normal, LDL is Very High, HDL is Low, then Degree of Risk is High.

The Degree of Risk will be a value between 0 and 1. A higher score represents a higher risk. The defuzzified output generated by the fuzzy Inference System will be categorized to the following levels:

- Level 1: "Degree of Risk" score from 0.00 to 0.50 represents Low Risk.
- Level 2: "Degree of Risk" score from 0.50 1.00 represents High Risk.

Those levels are decided by the physicians in our team.

C.4. Optimizing Fuzzy Weights and Parameter Using Genetic Algorithm

Our goal is to choose the weights of fuzzy rules and fuzzy parameters, so that residuals between the actual class labeled by physicians and the decision class label detected from the overall fuzzy system (described in section C.3.) can be minimized. The optimization technique used in the paper is Genetic Algorithm (GA) (Fig. 12). The main step in GA is to calculate the fitness value of each member in the population (i.e. fuzzy rule weights and parameters) [20]. Genetic algorithms make multiple-way search by creating a population of candidate solutions instead of just testing one single solution. GA starts by constructing a new population using genetic operation such as crossover and mutation through an iterative process until some convergence criteria are met [21] (Fig.13).

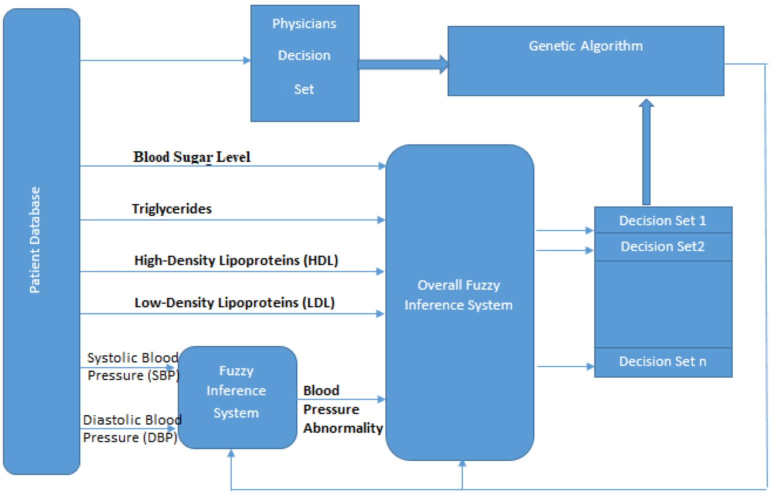

Fig. 12. Framework for optimizing fuzzy inference system

The resulted new population will be decoded back to its original format. The fitness value f_i of the i^{th} weight parameter is the objective function evaluated at this weight set. The fitness function is chosen to be the root mean squared differences between the correct decision specified by physician T and the decision given by the overall Fuzzy Inference System $\widehat{T}$. The Root Mean Squared Error (RMSE) is given by (4) [22]. Root Mean Square Error (RMSE) is the standard deviation of the residuals (prediction errors).

$$\text{Objective Function} = \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(T-\hat{T})^2}{n}} \quad (4)$$

Where n is the number of records in training data

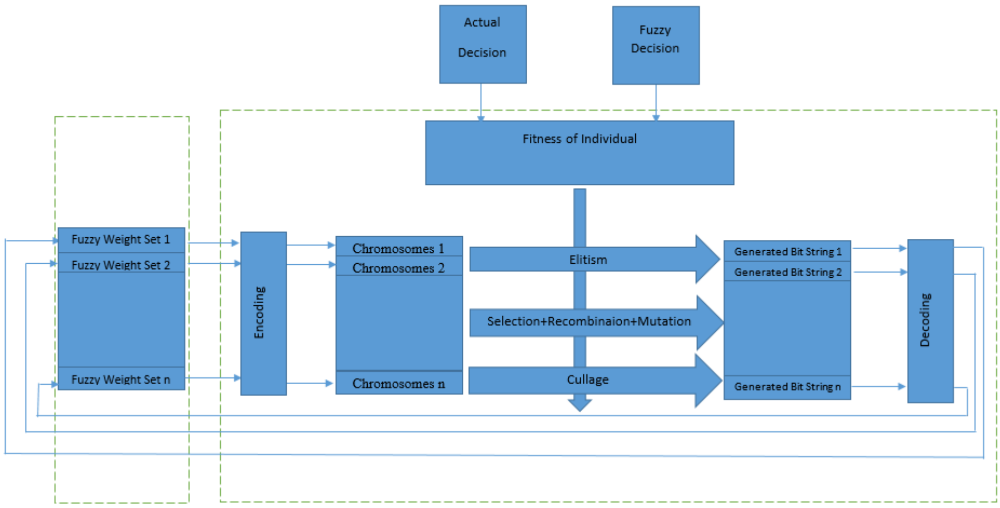

Fig. 13. Genetics algorithm model

By this definition, the lower the fitness, the better is the developed model. A fitness of zero means that the model achieves the desired behavior for all inputs. As long as a fitness measure ranks individuals accurately based on their performance, the exact form of fitness is irrelevant to the working of the algorithm.

D) Elderly Agent

D.1. Elderly Agent (EA) to Physician Agent (PA) Communication

The EAs has direct interaction with Elderly people. It is a combination of both hardware and software. The hardware part consists of the physical medical sensors and other electronic components (i.e. GSM module, LCD, Microcontroller, etc.) required to provide the suitable tools that ensure successful communication between different agents in the system. The software part consists of two software. The first one is responsible for managing communication between different agents available in the system (i.e. EAs and PAs). In this paper, JADE agent platform (Java Agent Development Framework) is adopted [34]. The second software is Decision Maker System (explained in section C) which is developed using freeware Fuzzy Jess [19]. Both software are programmed in Java and embedded in microcontroller. The communication process between EAs and PAs starts by a request from the either PA and his physician or pre-scheduled time slots stored in PA or EA to send the required medical status of the elderly (Fig. 14). After collecting and processing data to be in a suitable format, it will be directed to the Fuzzy Inference system in Decision Maker Unit. The Fuzzy Inference System diagnoses the medical condition of the elderly and assigns a label to the degree of risk as ”Very High,” ”High,” ”Medium,” ”Low,” or ” Very Low”. The microcontroller unit in the EA will notify the assigned PA and his physician by sending the assigned “Degree of Risk” label and the corresponding medical data set. This information can be sent to the physician medical kit, the hardware part of PA or to PA mobile Application (a software part of the PA). At the same time, data will be sent to a central database (i.e. hospital database).

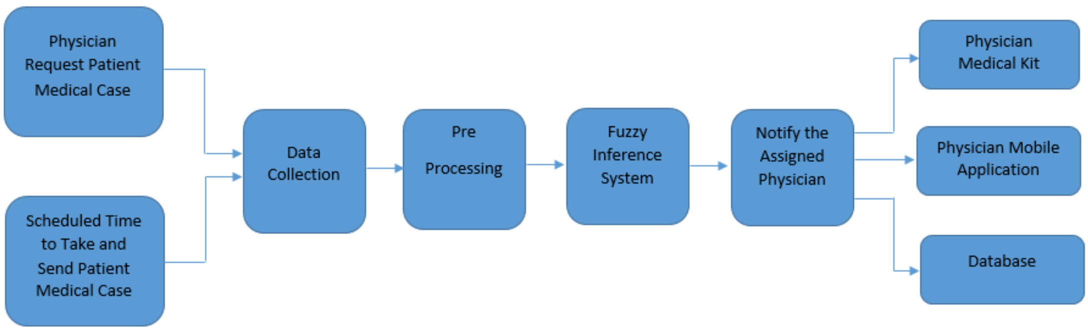

Fig. 14. EAs communication with PAs

D.2. Elderly Agent Medical Kit

Data will be collected using regular medical instruments. The medical information of the monitored elderly people may include but not limited to blood pressure levels, blood glucose levels, cholesterol levels, temperature, heart rate and oxygen level in blood. The Elderly Agent Medical kit shown in Fig. 15 consists of the medical sensor and the associated circuitry to get the physiological data of elderly people or patients. There are mainly four units in Elderly Agent Medical Kit: sensor unit, data collecting unit, microcontroller unit and GSM module unit. The output of the sensors unit is connected to a data collecting unit which is connected to the microcontroller. The Fuzzy Inference Engine in a microcontroller will use the gathered data and check if the “Degree of Risk” is within safe levels. If the “Degree of Risk” is High or very High, the microcontroller immediately triggers the Buzzer Alert Unit to activate an alarm; and LED Display Unit starts flashing. At the same time, the Microcontroller Unit sends an alert message about the situation to the assigned PA. The physiological data will be displayed on the LCD Display Unit. Multiple messages can also be sent to the elderly relatives, emergency units and the closest medical center with GPS location of the patient.

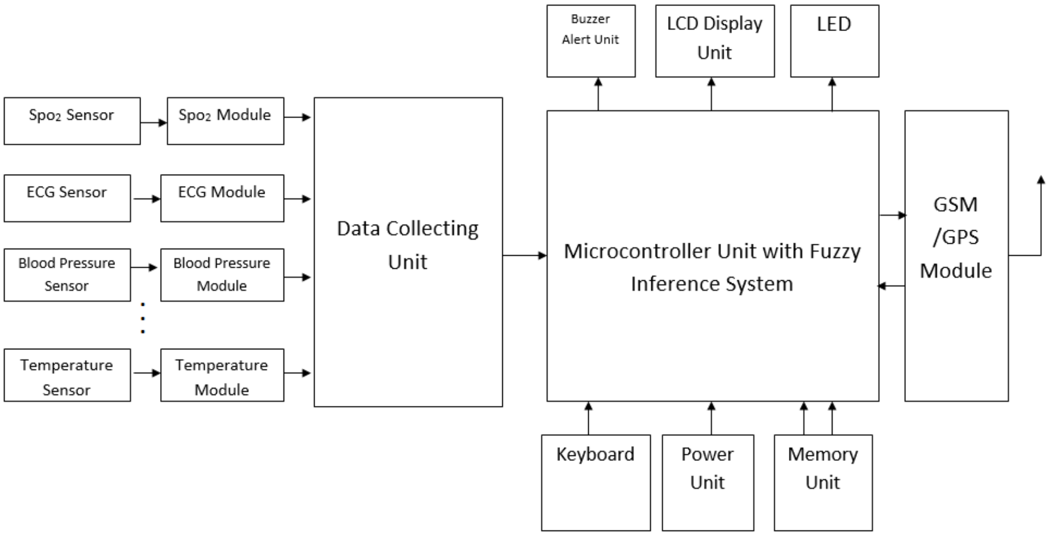

Fig. 15. The structure of elderly agent medical module

E) Physician Agent Unit

E.1. Physician Agent to Elderly Agent Communication

PA helps a physician acquire medical information of the elderly people. Physicians access patient databases either as a response to the patient's request or because of a received critical condition that has been classified by the Fuzzy Inference System in Decision Making Unit of EA or as a routine procedure to check on the condition and health status of the patient. The authorized physician can only respond to the pathological condition by using mobile applications and Physician Medical Kit or by accessing patients' databases (Fig.16). The Fuzzy Inference Engine of PA will provide its physician with initial assessment that can help make a decision regarding the health condition of the elderly. The PA has the ability to track further developments of the suspected cases with the assistance of other PA available in the system. The PA will save all the cases diagnosed by its physician in hospital databases. Patient records in the database will be updated as soon as new patient data become available.

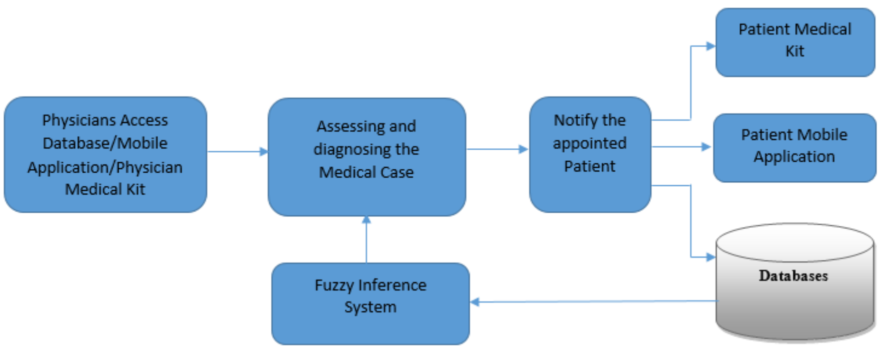

Fig. 16. PAs communication with EAs

E.2. Physician Agent Medical Kit

The functionality of Physician Medical Kit is divided into three main steps. In the initial step, the Physician Medical Kit receives the transmitted patient data with the initial decision made by its EA. After that, Microcontroller Unit sends an activation signal to other units attached with it such as Buzzer Alert Unit, LEDs Unit and LCD Display Unit. In the last step, if the medical case appears to be severe (i.e. "Degree of Risk" is *High* or *Very High*), buzzer will be activated, LED blinks and LCD shows patient data. The physician can respond to this situation by the Physician Medical Kit which confirms the initial decision. This can be done by selecting a suitable "Degree of Risk" level and sending it back to the patient for further treatments. The PA can decide to take any of the following actions depending on the decision reached, i.e., order some extra clinical tests, continue the same medical treatment, schedule another visit for the future or hospitalize the patient if his health condition has got worse. Patients can also be transferred from one of the health centers to another according to the patient needs. A physician will be supported from his PA by a decision regarding the medical case. The decision is based on the most reliable rules in the whole muli-agent system. The process of selecting these rules is described in section E. The medical decision which is supported from the Decision Maker Unit can be accessed from the Doctor Mobile Application or physician personal computer through GUI. The Logging and Security Unit allows the authorized physician only to get into the system.

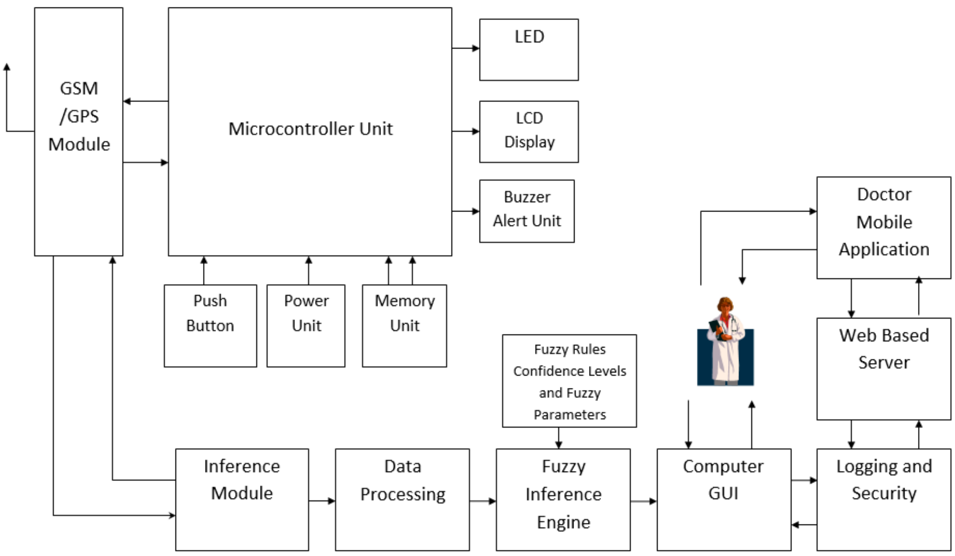

Fig. 17. Block diagram of physician assistant agent medical module

F) Knowledge Updater

The PA will randomly contact one or more PAs to be evolved in knowledge updater. The knowledge update is performed in Knowledge Updater as shown in Fig. 2. Knowledge update consists of fuzzy rules and confidence levels. Updating occurs at programmed times. Each PAA will provide its own rules to White Board (Fig. 2) to let other PA benefit from it. Knowledge Updater uses these rules and confidence levels to construct new decision rules that take advantage of the experience of other PAs. Agents will start the learning process by comparing their own rule factors with other agents' rule factors. They will add the factors that are not in the Decision Maker. In order to do that, the PA will compare confidence levels of the available rules of the missing factors and add the ones with the highest confidence levels

to the Decision Maker. At the same time, Knowledge Updater updates the corresponding inputs and outputs fuzzy sets of the new rules. After that, Knowledge Updater will update the other factors already existing in the Decision Maker. The unit compares the confidence level for each of its rules with the confidence level of the related rules in other PAs. Then, Rule and Confidence Level Updater adapts the rules that have the highest confidence levels. Then, the corresponding inputs and outputs fuzzy sets are updated. The gained rules through interaction will improve the decision making task performance.
Fig.18 shows an example of the updating methodology, where PA1 and PA2 are updating their rules. PA1 has rules involving Blood Pressure and Blood Sugar level while PA2 has rules involving Triglycerides and Blood Sugar level. PA1 will add PA2's Triglycerides rules to its knowledge base because it does not have such rules. For the Blood Sugar Level rules, PA1 will compare its rules' confidence levels with those of PA2's. If a PA2's rule confidence level is higher, PA1 will adopt PA2's Blood Sugar Level rule by overriding its own Blood Sugar Level rules. At the same time, PA2 follows the same procedure in updating its rules involving Triglycerides and Blood Sugar Level.

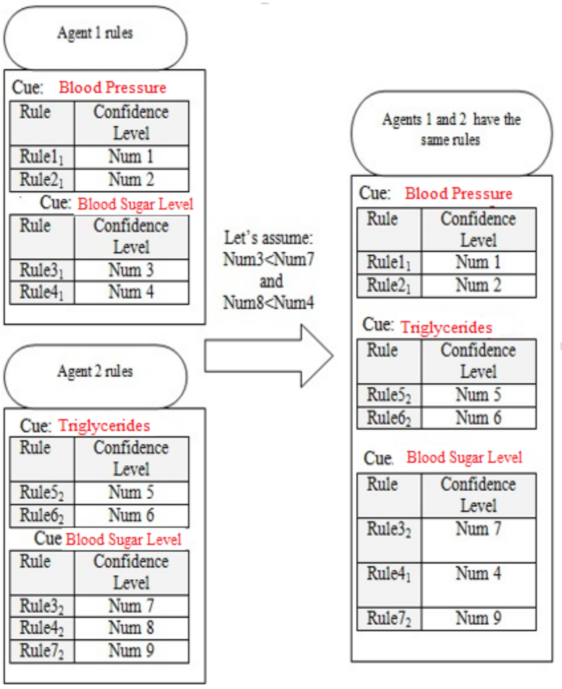

Fig. 18. Updating medical decision rules in two PAs using confidence levels

The confidence level of a rule will be updated each time a rule is used for evaluating either a new or old case. The physician can input new rules to the system at any time through sending a request from his personal computer or EA Mobile Application to Communicator Unit which then forwards the request to Knowledge Updater. Knowledge Updater adds the new input rules from the agent's physician to the agent decision rules.

III. IMPLEMENTATION

A) Software Implementation

For multi- agent system construction and execution, JADE agent platform is used [15]. JADE is an open-source software framework used to develop and execute agents' applications based on the specifications of the Foundation for Intelligent Physical Agents (FIPA). JADE provides a very well defined framework for implementing agent behaviors and common interaction protocols.

A JADE platform is composed of agent containers that can be distributed over the network. Agents live in containers. A container is a Java process that provides the JADE run-time and all the services needed for hosting and executing agents. Discussions between different agents take place in JADE containers. A special container, called the main container, represents the core part of a platform. It is the first container to be launched; and all the other containers must join it by registering with it. In our system, the main container hosts two EAs and two PAs. We have chosen four agents to be representative enough while computing time is still reasonable.

JADE version 4.4 was downloaded freely from the web site http://jade.tilab.com. The multi-agent system is developed and tested in Windows 7 platform that has an Intel Core 2 Duo processer and 4 GB RAM. RAM affects the computing time since agents will share it while evaluating patients' cases. The environmental factors of JADE were set properly under that platform. Java was selected as the development language; and J2SDK version 1.6.0_22 was used for the Java running environment. Access database 2007 was adopted for the development of database. Java database connectivity (JDBC), an application programming interface for the Java programming language, was used to access the database. JDBC could wrap a structured query language (SQL) statement, send it to the database, and retrieve the desired data.

For Decision Maker Unit implementation, FuzzyJess Toolkit is used. FuzzyJess is developed at National Research Council of Canada's Institute for Information Technology. It is a set of Java classes that provides the capability for handling fuzzy concepts and reasoning. It is compatible with JADE. It allows the user to use Java language to define membership functions, set antecedent and consequent of a fuzzy rule, and make a fuzzy inference. FuzzyJess uses Java Expert System Shell (JESS). JESS provides the basic elements of an expert system, including fact-list, knowledge base that contains all the rules, and an inference engine which controls overall execution of the rules. JESS includes a special class called Rete, which is used to embed JESS in JADE.

For Mobile Application Implementation, Android Studio [27] is used to develop Physician Mobile Application (Fig.19 left) and Elderly Mobile Application (Fig. 19 right). Android Studio provides the fastest tools for building applications.

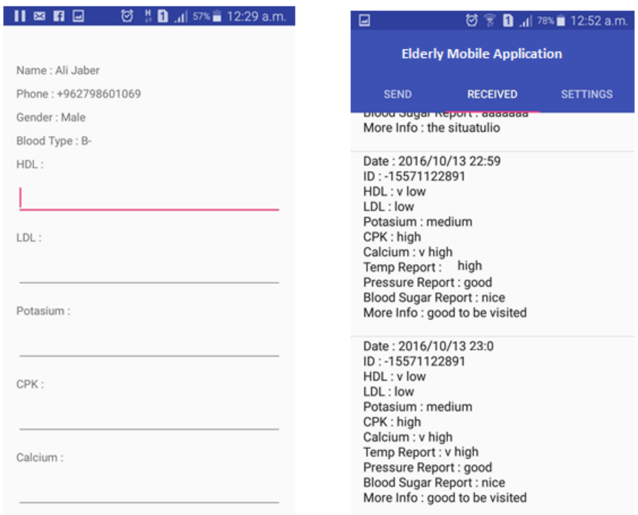

Fig. 19. Physician mobile App (left), elderly mobile App (right)

B) **Hardware** ***Implementation***

Medical sensors are used to monitor the state of a patient in order to be subsequently analyzed for medical diagnosis. Data Collecting Unit can be connected to different sensors such as pulse, oxygen in blood (SPO2), airflow (breathing), body temperature, electrocardiogram (ECG), glucometer, galvanic skin response (GSR - sweating), blood pressure (sphygmomanometer) and patient position (accelerometer). Fig. 20 shows body sensor network.

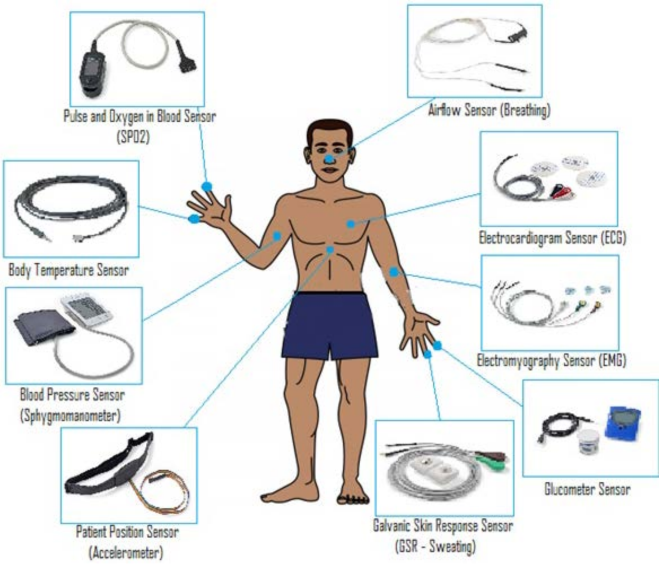

Fig. 20. Body sensor network

Table 1 shows different medical sensors and some diseases monitored by such sensors.

TABLE 1
THE MEDICAL SENSOR TYPE AND ITS MONITORED DISEASES

Medical Sensor Type	The Monitored Diseases
Glucometer sensor	Diabetes, general stroke care
Blood pressure sensor	Hypertension, heart disease, vascular disease, post operation monitoring, general stroke care
Electrocardiogram sensor	Heart disease, post operation monitoring
Pulse sensor	Heart disease
Oxygen in blood sensor	Asthma, post operation monitoring
Body temperature sensor	Infectious disease , post operation monitoring , general stroke care
Airflow sensor (breathing)	Asthma, general stroke care

A prototype design for Elderly Agent Medical Kit and Physician Agent Medical Kit are successfully developed. Fig. 21 shows the Elderly Agent Medical Kit prototype while Fig. 22 shows the Physician Agent Medical Kit prototype.

Fig. 21. Elderly agent medical kit

Fig. 22. Physician agent medical kit

A prototype design for a wireless receiving unit to be used by the database has been successfully designed. This database exemplifies a hospital database that is responsible for storing patient medical data in a central database. Fig. 23 shows the Wireless Receiving Unit prototype.

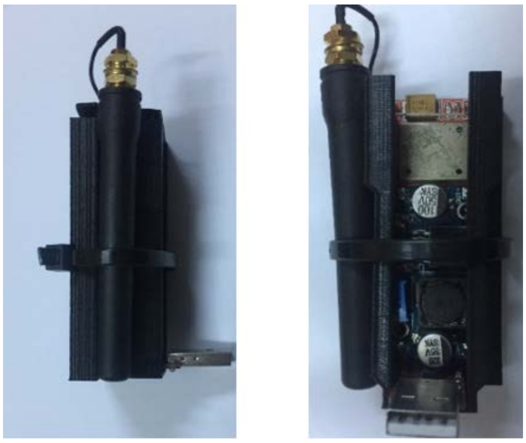

Fig. 23. Wireless receiving unit

Fig. 24 shows the Wireless Receiving Unit prototype connected to laptop (i.e. central database).

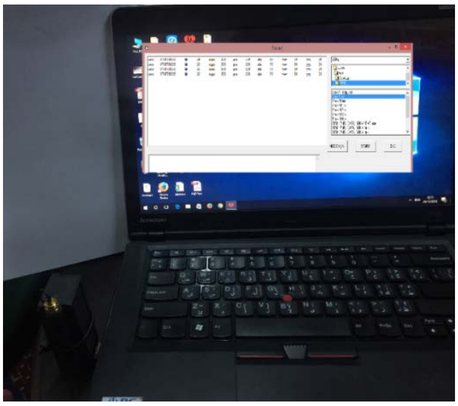

Fig. 24. Central database unit

IV. EXPERIMENTS VERIFICATION

To firmly establish the proposed multi agent system and demonstrate its practical utility, we carried out some evaluation experiments. In one of the experiments, we implement two PAs and two EAs. PAs are from different hospitals with their own databases. Each PA is responsible for one EA. PA has special knowledge that will help evaluate certain medical cases. In this scenario, the two PAs start talking with each other in order to monitor the two elderly people. Physician agents register with the ICA agent. They start communicating with each other to update their own decision rule. When the evaluation of the monitoring of the elderly people is done, PA1 and PA2 inform their physician about the evaluation results. The multi agent system works successfully as designed.

To evaluate the effectiveness of the developed Decision Maker Unit, we retrieved the electronic data of 308 patients who visited Tafila Technical University/Medical Center during the time period from June 9, 2014 to September 30, 2014 using systematic sampling [23]. The retrieved patient data includes laboratory testing such as Blood Sugar Level, Triglycerides, High-density lipoproteins (HDL) and Low-density lipoproteins (LDL). The retrieved data also contains demographic data and patient visit data. All the data was stored in a 2007 Microsoft Access database. If the best-fitting instances are selected with a genetic algorithm, this might lead to over-fitting. So, in order to make sure that there is no over fitting, 1/4 of the data was held (77 cases out of 308 cases) in order to be used in testing the proposed system.

We examined agreement between the results generated by the developed system and the one by the physicians. We constructed the confusion matrix for each class (Low or High "Degree of Risk"). The confusion matrix has the form shown in Table 2.

TABLE 2
CONFUSION MATRIX

		Predicted Class	
		Low Risk	High Risk
Actual Class	Low Risk	True Positive (TP)	False Negative (FN)
	High Risk	False Positive (FP)	True Negative(TN)

The performance measurements used for this paper were recall, precision, classifier F_1 rating and accuracy. They are defined as follows:

Recall (R) is the ratio of the relevant data among the retrieved data. Precision (P) is the ratio of the accurate data among the retrieved data. Their formulas are given as follows:

$$\text{Recall(R)} = \frac{T_P}{T_P+F_P} \text{ if TP+FN > 0, otherwise undefined} \quad (5)$$

$$\text{Precision(P)} = \frac{T_P}{T_P+F_N} \quad \text{if TP+FN} > 0\text{, otherwise undefined} \quad (6)$$

Classifier F1 rating is the harmonic mean of the classifier recall and precision. It is given as:

$$F_1 = \frac{2*P*R}{P+R} \quad (7)$$

Where *R* represents the recall; and P represents the precision. Accuracy, which indicates the fraction of correctly classified samples among all the samples, is obtained by:

$$\text{Accuracy} = \frac{T_P+T_N}{T_P+T_N+F_P+F_N} \quad (8)$$

Table 3 shows the Decision Maker Unit evaluation results. The proposed Decision Maker Unit shows high accuracy (up to 98.70%) in the test data. To further validate the results, 10-fold cross validation was used.

TABLE 3
OVERALL PERFORMANCE RESULTS (TRAINING AND VALIDATION SET)

Total Number of Instances	231
Correctly Classified Instances	228 (98.7013%)
Incorrectly Classified Instances	3 (1.2987%)
Kappa statistic	0.9731
Mean absolute error	0.0249
Root mean squared error	0.1122
Relative absolute error	5.1295 %
Root relative squared error	22.8059 %

Another performance indicated by the confusion matrix is shown in Table 4. This confusion matrix was built based on data testing. We constructed the confusion matrix for each class (Low Risk, High Risk). The confusion matrix has the form shown in Table 8.

TABLE 4
CONFUSION MATRIX (TRAINING AND VALIDATION SET)

	Low Risk	High Risk
Low Risk	136	0
High Risk	3	92

The performance measurements result is shown in Table 5.

TABLE 5
EVALUATION RESULTS (TRAINING AND VALIDATION SET)

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
1	0.032	0.978	1	0.989	Present
0.968	0.000	1	0.968	0.984	Not Present

Using the held 77 cases not previously used in training or cross validation, the achieved results are shown in Table 6 and Table 7.

TABLE 6
OVERALL PERFORMANCE RESULTS (TESTING SET)

Total Number of Instances	77
Correctly Classified Instances	75 (97.4026%)
Incorrectly Classified Instances	2 (2.5974%)
Kappa statistic	0.946
Mean absolute error	0.0328
Root mean squared error	0.1513
Relative absolute error	6.7592 %
Root relative squared error	30.6931 %

TABLE 7
CONFUSION MATRIX (TESTING SET)

	Low Risk	High Risk
Low Risk	45	0
High Risk	2	30

The performance measurements result is shown in Table 8.

TABLE 8
EVALUATION RESULTS (TESTING SET)

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
1	0.063	0.957	1	0.978	Present
0.938	0.000	1	0.938	0.968	Not-Present

The final performance of Decision Maker Unit has been improved. It is compared to initial performance of Decision Maker Unit before optimization as it is shown in Table 9.

TABLE 9
INITIAL DECISION MAKER UNIT PERFORMANCE RESULTS

Total Number of Instances	231
Correctly Classified Instances	179 (77.4892%)
Incorrectly Classified Instances	52 (22.5108%)
Kappa statistic	0.541
Mean absolute error	0.221
Root mean squared error	0.3875
Relative absolute error	45.6197 %
Root relative squared error	78.7337 %

The developed medical kits have been tested using real elderly people (Fig. 25). Four medical kits, i.e. two Elderly Medical Kits and two Physician Medical Kits, were implemented. We have tested the medical kit using 30 elderly people (20 men, 10 women) whose ages are between 45-80 years old. The experiment was conducted 15 times. The 30 elderly people were divided equally in order to be evaluated by the two Elderly Medical Kits. In each experiment, two elderly people were monitored by two physicians. The process of starting the agents involved their registration with JADE Main Container, which assigns a unique identifier to each active agent in the system. The developed Elderly Medical Kits and Physician Medical Kits effectively worked together to monitor the elderly. The received elderly physiological data matched exactly the transmitted data from Elderly Medical Kits. The decision made by physicians is sent back through Physician Medical Kits to Elderly Medical Kits to match the transmitted decision. The initial decisions made by Decision Maker Units in Elderly Medical Kits for the 30 cases have been evaluated by two physicians. The confusion matrix was constructed for each class (Low Risk, High Risk). The confusion matrix is shown in Table 8.

TABLE 10
CONFUSION MATRIX (ELDERLY MEDICAL KIT)

	Low Risk	High Risk
Low Risk	17	0
High Risk	0	13

We have utilized Kappa statistics to estimate the levels of agreement. The Kappa coefficient is an estimate of the agreement between two raters. Kappa scores range between 1 (complete agreement) and 0.The achieved result shows complete agreement (kappa Statistics=1) between the decision made by Decision Maker Units of Elderly Medical Kits and the one made by physicians.

Fig. 25. Testing the system using an elderly women

V. CONCLUSIONS

In this paper, we have developed a multi-agent system for patient monitoring systems. We have designed and developed a medical network for connecting physicians and their patients. The developed agents are supported with Fuzzy Inference Engine that is supported with fuzzy decision rules. The Decision Maker Unit helps in make initial decisions regarding the medical condition of the elderly patients. Elderly Agent and Physician Agent were designed, built and tested. Agents worked with each other as designed. The performance of the system was tested using real patients' data. The system achieved excellent accuracy in making decisions regarding the medical case of patients.

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