An automated system for Health Care and Monitoring driven by intelligent agents

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Abstract: Logical health care system is designed to diagnose specific disease where input is sequence of symptoms. Symptom is associated with a numerical value 0-1 and a random mathematical formulated value will reveal disease. The diagnosed disease would have another unique numerical value. Different categories have made to put similar symptoms corresponding to particular disease. Role of intelligent agents comes from mathematical formulated inputs which on the later phase diagnose disease. Taking symptoms as data samples the HCS trains itself then after refinement and preprocessing with factual representation directs towards result as per as minimum error. The accuracy of result depends on the degree of training conducted on the data samples. Another issue which makes result having minimal error is as number of operations HMS performs with data samples; it becomes more consistent and generates result with less error and adequate feasibility**.** Here authors try to develop a logical system for health care to promote availability of medical experts in rural areas where demand is more but infrastructure is less.

Key words: LHCMS, Symptoms, HMS, CDSS

1. Introduction

Many developed countries have announced initiatives to modernize their health care systems with investments in health information technology (IT). The goal of these initiatives is to use technology to improve the health care system by reducing costs, increasing patient safety and improving quality of care. Improving health care is a common goal for these countries, but there are wide disparities in the success with which nations have pursued this goal [1]. In particular, countries such as the United States have lagged behind some European nations in the adoption of health IT, such as electronic health records. Interoperable electronic health records are a prerequisite for a modern health care system and the key to delivering a number of benefits to health care patients and payers. For example, the computerized decision support systems used in hospitals provide patients the most benefit when they use a complete and accurate set of patient data. These systems can help ensure a return to the core principle of evidence-based medicine—that patients and doctors have the best evidence available when making a decision about treatment. While much attention has been paid to the degree to which

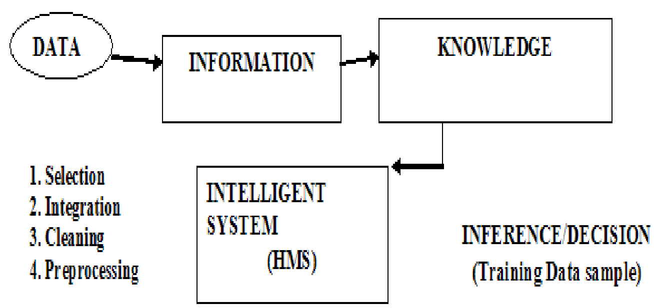


Fig1 . Flow of data in LHCMS

nations have made progress with investment in health IT, less attention has been paid to the level of investment in health IT research. Yet evidence-based medicine relies on high quality medical research. Moreover, as we enter an increasingly digital world, the amount of health data that will be available to medical researchers will be increasing substantially. While past medical researchers had only a few limited data points recorded on paper on which to base their hypotheses, in the future researchers will have massive online databases containing terabytes of data for their analysis. Some of the major benefits from modernizing our health care system are expected to come from the improvements in medical research that it will enable. For example, medical researchers will be able to use rapid-learning health networks to determine the effectiveness of a particular treatment for a certain population or to discover harmful side-effects of a drug. While some of this research will occur in the private sector, for example through private pharmaceutical research, public investment in this area will also be important. Already a variety of projects offer a glimpse into the possibilities that IT will allow for future medical research. But achieving this vision will require substantial leadership and effort on the part of nations to overcome the technical and social hurdles ahead

2. Background

2.1. Informatics in Health Care

Health care is becoming an increasingly data-intensive field as doctors and researchers generate gigabytes of medical data on patients and their illnesses. While a patient visiting the doctor 20 years ago may have only generated a few data points— basic information such as weight, blood pressure, and symptoms—a medical encounter today may leave a long trail of digital data from the use of high-definition medical imaging to implantable or wearable medical devices such as heart monitors. More importantly, as doctors and hospitals transition away from paper medical records, this data is increasingly being collected and made available in an electronic format. The availability of large data sets of digital medical information has made possible the use of informatics to improve health care and medical research. Often referred to as "in silico" research, informatics offers a new pathway for medical discovery and investigation. Informatics focuses on developing new and better ways of using technology to process information. Today, informatics is being applied at every stage of health care from basic research to care delivery and includes many specializations such as bioinformatics, medical informatics, and biomedical informatics. Medical informatics, or clinical informatics, focuses on using information processing to improve health care delivery. It covers various applications including using information technology within the clinical setting for medical billing, patient and resource scheduling, and patient care. An example of medical informatics is the use of clinical decision support systems (CDSS) which provide feedback and instruction to health care workers at the point of care. Such a system may, for example, provide warnings of potential drug interactions to a prescribing doctor based on a patient's existing medical history and known allergies. By integrating patient information with clinical guidelines, health care providers can help reduce medical errors. Adverse drug events alone account for an estimated 19 percent of injuries in hospitalized patients in the United States and cost hospitals over $2 billion per year, excluding medical malpractice expenses [5]. Biomedical informatics is a unique discipline that bridges multiple fields including medical research, clinical care and informatics. At its core, the objective of biomedical informatics is to develop new tools and technology to better collect, display, retrieve and analyze biomedical data. Such research can lead to new treatments, diagnostic tests, personalized medicine and better understanding of illnesses.

2.2. ***Building the Digital Platform for Medical Research***

Achieving this vision of an intelligent and fully-connected health care research infrastructure has not yet been realized. While various pilot projects have shown success and have demonstrated the potential benefits that can emerge from a ubiquitous deployment of informatics in health research, many technical obstacles still need to be overcome. These obstacles include making data accessible, connecting existing data sources, and building better tools to analyze medical data and draw meaningful conclusions. Much medical research data is not accessible electronically. For example, one challenge for the United States and the United Kingdom are the low rates of adoption of electronic health records among primary care providers and in hospitals. Electronic health records provide a complete medical history for a patient, including a full account of the patient's illnesses, treatments, laboratory results, medication history and known allergies. Among primary care providers, approximately one quarter use an EHR system in the United States and 89 percent use them in the United Kingdom. At hospitals, the rate of use is much lower with only about 10 percent or fewer of the hospitals in the United States and the

United Kingdom having adopted EHR systems [19]. Achieving the widespread use of electronic health records is a necessary requirement for creating the underlying data sets needed for biomedical informatics research. Access to the electronic health records of large populations will help researchers apply informatics to various problems including clinical trial research, comparative effectiveness studies, and drug safety monitoring. However, collecting medical data in electronic format is only the first step. Interoperability poses a substantial challenge for biomedical research. The vast amount of electronic medical data cannot fully be utilized by researchers because the data resides in different databases. Even when the organizations that collect and distribute biomedical data are willing to share data, incompatible data formats or data interfaces can create challenges for analyzing data across multiple data sets. As a result, researchers wishing to use multiple data sets must devote significant resources simply to managing the differences between the data and, as a result, have fewer resources available for working with the data [6]. For many years individuals in the research community have called for increased coordination and interoperability among data repositories to advance the use of informatics in health care. They have proposed various options to address interoperability although, to date, no proposal has achieved universal acceptance [6, 7]. One interim solution has been the development of online communities to share programming code to reduce the burden of working with diverse data sets. The most notable, Bio*, is a collection of open-source biomedical informatics projects that provide re-usable code for researchers to use that automate common computing tasks. For example, the project includes modular programming code to manipulate DNA sequences or combine data sets from different data sources [6].

3. A General Model

Healthcare applications have a number of additional requirements beyond the basic functions and representations that are common to many cognitive-system theories. (The "Related Work in Multi agent Healthcare Systems" sidebar describes four multi agent healthcare systems that, in different ways, illustrate these requirements.) On the basis of our experience with healthcare systems, we've identified three key requirements over and above the basic domino model:

• A communication capability for interactions between agents, which is important for multiagent systems but not supported by the formalisms proposed for modeling clinical guidelines, workflows, and so on.

• A well-developed model of decision making under uncertainty, which is generally regarded as fundamental to dealing with the complexities of clinical practice. Researchers have described how to embed this capability in an agent system and incorporate logical argumentation techniques for decision making.1, 6, and 7.

• The ability to access or communicate the knowledge and arguments used in specific decisions, a requirement that supports collaborative decision-making in multi agent applications. We extended the domino model to meet these requirements. Figure 1 shows the extended model. It's built around the six basic entities of the original domino model, which can itself be seen as an extension of the BDI agent model. In our terminology, beliefs are aspects of the agent's environment or its own mental states, which the agent holds to be true (that is, the agent will act upon them while they continue to hold). Goals are equated with "desires" and plans with "intentions." We view intentions as commitments to new beliefs or to carrying out certain plans or pursuing new goals in the future.

A fundamental capability of the agent model is the ability to make decisions under uncertainty—that is, to make choices between competing beliefs or alternative plans given a lack of certain knowledge about the true state of the environment or about the consequences of possible actions on the environment. The model introduces a four-step decision procedure in which an agent can identify decision options (competing beliefs or plans), construct arguments for and against the options, assess the relative strength of the sets of arguments for alternative options, and commit to the most-preferred option.1,6 The decision procedure reflects our primary ASPIC project activity—namely, to develop an agent framework that can integrate the different roles of argumentation in a principled way. Two features of the extended model accommodate this activity:

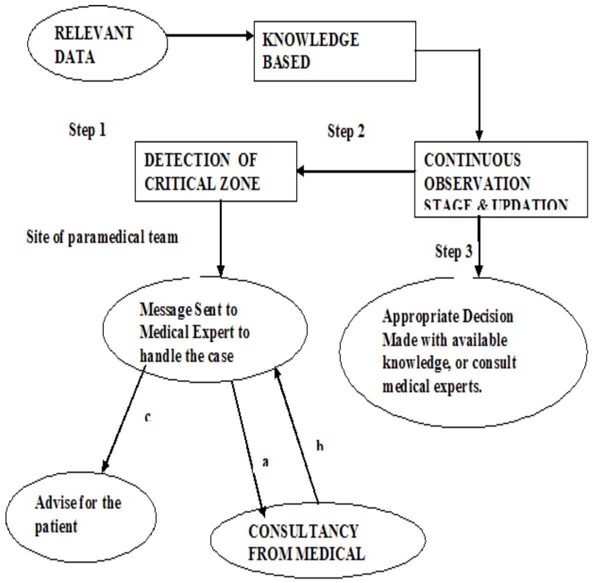


Fig 2. Building Blocks of LHCS

3.1 Interagent dialogue models. Project partners are developing and formalizing interagent dialogue models and we're incorporating the results into our extended model for use in the Carrel and CREDO applications described in the sidebar. eg we're extending standard FIPA-like per formatives to include those that facilitate coordination on collaborative tasks, such as joint decision making or service negotiation, where deliberative or dialectical argumentation between agents is required.

3.2 Machine learning. Project partners are investigating the relationship between argumentation and machine learning. Learning capabilities are especially important in healthcare applications, because human errors and system failures will occasionally occur no matter how well we design our systems. To support learning from experience and corrections to procedures, the agent platform should on all occasions maintain records of what happened, what decisions were taken and why, and what the outcomes were.

4. Intelligent Agents

Authors try to define symptoms as intelligent agents which will further help to diagnose disease. Although medical science is not based on linear equation but the methodology which has adopted here is based on knowledge based and expected to secure result with minimal error. Authors categorically have taken three disease and listed corresponding symptoms. It can be seen on following tables as Table 1 disease H1N1, Table 2 Jaundice and in Table 3 Malaria. In each table four attributes have been taken as serial no., symptom code, symptom name and symptom value. The symptom value is assigned randomly to every symptom for uniqueness and it is between 0 to 1.

5. The Algorithm

As symptom value is assigned randomly to every symptom for uniqueness and it is between 0 to 1. The reason behind assigning these random values is to ultimately let every disease comes out with another unique numerical value between 0 and 1. The algorithm executes in following steps:

i. **Take symptoms with assigned numerical values one by one.**
ii. **Make clustering according to symptoms as unique symptom index and general symptom index.**
iii. **Prepare matrices for unique symptom index and general symptom index.**
iv. **Assign variables U to unique symptom index and G to general symptom index.**
v. **The dot product of U and G will give us the value of disease.**

The numerical value which comes out would be unique for the disease.

5.1. Methodology & Implementation:

At very first stage as a sample three diseases as well as their corresponding symptoms have been taken up in three tables. Authors try to device the cluster for three major diseases viz. H1N1 flu, jaundice and Malaria.

Disease (H1N1). D1:

Sr. no	Symptom Code	Symptom Name	Symptom Value
1	S01	fever	0.1
2	S02	cough	0.01
3	S03	sore throat	0.19
4	S04	runny nose	0.35
5	S05	body aches	0.27
6	S06	headache	0.9
7	S07	chills	0.33

8	S08	fatigue	0.45
9	S09	diarrhea	0.6
10	S10	vomiting	0.019

Jaundice Disease D2:

Sr. no	Symptom Code	Symptom Name	Symptom Value
1	S11	Yellow skin	0.72
2	S12	Yellow eyes	0.81
3	S13	reddish urine	0.12
4	S14	Bronze skin	0.39
5	S15	Loss of appetite	0.01
6	S16	Furry tongue	0.79
7	S17	Pale feces	0.43
8	S18	Nausea	0.075
9	S19	Itching skin	0.16
10	S20	Lethargy	0.15

Malaria Disease D3:

Sr. no	Symptom Code	Symptom Name	Symptom Value
1	S21	Fever	0.91
2	S22	Rigors	0.05
3	S23	Headaches	0.49
4	S24	Myalgia	0.55
5	S25	Loss of appetite	0.12
6	S26	tiredness	0.59
7	S27	vomiting	0.23
8	S28	Nausea	0.045
9	S29	cough	0.14
10	S30	Enlarged liver/spleen	0.39

Now the equation of the form is given by:

$$\mathbf{D} = \prod_{i=1}^{n} \mathbf{F(SDi,SOi)}$$

SDi = unique symptom index for disease D1
SOi = General symptom index for disease D1

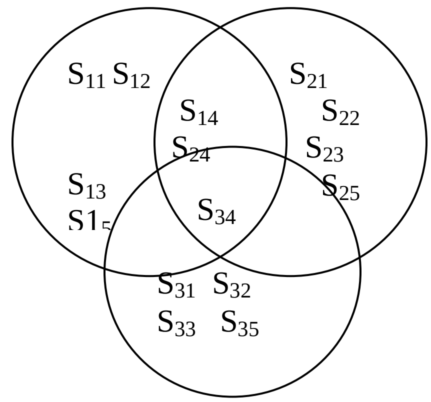
$$\mathbf{D1=} \begin{bmatrix} s11 \\ s12 \\ . \\ . \\ . \\ s1i \end{bmatrix} \mathbf{.\ [Si1\ Si2\ Si3\ .\ .\ .\ .\ .\ .Sin]}$$

$$\mathbf{D1=S11*Si1+\ S12*Si2+S13*Si3+\ldots+S1n*Sin.}$$

$$\mathbf{D}=\sum_{i=1}^{n} \mathbf{S1i*Si1}$$

5.2. ***Clustering:***

We try to train the system with the systems of disease and try to cluster the data. As an example



5.3. ***Error Analysis:***

The difference of mathematical model of unique symptom index and General symptom index will refer for error. So if only unique symptom index is used for calculation of disease, general symptom index to be ignored hence more accurate and estimated value would come out for analysis.

6. Justification for Analysis:

While developing mathematical model first analysis starts with clustering reason is as we have two symptom indexes called U and G. All those symptoms which are core symptoms of corresponding disease are in U and all those symptoms which are also part of other disease are in G. eg Pale nail symptom can help us to diagnose on Jaundice but shivering can lead diagnosis towards malaria and pneumonia as well. So to considering both the indexes we need to develop mathematical model.

7. Intelligence through Machine Learning & Advantages

As initially the system is empty and works on knowledge based system. So when ever very first time user will interact with the system it will generate result with error but as many times system will be trained much consistent and efficient knowledge base will be created and system will produce more correct result. Although the implication is limited but adequate training will make it feasible. Following advantages come out with training of the system:

i. Enhancement of knowledge base
ii. Quick updation of u and G indexes.
iii. Domain enhancement of U & G indexes
iv. As system gets trained more accurate result comes out.
v. • Case-based learning
vi. Argumentation-based machine learning
vii. A general domain knowledge repository

8. Limitation of LHCMS:

As authors repeatedly saying the fact that medical science does not allow any conclusion which comes out through linear equation or linear analysis but this mathematical model which is designed for the logical health care and monitoring system (LHCMS) produces result with gradually degradation in error. LHCMS is limited upto diagnosis only. The system cannot diagnose disease where the symptom has different degrees of parameter. eg in the symptom shivering one needs to clarify the degree of shivering a patient has. Otherwise it would be considered as standard input shivering. So this kind of behavior of symptoms to be avoided to let LHCMS work within its domain.

9. Conclusion:

LHCMS is an IT aid to provide medical expertness within the limit and an enhancement through computing. The system justifies itself with core idea of IT ie connectivity With relevance and it reaches to public health center with complete solution since the data collection and processing is done with more accuracy and hence becomes intelligent system. The challenges and future focus of the project is exhaustive data analysis, where study requires more accurate data representation.

Because more relevant data analysis takes place more intelligent system would be designed. Finally future focus from IT point of view is linking among various attributes to conclude more complex cases. After this diagnosis stage is over authors look forward to design the system for treatment as futuristic approach of this paper.

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