iHANDs: Intelligent Health Advising and Decision-Support Agent

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***Abstract*—This paper describes an intelligent health and decision support agent (iHANDs) built with various artificial intelligence mechanisms. Upon receiving the user's symptom descriptions, iHands conducts both web search and local medical knowledge database search, utilizing the user's electronic health records (EHR) to direct the search process. An information-fusion algorithm is developed based on Dempster-Shafer theory to merge the information from various sources with different reliabilities and generate the strength of support for each possible cause. A dynamic reference network is created and updated to record all information obtained during the interleaved search and reasoning process. iHands performs a bi-directional search: from symptoms to possible causes and also from possible causes to most likely symptoms and risk factors. Bayesian inference mechanism is used to identify the confidence level for each possible cause given the user's symptoms and EHR. When needed, an iterative broaden search will be conducted to increase the confidence level to exceed a pre-set threshold or to further distinguish a few possible causes with very close confidence levels. The preliminary experiment results show the promise of iHands in assisting individuals in their healthcare decision-making process.**

***Keywords*-health informatics, web knowledge mining, reasoning under uncertainty, decision support, intelligent agent**

I. Introduction

The Internet is becoming more a part of American's daily lives; it provides an entry to a large volume of information, from various sources, on almost every topic, including health care. This becomes a great opportunity for people to educate themselves and their family members on health-related issues. The National Institute of Health has developed a number of online medical information databases and digital libraries such as MedlinePlus [1], a health's web site for patients, and MedKB [2], a medical knowledge base. Although healthcare providers are the best source of this knowledge, more Americans are using the Internet for seeking health care information [3]. However, it is a difficult task for general users, who have no medical training, to navigate through the massive information network in order to find the right answer to their health-related questions. The challenges come from the following sources:

- *Online information reliability*. Online information comes from various sources and has different qualities. Some information sources are not as reliable as others. However, it is not easy to tell which information sources are more reliable. The top results returned by a search engine may not be the best information. In the healthcare domain, the reliability of information is critical and should be considered seriously.
- *Combine information from various sources*. It usually takes multiple pieces of information to answer a question related to complex health problems, and these pieces of information need to be organized, analyzed, and reasoned about in order to generate the right answer. This process is made more difficult by the usage of different vocabularies and the possible inconsistencies among these information sources.
- *Connect with personal health record*. Each person has his/her unique health situation. The general medical knowledge becomes much more useful when it is combined with one's personal health record [4]. Many hospitals and healthcare communities have started to develop electronic health records (EHR) for their patients, and this resource would and should be utilized to help people manage their own health-related problems [5].
- *User ability*. Among those people who seek answers to healthcare questions, many are seniors with multiple chronic illnesses and potentially low literacy; in fact, they represent one of the groups who need this type of help the most [6], [7]. Most of them are not proficient with information technologies and some of them have limited vision or motor skills caused by aging or illness [8].

The above challenges are addressed by our system in the following ways. iHands focus its web search on those **trusted** websites provided by health care experts and also explicitly consider information reliability in its reasoning process. We developed an information-fusion algorithm based on Dempster-Shafer theory to merge the information from various sources with different reliabilities. A dynamic reference network is created and updated to record all information obtained during the interleaved search and reasoning process. The user's electronic health records (EHR) is used to direct the search process, in order to find the

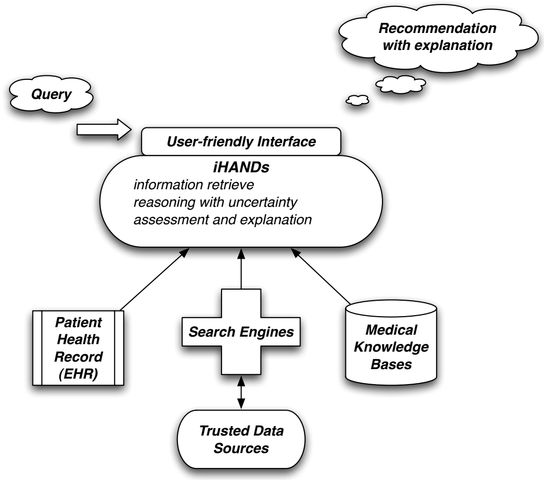

Figure 1. iHANDs Working Environment

most accurate and personalized decision support. iHANDs is designed for users without medical training and clinical knowledge; people who have limited experience with modern computer technology. Promoting ease-of-access, user-customization and the dynamic creation of content for an intelligent interface - getting smarter. Our system extracts relevant information according to the user's health record or preset preferences, create questions and choices specially related to the current user and is able to learn from the interaction history with one user and be adopted to better serve the user.

II. System Overview

We developed an intelligent health advising and decision-support agent (iHANDs), which assists and supports a person's healthcare decision, based on the patient's personal health record and knowledge from sources in public domains. iHands provides explanations and reliability measurement for its recommendations to help user understand and therefore better receive the recommendation [9].

Figure 1 depicts iHANDs working environment. Our system takes queries from a person who is seeking help for a complex health decision through a user-friendly interface. Based on the analysis of the query, additional information is retrieved from this person's electronic health record (EHR) and knowledge sources in the public domain, which include both well-structured information sources such as medical knowledge bases and less-structured information sources such as web pages. iHANDs conducts an inference process that interweaves reasoning on available information and dynamic searching of more information. Recommendations with explanations are generated as outputs of this process, and those explanations help the user understand how these recommendations are created, the credibility of the information sources and the certainty of the reasoning process.

The system, iHANDs, is expected to provide assistance in a patient's decision-making for immediate actions. For example, for an at-home patient with heart failure history, iHANDs provides recommendation of whether the patient should go to a hospital/emergency room, call the doctor's office or just stay at home, given the patient's past health record, current symptoms, and public knowledge. iHANDs also assist a patient with complex health problems to seek appropriate treatment. For example, iHANDs would help a patient to compare and evaluate multiple treatment plans, considering the pros and cons for each alternative, the patient's personal health record and the patient's own preferences. Additionally, iHANDs may assist a user to develop a long-term health management life style including an integrated exercise and diet plan that is suitable to the user's health situation. iHANDs monitors the execution of this plan and adjusts it according to the actual outcomes and the user's feedback. Actively engaging patients in treatment decision making and monitoring has been shown to be a good strategy to improve health outcomes for patients with chronic diseases [10], [11]. All above functions are envisioned for iHands and the current implement is focused on the cause diagnosis based on the input symptoms from user, which is described in details in this paper.

Different from an expert system that builds knowledge inside, iHANDs gathers information from public knowledge sources, which are maintained and updated by various organizations. iHands' knowledge-base is comprised from information collected from two trusted commercial domains, namely the ever popular WebMd and MayoClinic. WebMD was founded in 1996 an is primarily known for its public information regarding health and health care and reaches an average of 86.4 million visitors per month, WebMD is the leading health portal in the United States. MayoClinic is a not-for-profit medical practice and medical research group employing 3,800 physicians and scientists.

In addition, database PubMed owned and maintained by government, specifically its subsidiary MedlinePlus are exploited. PubMed offers free information retrieval services via the World Wide Web. The United States National Library of Medicine at the National Institute of Health maintains this database. 500,000 new records are added each year. It is providing 22.6 million records dating back to 1966. PubMed's subsidiary domain, MedlinePlus, provides services for accessing aforementioned information from PubMed and is accessed by over 150 million people from around the world a year. It produces XML data sets that are available for download and use based on keyword searches as requests which returns relevant health information.

Lastly but certainly not the least, information from a user's electronic health record is retrieved and expanded upon via indexing Medical Subject Headings. Electronic Health Records (EHR) provides users a unique presence over our system. The electronic health record is an evolving

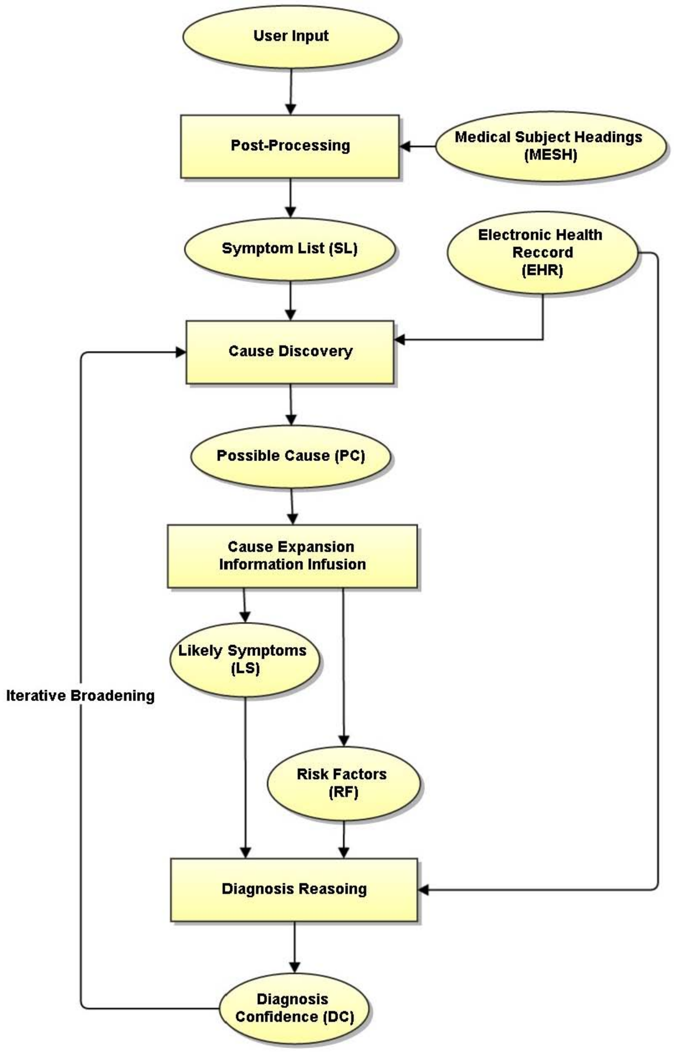

Figure 2. iHANDs System Workflow

concept providing health information regarding individual patients or populations. These digital records, stored in XML form, are capable of being shared across different health care settings and encapsulate an individual's demographics, medical history, medications and allergies, immunization status, vital signs and so forth. Utilizing EHR information enables iHands helping patients make a personalized and well-informed decision for their complex health problems.

Information retrieval of multiple sources is optimized by usage of Medical Subject Headings (MeSH). MESH is a comprehensive medical vocabulary, controlled by the National Library of Medicines. This medical thesauruses consists of sets of terms naming descriptors in a hierarchical structure that permits searching at various levels of specificity. This machine-readable database is accessible in XML form.

III. System Workflow And Processes

Figure 2 encapsulates the workflow of our system: rectangles depict system processes while ovals represent dynamically generated data content. The general procedure of our system is as follows, elaborated further in each subsection below. First, the user provides input via interface, which is processed to produce a unique symptom list (SL). SL in conjunction with content from the user's electronic health record (EHR) drive the discovery of possible causes (PC) via cause discovery. Cause discovery produces PC via parsing of web content over aforementioned parameters. PC is then expanded upon via cause expansion - a set of likely symptoms (LS) and risk factors (RF) are generated for each possible cause. LS and RF in conjunction with the user's SL and EHR are next merged via Dempster-Shafer theorem to produce numeric values called support strength for the diagnosis reasoning procedure. To identify the most likely cause, the system conducts a bi-directional search process: a diagnostic search from user input of symptoms (SL) for discovery of possible causes (PC) and cause-effect search from PC for discovery of likely symptoms (LS) and risk factors (RF). The overlap between SL and LS, and the overlap between EHR and RF are used to determine the probability of each possible cause - expressed in the diagram via transitional arrows. The diagnosis reasoning module encapsulates the mathematical models utilized for deriving dynamic diagnosis confidence (DC) measurements also referred as diagnosis probability. All possible causes are then ordered from most likely to least likely based on their confidence measurements. When DC falls below the acceptable system threshold, an iterative broadening search will be conducted, requiring additional processing and verification from the user and/or increasing the search space to gather more information. This iterative broadening search process will also be used to further distinguish a few possible causes with very close DC measurements.

A. User Input Processing

Our system supports input in both structured and unstructured form. Processing user input has two purposes. First, it guarantees the contents of symptom list (SL) are of highest accuracy - disallow spelling and grammar mistakes. Second, it expands the list of keywords via interfacing of the Medical Subject Headings (MESH) to increase web search space. Consider the following scenario.

Mona, a 50 year old female, with low vision, presents to her health care providers office with complains of pain to her right ankle to the point of not being able to walk well or wear shoes. There is swelling and increased redness to area of pain. She denies any injury to her foot and ankle. She reports drinking beer daily for the past several weeks but other than that their exist no significant changes to her daily life. Mona's medical history indicates she's been diagnosed as an obese individual. In 2007 she was diagnosed with Type 2 Diabetes and HTN. In 2010, three years later she was admitted to the emergency room for treatment of renal calculi. After searching in MESH, Mona's symptoms of "abnormal fluid accumulation" and "redness to area" are expanded upon, surfacing terms "Edema" and "Erythema". Figure 3 depicts the directed acyclic graph (DAG) generated from aforementioned scenario, including a total of three sets to represent Mona's unique scenario: symptom list (SL), medical history (MH) and demographics (D).

B. Cause Discovery

iHands agent then starts a cause discovery process. The discovery of possible causes (PC) is driven by the existence of sets SL, D and MH. iHands agent first conducts a series of three independent web-searches, these searches encapsulate aforementioned sets SL, D and MH as their input keyword parameters, deemed WS1, WS2 and WS3. WS1 uses only SL as search input, WS2 uses both SL and MH, and WS3 uses both SL and D. Web search is very sensitive to the input keywords. With too many or too specific keywords, little or none results may be found. On the other hand, too few or too general keywords may result in large amount irrelevant information. It is not easy to automatically choose the most appropriate set of keywords, so by performing three searches with different input keyword sets, iHands is aiming to increase the possibility of finding more relevant information. In context to Mona's scenario, the possible causes (PC) after the consolidation of results from search WS1, WS2 and WS3 are:

PC = {*Vein Disease, Ankle Sprain, Arthritis, Kidney Stones, Peripheral Vascular Disease, Secondary Hypertension, Gout*}

iHANDs maintains an internal knowledge inference network [12] to represent facts, discoveries, inferred outputs, confidence and uncertainties of the reasoning process. This knowledge inference network is a directed acyclic graph (DAG), each node represents a concept, could be disease, symptom, or treatment method, and each arc represents an inference relationship between two concepts. There is a confidence value associated with each node to represent how confident the system is on the existence of this concept in the current scenario. Additionally, there is a certainty value associated with each arc to represent how strong the relationship is between those two concepts. The inference network in iHANDs is dynamically constructed in this interleaved search and reasoning process. The inference network adopts a hierarchical structure; each node in the network can be a sub-network by itself.

The reliability of information is dependent upon both its source and the accuracy of the information retrieval process; some sources are more reliable than others. In current system implementation, only the source reliability is modeled. The measurement of the information retrieval accuracy will be added in our future work. We derived information reliability values for all user input (SL and EHR), for commercial domains and for government domains. We assumed government domains to be more reliable than commercial domains; hence in our experiment we assigned two different values of 0.75 and 0.90, respectively. The user input is considered very reliable hence a reliability value of 0.95 is assigned for user-input information such as symptoms. These values are what we use of current, based on our assumptions, assigned for our experiment. We do recognize these reliability values can be dynamically assessed and modified to reflect various search environments.

C. Cause Expansion

After the cause discovery process, iHands has a set of possible causes. To find out which one is the most likely cause for the user, iHands now conducts a cause expansion process to gather additional information on each possible cause.

Figure 4 is an extension of Figure 3 depicts the directed acyclic graph generated as a result of cause expansion in context to Mona's scenario, omitting four possible causes due to space restrictions. Cause expansion is performed over each possible cause (C_i) inside PC, resulting in two sub-sets: likely symptoms (LS) and risk factors (RF). The population of these two sets is dependent on the number of parsed web-searches over both commercial and government domains.

Elements belonging to likely symptoms (LS) set are those that occur both in the users symptom list (SL) and also in the web-search result. Content of web domains is parsed and searched against elements belonging to SL, all other symptoms are ignored. Such that the resulting LS by search cause Ci on web domain Wi equates for: $LS(C_i, W_i) = SearchResult(C_i, W_i) \cap SL$.

Each web domain search result $LS(C_i, W_i)$ is associated with an assessed reliability factor depending on the information source Wi. However, it is often difficult to find accurate information from searching only one domain given these two limitations. First, we, as humans, understand nothing can be accurate 100% of the time - no single domain cannot adequately cover all symptoms as some might not be reliable. Second, faults from text-processing can occur. So multiple web searches are conducted for most likely symptoms in order to gather more accurate information. This necessitated us to combine discovered evidence together across multiple web domains using the Dempster-Shafer theory as it pertains to uncertainty and also the lack of information.

Not only does LS serve as the list of likely symptoms but via Dempster-Shafer theorem, our system derives a numeric value pertaining to the support strength of any LS. We search one domain, construct its unique set, search another domain and then combine their reliability factors to derive a new LS. The end result is one comprehensive LS for each possible cause and an associated reliability metric pertaining to the

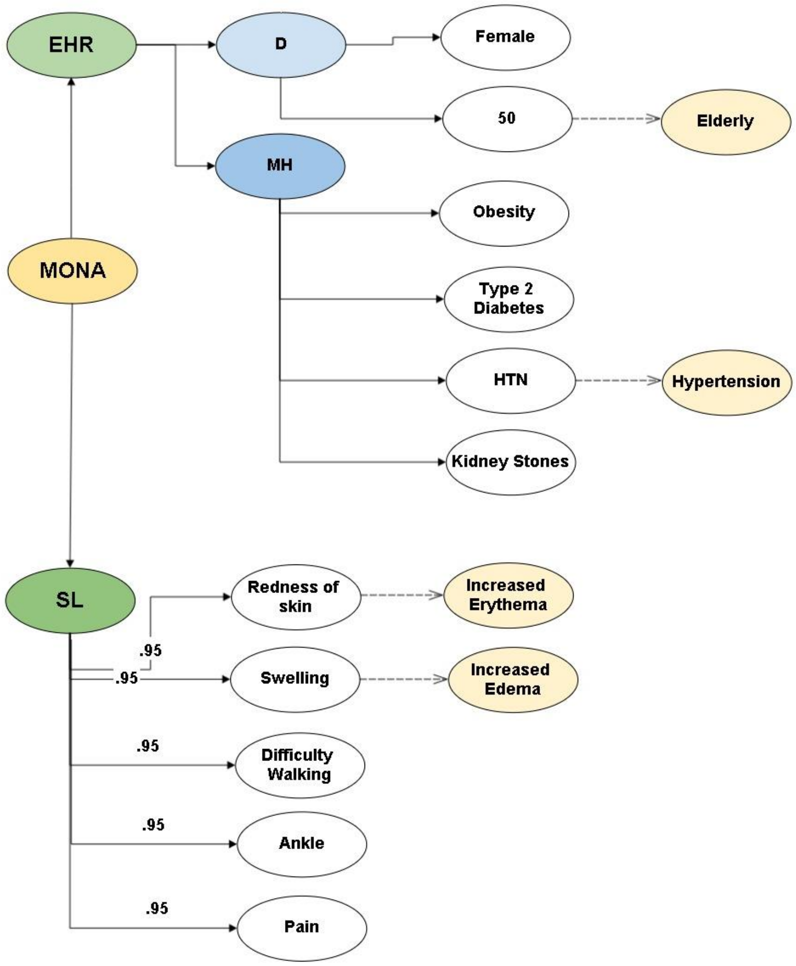

Figure 3. Mona's Directed Acyclic Graph - EHR and SL

support strength of LS. Figure 4 depicts the application of infusion information as a directed acyclic graph (DAG) and is the final result of cause expansion in context to Mona's scenario, omitting four possible causes due to space restrictions. For example, as shown in Figure 4, the possible cause Gout has likely symptom set LS as pain, swelling, ankle, difficulty walking, with the support strength as 0.993; resulting from searching 3 web domains. They is no adherent limit to the number of domains which can be merged. We refer to this procedure as the infusion of information.

Cause expansion over risk factor (RF) set differs slightly from LS. Risk factors play an important role in concluding the likelihood of a possible cause. The more risk factors the patient has for one possible cause, the more likely this cause is for this patient. Therefore the parsing of web domains encompasses all risker factor found. Unlike LS, derived from symptoms occurring in SL; RF is expressed as one set, adding new elements as they are discovered. Cause expansion consolidates RF, ensuring no two elements are similar, as one set - regardless of the number of domains parsed. For example, as shown in Figure 4, after searching for three web domains, the risk factor set RF found for possible cause Arthritis is Female, Obesity, Family History, Joint Injury.

Table I
MONA'S DIAGNOSIS REASONING $P(C_i|SL, EHR)$

C_i	$P(C_i\|SL, EHR)$
C7: Arthritis	0.28568
C4: Gout	0.18656
C3: Peripheral Vascular Disease	0.18402
C2: Ankle Sprain	0.06664

D. Diagnosis Reasoning

To derive an accurate diagnosis we've developed Equation 1 for calculating the diagnosis confidence measurement for

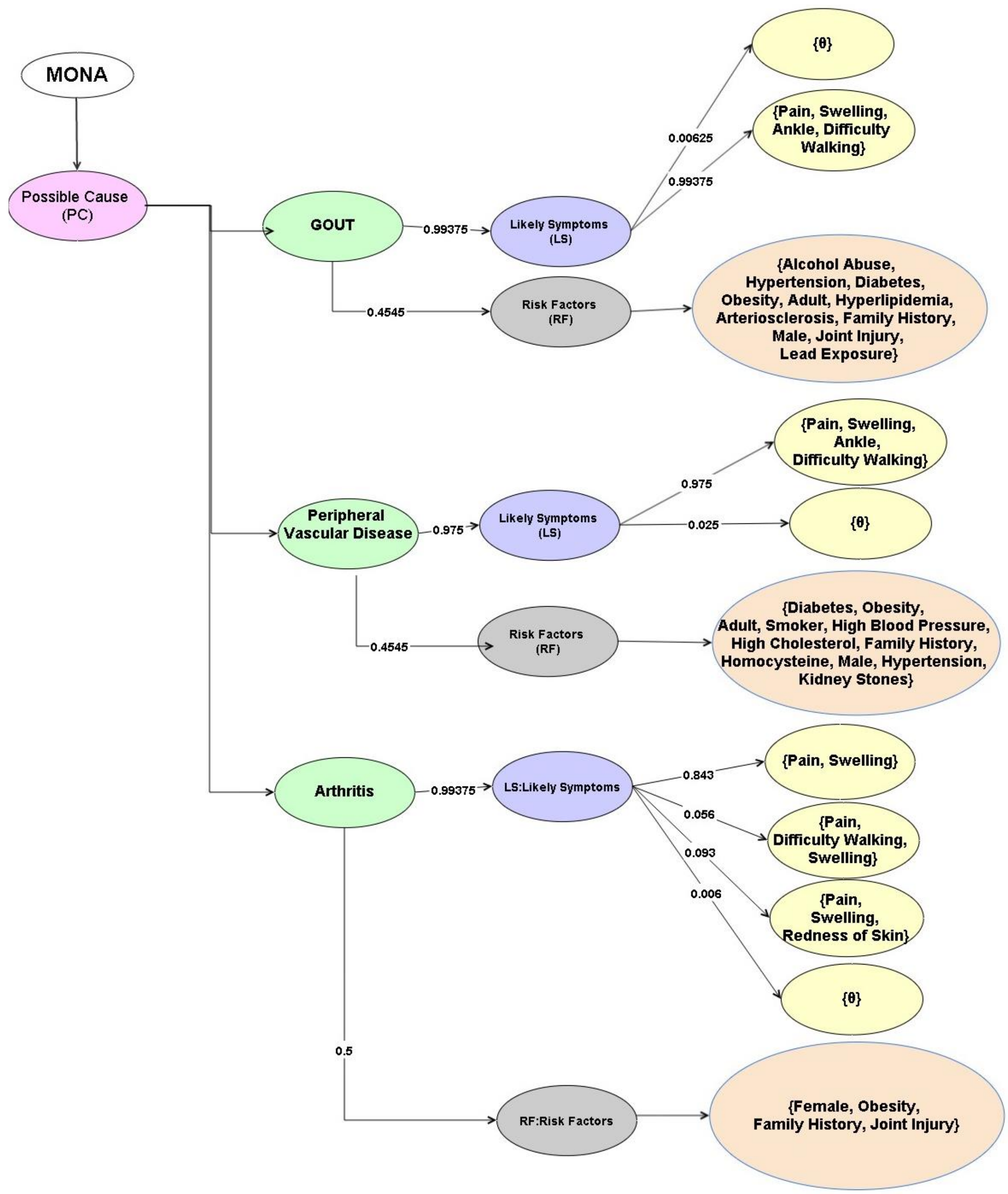

Figure 4. Mona's Directed Acyclic Graph - Cause Expansion

each possible cause C_i.

$$P(C_i|SL, EHR) = w * P(C_i|SL) + (1 - w) * P(C_i|EHR) \quad (1a)$$

$$P(C_i|SL) = P(SL|C_i) * P(C_i) \quad (1b)$$

$$P(SL|C_i) = (\#LS_i/\#SL) * Support\_Strength(LS_i) \quad (1c)$$

$$P(C_i|EHR) = \#[EHR \cap RF_i]/\#RF_i \quad (1d)$$

Viewed from a top-down hierarchy, Equation 1a describes the diagnosis confidence measurement $P(C_i|SL, EHR)$, which requires additional computation of conditional probabilities $P(C_i|SL)$ and $P(C_i|EHR)$. $P(C_i|SL)$, the probability of C_i having accounted for SL is computed by multiplying $P(SL|C_i)$ with the prior probability of the possible cause, $P(C_i)$, according to Bayesian rule (Equation 1b). Conditional probability $P(SL|C_i)$ is obtained via the product, of ratio, $\#LS_i$ and $\#SL$ [$\#LS_i/\#SL$] and the support strength of LS_i, shown in Equation 1c. $P(C_i)$ is derived via statistic data found from the web.

Lastly the conditional probability of C_i having accounted for EHR, $P(C_i|EHR)$ is computed with Equation 1d. This is accomplished by equating the ration of cardinality, denoted by symbol #, pertaining to $EHR \cap RF_i$ and cardinality of RF_i. This is based on the assumption that the more common elements there are between the user's health record EHR and the risk factor set RF_i, the more likely that the user has cause C_i.

To balance the support from symptoms and risk factors, a weight value (w) is utilized in the computation of $P(C_i|SL, EHR)$. In our experiment we used a value of 0.6. We do recognize to choose an appropriate value is a difficult task as it requires more art than science. All possible causes are ordered from highest to lowest according to their diagnosis confidence measurements, such that the most likely diagnosis appears first. Mona's diagnosis probabilities are displayed in Table I.

To account for low diagnosis confidence measurements pertaining to inadequate information or a lack-off information, our system adopts an iterative broadening search mechanism. When the highest diagnosis confidence measurement fails to exceed the system's acceptable threshold value, broadening search commences - expanding the search environment space for cause discovery by searching for more web domains and/or parsing more resulting pages. Instances of one or more possible causes with very close diagnosis confidence values, within 2% range of one another, iHands formulates question set (QS) to extract additional information from the user. QS is dynamically generated and can encapsulate likely symptoms and/or risk factors.

IV. Experimental Results

Besides the scenario presented in the previous section, regarding Mona (CS4), three more cases CS1, CS2, and CS3 were studied and the results are summarized in TABLE II. For each case, the column *Demographics (D)* and *Medical History (MH)* describe the patient's personal information and EHR information, the column *Symptom List (SL)* presents his/her current symptoms, and the column *Diagnosis Probabilities* lists the top 3 most likely causes and their diagnosis probabilities. We understand that the number of case studies is small and the sample space is huge; a much more intensive evaluation is certainly needed to move this project on the way to be a deployable application. Given the very limited time and manpower available, Dr. Sethares, a medical expert, has hand-picked these four cases to broaden the representativeness as much as possible. In these cases, patients have a variety background. They age from from 13 months to 58 years old, there are males and females, White and Africa America, smoker and alcohol consumer. They have diverse medical history such as Hypertension, Obesity, COPD, Asthma, Allergies, Diabetes and Kidney Stones.

Out of the four case studies conducted, in the first three cases, the top recommended causes by iHands concur with the expert's diagnosis. As shown in TABLE II, items of bold font pertain to the diagnosis of medical experts - PVD, Pneumonia and Meningitis. In the last case C4, namely Mona's case, the top recommendation of iHands (Arthritis) is a general term of the expert's diagnosis (Gout), which appears as the second-ranked recommendation of iHands. This can be understood as Gout is a common form of arthritis. These results are very encouraging, which demonstrate the potential of iHands as an assistant for users with non-medical training to seek information for their health-care needs.

V. Related Work and Closing Remarks

Researchers have used Bayesian network and Dempster-Shafer theory in medical related domains since 1990s[13], [14]. However, different from most expert systems using built-in knowledge, iHands dynamically gathers information from online knowledge sources, as well as utilizes personalized information for EHR. The novelty of our approach relies in the usage of a number of the most advanced methodologies in artificial intelligence and information retrieval including: purpose-driven search based on currently available information, dynamically constructing an influence network to represent known knowledge and its reliability, reasoning under uncertainty to deal with less-than perfect information and missing evidence, generating confidence measurement to help user to understand the reliability of the recommendation. Perhaps the most innovative component is the development of this technology for a user group that is rapidly growing and more adept at using this technology, older adults with chronic illness.

The purpose of this research is by no means to replace medical expert to perform diagnosis or critical treatment decision-making, given the complexity, liability and law requirement in medical practice domain. Rather the goal of this research is to help user to exploit the massive health-related information available online given their own personal background, to better understand their health problems, to compare different treatment plans, and to adopt a long-term health management life style personalized for themselves. These are the future features we plan to implement in iHands. The current experiments in diagnosis is to test the feasibility and quality of these information fusion technologies implemented. The preliminary results show the promise of combining multiple AI techniques to provide individualized diagnostic medical advice, which is encouraging for aiming for those future expected goals.

In the future, we will first develop a performance standard for acceptance and widespread use, and a methodologically sound approach to demonstrating that those targets are being met. We also plan to conduct much more case studies with iHands to better understand the strength and limitation of the current process and improve the decision accuracy. We will also looking forward to expanding the current iHands

Table II
CASE STUDIES

Case Study	Demographics (D)	Medical History (MH)	Symptom List (SL)	Diagnosis Probabilities (top 3)
CS1	age 58, African American, Male, Smoker	Hyperlipidemia, Hypertension, Obesity, COPD (Chronic Obstructive Pulmonary Disease)	leg cramping, need frequent rests, difficultly completing daily routines, difficulty walking, pain, leg weakness	**C2: Peripheral Artery Disease = 0.2300** C3: Restless Leg Syndrome = 0.1408 C5: Sjogen's Syndrome = 0.1334
CS2	age 13-months	Asthma, Allergies	cough, fever, nasal discharge, difficulty breathing, vomiting, weakness of muscles, wheezing	**C1: Pneumonia = 0.1119** C2: Nasal Congestion = 0.0237 C9: Reactive Airway Disease = 0.00000085
CS3	age 3, Male, White	None	nausea, vomiting, fever, increasing lethargy, stiff neck	**C2: Meningitis = 0.5716** C5: Mumps = 0.2 C6: Chicken Pox = 0.0013
CS4	age 50, Female, Consumes Alcohol	Diabetes, Hypertension, Obesity, Kidney Stones	ankle pain, difficulty walking, swelling, redness of skin	C7: Arthritis = 0.2857 **C4: Gout = 0.1866** (a common form of Arthritis) C3: Peripheral Vascular Disease = 0.1840

system with those envisioned functions such as providing immediate action recommendation, treatment plan comparison and long-term health life-style management. We are very excited by the great potential of applying intelligent computing technologies in improving people's health!

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