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ABSTRACT

Despite the use of Electronic Medical Record Systems (EMRs) in primary care, physicians still lack decision support tools to help with decision making in the delivery of health care. In this paper we propose a framework for an Intelligent Decision Support system that uses hybrid architecture and combines the concepts of data mining of knowledge bases (KB) and artificial neural networks (ANN). The model is presented in the context of the primary health care system, with an aim to create and track patient profiles for use in pattern recognition to identify unusual test readings and trigger alerts, support decision making by recalling past information, produce domain knowledge from the recalled information, perform reasoning from "new" domain knowledge and serve as a predictive tool in decision support. Our approach focuses first on building descriptive and predictive models for the particular domain, and then using these models to formulate the hybrid system. We present a case study to show how the system would be applied in a clinical setting.

Keywords:

IDSS, Intelligent Decision Support, Artificial Neural Network, ANN, Data Mining

INTRODUCTION

Many primary care physicians are now using Electronic Medical Record (EMR) systems to store a large number of medical records, each of which includes information on laboratory tests, symptoms, diagnoses, and treatments for individual patients. Despite the use of EMRs, physicians may still encounter problems in decision making that limit optimal patient care. Failure to track and follow-up on abnormal tests, to comply with clinical guidelines, and to remind patients with chronic disease about specific tests and examinations are major problems plaguing the primary care system. Limitations of the human memory as well as limited knowledge of specific domains of medicine and inadequate awareness of the growing number of medical facts being published in medical journals further hinders physicians' capacity to diagnose and treat patients. With an increasing number of patients and possible symptoms to observe and track for each patient, as well as a growing number of new drugs and diseases, more and more physicians are relying on decision support tools to assist them with patient care[16].

One approach for addressing these problems is the use of an EMR integrated with a Clinical Decision Support System (CDSS) that would assist physicians in decision making to prevent adverse drug events (ADEs), create and track patient profiles and trigger alerts for possible intervention. The focus of this paper is on a CDSS that would create and track patient profiles in primary care management. Our proposed model for this CDSS is a hybrid architecture that combines data mining of knowledge bases (KB) and artificial intelligence from artificial neural networks (ANN). We call the system the KB-ANN model adapted from Viademonte et al[2]. The aim of this proposed model is to create and track patient profiles for use in pattern recognition, support decision making by recalling past information, produce domain knowledge from the recalled information, perform reasoning from "new" domain knowledge and serve as a predictive tool in decision support.

CDSS has been defined as —an automated process for comparing patient-specific characteristics against a computerized knowledge base with resulting recommendations or reminders presented to the provider at the time of clinical decision making[3]. Even though the definition is fairly specific, the implementation of CDSS varies greatly. The major components of CDSS that are identifiable in almost all implementations and that make CDSS different from other types of decision support include an automated process for delivery of alerts or reminders at the point of care resulting from the comparison of patient information against knowledge rules or guidelines[4]. Our proposed approach incorporates this component and also the concept of Artificial Neural Network for patient pattern recognition. Intelligent financial surveillance systems have been for long, using the concept of customer behavioral pattern recognition to identify suspicious transaction for potential fraud prevention[5]. Using this concept for patient profiling, to the best of our knowledge, is a new approach in health care industry.

The remainder of this paper has been organized as follows. In Section 2 we provide an overview of related work as reviewed in existing literature. We present our methodology and architecture in Section 3, and provide a case study in Section 4 to examine our approach in a clinical setting. Section 5 provides a discussion and future scope of work.

RELATED WORK

Most CDSSs in use today fall under the Knowledge-base umbrella, incorporating knowledge bases, inference engines and mechanisms to communicate. Much work has been done outside of the clinical setting, on decision support systems that are based on an incorporation of domain knowledge and artificial intelligence, but success has been achieved mainly in the aviation, military and meteorology fields. Additionally, research on such domain knowledge / Artificial Intelligence-based decision support in the clinical setting, has focused mostly on disease diagnosis and management of epidemics and pandemics.

Burstein et al[15,17], proposed a model to support decision making within a university administration setting, that uses past decisions to formulate new scenarios, and is built around a compilation of organizational knowledge, and uses an intelligent advisory system. In their model, the intelligent advisory system is comprised of a combination of case bases used to present past decisions, databases to store information and rule bases used to describe existing policies and regulations.

Similarly, Viademonte et al[13], presented a model for decision support in meteorology, which uses past information to create domain knowledge, and then applying —intelligent techniques to formulate conclusions based on patterns and predictions in a specific domain. In their model, a hybrid intelligent advisory system capable of learning and reasoning from past experiences, acquires knowledge after data mining operations are performed on case bases and knowledge bases, and then trained by a neural network to provide decision support.

Data mining is employed in order to extract appropriate relationships from case bases, and to present specific knowledge as cases. Association rules are then applied to produce general knowledge which is stored in knowledge rule bases, and obtained through an association rules generator algorithm. Bayesian statistical methods which may use decision trees to analyze data through the use of prior knowledge is often used in data mining models. An application of this has been used in finding protein-protein interactions in bio-informatics[18]. Although decision trees are used to extract classification patterns form data, they are rarely used in clinical settings. Data mining models have previously been used in health care for representing trends in clinical datasets[1], for screening and diagnosis of disease. The training provided by the neural network equips the hybrid CDSS with the capacity to learn and reason based on knowledge and recognition of patterns within a specific domain, and as such provides the user with suggestions to aid in decision support. Within the health-care domain, neural networks have been used for pattern analysis[18,19], clinical diagnosis[21], image analysis and interpretation, signal analysis and interpretation[22,23], and drug development[24]. The PAPNET system used in screening of cervical cancer is an application of pattern analysis in health care[18]. Imaging is another important area for the application of ANN pattern recognition techniques. It is widely used to identify and extract important features in medical imaging such as radiographies, ECTs and MRIs[19]. Aizenberg et al presented a framework for filtering, segmentation and edge detection techniques using cellular neural networks to improve resolution in brain tomographies for detection of micro-calcifications in mammograms[25].

The concepts that we use in this paper draws from a similar architecture presented by Viademonte et al[13] in presenting an intelligent decision support system for use in meteorology. Although the incorporation of domain knowledge and artificial intelligence in decision support has previously been explored, to the best of our knowledge, the concept of using such a hybrid CDSS for patient profiling in primary care practice management is an approach that has not yet been explored.

APPROACH

In this section, we define some terms and concepts that are used in our proposed model and discuss our methodology and architecture.

Definition of Terms

Clinical Decision Support Systems (CDSS): Computer tools or applications that assist clinicians in decision making, by providing evidence-based knowledge in the context of patient specific data[6] .There are two main types of CDSS, namely, Knowledge-base and Non-Knowledge-base. Knowledge-base CDSS has three parts, namely, knowledge-base, Inference Engine and Communication Mechanism. Knowledge-base compiles information that is often, but not always, in the form of if–then rules or probabilistic association. The inference engine contains the formulas for combining the rules or associations in the knowledge-base with actual patient data. And the communication mechanism is the way of getting the patient data into the system (manual or automatic) and getting the output of the system to the user, the final decision maker. Non-Knowledge-base CDSS uses artificial intelligence and consists of two types, the Artificial Neural Networks and the Genetic Algorithm[7,8,10].

Artificial Intelligence (AI): The capability of a device or a computer system to perform complex functions mirroring the workings of the human mind / intelligence, such as reasoning, gathering structural knowledge, problem solving and optimization through experience. AI is the branch of computer science that attempts to approximate the results of human reasoning by organizing and manipulating factual and heuristic knowledge[9].

Artificial Neural Network (ANN): Is a mathematical model or computational model that tries to simulate the structure and/or functional aspects of biological neural network. It is inspired by the way biological nervous systems, such as the brain processes information. It is composed of a large number of highly interconnected processing elements (neurons / nodes) working in unison to solve specific problems. ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. ANNs, like people, learn by example and has the ability to identify meaning from complicated data and extract patterns to detect trends that are too complex to be noticed by either humans or other computer techniques. A trained ANN can be thought of as an "expert" in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer "what if" questions[7,8].

Intelligent Decision Support System: Incorporates specific domain knowledge and perform some type of intelligent behaviour, such as learning and reasoning, issuing recommendations and drawing justifications in order to support decision making. IDSS has a large number of options to analyse and has the ability to improve and expand its analytical capabilities to find the optimal solution is a short time[2].

Proposed Model

Framework and Architecture

Our proposed approach for the CDSS includes a hybrid architecture that combines an association rule-generator algorithm for data mining of knowledge bases (KB) with an artificial neural network (ANN) system. We call it the KB-ANN model adapted from Viademonte et al[2, 13].

This KB-ANN model is intended to create domain knowledge to support decision making. Domain knowledge is created from recalled information, and then reasoning is applied to this —new information such that conclusions can be reached for specific instances. Additionally, it serves as a predictive and classification tool in the context of the health care system, and is intended to create and track patient profiles in primary care management. The building blocks for the KB-ANN model are domain specific, and include descriptive models which are stored in knowledge bases, and predictive models which are the results of processing done by the neural network.

The KB-ANN model architecture includes a data and a process layer. The data layer consists of all data repositories used during the decision support process, including data warehouses, data models and knowledge bases. The process layer consists of data mining algorithms which extract domain knowledge from databases and data warehouses, and artificial neural network processing which applies reasoning to the knowledge extracted in order to provide decision support.

As data are extracted from data warehouses and pre-processed, sets of domain specific cases and case bases are created, forming data models. A case represents an instance of a problem being addressed in a specific domain, and falls into defined classes consisting of attributes and values[13]. Multiple instances of cases make up a case base. The use of data warehouses for building cases ensures the consistency of data within a specific domain.

Data mining is employed in order to extract appropriate relationships from case bases, and to present specific knowledge as cases. Association rules are then applied to produce general knowledge which is stored in knowledge rule bases, and obtained through an association rules generator algorithm. In a clinical setting, specific medical cases and clinical practice guidelines can serve as case bases upon which data mining can be performed in order to produce descriptive clinical features into which clinical conditions can be categorized[20]. Expressed as a set of rules, this implementation may use the Apriori algorithm for association rules in which a rule is expressed as XY and where X and Y are predicates and X is the precondition of the rule in disjunctive normal form and Y is the target post condition[2]. An example of this is provided:

X= {E1, E2} and Y= {Drug-Drug Interaction}, rule confidence=99%

Where X→Y

E1= Drug 1

E2= Drug 2

If patient taking Drug 1 is prescribed Drug 2, then a drug-drug interaction can be predicted with a 99% degree of confidence, and as such an alert would be generated by the CDSS. Descriptive models are designed using descriptive methods, and are built after data mining algorithms are applied to data models – a term called —training - and are stored in knowledge bases. Knowledge bases consist of knowledge corresponding to associations and patterns from case bases. Multiple data models can be used to create multiple descriptive models for a particular domain. Through a set of predictive methods, predictive models are obtained after neural network processing is applied to descriptive models. Training datasets obtained during the predictive method stage are used to discover predictive relationships based on appropriate patterns recognition. Here, multiple descriptive models can be used to create multiple predictive models for a particular domain.

Figure 1 illustrates the components of the KB-ANN Model architecture and their interactions with each other.

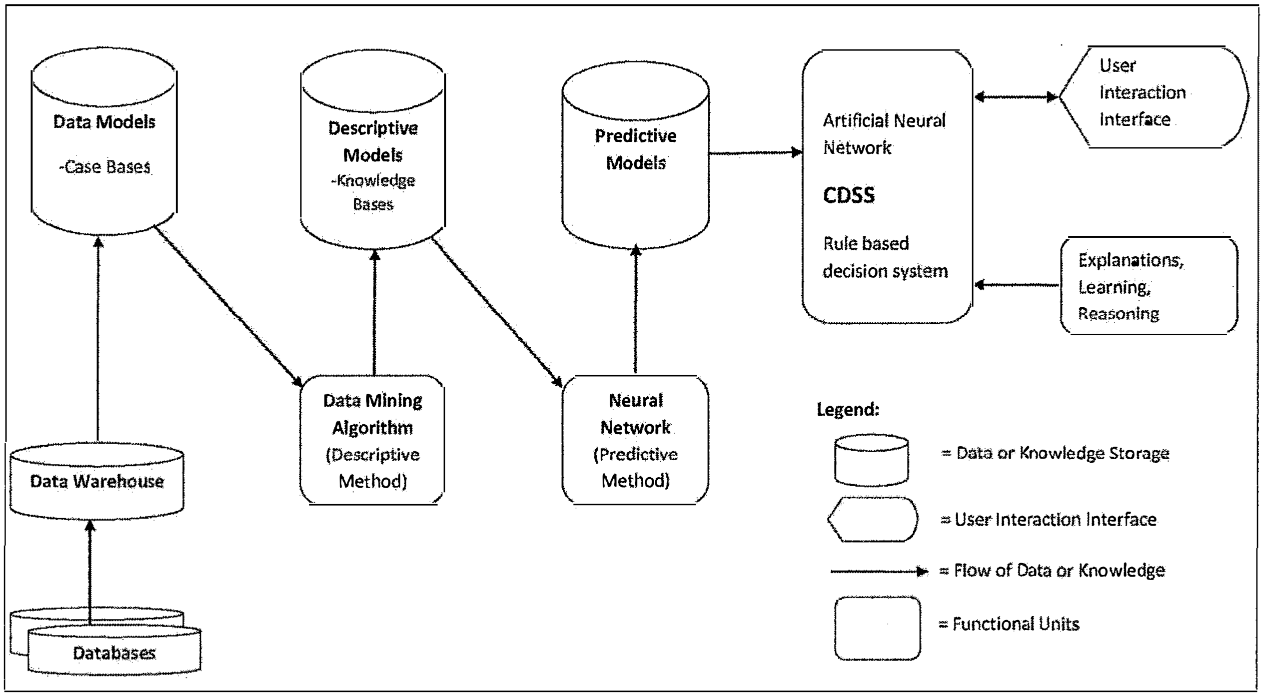

Figure 1: Main building-blocks of the KB-ANN model

Neural networks consist of several layers of interconnected nodes /neurons[20] that have weighted connections based on a mathematical or computational model. In a clinical setting, a NN may be designed to match a set of patient characteristics with a set of required clinical tests. Every characteristic, representing an input node, when combined with one or more other characteristics (representing another input node) would be assigned one or more corresponding required clinical tests. Using a simple one-layered example (in actuality, in a multi-layered environment, there would be several input and output nodes):

If Age = 50 years
Gender = Female
Disease 1 = Type 2 Diabetes
Test 1 may be Diabetes Foot Check
Test 2 may be PAP Smear
Test 3 may be Mammogram

The input nodes produce a pattern of data, while the output nodes classify the data. Based on the output node that receives the highest weight, an alert to perform a specific test is provided. A simple diagram is presented in Figure 2 to show this interaction[20].

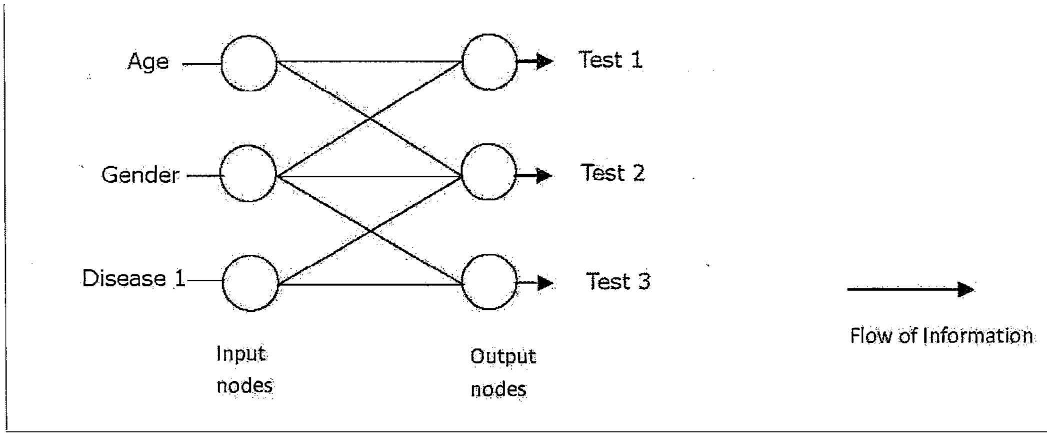

Figure 2: Simple 2-Layer Neural Network adapted from Coiera, 2003[20]

Additionally, over a period of time, the weights placed on the connections form a pattern that can be recognized by the output nodes – a process called training. This process forms the basis for reasoning performed by the system. Connection weights can be adjusted to produce desired outputs as necessary. The training provided by the neural network equips the hybrid CDSS presented in this architecture with the capacity to learn and reason based on knowledge and recognition of patterns within a specific domain, and as such provides the user with suggestions to aid in decision support.

Based on its ability to learn, reason, and make suggestions for decision support, it is known as an Intelligent Decision Support System that interprets and presents information in a clinically meaningful way.

CASE STUDY

We provide a sample scenario to examine the efficacy of our proposed model.

A 41 year old female patient with diabetes takes Metformin, Aspirin and Lipitor. She has been consulting the same family physician for the last 8 years. Her average blood pressure (BP) is 108/55 mmHg and her average heart rate is 60 BPMs (beats per minute). On a particular day she comes to the clinic with a mild chest pain. She had no prior history of cardiac diseases and no coronary risk factor. On physical examination, her BP was found to be 120/70 mmHg (Millimeters of mercury) and her heart rate was 80 BPM. A mild systolic ejection murmur was noticed at the left sternal border. Electrocardiography revealed sinus rhythm, ST segment elevation in leads V1-6, and reciprocal ST segment depression in leads DII, III and AVF[11].

In this situation the physician using an EMR without a CDSS, would initiate a dose-adjusted, medium-intensity Warfarin oral anti-coagulation therapy for the patient. This patient, who is taking Aspirin, if given Warfarin, a blood thinning medication (anticoagulants) would be susceptible to an increased risk of bleeding. At this point, if the physician had used the proposed KB-ANN system, this would trigger two alerts and suggest some recommendations.

The KB-ANN over a period of time would create and track the patient profile, and is intelligent enough to recognise the patient's BP and heart-rate pattern and thus trigger alert whenever the reading are substantially different from her pattern. In this case since her BP and heart-rate were found to be 120/70 mmHg and 80 bpm respectively, the system would trigger an alert saying that the readings are significantly different from her normal readings and an intervention is necessary. Even though for most individual, a BP of 120/70 and a heart-rate of 80 BPM are considered normal for this patient it is not the case and the pattern recognition feature of the system helped to trigger the alert.

The second alert triggered would be for drug-drug interaction because the patient taking Aspirin is given Warfarin. The combined dosage of these two medications increases the risk of bleeding. The data mining and the knowledge-base features of the proposed system invokes the alert and simultaneously suggests a recommendation to limit the aspirin dosage to 100 mg per day and monitor INR (International Normalized Ratio)[12].

Table 1: Potentially Clinically Significant Drug-Drug Interactions[12,14]

Interaction	**Potential effect**	**Trigger Alert**	**Recommendations**
Acetylsalicylic acid (Aspirin) *plus* Warfarin	Increased bleeding, increased INR	Yes	Limit aspirin dosage to 100 mg per day and monitor INR.
Lipitor *plus* Amoxicillin/Clarithromycin/ Lansoprazole	Inhibits CYP450 3A4 and may elevate the plasma concentrations of HMG-CoA reductase inhibitors which increases risk of musculoskeletal toxicity associated with high levels of HMG-CoA.	Yes	Macrolide therapy should be carefully selected in patients treated with Lipitor (Atorvastatin, Cerivastatin, Lovastatin, Simvastatin). Azithromycin and Dirithromycin may be safer alternatives in these patients, since they are generally believed to have little, if any, effect on CYP450 3A4

INR = International Normalized Ratio; CYP450 3A4=Cytochrome P450 3A4
HMG-CoA =3-hydroxy-3-methyl-glutaryl-CoA reductase

Table 2: CDSS Intervention in Patient Specific Scenario

Reading Name	Average Reading of Patient	Scenarios and CDSS Intervention
Blood Pressure (BP)	108/55 mmHg Systolic pressure (SBP) = 108 Diastolic pressure (DBP) = 55	If SBP > = 120 and if DPB >= 70 then KB-ANN System would trigger an alert for higher than patient's normal reading.
		IF SBP <= 90 and DBP <= 45 then KB-ANN system would trigger an alert for lower than patient's normal reading
		If 120 <SBP > 108 and if 70 <DBP> 45 then KB-ANN System would NOT trigger any alert because the reading are within patient's normal range of reading.
Hear Rate (HR)	60 BPM	If HR >= 80 then the system would trigger alert for higher than patient's normal heart rate.
		If HR <=50 then the system would trigger alert for lower than patient's normal heart rate.
		If 80 <HR > 50 then the system would NOT trigger alert any alert since the heart rates are within patient's normal range.

BPM=Beats per Minute; mmHG= Millimeters of mercury

DISCUSSIONS AND FUTURE SCOPE

In this paper, we have proposed a model, the uniqueness of which lies in the hybrid nature of the system where we propose to deploy both data mining algorithms of a knowledge base as well as the reasoning capability of a neural network. In proposing the solution / model, we have recommended the use of Apriori algorithm for association rules to generate knowledge. The solution is based on simple system architecture with a data layer and a process layer, having all components of data and knowledge-generative algorithms. The CDSS is hybridized as the neural network provides the training to learn on the basis of rules generated by the knowledge base.

This approach can have wide applications given its novel character of recognizing patterns from patient data. Clinical decision support systems in acute care, tertiary care, long-term and extended care facilities as well as community healthcare organizations can use this concept for patient profiling where a knowledge base of a particular condition among patients can be used to train the system for intelligent clinical decision support. Future applications may also include application in pharmacy systems to help individuals with adherence to a medication regimen by creating a patient-specific profile and triggering alerts if it deviates from that threshold.

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