Conceptual Framework for A Perinatal Decision Support System using a Knowledge-Based Approach

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ABSTRACT

This paper discusses the development of a knowledge based perinatal clinical decision support system (CDSS) to predict preterm labour. It consists of a knowledge-base, a workflow engine, and a mechanism to communicate results. The knowledge base contains rules or associations related to the desired predictions; the workflow engine combines the rules in the knowledge base with the patient data; and the communication mechanism allows entry of the patient data into the system, and output of results in the form of notifications, alerts or emails. This system will help physicians to inform families and to initiate preventative care, monitoring, and treatment. The final form of the CDSS is to be integrated to an electronic medical record (EMR) and thus allow for auto-population of the patient data into appropriate fields. A web-based collaborative platform that meets the legal and regulatory accreditation standards will be used to deliver information relevant to clinical users.

INTRODUCTION

In Ontario about 8% of babies are born preterm[1]accounting for nearly 75% of all perinatal mortality and over 50% of long term morbidity.[2] Preterm babies are at an increased risk of perinatal or infant death, physical and cognitive disabilities, and various chronic health problems.[3] Preterm birth results in a disproportionately high percentage of healthcare costs among newborns.[3]

Early identification of women at risk for preterm labour may lead to more efficient allocation of resources and facilitate antenatal monitoring to ensure a timely response to medical problems which may arise during pregnancy. Prompt recognition of factors, signs and symptoms during pregnancy, and linking this information with the vast amount of medical data available within healthcare institutions would facilitate the development of computational tools to assist healthcare providers in extracting useful information.

Ideally, a web based collaborative system in the clinical environment that meets the legal and regulatory accreditation standards will allow healthcare personnel to share opinions, exchange clinical data, and access clinical information regardless of their geographic location. Furthermore, the development of a high quality, low cost clinical decision support system to augment human decision-making on a collaborative platform will improve the quality of care provided, and possibly reduce human errors.

BACKGROUND

Previous work on building a CDSS for predicting preterm labour focused on artificial intelligence and then later a hybrid model was introduced. Catley et al. created and tested a CDSS that integrated Artificial neural networks (ANNs) and Case-Based Reasoning (CBR) tools.[4] This model resulted in increased network sensitivity of 54.8%, which is 20% higher than the non-artificially distributed preterm birth model.[5]

Later, a study was conducted on the effectiveness of a hybrid pattern classifier for predicting preterm labor. This model used a hybrid classifier consisting of a decision-tree (DT) to eliminate variables with little impact on predicting the outcome of interest; the remaining variables were processed through an artificial neural network with weight elimination (ANN-we). The hybrid classifier predicted preterm birth with an accuracy as high as the clinically invasive fetal fibronectin test, using 19 variables available before 23 weeks of gestation for parous women, and was able to predict preterm birth in nulliparous women with slightly less accuracy, however this was higher than any other method found in the literature.[6]

Data Mining and CDSS

Data mining and predictive modeling can be split into supervised and unsupervised learning. Supervised learning assumes that the classes and examples of each class are available, and the knowledge is transferred to the system through a process called training. In unsupervised learning, the system is presented with a set of data, but there is no information available on how to group the data into more meaningful classes.

For our framework, the data used for predicting preterm labour is derived from the Niday Perinatal Database created in 1997 under the direction of the Perinatal Partnership Program of Eastern and Southeastern Ontario (PPPESO) and collaboration of all hospitals across Eastern and Southeastern Ontario.[7]

Classifiers for Supervised Learning

There are various techniques available to obtain good classifiers; the most common include decision trees, neural networks, and the nearest neighbor method. We began our work with decision trees, as they are an intuitive and widely used method that falls under the category of supervised learning. Figure 1 represents a decision generated using c5.0 algorithm. A decision tree typically adopts a top-down strategy for producing an outcome.

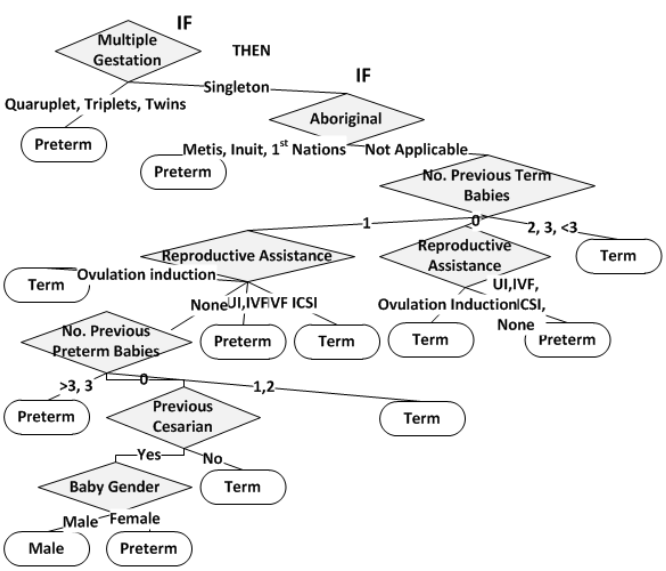

Figure 1: DT Generated using c5.0 for Predicting PTB

SYSTEM METHODOLOGY

Design Consideration and Goals

There are several design elements that must be taken into consideration to produce a successful implementation. System builders often focus on building a CDSS that produces good decisions, yet researchers have shown that the ability to produce a correct diagnosis is only one part of the formula for success. It is important to recognize that systems can fail if they require that the practitioner interrupt a normal work pattern to shift to another station to start up a non-intuitive software program that contains time consuming start-up procedures.[8]

Successful implementation of a CDSS will be facilitated by a simple, intuitive and user- friendly interface, an easily accessible and mobile-friendly platform, the production of timely results and automated decision support with workflow integration, low cost, and the ability to support continuous knowledgebase and user interface updates.[9]

Collaborative System Design using KBA

CDSS may be described using various dimensions. CDSS may be categorized as a knowledge-based system or non knowledge-based system. Non knowledge-based systems use artificial intelligence in the form of machine learning to allow the computer to learn from past experience or analyze and detect patterns in clinical data. Two types of non-knowledge based systems include artificial neural networks and genetic algorithms.[10]

Our framework is focused upon a knowledge based system; there are three main parts to this system, including the knowledge base, a workflow engine, and a mechanism to communicate results. The knowledge base contains rules or associations related to the desired predictions. These rules are derived from the decision tree employed by the c5.0 algorithm. The workflow engine combines the rules in the knowledge base with the patient data; and the communication mechanism allows entry of the patient data into the system and the results out of the system to be displayed to the user, who will then make the final decision.

Most systems to date use knowledge based systems with rules, guidelines or compiled knowledge which is commonly derived from the medical literature.

System Overview

The proposed framework utilizes a web-based modular design that allows for extensibility and scalability and is designed for the health care industry where retrieval and processing of real-time patient information is crucial. The solution architecture of a web-based clinical decision support system allows for 'anytime and anywhere' utilizing an asynchronous data-driven design to allow for real-time information flow and user access from the convenience of a hand held device such as a mobile phone, PDA etc. or a laptop/desktop. This framework can be viewed as a 6-layer encapsulated system (Figure 2).

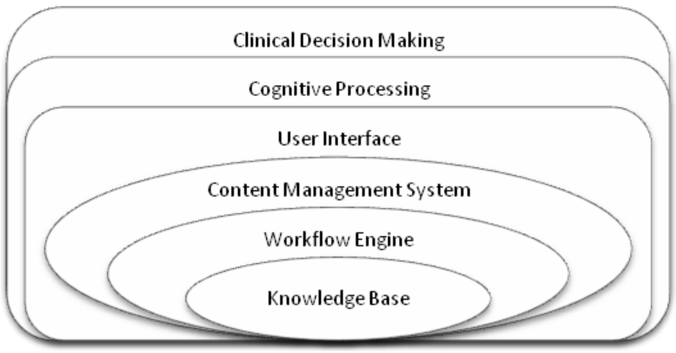

Figure 2: Integration of Technical and Clinical Processes

This architecture is highly scalable and can easily be extended to multiple new users at low cost.[12]

<u>System Architecture</u>

The system architecture of a web-based clinical decision support system consists of the components as outlined in Table 1 and Figure 3.

Table 1: Components to Build Web Based CDSS

Components to Build a Web Based CDSS	
Components	**Description**
Authentication Server	Required to authenticate users and comply with the confidentiality and privacy requirements
Content Management System	Required to display, search, and process the data based on the user request.
Workflow Engine	Required to automate alerts, warning and actions.
External Data Source	A repository of the patient, or user information
Directories	A database of user information, etc.
Other Web Servers	Other servers required to operate the CDSS
ASP.Net	The interface presented to the user.

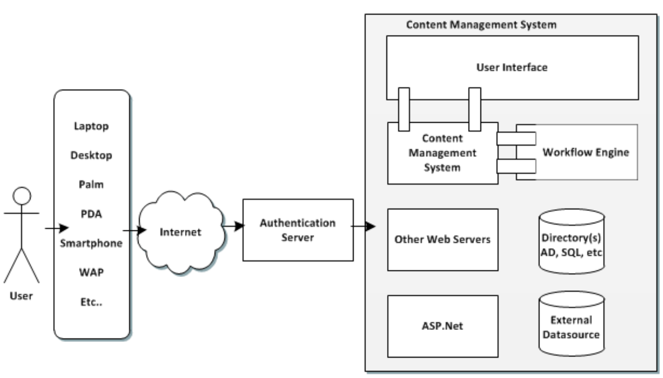

Figure 3: System Architecture of Web Based CDSS

Details of each of the main systems are explained below:

- <u>Authentication Server</u>

The authentication server is used to verify that the user accessing has the appropriate privileges to view content on the page. The end user typically will need to provide a username and temporary password, and this information is checked to see if it matches the credentials stored in the system directory. This step is required to comply with data security and confidentiality requirements to ensure that the transmission of data is in keeping with current privacy legislation. This is especially important for medical applications.

- <u>Content Management System</u>

A web-based content management system is required to host the clinical decision support system and to integrate with the external data source and workflow engine. The interface that is developed is published to the content management system. The content management system also supports advanced features including audience targeting, where filters can be set up based on the user logged in, so that varying levels of user-groups are presented with filtered views on what is relevant to them (Figure 4).

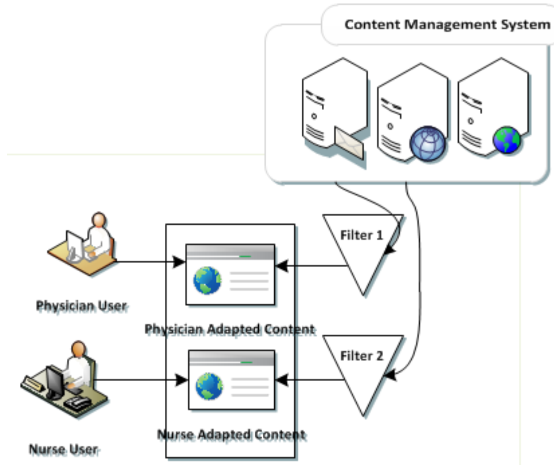

Figure 4: Custom Views based on Audience Targeting

- <u>Workflow Engine</u>

A workflow engine technology represents a new class of software which supports representation of graphical model step-based knowledge, this is required to automate the knowledge base.[11] The workflow tool will have the ability to model the process in a graphical flow chart editor and execute the final process in a workflow engine.[11] The workflow can incorporate various actions including sending out timed alerts, warnings and recommendations. The workflow must meet the users' needs as this will ultimately lead to increased efficiency, ease of use, and usefulness.

- External Data Source:

The external data sources will contain various SQL based databases, including the patient information extracted from an EMR or HER, and the user information. A connection from the content management system to the external data source will be established for authenticated users to store and retrieve patient information.

EVALUATION METHOD

Methods used in evaluating CDSS from previous studies were adapted for our goal: 1) evaluate the acceptability of the results produced by the CDSS; 2) compare and review the content and knowledge representation to the end user needs and 3) seek advice from an expert panel to evaluate the usability and the acceptability of this tool. The expert panel may be composed of neonatologists, engineers, or computer scientists, nurses, and other health caregivers.[12]

CONCLUSION AND FUTURE WORK

We developed a framework to build a web-based CDSS for predicting preterm labour. The system will aid physicians by increasing their ability to predict women at risk for preterm labour, thus ensuring a timely response to various medical problems which may arise during pregnancy. This low cost, user-friendly system will help improve the quality of care provided by aiding with informed decision making.

In future work, we plan to convert the currently proposed stand alone system which requires patient data to be entered manually to a system that integrates with an EMR to auto-populate the patient data into appropriate fields from the information available in the EMR.

Furthermore, a clinical evaluation will be conducted by participating hospitals to validate the usefulness of the tool.

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BIOGRAPHY

Marry Gunaratnam received a B.Eng degree in biomedical and electrical engineering from Carleton University, Ottawa, Canada in 2010. She has a background in Software Development and has been employed in the federal government. In 2011, she was selected the Technical Lead and Project Manager for the Interagency eReferral Information System initiative across the Champlain Region. She is a member of the Professional Engineers of Ontario and Ontario Society of Professional Engineering.

Monique Frize is a member of CMBES and a Fellow of IEEE. She is a Distinguished Professor in Systems and Computer Engineering, Carleton U., and Professor Emerita in the School of Electrical Engineering and Computer Science at and the University of Ottawa. She is a Felllow of the Academy of Engineering and of Engineers Canada.

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