Computerized Detection of Nosocomial Infections in Newborns

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Hospital-acquired infections are responsible for an increase in patient mortality and costs. Their detection is essential to permit better infection control. We developed an expert system specifically to detect infections in pediatric patients. The expert system is implemented at LDS Hospital that has a level three newborn intensive care unit and well baby units. We describe how the knowledge base of the expert system was developed, implemented, and validated in a retrospective study. The results of the system were compared to manual reviewer results. The expert system had a sensitivity of 84.5% and specificity of 92.8% in detecting hospital-acquired infections when compared to a physician reviewer. The Cohen's kappa between the expert system and the physician reviewer was 0.62 (p<.001).

INTRODUCTION

Hospital-acquired infections (HAIs) are a major health problem nowadays [1]. They are responsible for increased mortality and costs [2,3]. HAIs are a leading cause of death in the United States, responsible for at least 30,000 deaths each year [2,3]. Furthermore, HAIs cause an increase in the length of hospital stay by 5 to 10 days. The cost to treat HAIs in the USA has been estimated to be between 5 and 10 billion dollars annually [2].

The detection of HAIs is essential for enabling prompt treatment, reduce transmission, and enabling preventive interventions. The current detection methods usually involve manual surveillance that is not only time consuming and expensive, but typically produces results only after the patient is discharged. The ideal detection system would detect the infection immediately after the patient had any positive results indicating an infection. Such an early detection system would permit earlier interventions and could potentially reduce the morbidity and mortality of the disease.

Computers have been used to speed up the infection detection process [4-7]. One successful example of an automated surveillance is the Computerized Infectious Disease Monitor (CIDM) [4,5]. CIDM was designed to detect HAIs primarily in adult patients. However, to our knowledge, little work has been done in the area of pediatrics to improve the detection of HAIs using a computer.

Based on our group's previous experience, we developed an expert system to detect HAIs in pediatric patients. The system is currently implemented at LDS Hospital, Salt Lake City, Utah. LDS Hospital is a tertiary care hospital with a level three (most severe) newborn intensive care unit and well baby units.

Our goal was to determine if an expert system using Boolean logic could improve the detection of HAIs in the pediatric patients. We developed a rule-based expert system and tested its performance in a retrospective study against the newborn patient data stored in the hospital database for a period of two years. In the following sections, we describe the development of the expert system's knowledge base, its implementation, and its validation.

METHODS

The development of the expert system can be divided in three main phases: development of the knowledge base, its implementation, and validation.

Development of the Knowledge Base

The first step in the development of our expert system was the medical knowledge acquisition to create the knowledge base (KB) to detect HAIs. This knowledge was acquired through medical knowledge engineering sessions [8].

Medical knowledge acquisition was necessary to create the rules for detection of HAIs. Review of published literature [9,10] and experts' experience were fundamental in the knowledge acquisition process. During the knowledge acquisition process, the principal author interacted with experts in the field of pediatric infectious disease to acquire the knowledge necessary to build the system. The principal author and two medical experts adapted published rules for detecting hospital-acquired infections to a pediatric setting, and created new rules when necessary.

The rules for detect patients with hospital-acquired infections were developed through knowledge

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engineering sessions over a period of two years which involved over 100 hours of interaction. During these knowledge engineering meetings, methods of detecting and managing the infections were also discussed. These sessions were of one hour duration and were audio taped. After each meeting, the knowledge obtained was organized into Boolean rules by one of the authors (BHSCR). At the beginning of each knowledge engineering session, the rules from the previous session were presented and reviewed. Corrections and additions were made and then a new infectious disease topic was discussed. From these knowledge engineering sessions, 154 rules were created.

These rules obtained during the knowledge acquisition form the knowledge base of our computerized expert system. Examples of rules used in the expert system are shown in Figure 1.

Figure 1: Two examples of the rules in the knowledge base

If there is a positive blood culture for Escherichia coli, *then* give an alert for definite bacteremia.
If there is a positive tracheal aspirate culture for Enterococcus, *then* give an alert for possible lower respiratory infection.

Implementation of the Knowledge Base

After the knowledge engineering process, the second phase of the project was to implement the knowledge base. The knowledge base was developed in frames using the programming language PAL (PTXT Application Language), that was developed in house. The HELP (Health Evaluation through Logical Processing) Hospital Information System (HIS) was the platform used for the development of the expert system [11,12]. HELP is a comprehensive HIS with clinical modules, such as, pharmacy, laboratory, radiology, etc.. All information is stored in an integrated patient database in a coded format. This clinical database is continuously available. The HELP system also has a long term patient database, which contains clinical information stored for the past ten years.

The HELP system has the ability to be both "data" and "time" driven. "Data" driven is the capability of the HELP system to activate the expert system frames each time data required by the system's knowledge base is stored in the patient database. For example, every time a positive microbiology culture result is stored in the patient database, the expert system is activated and determines if the patient has an infection. Examples of the types of data that activate the expert system are positive microbiology culture results, cerebral spinal fluid (CSF) study results, and bacterial antigen detection assays results. "Time" driven is a capability of HELP system that activates the knowledge base at specific times. For example, a program to print the reports with the results for the infectious disease department is "time" driven and activated once each day at 1:00 PM.

Figure 2, is a block diagram schematic showing how the expert system is implemented. As soon as the microbiology results or other results are available, they are entered in the hospital's laboratory computer system. This computer immediately transfers the coded results to the HELP patient database, where they are stored. When the data is stored in the patient database, the program to detect HAIs is automatically "data" driven. Using the rules in its knowledge base, the system determines if the patient has an infection. Positive results generated by the expert system are called alerts. When an alert is generated, it is immediately stored in an alert file. From this file, the alerts can be printed as a report, or presented on a bedside terminal. The whole process just described takes less than five minutes.

There are three types of alerts for HAIs: definite, probable, or possible infections. A "definite" alert means that there is a 100% chance that the patient has an infection. For example, a positive cerebral spinal fluid culture for Neisseria meningitidis would be a "definite" infection. "Probable" alert means that there is about a 75% chance, or in other words, a high probability that the patient has an infection. For example, a positive antigen detection in stool specimen for Rotavirus would be a "probable" infection. A "possible" alert means that there is about a 50% chance that the patient has an infection, for example, one positive tracheal aspirate culture for Aspergillus would indicate a "possible" infection. Each infection is also classified as hospital-acquired or not, depending on when the infection was detected.

Our expert system was developed to detect eight common types of hospital-acquired infections. These are bacteremia, central nervous system infections, conjunctivitis, diarrhea, lower respiratory tract infections, surgical or wound infections, urinary tract infections, and viral infections.

The rules of the expert system were improved by analyzing the data for all newborn patients, who were in LDS Hospital for a 20 months period (Jan. 92 to Aug. 93). The expert system determined if the patient had an infection or not. The results produced by the expert system were reviewed by the knowledge engineers and necessary corrections or modifications to the rules were done in this phase.

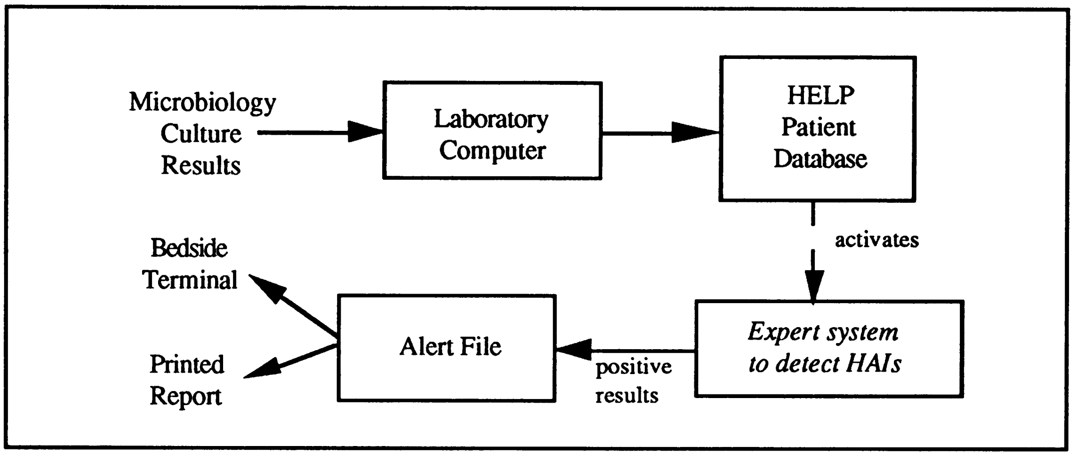

Figure 2: System functioning

Validation of the Knowledge Base

Finally, to validate the KB of the expert system and to test our hypothesis - that an expert system was able to detect HAIs in pediatric patients - we tested the expert system against a different set of patients. The system analyzed the data of all newborn patients in the hospital between Jan. 90 and Dec. 91 (24 months).

One physician expert in pediatric infectious diseases (AP), reviewed only the patients with some information that might indicate an infection and that was used by the expert system's knowledge base. This consisted of all patients with a positive microbiology culture result, with cerebral spinal fluid (CSF) study results, and with bacterial antigen detection assays results. The reviewing physician did not know the rules used by the knowledge base. He estimated the chance of the patient having an infection, as "definite", "probable", "possible", or "no infection", without knowing the results generated by the computer. The results produced by the manual reviewer were compared to the results produced by the expert system. The physician reviewer was considered to be the "gold-standard".

RESULTS

The expert system analyzed all newborns admitted to the LDS Hospital for the 24 months, period from January of 1990 through December of 1991. The positive and negative results, as well as the data and rules used to reach these results, were stored in a computer file. The number of newborn patients admitted to the hospital during this period was 5,201 (Table 1). For these patients, the computer system was activated 605 times; 514 were activated by positive microbiology cultures and 91 for CSF analysis results. Since the information of the CSF analysis was not complete in the database for this period of time, it could not be analyzed. Therefore, the results produced by the expert system and the physician reviewer for CSF analysis are not reported in this study. During this period, 92 alerts were generated (by positive microbiology cultures), which corresponds to 17.9% of the total number of times the system was triggered by microbiology results (Table 1).

Table 1: Population analyzed

• Total of patients admitted: 5,201
• No. of times the expert system was activated: 605
- by positive microbiology cultures: 514
- by CSF analysis: 91
• Number of alerts generated by microbiology cultures: 92 (17.9 %)

The results produced by the expert system and the physician reviewer are presented in Table 2 and Table 3. Classifying alerts by type, there were 13 alerts for "definite" infections, 15 alerts for "probable" infections, and 64 alerts for "possible" infections generated by the expert system (Table 2). The most common alert generated by the expert system was "possible" conjunctivitis infection, issued 35 times (Table 3). The physician reviewer classification

Table 2: Number of alerts generated by the expert system (ES) and physician reviewer (MD).

		MD				
		definite	probable	possible	no inf.	total
ES	def.	13	0	0	0	13
	prob.	8	5	2	0	15
	poss.	0	2	30	32	64
	no inf.	0	1	10	411	422
	total	21	8	42	443	514

	Definite inf.		Probable inf.		Possible inf.		Total	
	ES	MD	ES	MD	ES	MD	ES	MD
bacteremia	13	18	7	1	7	9	27	28
lower respiratory tract infection	0	1	4	3	14	19	18	23
central nervous system infection	0	2	2	0	3	3	5	5
urinary tract infection	0	0	0	0	4	7	4	7
surgical or wound infection	0	0	1	2	1	0	2	2
conjunctivitis	0	0	1	2	35	4	36	6
Total	13	21	15	8	64	42	92	71

Table 3: Number of alerts by type of infection generated by the expert system (ES) and physician reviewer (MD).

generated 21 "definite" infections, 8 "probable" infections, and 42 "possible" infections (Table 2).

The results comparing the expert system to the physician reviewer ("gold standard") are presented in Table 4. To create the contingency table, the "definite", "probable" and "possible" classifications were considered to be a positive infection and the classification "no infection" was considered to be a no infection. The sensitivity of the expert system was 84.5% and the specificity was 92.8%.

Table 4: Contingency table comparing expert system to physician reviewer

True positive rate:	84.5 % (sensitivity)
False negative rate:	15.5 %
False positive rate:	7.2 %
True negative rate:	92.8 % (specificity)

The Cohen's kappa (coefficient of agreement) [13] between the alerts given by the expert system and the physician reviewer's classification was 0.62 ($p<.001$). Agreement occurred when the physician reviewer gave the same classification ("definite", "probable", "possible", or "no infection") as the expert system did.

DISCUSSION

The main difference when comparing our expert system with the existent ones [4-7], was that our system was specifically developed to detect HAIs in pediatric patients. Other systems were developed to do HAIs surveillance in populations composed primarily of adults, applying the same rules when a pediatric patient was encountered. Pediatric patients are different from other age groups. They have very specific types of infections requiring specific rules to detect them. Another difference was that our system was developed not only to detect infections based on positive cultures, but also give alerts for other types of exams, such as cerebral spinal fluid chemical analysis.

Our expert system when tested with newborns patients had performance similar to other expert systems [4-6] in sensitivity and specificity. Overall, the expert system had a good sensitivity and a high specificity. The system was unable to detect only 11 infections identified by the physician reviewer. There was only one "probable" infection and 10 "possible" infections undetected. This number is less than three percent of all the times the system was activated. These false negatives were spread among the different types of infections. We plan to improve the expert systems' performance in this area by adding new rules to the knowledge base, and by correcting some of the existing ones. Some inappropriate alerts were generated, but in a very reasonable amount. There were 32 false positive alerts and all of them were generated by the same rule used in the detection of "possible" conjunctivitis. Correction to this rule would avoid all false positives. In general, the rules developed were able to detect infections very well.

Other expert systems classify only if an infection is present or not [4-6]. However, an infection can be present in different degrees of probability. For example, a positive CSF culture result for Enterococcus is definitely an infection, while a positive tracheal aspirate culture for Bacillus cereus may or may not be an infection. The capability of the expert system to classify the infections as "definite", "probable", or "possible" is very useful. This feature is very helpful when reviewing the results and analyzing the patient data. Normally, physicians and nurses reason with a certain degree of uncertainty, and these classifications can help them in their reasoning. The presence or absence of an infection is not always clear, and these classifications can help the user interpreting the alert.

The comparison between the physician reviewer ("gold standard") and the expert system resulted in a significant Cohen's kappa of 0.62, meaning that there was good agreement between the two. The physician reviewer agreed with all 13 "definite alerts" given by the expert system. The system proved to be sensitive and highly specific for these infections. None of the "definite" infections according to the physician reviewer were classified as "no infection" by the expert system. The infections classified as "definite" by the physician reviewer, and that were not classified as "definite" infection by the expert system, were classified as "probable" infections by the computer.

There was a lower agreement for both the "probable" and "possible" infections. The physician reviewer disagreed with the results of two rules to detect "probable" infections (one for bacteremia and one for central nervous system infection), and considered all these infections to be "definite" infections as discussed above. The great majority of disagreements for the "possible" infections were caused by one rule, the one that caused all the false positives. With changes in the two "probable" rules and removal of the "possible" rule that caused the problems, the Cohen's kappa would increase to 0.84. The agreement for "no infections" was very high, showing that the false negatives were small. This characteristic is important since the false negatives should be avoided in the case of an infection.

From these results, it seems possible for an expert system to help with the surveillance and detection of hospital-acquired infections in newborns. Despite these good results, the system needs to be tested in a prospective study. We plan to verify its performance and effect in daily use. The expert system is currently operational at LDS Hospital and will soon be implemented at Primary Children's Medical Center, Salt Lake City, Utah. We plan to do a prospective study during which the results of the expert system will be compared with the manual surveillance done by the Infectious Control Nurses. The system will also be tested for other age groups (older children) that were not available at LDS Hospital. If the system proves to be successful, the effect of the alerts on physicians behavior will be tested. We plan to present the alerts directly to the attending physician through bedside terminals. We want to determine if giving the alerts directly to the attending physicians, can reduce the time to intervention and reduce the morbidity and mortality of the infection.

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