IMPLEMENTATION OF A CLINICAL DECISION SUPPORT SYSTEM FOR INTERPRETATION OF LABORATORY TESTS FOR PATIENTS

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Abstract. The paper presents the results of the development and implementation of an expert system that automatically generates doctors' letters based on the results of laboratory tests. Medical knowledge is expressed using a first order predicate based language. The implementation of the system allowed increasing the number of patients who refer to a doctor after laboratory tests by 14%. A qualitative study with 100 patients demonstrated a high acceptance of the system. The majority (82%) of the patients reported that they trust the system and follow its advice to visit a doctor if necessary.

Introduction

In Russia many patients address laboratory services directly without a doctor's referral [1; 2]. This causes the problem of interpretation of laboratory test results by the patients who don't have a proper medical background [3-5]. So the patients require that the laboratory services provide not only the results of the tests but also their interpretations. Automated decision support systems that have proved their efficiency for doctors can be a good solution for this problem [6]. The experience of development and implementation of decision support systems for doctors [7-10] shows the efficiency of such solutions for the doctors, however, developers face problems when it comes to the decision support for patients. They require different approach in data presentation and interpretation [11-14].

The goal of this paper is to present a research and development of a decision support system for the patients of a laboratory service.

To achieve this goal we have developed a decision support system that solves a classification problem and defines the following parameters based on the results of laboratory tests:

- Diagnosis (group of diagnoses)
- Recommendations to run other laboratory tests
- Recommendation to refer to a specialist doctor

Methods

To achieve the described above goal a decision support system must solve a classification problem by associating a vector of test results to a set of diagnoses and find a set of recommendations associated with every diagnosis from this set.

On the next step we have developed a classification algorithm that has the following possible outcomes:

- Found a set of diagnosis that can be associated to the results of the laboratory test
- No diagnosis found
- Found a set of diagnosis, but the system requires extra test or vital signs to choose the proper diagnosis form this set.

To organize a communication between the system and an expert we have implemented a knowledge representation language (KRL) that is based on the first order predicate logic [15].

After the knowledge representation language was implemented, we have developed a graphical user interface to allow experts filling in the knowledge base. For the pilot project, we have chosen a limited set of laboratory tests that could be interpreted by the system to test the feasibility of the approach. We have invited 3 laboratory doctors and 3 specialist doctors (gynaecologist, urologist and general practitioner) to fill in the system's knowledge base.

The knowledge representation language, knowledge base and the classification algorithm were developed as a Doctor Ease decision support system, which was implemented in the Helix laboratory service in Saint-Petersburg, Russia.

To evaluate the system, we have measured the correctness of the decision support by submitting a randomly selected sample of 200 generated doctors' letters to 2 experts. The result of this review was used to calculate precision, recall, and F-measure.

After the system has been implemented we made a qualitative research to evaluate the acceptance of the system among the patients with 100 participants.

Results

The developed decision support system has a traditional structure [16] and consists of the following modules:

- Data base;
- Data extraction system
- Knowledge base;
- Inference engine;
- Knowledge base editor;
- Explanation system
- Results generator

A structural scheme of the system is presented in the figure 1.

Each module provides the following functionality to the expert system:

- Data base with a dynamical structure stores facts (test results) and intermediate results of the logical inference. The facts are taken from a laboratory information system (LIS).
- Knowledge base of the DoctorEase stores expert knowledge and inference rules

• Inference engine applies knowledge and rules form the knowledge base to the facts form the data base to solve the classification task.

• Knowledge base editor provides a user interface to define new knowledge and rules.

• Explanation system analyses the sequence of the rules to explain how the system achieved the result.

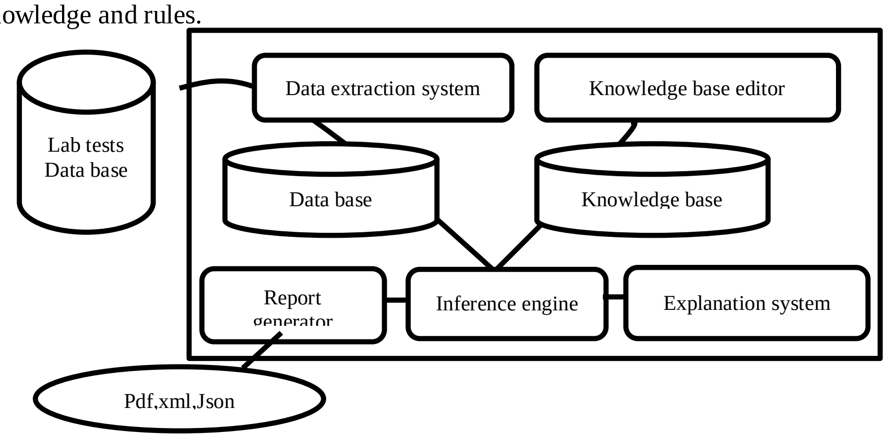

Figure 1. Structural scheme of the decision support system

The developed decision support system has two main use cases: knowledge acquisition and decision support. Knowledge acquisition mode allows defining inference rules, which are complex objects and each of them adds its element to the resulting inference. The knowledge is defined by associating test results and its reference value to a set of diagnosis [17]. In the decision support mode, the system generates recommendations applying a set of knowledge and rules to the facts that are derived form a LIS data base.

DoctorEase decision support system allows creating queries in the language that is closed to natural. The knowledge representation language is based on the first order logic and the predicates and relationships have meaningful names in Russian so the experts can define knowledge and rules using the terminology they are used to.

1.1. Knowledge base organization

The structure of the knowledge base of the system is presented in the figure 2.

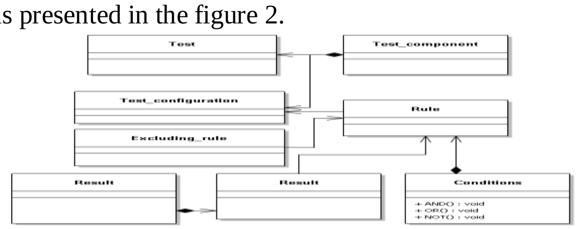

Figure 2. Object model of DoctorEase

On the first step we define a configuration of a laboratory test, which is a complex object consisting of the parameters that are sufficient to make an inference.

• A configuration consists of a laboratory test and inference rules, that can be applied to the test.

• A direct rule is an object that is defined for each parameter of a laboratory test along with the conditions for processing these parameters.

• Each rule has a list of exclusion rules, which can exclude direct rules from the inference provided that their conditions are true.

• Laboratory test is a template that consists of laboratory tests' components. For example a Complete blood count consists of 22 components.

• Laboratory tests are grouped into "orders", which are commercial units that can be ordered by the patients.

• Each rule has a set of conditions that work with comparison operators: =, <>, includes (>= or =<), excludes (>= and =<).

• Conditions are associated with each other by logical operators "and", "or" and "not".

1.2. Inference process

After the system has received a notification that the laboratory test results are available it starts the inference according to the following algorithm:

1. Patient's order is analyzed to understand if there exist configurations for such orders.
2. Fact (test results) are loaded to the decision support system's data base
3. The inference engine defines a sequence of rules from the knowledge base to be applied to the facts
4. Exclusion rules are applied to the facts to exclude non valid rules from the inference
5. Result blocks are added to the result file according to the rules' sequence.

1.3. Implementation

The system was implemented in the Helix laboratory service in Saint-Petersburg, Russia. At the moment it generates about 3500 reports a day.

A randomly selected sample of doctors' letter generated by the system was independently reviewed by two experts. The results of evaluation are presented in the table 1. Cohen's kappa was calculated to check the inter-rater agreement between the two experts. The experts showed no disagreement so the value of Cohen's kappa is 1. 2 mistakes (1%) found by the experts show that the system produces reliable results.

Table 1. Decision support quality metrics

Generated letters	Mistakes	Precision	Recall	F-measure	Cohen's kappa
200	2	0.99	0.99	0.99	1

The implementation of the system allowed increasing the number of patients who refer to a doctor after laboratory tests by 14%. A qualitative study with 100 patients demonstrated a high acceptance of the system. The majority (82%) of the patients reported that they trust the system and follow its advice to visit a doctor if necessary.

Discussion

The paper presents a process of development and implementation of a decision support system for laboratory service patients. The system allows patients reading and understanding medical records in natural language. For the laboratory service the system allowed increasing the level of satisfaction of the patients and the number of patients who came back to the laboratory service for more detailed testing.

Current research is focused on the extension of the knowledge representation language by adding an ability to work with fuzzy sets [18]. This will provide experts with flexibility in definition of knowledge and rules. We also are studying the possibility to validate the reports that are produced by DoctorEase to enable the system acquiring knowledge based on its experience applying case based reasoning approaches [19-21].

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