A bipolar view on medical diagnosis in OvaExpert system

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Abstract. In the paper we present OvaExpert - a unique tool for supporting gynecologists in the diagnosis of ovarian tumor, combining classical diagnostic scales with modern methods of machine learning and soft computing. A distinguishing feature of the system is its comprehensiveness, which makes it usable at any stage of a diagnostic process. We gather all the results and solutions making up the system, some of which were described in our other publications, to provide an overall picture of OvaExpert and its capabilities. A special attention is paid to a property of supporting uncertainty modeling and processing, that is an essential part of the system.

Keywords: supporting medical diagnosis, incomplete data, bipolar information, uncertainty, aggregation, interval-valued fuzzy sets, Atanassov's intuitionistic fuzzy sets

1 Introduction

OvaExpert, an intelligent system for supporting ovarian tumor diagnosis, is being developed by a team of scientists from two universities from Poznań, Poland: Adam Mickiewicz University and Poznan University of Medical Sciences. This interdisciplinary cooperation was motivated by an alarmingly high mortality rate among women caused by ovarian tumor. The correct and early diagnosis of that kind of tumor is still a problem especially for inexperienced gynecologists and in small medical centers that lack specialized equipment and money for medical examinations. Such deficiency implies problems with collecting all the data by a physician during examinations that, in turn, hinders making a final decision.

To support gynecologists in a diagnostic process a wide range of preoperative diagnostic models have been developed, where the goal is to predict the type of malignancy of a tumor. The most common diagnostic scales are based on scoring systems [1, 10] and logistic regressions [12]. Both the sensitivity and specificity of that models rarely exceeds 90% in external evaluation [13, 7]. Another limitation of those models is that they cannot be applied when some of the attributes' values are missing which is a common problem resulted e.g. from technical limitations of the health care unit, high costs of medical examination or high risk for patient's health.

OvaExpert is meant to be an answer to the problem of low-quality diagnosis in a presence of missing data. Its main aim is to equip a physician with a comfortable tool to collect and manage patient's data in a standardised format, to minimise a negative influence of incomplete data on the final diagnosis, to improve the reliability and efficacy of the diagnosis, also when some data is missing, and finally to present the result in a way that gives maximum information to a doctor. The system is easy to use and intuitive, yet it utilizes modern methods mainly from the area of machine learning, soft computing and fuzzy sets theory. In the following we describe the system in details, focusing on its ability to deal with imprecision, incompleteness and uncertainty. We present main features and components of OvaExpert, some of its theoretical background and we discuss how the above mentioned problems were successfully solved and what is still left to be done.

2 Features of OvaExpert

OvaExpert was meant to integrate present knowledge about ovarian tumors (models, scoring systems, reasoning schemes, etc.) into a single computer-aided system. Its modular architecture enables plugging existing and new methods for supporting ovarian tumor diagnosis into the system as modules and then integrate them to increase the reliability of diagnosis. Its prototype version was implemented and is available at http://ovaexpert.pl/en as a demo to provide insight into all functions of OvaExpert. It offers convenient access on PCs, tablets and smartphones. The preliminary concept of the system, together with its architecture, was presented in [4]. In the following we discuss in brief the basic features of the system.

At the very beginning of diagnostic process OvaExpert provides physicians with an comfortable and intuitive interface that allows collecting data about patients in a standardized form and then managing data safely. The system gathers knowledge about symptoms, results of medical examinations and final diagnoses for different types of tumors. The design of the interface was carefully consulted with gynecologists to meet the need for ease of use in all conditions, also on mobile devices, especially on smartphones. An example screenshot of OvaExpert interface is depicted in Fig. 1. So far, data was collected by individual doctors using traditional methods, like spreadsheet or notebook, without paying sufficient attention to the quality and format of these data. Thanks to OvaExpert standardized format we initialized building a knowledge base about different medical cases and set up a continuous learning system. This also enables quality assessment of the diagnostic decisions taken by the system, performed by specialists from different medical centers, and a collection of data for further scientific research.

At any time, the attending physician can be provided with the history and the visualization of the patient's diagnostic process. During the whole process a

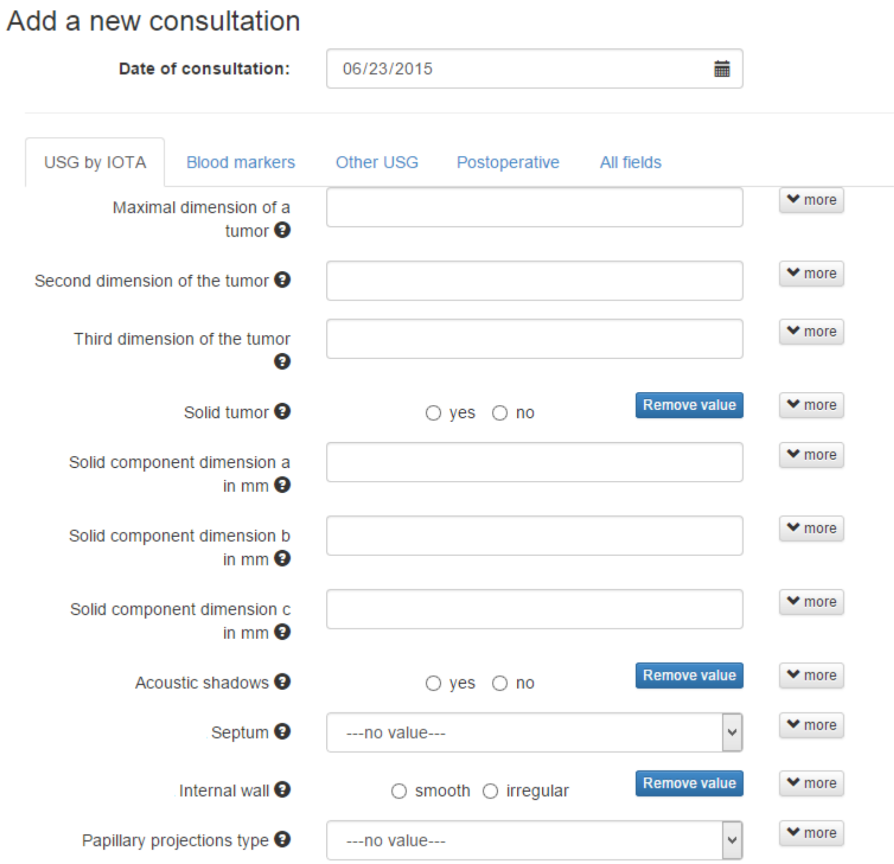

Fig. 1. Adding new consultation using OvaExpert interface

gynecologist is accompanied by a system that supports him or her by identifying further research, the execution of which may increase the likelihood of giving accurate diagnosis. Such solution is a great help for inexperienced gynecologists and, moreover, allows to avoid unnecessary examinations and costs related to them.

The main aim of OvaExpert is to support physician in making a final diagnosis, that is in assessing malignancy of the tumor. This complex issue is pursued by many different methods. First of all, OvaExpert implements known prognostic models, including models of IOTA group (International Ovarian Tumor Analysis Group) and RMI. Many gynecologists are familiar with those methods and trust their results. However, those scales had not been prepared to handle incomplete data, while the incompleteness is common in medical practice. For that reason some solutions, for example based on aggregation methods, were proposed and implemented in OvaExpert that allow to make an effective diagnosis in the presence of incomplete or missing diagnostic tests. The details of that solutions are presented in next sections. What is important, OvaExpert system achieves higher efficiency than any of the known models separately.

Finally, OvaExpert presents the result of a diagnostic process in a bipolar way, giving the possibility of diagnosis towards malignant and towards benign together with a degree of impossibility of determining the nature of malignancy. Such presentation informs a physician about the reliability and completeness of a diagnosis.

OvaExpert is a unique tool for many reasons. To the best of our knowledge it is the first time when incompleteness of data was taken into account and incorporated into a system for ovarian tumor diagnosis in a comprehensive way, either at the stage of collecting data about the patient, at the stage of data processing and finally at the stage of presenting the results. This issue is discussed in details in the next section.

3 Uncertainty handling in OvaExpert

3.1 Uncertainty in medicine

Uncertainty has attracted increasing attention in health care practice and medical publications as a pervasive and important problem. As studied in [5] there are multiple meanings and varieties of uncertainty in medicine, each of them having unique effects for diagnosis and warrant different courses of action. A lot of forms of uncertainty have been identified, like complexity or ambiguity, that arises from conflicting or incomplete information, as well as from multiple interpretation of some phenomenon, and vagueness that arises from lack of well defined distinctions or imprecise boundaries. Another sorts of uncertainty can be distinguished according to its nature - whether it is objective (arises from a complex or probabilistic nature of a phenomenon), subjective (personal opinion or interpretation) or comes from low quality of information, e.g. incompleteness.

Uncertainty is experienced both by a patient and by a doctor. Functioning in such conditions is an everyday experience in medical practice and is impossible to eliminate completely. However, many tools that support gynecologists, like before mentioned diagnostic scales, neglect that problem and shift the responsibility for good-quality data to a doctor. A different approach is proposed in OvaExpert system. OvaExpert takes into account the uncertainty issue and implements solution for: modeling incomplete data (see Sub. 3.2), reasoning from incomplete data (see Sub. 3.3, 3.5, 3.4) and presenting the final results that incorporates uncertainty factor (see Sub. 3.6).

3.2 Interval data modeling

In OvaExpert it is possible to gather over 60 attributes to describe the patient's condition. Some of those attributes are always available for physician, like age or weight, while others are subjective (ultrasound) or may be difficult to obtain (blood markers). Consequently, there is a group of attributes that are imprecise, not well defined, incomplete or not defined.

Formally, in a classical approach, a patient is modelled by a vector $\mathbf{p} = (p_1, p_2, ..., p_n)$ in a space $P = D_1 \times D_2 \times ... \times D_n$, where $D_1, D_2, ..., D_n$ are real closed intervals denoting domains of attributes that describe patients. In OvaExpert we extend this representation by introducing a possibility to model incompletely known data. Each attribute D_i is substituted by its interval version $\hat{D}_i = \mathcal{I}_{D_i}$ and a patient is a vector $\hat{\mathbf{p}} \in \hat{P} = \hat{D}_1 \times \hat{D}_2 \times ... \times \hat{D}_n$. It is thus possible for a doctor to introduce an approximate value of an attribute instead of an exact one, using interval representation. If the value of the attribute is totally unknown than it is calculated as

$$\hat{p}_i = [\underline{p}_i, \overline{p}_i] = [\min_{d \in D_i} d, \max_{d \in D_i} d].$$

3.3 Uncertaintification of scales

OvaExpert implements six diagnostic scales: SM [10], Alcazar [1], LR1 [12], LR2 [12], Timmerman [11] and RMI1 [6] in two versions: original one and extended, suitable for interval representation. The second version is a novel contribution of OvaExpert into the area of decision-making under incomplete information. It is easy to add another scale to the system if needed, work on ROMA and Adnex indexes is in progress now.

Original diagnostic scale is formalised as a function $m : P \to [0, 1]$. Values returned by a function indicate malignancy of a tumor and are interpreted in the following way:

- $m(\mathbf{p}) > 0.5$ – diagnosis towards malignant;
- $m(\mathbf{p}) < 0.5$ – diagnosis towards benign;
- $m(\mathbf{p}) = 0.5$ – indicates the impossibility of determining the nature of malignancy.

It was crucial to adapt existing diagnostic scales so as they were able to operate on interval-valued representation of a patient described in Sub.3.2. Therefore, an extended diagnostic scale $\hat{m} : \hat{P} \to \mathcal{I}_{[0,1]}$ was constructed as:

$$\hat{m}(\hat{\mathbf{p}}) = \left\{ m(\mathbf{p}) : \forall_{1 \leq i \leq n} \quad \underline{p}_i \leq p_i \leq \overline{p}_i \right\} = \left[\min_{\mathbf{p} \in \hat{\mathbf{p}}} m(\mathbf{p}), \max_{\mathbf{p} \in \hat{\mathbf{p}}} m(\mathbf{p}) \right] \qquad (1)$$

where by $\mathbf{p} \in \hat{\mathbf{p}}$ we denote that $\mathbf{p}$ is an embedded vector of $\hat{\mathbf{p}}$.

The resultant interval represents all the possible diagnoses that can be made basing on an interval patient description. The more incomplete description, the more uncertain the diagnosis. However, two aspects are worth noting. Firstly, uncertain diagnosis gives more information then no diagnosis at all, which would be the case if original diagnostic scales had been used. Secondly, even such uncertain information could be sufficient to make a proper diagnosis in many cases, since some amount of missing values is acceptable and would not affect the final result significantly.

3.4 Interval-valued aggregation

The number of different diagnostic scales is large and it is not commonly accepted which one should be used in a particular situation. Moreover, in case of missing data, the result of a single diagnostic scale given by (1) is often uncertain and not so easy to apply by a physician. The biggest challenge was thus to support a physician in making an effective final diagnosis under incomplete information. One of the proposed approaches is to take advantage of the diversity of diagnostic scales and to aggregate their results to benefit from synergy effect. In OvaExpert different interval-valued aggregation methods were implemented and tested. They were divided into groups of aggregation operators based on: arithmetic mean, weighted mean, sum and intersection from the set theory, interval OWA and voting [14]. The conducted evaluation of those methods proved that aggregation is a powerful method to improve the quality of diagnosis as well as to minimise the impact of the lack of data and uncertainty. As can be seen in Fig. 2, even the simplest methods received efficacy which exceed individual diagnostic scales, both in terms of accuracy and the number of diagnosed patients, despite missing data. More details concerning aggregation methods and evaluation methodology can be found in [17].

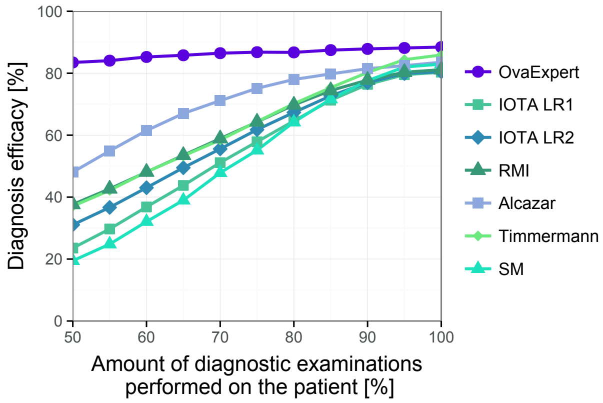

Fig. 2. Efficacy comparison of selected diagnostic models

3.5 Interval-valued fuzzy classifier

As a separate module, OvaExpert implements a novel concept of an interval-valued prototype-based fuzzy classifier based on the uncertainty-aware similarity measure. The idea is to preserve full information – including the uncertainty factor – about data during the classification process. The classifier is designed to deal with situations in which both the classified objects and the classes themselves are imprecise, subjective and/or incomplete. In such cases, the resulting classification would also be imprecise or incomplete.

There are two ways to divide patients into classes. A basic, binary classification, discriminates two kinds of tumor: malignant and benign. A multi-class classification allows more sophisticated discrimination into histopathological types of tumor. For each class, one prototype vector which represents the entire class is constructed. We assume that class prototypes as well as objects to be classified (patients) are coded as IVFSs (interval valued fuzzy sets, see [15]). Then, the assignment of patient p_i to classes from $\mathcal{C}$ using the singleton notation can be stated as follows:

$$\widetilde{A}_{p_i} = \sum_{c \in \mathcal{C}} {}^{sim_{IF}(\widetilde{iv}(c), \widetilde{iv}(p_i))}/_{c} \tag{2}$$

where sim_{IF} is an uncertainty-aware similarity measure. This approach was discussed in details in [8].

The crucial issue for this approach is the method of constructing prototypes. Prototypes can be formed from data, for example by using clustering algorithms such as k-means, or can result from the application of expert knowledge. Thus the proposed method gives the valuable opportunity to integrate knowledge taken from data and from expert in one tool.

3.6 Bipolar presentation of a medical diagnosis

A classical approach to medical diagnostic process involves identifying the most adequate diagnosis. However, it is also possible to follow the criteria that exclude certain diagnoses. It is apparent that in case of doubts regarding the diagnosis, such bipolar - positive and negative - perspective is valuable and carries more information for a doctor.

OvaExpert uses an approach based on Atanassov's intuitionistic fuzzy sets [16, 2] to model bipolarity in the diagnostic process. This concept is innovative in medicine, its use in the diagnosis having only been indicated as a possibility [3, 9]. It is coherent with a basic premise of OvaExpert system that is to accept and to cope with uncertainty. Methods of data modeling and processing presented in previous subsections utilize interval representation to preserve information about the completeness of data. Next, the positive and negative information (diagnosis) is extracted from the obtained results and presented in a bipolar way to a user in a form of a bar chart, as presented in Fig. 3. On the one hand, the patient's condition is described by a degree that indicate a tumor being malignant, and on the other - being benign. Those two degrees sum up to 100% when all the necessary information about patient's attributes is available. Otherwise, the system suggests further examination to increase the reliability and completeness of a diagnosis. The chart may be displayed in aggregated form or with details about diagnostic scales. Apart from the diagnosis itself (whether malignant or benign), the gynecologist is equipped with the additional information about the reliability of that diagnosis, that consists of two factors: a degree of belief towards certain diagnosis (a high advantage over the opposite

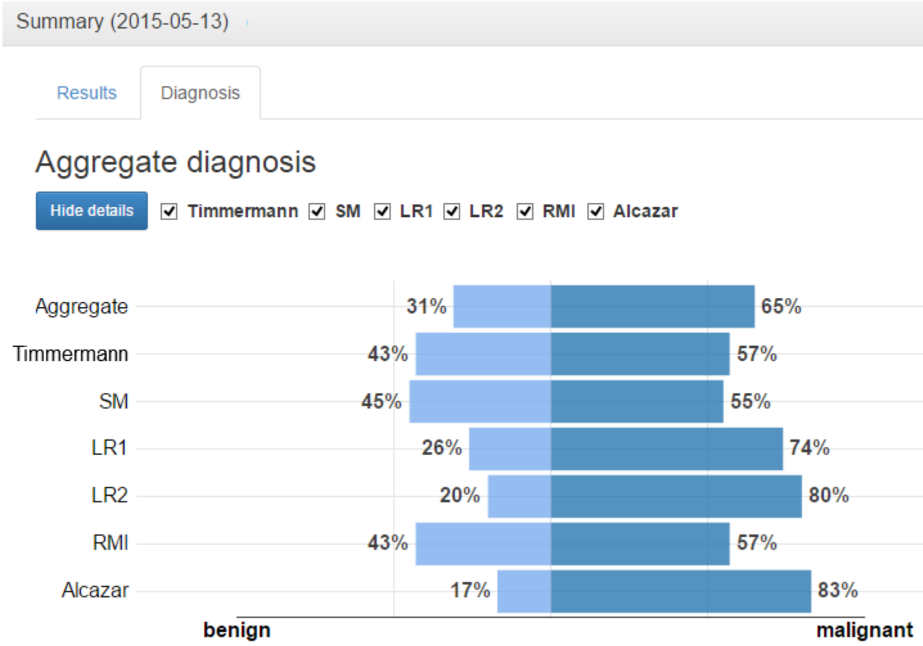

Fig. 3. Bipolar presentation of a diagnosis of ovarian tumor

diagnosis makes it more reliable) and a completeness of a diagnosis (expressed by a length of a bar on the chart); obviously, the diagnosis that was based on incomplete data is less reliable. However, as outlined earlier, our approach makes it possible to make a good-quality diagnosis at the early stage of a treatment process, even if some data is missing, and improve it later, when the examinations will be complemented.

4 Conclusions and further work

OvaExpert is an innovative system based on machine learning techniques and computational intelligence. It addresses the need for a tool that not only supports a gynecologist in the final diagnosis, but also assists him or her during the whole diagnostic process, beginning with collecting data about the patient.

The primary advantages of the system are transparency and ease of comprehension of the principles, the ability to take into account knowledge derived both from experts and from data, and the built-in possibility of representation and processing of subjective, imprecise and uncertain information. The system was designed to support less experienced gynecologists and it allows a continuous improvement of the quality of diagnosis.

Moreover, we believe that OvaExpert can connect the medical community in the exchange of experience and verification of knowledge.

In our future work we plan to add new features: ability to integrate expert knowledge into the system, fuzzy rule-based diagnostic module and diagnostic path wizard.

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