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# Bayesian Networks and Decision Trees in the Diagnosis of Female Urinary Incontinence

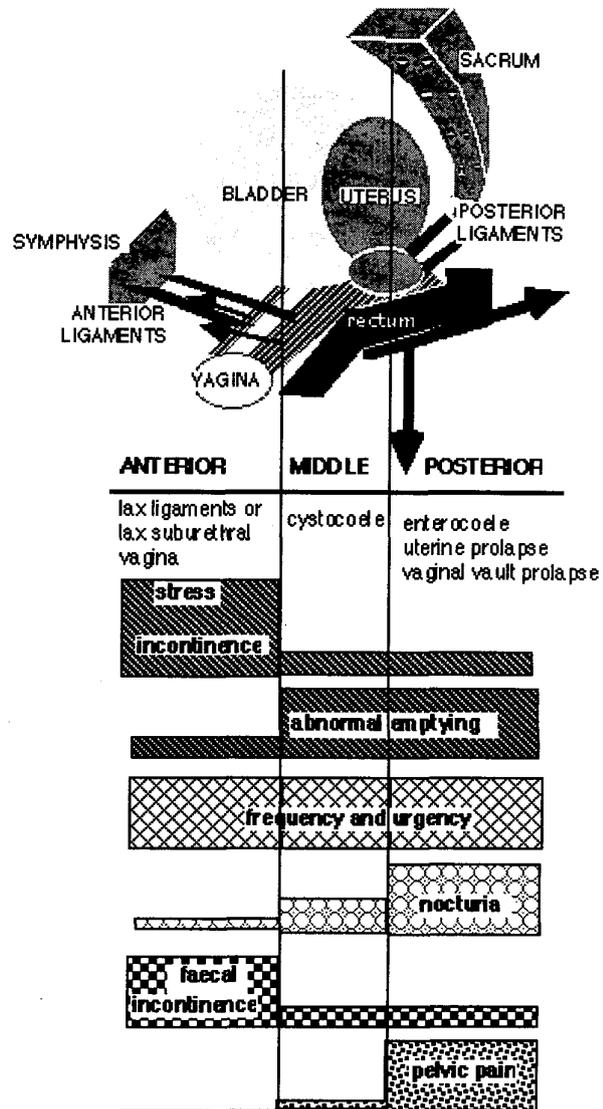
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**Abstract-** This study compares the effectiveness of Bayesian networks versus Decision Trees in modeling the Integral Theory of Female Urinary Incontinence diagnostic algorithm. Bayesian networks and Decision Trees were developed and trained using data from 58 adult women presenting with urinary incontinence symptoms. A Bayesian Network was developed in collaboration with an expert specialist who regularly utilizes a non-automated diagnostic algorithm in clinical practice. The original Bayesian network was later refined using a more connected approach. Diagnoses determined from all automated approaches were compared with the diagnoses of a single human expert. In most cases, Bayesian networks were found to be at least as accurate as the Decision Tree approach. The refined Connected Bayesian Network was found to be more accurate than the Original Bayesian Network. This is likely due to the more generalized nature of the Connected Network. The Original Bayesian Network accurately discriminated between diagnoses despite the small sample size. In contrast, the Connected and Decision Tree approaches were less able to discriminate between diagnoses. The Original Bayesian Network was found to provide an excellent basis for graphically communicating the correlation between symptoms and laxity defects in a given anatomical zone. Performance measures in both networks indicate that Bayesian networks could provide a potentially useful tool in the management of female pelvic floor dysfunction. Before the technique can be utilized in practice, well-established learning algorithms should be applied to improve network structure. A larger training data set should also improve network accuracy, sensitivity, and specificity.

**Keywords:** Urinary Incontinence, Bayesian Network, Decision Tree, Expert System

## INTRODUCTION

The Integral Theory of Female Urinary Incontinence suggests that urinary dysfunction is the result of soft tissue laxity or other defects in a given zone of the pelvic floor, as shown in Figure 1 [1, 2]. A diagnostic algorithm based on this theory has been investigated at various institutions, incorporating clinical measurements made during a physical examination, together with subjective data supplied by the patient in a questionnaire [3,4].



**Figure 1. Various diagnoses and the relationship to defects in a given anatomical zone**

The goal of the present study was to investigate the effectiveness of Bayesian Networks and Decision Tree approaches in automating the diagnostic process to make it available to a wider audience, and to supplement the training of specialists.

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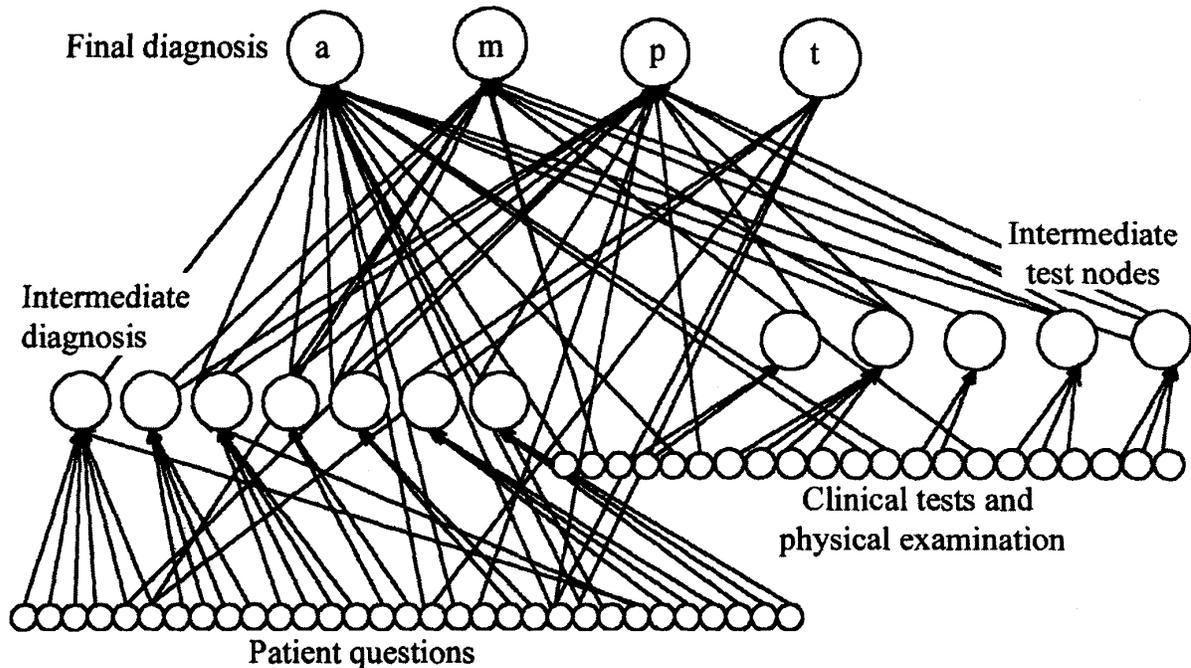


Figure 2. Bayesian Network output nodes (top row) predicting the likelihood of defects in the anterior (a), middle (m), or posterior (p) zones, or a diagnosis of tethered vagina syndrome (t). Intermediate diagnosis and test, and patient questions and clinical test nodes are as shown.

**BACKGROUND**

Bayesian Networks[5], Neural Networks[6], and Decision Trees [7] have all been used to implement medical expert systems.

Bayesian Networks encode conditional interdependence relationships through the position and direction of edges in a directed acyclic graph [8]. The relationship between a node and its parent is quantified during network training [9].

Decision Trees, in contrast, encode a set of rules for interpreting the input data [10].

**METHODS**

Data used in this study was compiled from the medical records of 58 adult female patients with a history of urinary dysfunction. Data included answers to a patient questionnaire and the results of clinical tests conducted during routine examinations. A human expert trained in the Integral Theory Diagnostic Algorithm supplied a diagnosis for each patient [3, 4]. The diagnosis consisted of inferring laxity defects in a combination of anterior, middle and posterior zones of the pelvic floor. An alternate diagnosis of tethered vagina syndrome was also possible for those patients who had undergone previous pelvic surgery. To limit computational complexity, parameters with continuous values were mapped to discrete ranges.

Two Bayesian networks were designed and trained using the same data training set. The structural design of the first

Bayesian network (Original Bayesian Network) was developed in consultation with a human expert, and is depicted in Figure 2. In the figure, network nodes along the bottom correspond to questionnaire items or specific clinical tests and observations of the physician during routine examinations. These nodes were linked to intermediate and final diagnoses nodes to represent inferential knowledge.

The second Bayesian network (the Connected Bayesian Network) was developed by making a more complete network. Instead of connecting a node with only the diagnoses that were perceived to be directly influenced by a positive occurrence, the nodes were connected to all four final diagnoses.

Matlab and the BN Toolbox developed by Kevin Murphy [11] were used to build and train both Bayesian networks. Murphy's toolbox has facilities that enable model specification, inference and learning.

Computational complexity was alleviated by using a technique called divorcing [8]. Intermediate nodes were introduced, representing simplifying assumptions. In the Original Bayesian Network, binary intermediate nodes were added that corresponded to the intermediate diagnoses made from questionnaire results. These included indications of stress incontinence, deficient emptying of the bladder, urge incontinence, bowel problems, elevated frequency of micturition, previous surgery and pelvic pain. Nodes

	Original Bayesian Network	Connected Bayesian Network	Decision Tree approach
<b>Anterior</b>			
accuracy	52%	76%	88%
sensitivity	29%	100%	94%
specificity	100%	25%	75%
<b>Middle</b>			
accuracy	56%	64%	56%
sensitivity	58%	67%	58%
specificity	54%	62%	54%
<b>Posterior</b>			
accuracy	72%	92%	88%
sensitivity	74%	100%	92%
specificity	50%	0%	0%
<b>Tethered</b>			
accuracy	88%	96%	92%
sensitivity	100%	0%	0%
specificity	88%	100%	96%

**Table 1. Accuracy, sensitivity, and specificity results on unseen data for the Original and Connected Bayesian Networks, and for the Decision Tree approach.**

representing test and examination results were combined according to groupings arising from the contribution to the final diagnoses of an anterior, middle and posterior defect or tethered vagina syndrome.

In the Connected Bayesian Network, intermediate nodes were added in a similar manner to the Original Bayesian Network to represent intermediate diagnoses based upon the questionnaire. Test and examination results were grouped by test category. For example, the Pad Tests (capacity, cough, star and 24 hour) were grouped and an intermediate node inserted. Intermediate nodes were also added to represent the preliminary anterior, middle, posterior, tethered diagnosis attained by both the questionnaire and test portions of the network.

Parameter learning accommodated for missing data in the training data set. A generalized Expectation Maximization (EM) algorithm in batch mode was used [12]. Carrying out diagnostic inference in the Original and Connected Bayesian Networks involved the computation of the posterior marginal probabilities of the four diagnoses given a set of observed findings. This inference was achieved using junction trees [13].

The Bayesian networks were trained using a majority of the data samples and then tested on the balance - ensuring that the test data was unseen by the network during training. Tests were also done using the training data. The results obtained by querying the network, for any individual case, were

compared with the diagnosis obtained from the human expert. These comparisons form the basis of the evaluation of the system.

Results from both Bayesian Networks were compared to those produced using See5. See5 (C5.0) is a tool that analyzes data to produce decision-trees and/or rule-sets that relate a case's class to the values of its attributes [14].

Values for the questionnaire, examination and test results were assigned with the same discretization process used for the Bayesian networks.

In this type of classification, it was necessary to produce a decision tree for each diagnosis - anterior, middle, posterior and tethered vagina. In each data case, a classification was made based on the presence or non-presence of the particular diagnosis, for example anterior/not anterior.

Boosting is a feature of See5 that was utilized to improve the predictive accuracy of the classifier [14]. The technique generates and combines multiple classifiers.

Each classifier was trained using the training set of 33 data samples and then tested on the unseen set of 25 test samples. Measures of accuracy, sensitivity and specificity were calculated.

**MODEL VALIDATION**

Each classifier was trained using the training set and then tested on the same seen data. This was to determine whether the data and features used to classify were discriminating. In both Bayesian networks and the Decision Tree approach, results for accuracy, sensitivity and specificity ranged from 90% to 100% for each diagnosis. The exception to this is a 50% specificity score for the Original Bayesian Network in the diagnosis of a posterior defect.

**RESULTS**

Results on unseen data are shown in Table 1.

The Connected Bayesian network achieved greater accuracy than the Original Bayesian network.

In most cases, Bayesian networks were at least as accurate as the Decision Tree approach. The exception to this was in the anterior zone where the Decision Tree achieved 88% accuracy, compared to the Connected Bayesian network's 76%. One explanation for this result is that the Decision Tree approach closely follows the algorithm used by human experts [3,4], for whom anterior defects are readily treated surgically [15].

The Connected Network and the Decision Tree approach did not generate true negatives in the classification of the posterior defects (0% specificity).

The Connected Network and the Decision Tree did not generate true positives in the classification of tethered vagina syndrome (0% sensitivity).

This suggests that the Connected Network and Decision Tree failed to generalize in these cases. The Original Bayesian Network achieved high levels of accuracy (88%), sensitivity (100%) and specificity (88%) in its diagnosis of Tethered Vagina Syndrome. In the diagnosis of a posterior defect, the Original Bayesian network generated true negatives in half the cases (50% specificity). This is consistent with results for seen data. While the more accurate classifiers failed to generalize, the Original Bayesian Network displayed discriminating behaviour.

#### DISCUSSION

The Decision Tree approach, while attaining reasonable levels of accuracy, did not address the interconnectedness of the diagnoses. In the Decision Tree method the classifier had to be executed four separate times, once for each diagnosis. The benefit of the Bayesian Network approach was that the diagnostic process could address the defects concurrently.

In this application of Bayesian networks to the diagnosis of urinary incontinence, a number of simplifying assumptions were made based on the conditional independence of nodes contributing to a diagnosis. These assumptions were necessary to inhibit the size and complexity of the networks. A more accurate model may be obtained by improving network topology. This could be achieved by using well-established structural learning algorithms [9].

In general, the Connected Bayesian Network and the Decision Tree approach produced consistent results. However sensitivity and specificity could be improved with a larger training sample. For example, the human expert categorized only four of the 33 cases in the training set as not meeting the criteria for posterior defects; the human expert categorized only two of 25 cases in the test set as not meeting the criteria for posterior defects. Before the present automated expert system can be employed in clinical practice, a larger training set is required, including more cases exhibiting tethered vagina syndrome and not showing posterior defects.

The Original Bayesian Network was found to provide an excellent basis for graphically communicating the correlation between symptoms and laxity defects in a given anatomical zone. The graphical representation of the Original Bayesian Network should enhance the training of new practitioners in the use of the Integral Theory diagnostic process.

#### CONCLUSIONS

Results indicate that Bayesian networks could provide a potentially useful tool in the management of female pelvic floor dysfunction. In most cases Bayesian networks were found to be at least as accurate as using Decision Trees.

An advantage of using Bayesian networks is that the accuracy, specificity and sensitivity will improve as the number of test cases available for training increases. In contrast, using Decision Trees is a relatively static process that is not easy to enhance incrementally.

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