DIAGNOSIS OF DEMENTIA AND ITS PATHOLOGIES USING BAYESIAN BELIEF NETWORKS

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Abstract: The use of artificial intelligence techniques in medical decision support systems is becoming more commonplace. By incorporating a method to represent expert knowledge, such systems can aid the user in aspects such as disease diagnosis and treatment planning. This paper reports on the first part of a project addressing the diagnosis of individuals with dementia. We discuss two systems: DemNet and PathNet; developed to aid accurate diagnosis both of the presence of dementia, and the pathology of the disease.

1 INTRODUCTION

The assessment and correct management of individuals with dementia is complex, and requires a high level of expertise. The first stage of our research has focused on the development of a disease diagnosis system. The system can be viewed as two parts: DemNet which aids a clinical decision maker in diagnosing the likelihood of dementia; and PathNet which provides a dementia consultant with an indication of the possible disease(s) causing the dementia. Both systems utilise the technique of Bayesian Belief Networks (BBNs) to provide probabilistic information pertaining to the presence of dementia and likely pathologies. The BBN formalism offers a natural way to represent the uncertainties involved in medicine when dealing with diagnosis, treatment selection, planning, and prediction of prognosis (Gill et al., 2005). This is due to the fact that the influences and probabilistic relations among variables can be described readily in a BBN, alternatively thought of in terms of cause-effect relationships. Another attractive feature of the formalism is that any probabilistic statement (often causal) can be computed, where the user may wish to query either a single variable, or more commonly, combinations of variables. Further advantages of using BBNs over other techniques are the flexibility of the networks in the amount of information they receive and their transparency in detailing why a particular decision was reached. Techniques such as decision trees can be difficult to use when only partial information is available and other techniques such as Artificial Neural Networks (ANNs) fail in providing a sufficiently good explanation facility, making it difficult for users to determine factors that have contributed to the decision.

In this paper, we begin by providing the reader with a brief description of the dementia syndrome, common pathologies, and current ways in which the disease is diagnosed. The two prototype systems developed, DemNet and PathNet are then discussed in detail. The paper concludes with a report on preliminary findings and the potential for future work.

2 DEMENTIA

2.1 About Dementia

Dementia is a term used to describe a syndrome caused by a variety of brain disorders that have in common a loss of brain function, which is usually progressive and eventually severe (Alzheimer's Society, 2005). Symptoms of dementia may

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include: loss of memory, confusion and problems with language, executive function, and social function. The clinical decision support system (CDSS) we have developed focuses on providing support in diagnosing dementia and distinguishing between the four most common dementias of old age: Alzheimer's disease (AD), Vascular dementia (VaD), Dementia with Lewy bodies (DLB), and Fronto-temporal dementia (FTD).

The current method adopted for diagnosing dementia involves evaluation of the clinical syndrome based on history and examination, supported by screening investigations, and, where appropriate, additional more specialised investigations. In progressive degenerative dementias, during the very early stages cognitive deficits are usually subtle and their manifestations, though representing change from pre-morbid function in an individual, may remain within the normal range for the general population. This presents considerable challenges to early diagnosis. However, early diagnosis and an understanding of the underlying pathologies is of value in planning treatment and, in some cases, initiating specific drug intervention.

Systems to aid in medical decision making, and in particular, disease diagnosis were introduced in the medical field over 25 years ago. Despite their potential usefulness in helping to provide early and accurate diagnosis, relatively few are in general use (Kaplan, 2001). This can be attributed to the difficulties of integrating such systems into a clinical setting which can generally be described as complex systems consisting of involved algorithms, procedures, and protocols. By addressing this complexity and our continued interaction with those who would potentially use the clinical decision support system (CDSS), we hope to ensure our system is adopted and is found a useful aid in the diagnosis procedure.

2.2 Disease Diagnosis Systems

Many different operational research and artificial intelligence techniques have been adopted by CDSSs. Such techniques include the use of mathematical models (Werner and Fogarty, 2001), neural networks (Dybowski et al., 1996) and more recently, optimisation techniques (De Toro et al., 2003). Further details of the use of such techniques are detailed in Oteniya et al, 2005.

CDSSs have also been developed that address the specific area of dementia diagnosis. García-Pérez et al. (1998) use data mining and neural network techniques and Mani et al (1997) apply decision-trees and rule-based approaches to differentiate between Alzheimer's disease and Vascular dementia.

Our CDSSs extend such systems by providing a means of identifying the presence of dementia and the likelihood of underlying pathologies. In addition, by using BBNs, our systems overcome some of the difficulties other data mining techniques can present (as detailed in Section 1).

3 DEMNET

DemNet uses a probabilistic model of dementia diagnosis that incorporates patient history features and physical findings. In an attempt to optimise user friendliness and utility in a busy primary care setting, the model seeks to use as numerically few and as simple to use parameters as is consistent with reasonably high diagnostic accuracy. DemNet is described in terms of two components: the user interface and underlying BBN. Each node of the BBN relates to a question asked of the user. The more answers to questions the user can provide, the more accurate the system in diagnosing the presence of dementia.

DemNet is designed to be used by clinical practice nurses, who are involved in the primary level assessment of patients.

In order to facilitate a hand crafted BBN, information was elicited from our domain expert (a practicing dementia consultant) via a number or technical workshops. The process involved deciding on key diagnostic variables and the relationships between them, as well as quantifying the relations probabilistically. In an attempt to optimise user friendliness and utility in a busy primary care setting, the models seeks to use as numerically few and as simple to use variables as is consistent with reasonably high diagnostic accuracy. This process brought to light both advantages and disadvantages of this technique. Further information on these, the elicitation process and the methodology adopted is given in Oteniya et al, 2006..

3.1 The Bayesian Belief Network

The underlying DemNet BBN is given in Figure 1. In the model, the nodes on the periphery of the network collect evidence relating to: the individual's current functioning, global severity of cognitive impairment, individual's age, duration of impairment, and whether clear progression is identifiable.

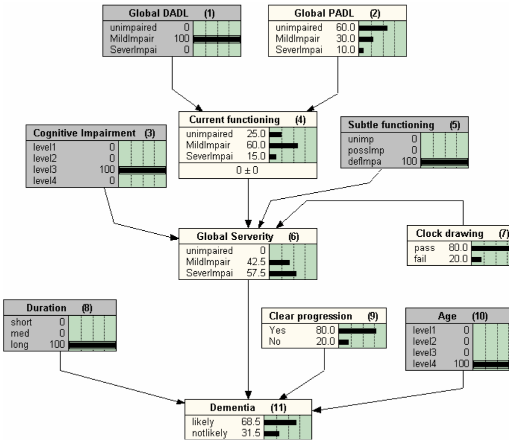

Figure 1: DemNet Bayesian Belief Network.

With each piece of evidence presented, the model recalculates the posterior probability of the related child nodes. For example, in our model, the state of node 4 (current functioning) combined with evidence presented to nodes 3, 5, and 7 will cause the recalculation of posterior probabilities for child nodes 6 and 11. This implies that information given regarding the level to which cognition is impaired (node 3) and the degree to which subtle functioning is effected (node 5), combined with the state of current functioning (node 4), influences a patient's global severity (node 6) and ultimately the likelihood of the patient having dementia (node 11). The network also incorporates the level of influence which data has on increasing a related node's probability. In Figure 1, we can see that a subset of information has been provided about a given patient (denoted by dark grey nodes). Given the information provided, we can see that this patient has a 69% chance of having dementia.

3.2 User Interface

An intuitive user interface guides the user through a series of questions representative of each node in the BBN. This interface is depicted in Figure 2. The interface is divided into 3 areas, namely the model pane, diagnostic pane, and results pane. The model pane displays the underlying DemNet model which can be helpful to the user in identifying which pieces of data they have provided (denoted by dark grey nodes) and some notion of how each piece of data relates to the diagnosis given. The diagnostic pane displays the question associated with a selected diagnostic node. Each node has a number of possible states. Each of these states relate to possible answers to the diagnostic questions. The user is therefore restricted in the response they give by choosing the appropriate answer from a drop down menu. The results pane for DemNet shows 3 sets of results relating to current functioning, global severity, and dementia. The first two sets of bars in the results pane relate to nodes in the model that are crucial to determining whether dementia is present, and are nodes which rely heavily on the answers/evidence given to other nodes. The three bars associated with Current Functioning and the three bars associated with Global Severity are representative of the 3 states possible for these nodes. The dementia bar indicates the likelihood of the disease being present.

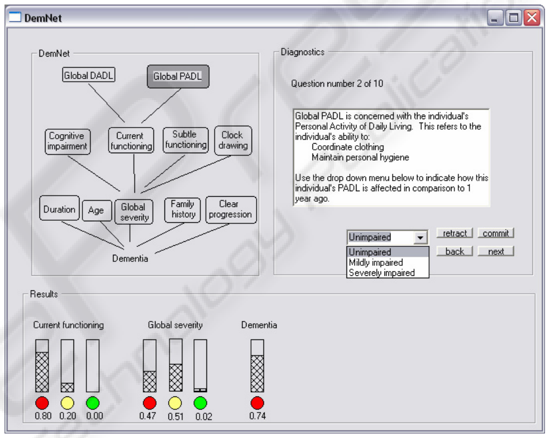

Figure 2: DemNet User Interface.

4 PATHNET

PathNet is an extension of DemNet for use by domain experts (usually dementia consultants) within the primary care setting. The system allows the decision maker to identify the underlying pathologies of a given case of dementia. A number of different pathologies can lead to the syndrome of dementia, either singly, or in combination. It is the four most common dementias of later life: Alzheimer's disease, Vascular dementia, dementia with Lewy bodies and Fronto-temporal dementia that PathNet aims to identify.

As with DemNet, the system can be divided into the user interface and underlying BBN. As the dementia syndrome may be caused by multiple co-existing pathologies, we have designed our model such that it is capable of identifying the likelihood of different types of dementia, either singularly, or, as is often the case, co-existing with other dementia diseases. In addition, if dementia is suspected, but none of the four most common pathologies can be identified, the system indicates the presence of dementia (other), that is, a form of dementia not identified by the system.

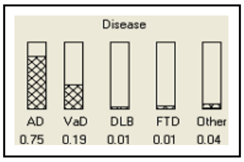

Figure 3: PathNet results pane.

The PathNet interface is identical in layout to the DemNet Interface but has one main difference in the results pane. This incorporates information relating to the likelihood of the different dementia pathologies. This is shown in Figure 3. As can be seen from Figure 3, the user is provided with a visual representation of the probability distribution across each of the diseases.

5 CURRENT FINDINGS AND FUTURE WORK

5.1 Evaluation of Prototypes

To date, validation of the systems has involved a workshop with expert physicians and informal discussions with expert clinicians in the field. The main purpose of the workshop was to discuss the structure of the model, that is the variables and their relations, and secondly, to discuss the validity of the diagnostic output of the model for a number of trivial and non-trivial typical scenarios. Recently, we have initiated a small clinical trial which seeks to collect clinical data relating to the diagnosis of dementia and the pathologies. Once the data collection study is complete (anticipated to be October 2006), we will analyse the data using a tool currently being developed which automatically learns the structure and parameters from a given dataset (see Section 5.2). This new model will be compared with the hand-crafted models developed to date.

5.2 Inducing the Network

Current work is focused on collecting data from clinical practitioners conducting dementia diagnosis. We hope to build up a sufficient body of data to be able to induce a BBN, and ultimately compare the structure and diagnostic accuracy of the network derived with original hand-crafted models, allowing insight into the potential advantages and disadvantages of each approach for building BBNs.

6 CONCLUDING COMMENTS

Although this research is still in its preliminary stages, we feel confident that the systems developed have great potential in aiding in dementia diagnosis. Through presentations and informal discussions, we have been able to gain some initial feedback from practitioners involved in this area. This feedback has been extremely enthusiastic and encouraging.

Over the next few months we hope to be able to produce some results from the comparison with the data-derived BBN and the expert-derived BBN. These results will hopefully give useful indication of the benefits of each approach as well as provide insight for the direction of future research. Further details of the project can be found on the project website: http://www.cs.stir.ac.uk/~lot/dotpi/

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