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RESEARCH ARTICLE

Using Bayesian Network as Decision making system tool for deciding Treatment plan for Dental caries

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Abstract

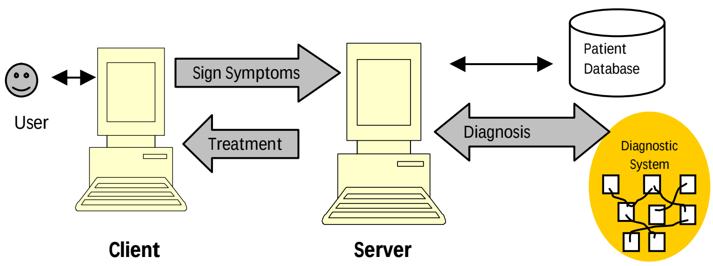
Suggesting a correct treatment plan for dental caries based on inter-causal association between different sign-symptoms is really a thoughtful task for dentist. A novel approach for diagnosing and deciding the course of treatment for dental caries is presented here. The inference mechanism based on the Bayesian Network (BN), has been designed to decide among various treatment plans. BN has been used since it provides a strong mathematical foundation for tackling such problems. There are only two possible outcomes by BN: true and false with certain degree.

Keywords: Bayesian network, dentist, dental caries, dental treatments, uncertainty, GeNIe.

Introduction

Bayesian Network (BN), which is based on robust mathematical foundation, is one of the appropriate techniques for dealing with uncertainty that is prominent in medical domain. This study presents the decision making based on BN for diagnosing of the presence of dental caries and its related treatments. In every age, human being is affected by dental caries. World's largest population, mainly school going children are under clinches of this disease. A recent study shows an estimated 90% of school children worldwide and most adults have experienced caries with more prevalence in Asian and Latin American countries and least occurrence in African countries (World oral health report, 2003). Over the age of fifty, between 29 and 59% of adults are attacked by caries (Jamison *et al.*, 2006). In US and Europe, 60-80% of cases of dental caries occur in 20% of the children population (Touger-Decker *et al.*, 2003). It is really a tough task for dentist to diagnosis caries by old-fashioned methods. A minor difference in sign-symptoms can change the course of treatment and hence the cost can vary considerably. This paper studies the sign-symptoms of the dental caries and suggests a treatment based on BN. The BN based diagnosis system described in this study is to be made online for general dentists and for public, henceforth called as user, so that the best treatment can be carried out. The system uses the sign-symptoms as the input to the system for calculating the probabilities of the related treatments and chooses among the best. The abstract model is shown in Fig. 1. The user selects the sign-symptoms present in patient suffering from dental caries, for instance, 'presence of cavities' and 'pain on percussion'. On the basis of the nature of cavity i.e. deep, shallow, low or other and if pain is felt on percussion, the relative treatment is being suggested by a dentist.

Fig. 1. Abstract model of dental caries diagnosis system.



This information is sufficient for diagnosing caries. But, the same information in presence of few more symptoms make it multifaceted problem that is faced by dentist. So there is a need to tackle such uncertainty, and BN provides a suitable environment. The usefulness of Bayes's theorem has been accepted in medical domain long time back. It suits to medical domain since information needed in decision making is probabilistic (Russell and Norvig, 2002). The Bayes's theorem delivers accurate results where specific manifestations have high frequency and high specificity (Peng *et al.*, 1996). Lot of experimentation is undergoing to utilize BNs in current scenarios also. For example, discovering temporal-state transition patterns during Hemodialysis has been discussed by Lin *et al*. (2002). But there has been criticism of Bayesian based probabilistic systems also. The main limitation is to obtain realistic prior probabilities. This can be tackled by involving domain experts for deciding probabilities or utilizing statistical data as being done by Blinowska *et al.* (1992) for diagnosing hypertension. Nikovski (2000) has constructed a BN for medical diagnosis from incomplete and partially correct statistics in a research at Siemens corporate research.

He demonstrated the correct uses of the statistical data with Conditional Probability Tables (CPTs) for Medical Diagnosis. A Problem-Based Learning (PBL) as an alternative to the traditional didactic medical education has been created by Suebnukarn and Haddawy (2006). Traditional pedagogy is subject-based where the students are told what they need to know, a course outline is provided, often a required text is specified, the teacher lectures and the students solve problems afterwards. In contrast, in the PBL paradigm a problem situation is posed first; the students must identify what they need to know to solve the problem; they learn it and use the new knowledge to solve the problem.

A Bayesian Decision-Support System (BDSS) for Ventilator-Associated Pneumonia (VAP) has been suggested by Carolina *et al.* (2010). Two specialists diagnosed VAP infected 872 patients along the predication made by system designed. It has been observed that the decision made by the system is nearly equals to the physicians. Bartosz (2011) in this master's thesis also designed a diagnosis tool using BN. Representational State Transfer (REST) and Service Oriented Architecture (SOA) along technologies like C# are used to design the whole system. BN model (Bayes Server) has been deployed as a web service. The web service is consumed by thin clients and there is no need for installation of software at client site. In three different expert systems are developed for diagnosis breast cancer, ovarian cancer, and tongue cancer (Allen, 2010). The author concluded that BN outperforms Artificial Neural Network classifier by 1%. The system successfully classified approximately 88% out of 77 instances correctly. The network produces a confidence interval of 75 to 97.8% showing that results are significant. The discussion above concludes that BNs can work well in the medical diagnosis systems for health care domain. In this study, we design and evaluate the BN for diagnosis of dental caries and selection of appropriate treatment. In the subsequent sections we introduce the fundamentals of BN. The basics of BN, specific to our problem, will also be discussed and then we will design the probabilistic network with the help of GeNIe (genie.sis.pitt.edu). A web-based GUI system is designed for user-friendliness and abstraction of the system.

Materials and methods

In this section we describe the design of BN and briefly discuss the diseases for which BN has been constructed.

Dental caries: Uncertainty flourishes in their risk for dental carious lesion; diagnostics and treatment alternatives; and in the consequence of clinical strategies. It always prohibits conducting a arbitrary clinical trial on every aspect.

Table 1. Sign-symptoms and its description.

Sign-symptoms	Description
Cavity	A hole developed in tooth due to mineralized tissues of the tooth undergoes progressive destruction from the surface of the tooth. It is caused by bacteria that colonize the tooth surface and, under certain conditions, produce sufficient acids to demineralize the enamel covering of the tooth crown or the cementum covering the root, and then the underlying dentin
Pain	An unpleasant sensory and emotional experience associated with actual or potential tissue damage or described in terms of such damage.
Pulp exposure	The result of pathological changes in the hard tissue of a tooth caused by carious lesions, mechanical factors, or trauma, which render the pulp susceptible to bacterial invasion from the external environment.
Pain on percussion	An abnormal pain felt by hitting with percussion instrument on the affected area of tooth.
Partial denture	A partial denture is a removable dental appliance that replaces multiple missing teeth. It can be attached to the teeth with clasps (clasp or conventional partial) or it can be attached to the teeth with crowns with precision attachments (hidden clasps). Both types have a metal framework and plastic teeth and gum areas
Food lodgment	Debris of food which logs in tooth due to cavity.
Fistula	A tunnel conducting pus from one infection to the site of another. More generally it is due to destruction of intervening tissue, between the two sites and is a major component of a periapical abscess. Inflamed pus forms an abscess causing a pressure increase in the surrounding tooth area. If the pus that accumulates at the end of the tooth has no alternate pathways for drainage over time spontaneous drainage may occur through bone next to the root end. The pathway through which the pus has burrowed is called a fistula.
Swelling (Gingivitis)	Gingivitis is a form of periodontal disease. Periodontal disease involves an inflammation and/or infection that results in the destruction of the supporting tissues of the teeth, including the gingiva (gums), the periodontal ligaments, and the tooth sockets (alveolar bone). Gingivitis is the inflammation of the gums, and often includes redness, swelling, bleeding, exudation, and sometimes pain. Gingivitis can be chronic or acute, but is usually a chronic condition.
High filling	Presence of high dental filling material used to artificially restore the function, integrity, and morphology of missing tooth surface.
Sensitivity	Tooth sensitivity is a common name for dentin hypersensitivity or root sensitivity. If hot, cold, sweet or very acidic foods and drinks, or breathing in cold air, makes your teeth or a tooth sensitive or painful then you have sensitive teeth

Table 2. Treatments and its description.

Treatments	Description
Relieve high points	Check for the high points with the articulating paper and remove if any. Put on symptomatic medication, if required.
Root canal treatment	To cure the infection and save the tooth, the dentist drills into the pulp chamber and removes the infected pulp by scraping it out of the root canals. Once this is done, the dentist fills the cavity with an inert material and seals up the opening.
Palliative treatment	Put a patient on antibiotics and analgesics/anti-inflammatory.
Direct pulp capping	When a small amount of pulp becomes exposed during removal of decay or following a traumatic injury, medication is placed directly on the exposed but healthy pulp to prevent further damage. Direct pulp caps have a lower success rate in primary teeth than in permanent teeth, so they are recommended less often for primary teeth.
Indirect pulp capping	When the decay has come very close to the pulp but does not reach it, most of the infected parts of the tooth are removed and a protective dressing is placed over the slight amount of remaining decay. This prevents exposing the pulp and stimulates healing. A filling is then placed in the tooth.
Restoration	The tooth may be restored with a composite filling material if it is a front tooth and the cavity is small, but back teeth in many cases will need a crown.

To tackle such uncertainty, a BN is designed along sign-symptoms and related treatments, which are explained in Table 1 and Table 2 respectively.

Inference mechanism: The probabilistic inference of the system is governed by the Bayes' theorem.

That is,

$$\Pr(Treatment \mid Symptom) = \frac{\Pr(Symptom \mid Treatment).\Pr(Treatment)}{\Pr(Symptom)}$$

In this experimental work the conditional probability tables are estimated with the help of a dentist. This ensures that the estimations are accurate.

Bayesian network: Figure 2 represents the BN of dental caries. It consists of caries, cavity, fistula, swelling, food lodgment, previous broken filing, sensitivity, pain, pain on percussion, partial denture, pulp exposure, high filing as sign-symptom nodes and palliative, RCT, Relieve high points, direct pulp capping, indirect pulp capping, resolution as treatment nodes.

Fig. 2. Dental caries Bayesian network using GeNIe.

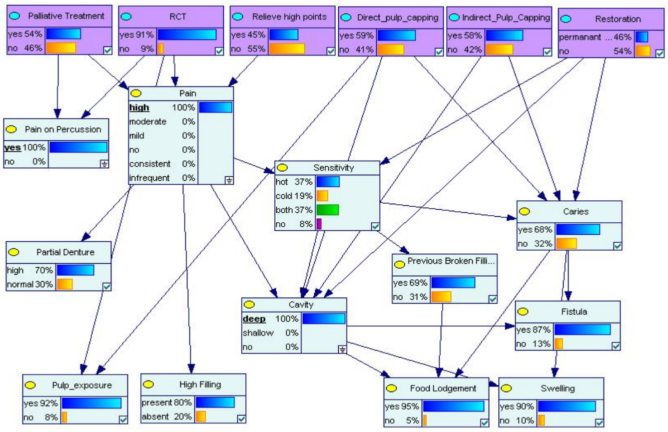


Figure 2 represents the BN of dental caries as Directed Acyclic Graph (DAG). The pink color nodes signify treatments and cyan color node denotes sign-symptoms. The dependency is shown by the help of vertices. In this figure, an illustration is shown for the conditional probability of RCT with 91% when deep cavity, pain and pain on percussion are tested on sample.

Implementation: The pseudo code for the diagnosis system is represented as an algorithm described below:

function GetMostRecTreatment *is*

input: network N,
symptom S_i,
treament T_i

output: treatment T_i

for each Selected(S_i) in N_E *do*
SetEvidence(S_i)

while there exists a treatment T_i which is effected by above operation *do*
if (GetMaxValueOfTraetment(T_i))
return T_i

end function

Fig. 3. View of different sign-symptoms as an input to the BN system.

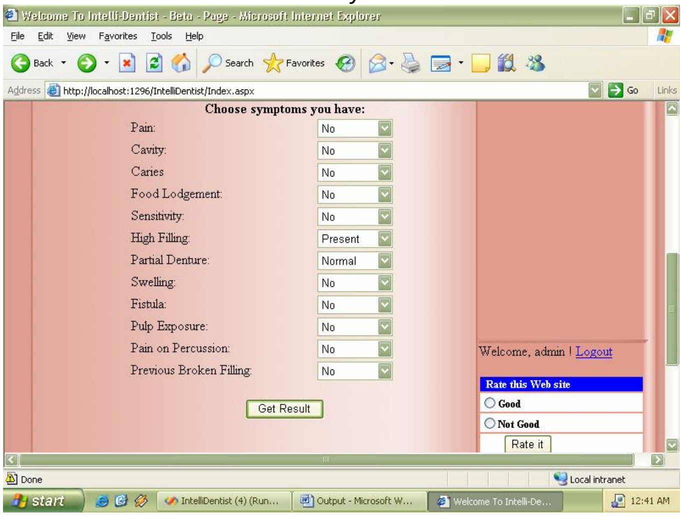
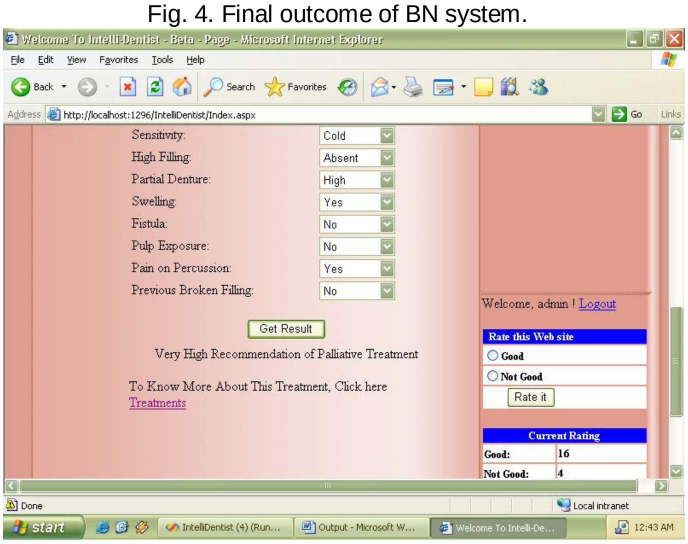


Fig. 4. Final outcome of BN system.



Results and discussion

The results of implementing BN for deciding the effective treatment plan for dental caries are really effective. The final website embedded with BN for deciding treatment plan was made available to both dentists and some patients (Fig. 3 and 4). Both found the system a real boom in assistance. Dentists were overwhelmed the results generated and effectiveness of whole system. This system can be extended to decide other tooth problems in future with more sign-symptoms and treatment plans.

Conclusion

There are many treatment plans that can be carried out as per the prevalent sign-symptoms and dentist usually face a problem in deciding which course of treatment is to be undertaken. To deal such uncertainty, a BN has been designed that suggests a treatment amongst various treatments. This would help a dentist to treat the patient with high level of confidence and hence improve the overall performance. This research is constrained to dental caries only, but can incorporate other oral diseases. In future, interpretation of digital radiographs will be used in decision making of other oral problems.

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