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ORIGINAL PAPER

Application of Bayesian Classifier for the Diagnosis of Dental Pain

Subhagata Chattopadhyay · Rima M. Davis · Daphne D. Menezes · Gautam Singh · Rajendra U. Acharya · Toshio Tamura

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Abstract Toothache is the most common symptom encountered in dental practice. It is subjective and hence, there is a possibility of under or over diagnosis of oral pathologies where patients present with only toothache. Addressing the issue, the paper proposes a methodology to develop a Bayesian classifier for diagnosing some common dental diseases (D=10) using a set of 14 pain parameters (P=14). A questionnaire is developed using these variables and filled up by ten dentists (n=10) with various levels of expertise. Each questionnaire is consisted of 40 real-world cases. Total 14*10*10 combinations of data are hence collected. The reliability of the data (P and D sets) has been tested by measuring (Cronbach's alpha). One-way ANOVA has been used to note the intra and intergroup mean differences. Multiple linear regressions are used for extracting the significant predictors among P and D sets as well as finding the goodness of the model fit. A naïve Bayesian classifier (NBC) is then designed initially that predicts either presence/absence of diseases given a set of pain parameters. The most informative and highest quality datasheet is used for training of NBC and the remaining sheets are used for testing the performance of the classifier. Hill climbing algorithm is used to design a Learned Bayes' classifier (LBC), which learns the conditional probability table (CPT) entries optimally. The developed LBC showed an average accuracy of 72%, which is clinically encouraging to the dentists.

Keywords Bayesian classifier · Dental pain · Hill climbing algorithm · Learning rate · Regressions

S. Chattopadhyay (✉)
School of Computer Studies,
Department of Computer Science and Engineering,
National Institute of Science and Technology,
Berhampur 761008 Orissa, India
e-mail: subhagatachatterjee@yahoo.com

R. M. Davis · D. D. Menezes · G. Singh
Department of Biomedical Engineering,
Manipal Institute of Technology, Manipal University,
Manipal 576 104 Karnataka, India

R. M. Davis
e-mail: rimadave10@yahoo.co.in

D. D. Menezes
e-mail: daphnedebbie@gmail.com

G. Singh
e-mail: gautam1222@gmail.com

R. U. Acharya
Department of Electronic and Communication Engineering,
Ngee Ann Polytechnic,
Clementi 599489, Singapore
e-mail: aru@np.edu.sg

T. Tamura
Department of Medical System Engineering, Chiba University,
Chiba 263-8522, Japan
e-mail: tamurat@faculty.chiba-u.jp

Introduction

Diagnoses of oral pathologies are often difficult and confusing in dentistry, especially for a novice dental student. Kiani and Sheikhazadi [1] noted that for about 56.7% of clinical cases and 40% of non-clinical cases of malpractice claimed that dentists were at faults. Dental diagnosis is a complex process as the dentists' expertise has to comply with the subjectivities in the symptoms. In other words, while assessing the probability of a disease, doctors use cognitive heuristics, which is a mental process of learning, memorizing or processing the information [2] that might be below the mark for a novice intern or student. The

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result is under or over diagnosis for deceptive dental situations [3] leading to litigations.

Pain or toothache is the most common occurrence in dental practice [4] and based on only toothache dentists cannot provide a pinpointed diagnosis to any particular disease involved. Hence it is a huge challenge to develop an automatic decision support system [5], especially where the human knowledge base is inadequate, as seen in trainee dental students, or inexperienced dentists [6]. The tool may help in two ways—(i) it may directly assist in disease diagnosis and (ii) may help students and trainees in gaining confidence so that given similar cases they should be able to diagnose by themselves with time. Hence, this decision tool can serve as an adjunct tool for the doctors to cross check their diagnosis.

Conventional methods of dental diagnosis

Although there have been advances in dental pain research over the past few years, no fundamental development in dental diagnosis has been proposed yet [7], except for some specific illnesses/conditions, such as dental ankylosis [8], dentin hypersensitivity [9], Cerebellopontine angle tumor [10] etc. Probing, sensitivity and percussion testing (which are quite painful procedures) as well as X-ray exposure are still the widely used techniques by dental practitioners. There are also other objective methods such as tooth pulp vitality [11]. However, this paper focuses on toothache-based assessment methods, which are much more subjective and hence lays the research challenge. Such manual assessment has two fold issues—(i) pain perception varies from one person to the other and (ii) manual grading of pain could be biased. Therefore, these procedures are constantly used in dentistry irrespective of the actual need.

Computer aided dental diagnosis

The computers were introduced as an educational tool in dentistry [12] and computer aided learning played an important role in training the dentists [13]. Computer-assisted learning [14] is an acceptable form of education for dental practitioners. However, critical assessment of program structure and content were required to obtain maximum benefits [15]. In several other studies, computer-assisted dental diagnosis has been discussed from the perspective of decision-making processes. The computers have enhanced the diagnostic capabilities [16, 17] of practitioners has and automated the future dental practice [18, 19].

The aim of this paper is to design a methodology for dental decision making using exclusively toothaches, which is a novel research challenge. The basic focus of this work is to mathematically identify some dental diseases (D) based on a set of pain parameters (P) using the concept of Bayesian probabilistic modeling. It is worth mentioning that the P values are obtained from the experts as the probability of occurrences given a case/scenario. This is because of the fact that Bayesian methods are not new applications in health sciences. Bayes' theorem has in fact been used successfully in medical expert systems for decades [20].

The rest of this paper is organized as follows—"Current state of art" describes the current state of art, where various Bayesian applications are discussed in relation to dentistry; "Materials and method" elaborates the Materials and method where the processes and techniques used in this study has been detailed; "Results and discussions" shows and discusses the results, and finally paper concludes in "Conclusions and future work" with the future scopes.

Current state of art

Bayesian methods are being used increasingly in clinical research [21, 22]. The Bayesian approach is ideally suited in adapting ever accumulating information, which is encountered in medical practice [21]. Another advantage of the Bayesian approach is that, it is able to formally incorporate relevant external information in the analysis [23]. For example, in a clinical trial, the trial data can be explicitly combined with the data from similar trials and later can be adapted despite of the subjectivities involved with the clinical scenarios. Such appending and adaptation helps us in making meaningful inferences. It is shown that, Bayesian methods are effective in giving accurate diagnosis results in health sciences [25]. Stojadinovic et al. [24] designed a Bayesian model to predict malignancy in thyroid nodules based on dependence relationships between independent covariates. This model was effectively able to predict malignancy in thyroid nodules.

Nissan et al. [25] developed a probabilistic Bayesian model to predict tumor within a sentinel lymph node, which is a difficult task for the oncologists even after radiologic mapping and biopsy. The model effectively predicted false positive as well as false negative tumors in the suspected lymph nodes.

Bayesian modeling enhanced the interpretation of dental data through the synthesis of dental information as seen in the study of Gilthorpe et al. [26]. Nieri et al. [27] explored the possible causal relationships among several variables for root coverage procedure using a structural learning algorithm of Bayesian networks. They showed that, Bayesian network facilitated the understanding of the relationships among the variables considered.

The use of the Bayesian approach has also been very useful in deciding the course of treatment in dental caries. Mago et al. [28] designed a system based on the Bayesian

net to decide possible treatment plans for dental caries. Its operational effectiveness was attributed to the use of the Bayesian net. Another system using the Bayesian net was designed to detect the presence/absence of dental caries [29]. It demonstrated accurate predictions indicating the higher efficiency of the Bayesian net. The usefulness of the Bayesian approach has been illustrated again by Komarek et al. [30]. In their study the authors examined the effect of fluoride-intake on time to caries development of the permanent first molars in children.

Hence, the accuracy of the outcomes using the Bayesian network has motivated us to design our classifier using Bayesian approach.

Materials and method

The objective of the paper is to design a methodology for diagnosing D given a set of P. The proposed method used for this work is shown in Fig. 1. "Processes involved" discusses the processes of data collection in various sequential steps. "Techniques used" explains the methods of data analyses using the statistical tool SPSS 17 [31] and Bayes' classifier design.

Processes involved

Dental decision making is a complex and challenging task because of its subjectivity, non-linearity in information, and ever increasing volume of raw data as discussed before. The list is expected to show a tendency to grow further and hence was difficult to include each and every symptom and disease in our model.

Step 1: in this step, we have gathered the information of a set of P and the corresponding D (i.e., the cause-effect relationships) from a group of dentists. Fourteen pain parameters *(P)* and its corresponding ten dental diseases *(D)* have been identified (refer to Table 1). It was chosen by the dentists according to its frequency of its occurrence in their day-to-day practice, which is a popular method of acquiring the symptoms-diseases information [32, 33].

Step 2: *Designing the matrix:* fourteen pain parameters and ten diseases were then used to design the matrix for 40 such cases using Eq. 1

$$P_i \times N_j \rightarrow D_k \cdots \quad (1)$$

Where, N = number of cases; P = the pain parameters; D = dental diseases; i varies from 1 to 14; j varies from 1 to 40; and k varies from 1 to 10.

Step 3: *Questionnaire generation:* using the above matrix, a questionnaire was generated by obtaining the initial weights/values [0,1] for all P_i and the dentists were asked to give the probability values of D_k for 40 real-world cases. This is highly subjective in nature and here lies the research challenge. Ten dentists of various levels of expertise were consulted in this study, one is the senior Dean having over 20 years of practice and the remaining are at the junior levels with the average experience of 7.5 years. Appendix 1

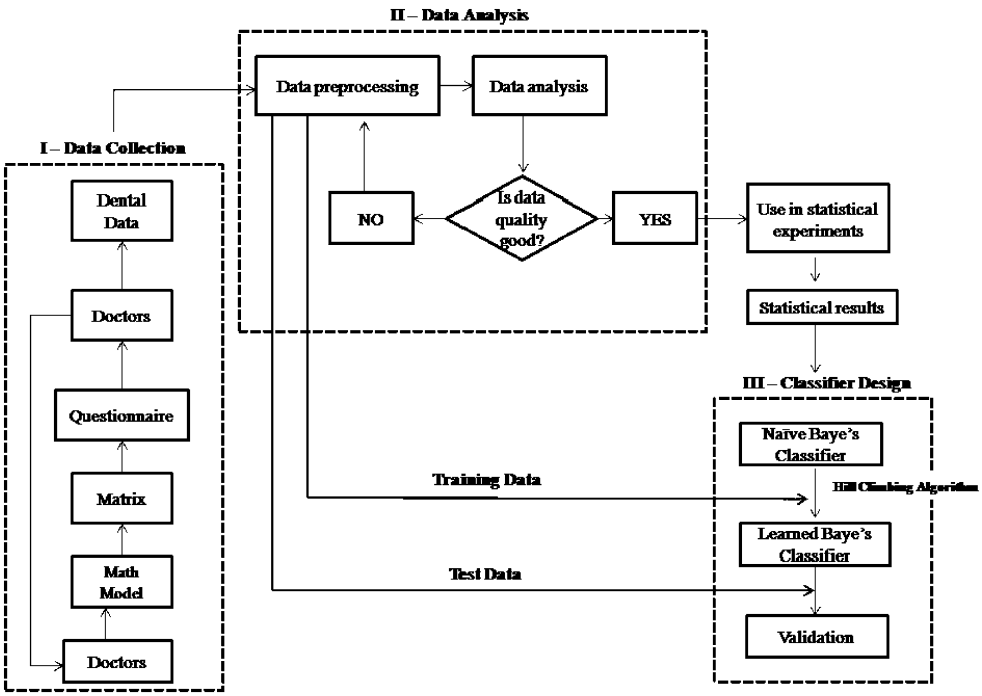

Fig. 1 Flowchart of the proposed methodology

Table 1 Pain parameters and corresponding diseases obtained from dentists (P_i denotes pain parameters where 'i' varies from 1 to 14 and D_k indicate dental diseases, 'k' varies from 1 to 10)

P1	Duration of pain
P2	Caries/trauma/fracture/wasting disease/leakage of restus
P3	Ability to reproduce pain during examination
P4	Quality of pain (severe, throbbing)
P5	Localisation of pain
P6	Sensitivity to temperature, digital pressure
P7	Tenderness on percussion
P8	Drifting of teeth
P9	Facial swelling
P10	Swelling of gums
P11	Bleeding gums
P12	Pus discharge
P13	Pain caused by biting/chewing
P14	Pain caused by opening and closing of jaws
D1	Dentinal pain
D2	Acute pulpitis
D3	Apical periodontitis
D4	Chronic pulpitis
D5	Periodontitis
D6	Acute alveolar abscess
D7	Gingivitis
D8	Periodontal abscess
D9	Acute periodontitis
D10	Cracked tooth

shows the generated matrix as the initial questionnaire and Appendix 2 shows the completed questionnaire. In this study we have consulted ten dentists and hence have ten such questionnaires. The motivation for selecting the training data are the data (i) that has been obtained from the senior Dean having highest level of expertise and (ii) from where maximum number of significant pain parameters could be extracted using statistical technique. Remaining datasheets are then used for testing the classifier and was described below in detail.

Techniques used

Following steps were taken for data exploration, analysis and then developing the Bayes' classifiers.

Step 1: *Exploring the data*

The secondary dental data obtained were assessed for its internal consistency and nature using SPSS-17 statistical software.

Cronbach's α [34, 35] is a popular measure to check the internal consistency of any secondary data (refer to the Eq. 2, below). Its' value increases as the intercorrelations among test items increase. Thus, it is most appropriately used when the items measure different substantive areas within a single construct. It is not a statistical test but rather a coefficient of consistency. It measures how well a set of variables measures a single one-dimensional latent construct. The α is defined as,

$$\alpha = \frac{k}{k-1} * \left[1 - \frac{\sum_{i=1}^{k} \sigma_{\gamma_i}^2}{\sigma_x^2} \right] \cdots \quad (2)$$

Where '*k*' denotes the number of components, σ_X^2 is the variance of the total pain parameters for the current sample of patients, and $\sigma_{\gamma_i}^2$ is the variance of component 'i' for the current sample of patients. After checking the internal consistency and the nature of data, the pain parameters are then regressed (Han and Kamber 2006 [36]) on each of the ten dental diseases to mine the significant relationships. Significant P and D combinations (refer to Appendix 3) were then used to develop the Bayes' classifiers. We have also performed Analysis of Variance (ANOVA) test (refer to Appendix 4) to determine within group and between group differences of the variance (Han and Kamber 2006) using SPSS statistical software.

Step 2: *Designing of Bayesian classifier*

In this step we discuss the development of probabilistic Bayesian classifiers as follows.

a) *Naïve Bayes classifier (NBC)*

NBC is one of the most efficient and effective learning algorithms for machine learning and data mining and is particularly suited when the dimensionality of the inputs is high (Han and Kamber 2006). This classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature. Given the symptoms, the NBC can be used to compute the presence/absence or true/false of various diseases.

A classifier for diagnosing dental diseases from pain parameters (P_i) has been developed. Dental data collected from experts are also explored for its experimental suitability and are now used to develop the classifiers. Bayesian probability estimation techniques (Wong et al. [37]) have been used for diagnostic decision making.

As mentioned, the pain parameters (P_i) of a patient were assigned weights by the experts who also rendered their diagnostic predictions in questionnaire templates. We, performed a Bayesian statistical

analysis to estimate a first hypothesis-conditional probability density function *p(x|D1)* where the hypothesis *D1* relates to a diagnosis condition (i.e. diagnosis of dentinal disease) given pain parameters *(Pi) x(x=P1,...,P14)*, and similarly we have estimated the conditional probability density function for *p(x|D2)...p(x|D10)*. Next, a prior probability density function *p(D)* is determined for the disease hypothesis *D1*, *D2*, *D10*. Further a posterior conditional probability density function *p(D|X)* is determined for each of the hypothesis *D1*, *D2,..., D10*. Pain parameter *(P)* values are represented by *X* (refer to Eq. 3, below). This technique represents an application of Bayesian probability estimation to dental data. This methodology can be useful in identifying unapparent diseases from the clinical data, while screening tests for a disease condition are not readily available. The formula can be summarized as follows:

$$p\left(\frac{D}{X}\right) = \frac{p(D)p\left(\frac{X}{D}\right)}{p(X)}\cdots \tag{3}$$

- $p(D)$ is the prior probability of the probability that D is correct before the data X is seen.
- $p\left(\frac{X}{D}\right)$ is the conditional probability of seeing the data X given that the hypothesis D is true.
- $p\left(\frac{X}{D}\right)$ is called the likelihood.
- $p(X)$ is the marginal probability of X.
- $p\left(\frac{D}{X}\right)$ is the posterior probability: the probability that the hypothesis is true, given the data and the previous state of belief about the hypothesis.

As mentioned earlier, the datasheet obtained from the highest expertise level has been selected as the training data set in this study. Also, the same datasheet could render the maximum significant pain parameters. The remaining nine datasheets are kept for testing the classifier. Results are shown and discussed in "Results and discussions".

b) *Learned Bayes classifier (LBC)*

Naïve Bayes' classifier has several limitations (Russel and Norvig [38]) and hence LBC is used to predict the dental diseases using significant pain parameters. From the regression results it was seen that out of the 14 pain parameters, only six, i.e., *P3, P4, P7, P8, P9, P11* and its related diseases, i.e., *D1, D2, D3, D4, D6, D7* were significant and the rest were redundant. Hence a revised matrix has been generated and shown in Table 2 below.

Hill climbing search algorithm (Rosenbrock [39]) was used to train the classifier and compute the conditional probability table (CPT) entries (refer to Fig. 2) and is explained below.

Let D be the training set of data tuples (in batch of) $X_1, X_2, \ldots X_{|D|}\big|$. Training the Bayesian network means that it must learn the values found as the CPT entries. Let W_{ij} be a CPT entry for variable $Y_i = y_{ij}$ having parent nodes $U_i = u_{ik}$, where, it could be stated that $w_{ijk} = p\left(Y_i = y_{ij} | U_i = u_{ik}\right)$. '$p_w$' are basically the predictive probability of occurrences of diseases, while w_{ijk} are the CPT entries, Y_i denote diseases; y_{ij} is its Boolean value; U_i lists the parent nodes of Y_i i.e., the pain conditions and u_{ik} lists the values of the parent nodes.

The w_{ijk} values are viewed as weights. The weights are initialized to random probability values. Gradient descent strategy is the performed on these weights. In each of the iterations the weights are updated and eventually converge to an optimum solution. The algorithm proceeds as follows:

i) *Compute the gradients*: for each i, j, k, compute,

$$\frac{\partial \ln p_w(D)}{\partial w_{ijk}} = \sum_{d=1}^{|D|} \frac{p\left(Y_i = y_{ij}, U_i = u_{ik} | X_d\right)}{w_{ijk}}\cdots \tag{4}$$

ii) *The direction of the gradient*: The weights are updated by

$$w_{ijk} = w_{ijk} + (l)\frac{\partial \ln p_w(D)}{\partial w_{ijk}}\cdots \tag{5}$$

Where l is the learning rate representing the step size $\frac{d \ln p_w(D)}{dw_{ijk}}$ is computed from (4).

iii) *Renormalize the weights*: Because the weights w_{ijk} are probability values, they must be between 0.0 and 1.0, and $\sum_j w_{ijk}$ must equal 1 for all *i,k*.

Next, the performance of LBC is tested after confirming the best learning rate through parametric studies, where 'l' is varied to note the updating of weight values. Results of parametric study are shown in the next section.

Sensitivity, specificity and accuracy are measured to assess the performance of LBC. Refer to Eqs. 6, 7 and 8 as shown below.

$$sensitivity = \frac{t_{pos}}{pos}\cdots \tag{6}$$

$$specificity = \frac{t_{neg}}{neg}\cdots \tag{7}$$

$$accuracy = sensitivity\frac{pos}{pos+neg} + specificity\frac{neg}{pos+neg} \tag{8}$$

In Eqs. 6–8, t_{pos}, pos, t_{neg}, neg denote 'true positive', 'true + false positive', 'true negative', and 'true + false negative' cases, respectively.

Table 2 New Revised Matrix: significant pain (P) parameters and diseases (D)

S.NO	P3	P4	P7	P8	P9	P11	D1	D2	D3	D4	D6	D7
1	0.7	0.1	0.05	0.05	0.05	0.05	0	0	0	0.8	0	0
2	0.5	0.3	0.05	0.05	0.05	0.05	0	0.8	0	0	0	0
3	0.35	0.1	0.35	0.1	0.05	0.05	0	0	0.9	0	0	0
4	0.15	0.3	0.3	0.1	0.1	0.05	0	0.1	0.9	0	0	0
5	0.05	0.1	0.05	0.05	0.05	0.7	0	0	0	0	0	1
6	0.3	0.3	0.2	0.1	0.05	0.05	0	0.9	0	0	0	0
7	0.5	0.3	0.05	0.05	0.05	0.05	0	0	0	1	0	0
8	0.4	0.4	0.05	0.05	0.05	0.05	0	1	0	0	0	0
9	0.35	0.15	0.35	0.05	0.05	0.05	0	0	1	0	0	0
10	0.5	0.15	0.2	0.05	0.05	0.05	0	0	0	0.9	0	0
11	0.05	0.2	0.05	0.05	0.05	0.4	0	0	0	0	0	1
12	0.25	0.4	0.25	0.05	0.05	0.05	0	0.2	0.8	0	0	0
13	0.4	0.4	0.05	0.05	0.05	0.05	0	0.9	0.1	0	0	0
14	0.3	0.5	0.05	0.05	0.05	0.05	0.4	0.6	0	0	0	0
15	0.3	0.3	0.05	0.15	0.05	0.15	0	0.6	0	0	0	0
16	0.1	0.1	0.05	0.05	0.05	0.65	0	0	0	0	0	1
17	0.35	0.25	0.25	0.05	0.05	0.05	0	0	1	0	0	0
18	0.5	0.1	0.1	0.1	0.1	0.1	0	0	0	1	0	0
19	0.4	0.4	0.05	0.05	0.05	0.05	0.8	0.2	0	0	0	0
20	0.35	0.15	0.4	0.05	0.05	0.05	0	0.2	0.8	0	0	0
21	0.15	0.3	0.15	0.15	0.15	0.1	0	0	0	1	0	0
22	0.15	0.35	0.15	0.15	0.15	0.05	0	0	0	0	1	0
23	0.05	0.05	0.05	0.05	0.75	0.05	0	0	0	0	0	1

The test cases are validated by calculating the sensitivity, specificity and accuracy of the classifier. The accuracy of the classifier on a given test set is the percentage of test set tuples that are correctly classified by a classifier. This is known as the overall recognition rate of the classifier. The tuples can be termed as positive tuples (i.e., presence of disease) and negative tuples (i.e., absence of disease). True positives are the positive tuples that were correctly labeled by

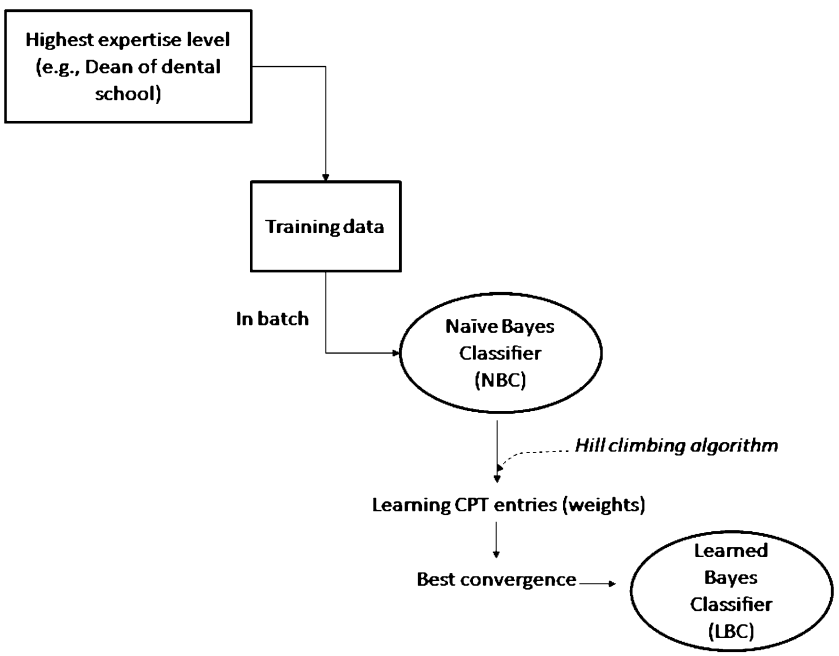

Fig. 2 A schematic diagram explaining the classifier training process

Table 3 Parametric study: updating of weights by varying learning rate 'l'

D7					
Updated weights	S,NO	Initial weight	Learning rate		
			0.2	0.5	0.7
	1	0.4	0.4	0.4	0.4
	2	0.4	0.4	0.4	0.4
	3	0.4	0.4	0.4	0.4
	4	0.4	0.4	0.4	0.4
	5	0.2	0.2	0.2	0.2
	6	0.4	0.4	0.4	0.4
	7	0.2	0.2	0.2	0.2
	8	0.4	0.4	0.4	0.4
	9	0.4	0.4	0.4	0.4
	10	0.4	0.4	0.4	0.4
	11	0.4	0.4	0.4	0.4
	12	0.2	0.2	0.2	0.2
	13	0.4	0.4	0.4	0.4
	14	0.2	0.2	0.2	0.2
	15	0.4	0.4	0.4	0.4
	16	0.2	0.2	0.2	0.2
	17	0.4	0.4	0.4	0.4
	18	0.4	0.4	0.4	0.4
	19	0.2	0.2	0.2	0.2
	20	0.2	0.2	0.2	0.2
	21	0.1	0.1	0.1	0.1
	22	0.2	0.2	0.2	0.2
	23	0.4	0.4	0.4	0.4
	24	0.2	0.2	0.2	0.2
	25	0.4	0.4	0.4	0.4
	26	0.2	0.2	0.2	0.2
	27	0.2	0.2	0.2	0.2
	28	0.4	0.4	0.4	0.4
	29	0.2	0.2	0.2	0.2
	30	0.2	0.2	0.2	0.2
	31	0.1	0.1	0.1	0.1
	32	0.1	0.1	0.1	0.1
	33	0.2	0.2	0.2	0.2
	34	0.4	0.4	0.4	0.4
	35	0.2	0.2	0.2	0.2
	36	0.2	0.2	0.2	0.2
	37	0.1	0.1	0.1	0.1
	38	0.2	0.2	0.2	0.2
	39	0.2	0.2	0.2	0.2
	40	0.1	0.1	0.1	0.3
	41	0.2	0.2	0.2	0.3
	42	0.2	0.2	0.2	0.3
	43	0.4	0.4	0.4	0.7
	44	0.4	0.4	0.4	0.6
	45	0.2	0.2	0.2	0.5
	46	0.2	0.2	0.2	0.3
	47	0.2	0.2	0.2	0.7
	48	0.1	0.1	0.1	0.6
	49	0.1	0.1	0.3	0.4
	50	0.2	0.2	0.3	0.7
	51	0.1	0.1	0.2	0.8
	52	0.1	0.1	0.3	0.3
	53	0.1	0.1	0.2	0.5
	54	0.2	0.2	0.2	0.6
	55	0.2	0.2	0.4	0.8
	56	0.2	0.2	0.3	0.9
	57	0.1	0.1	0.1	0.2
	58	0.2	0.2	0.2	0.3
	59	0.1	0.2	0.3	0.9
	60	0.1	0.2	0.3	0.8
	61	0.2	0.2	0.3	0.8
	62	0.1	0.2	0.4	0.8
	63	0.2	0.2	0.3	0.9
	64	0.1	0.2	0.3	0.9

the classifier, while the true negatives are the negative tuples that were correctly labeled by the classifier. False positives are the negative tuples that were incorrectly labeled (absence of the disease for which the classifier labels as presence of the disease). False negatives are the positive tuples that were incorrectly labeled (presence of the disease for which the classifier predicts as absence of the disease).

Results and discussions

This section shows the results of the experiment in a sequence of "Materials and method" and validates the performance of the LBC.

Results of data exploration

Cronbach's alpha and multiple linear regressions (MLR) were carried out. The reason for applying MLR is the note the goodness of the model as well as extracting the significant pain parameters (i.e., the predictors). After analyzing these values for all the ten datasheets, it was seen that datasheet 1 outperformed other by quality—it has the highest Cronbach's alpha value, 0.75 and the regressions studies with confidence interval of 95% (Campbell and Gardner [40]) showed that the average correlation coefficient (R) for the model is close to 60% that does not indicate a bad model fit. From the regression results it maybe noted that P3 (Ability to reproduce pain during examinations) is a significant association of D6 (Acute alveolar abscess); P4 (Quality

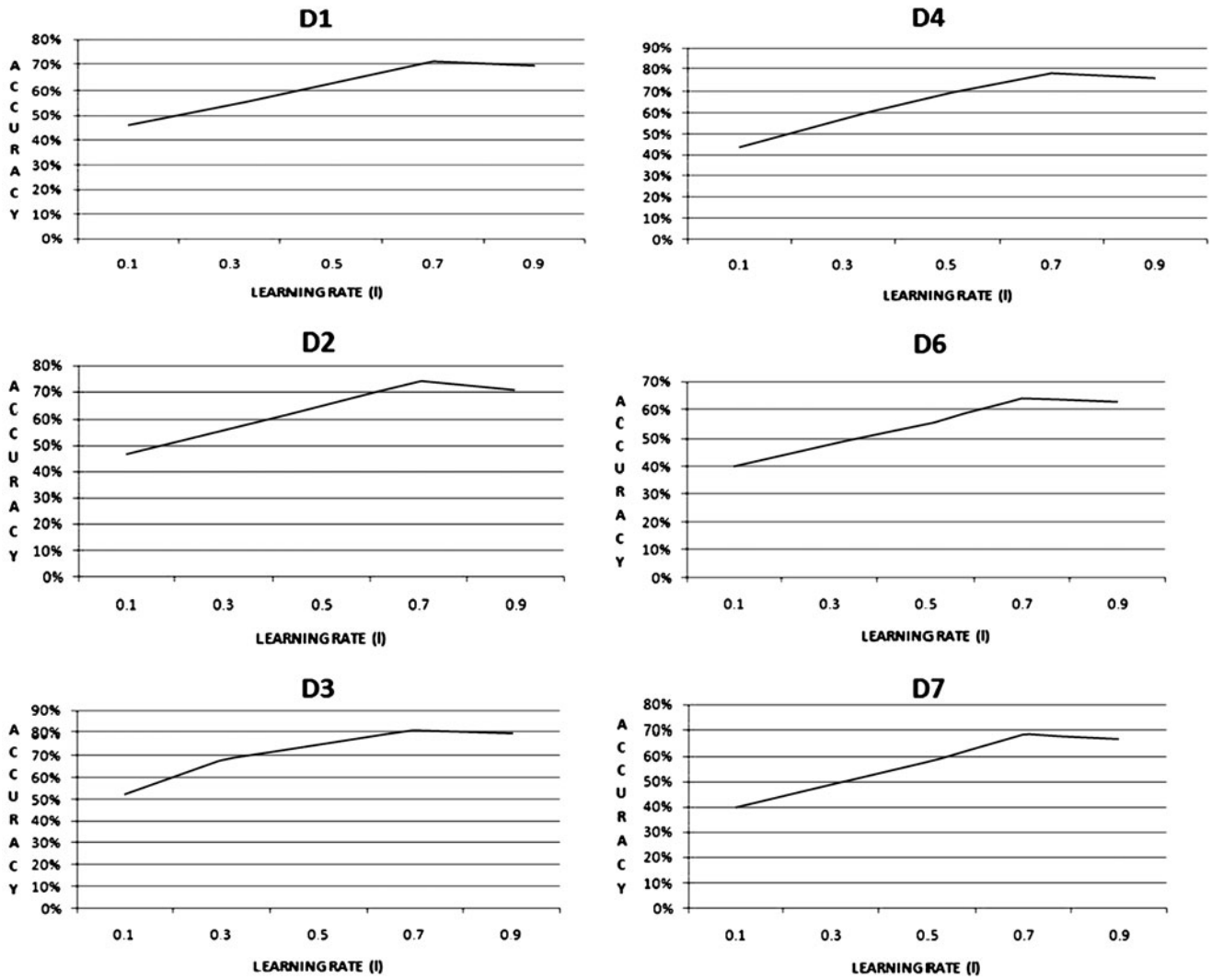

Fig. 3 Plots of accuracy vs. learning for dental diseases

of pain) indicates a significant association with D1 (Dentinal pain), D2 (Acute pulpitis), and D3 (Apical periodontitis); P7 (tenderness on percussion) is a significant association of D2 and D4 (Chronic pulpitis); P8 (Drifting of teeth) is significantly associated with D6 and D7 (Gingivitis); P9 (Facial swelling) is significantly exists with D6; and finally P11 (Bleeding gums) significantly associated with D7. It can be seen that out of the 14 pain parameters, six are significant, i.e., *P3, P4, P7, P8, P9, P11* that are related to *D1, D2, D3, D4, D6, D7* and the remaining are not much interesting for this model. Hence the training data matrix has been revised to pinpoint diagnostic decision making.

The Analysis of variance (ANOVA) results have been tabulated in Appendix 4. It compares the *means* between the ten diseases. Sigma seeks to improve the quality of process outputs by identifying and removing the causes of defects (errors) and minimizing variability [41]. The low sigma values in Appendix 5 signify that the matching is effective with minimal errors. In Appendix 5, dental diseases *D1*, *D2*, *D3*, *D4*, *D6*, and *D7* are significant to explain the ANOVA model for the datasheet 1.

Datasheet-1, has been chosen as the master training data set while the remaining datasheets are taken as test data. The statistical results for datasheet-1 are shown in Appendix 3 and 4.

Results of development of NBC

NBC assumes the conditional class independence to exist, which may not be true. The variables may not be independent for each other for all cases [42]. In this study, using C++ language an NBC is developed at first, which infers for a particular disease (in this case *D1, D2, D3, D4, D6, D7*)

given a set of conditions (*P3*, *P4*, *P7*, *P8*, *P9*, *P11*) either true/false [1/0]. The CPT (refer Appendix 5) shows the combinations of pain parameters predicting dental diseases.

In the next phase, Hill climbing algorithm has been used in NBC to inject maturity in decision making and the maturity depends on varying learning rates (incremental), reflected by updating of weights. In the next section we show and discuss (i) the parametric study to optimize the learning rate and (ii) the performance of LBC.

Results of development Learned Bayes' classifier (LBC)

Hill climbing algorithm has been used to train the NBC. The gradients are first computed using Eq. 4. The weights are then updated using Eq. 5. It is important to mention here that the datasheet-1 is used as the training set for the proposed classifiers. The learning rate (*l*) computed for the datasheet 1 is 0.5 as there is not much significant change of initial weights even after increasing the *l* value and hence we call it as the optimized '*l*'. Now for each test data i.e., data sheet 2–10, the CPT has been tabulated for 64 combinations (see Appendix 5).

Using the '*l*' values ranging from 0.2 to 0.7 the corresponding weights (i.e., the probability of diagnosing a specific disease) are updated (i.e., to render proper diagnosis), because if the weights are constant we are still either under diagnosing or over diagnosing the disease. It is found that '*l*'=0.7 is the most optimum learning rate, as beyond this value the weights are not being updated much. The result for disease *D7* of datasheet-2 (one of the test sets) has been shown in Table 3. Similarly, the weights for *D1*, *D2*, *D3*, *D4*, *D6* are also updated for all the remaining datasheets with *l*=0.7. The graphs, below showing accuracies versus learning rate (*l*) variations for each of the diseases are shown below (Fig. 3).

Testing the performance of the LBC

The performance of LBC has been tested using 9 data sheets on classifying 6 diseases (*D1*, *D2*, *D3*, *D4*, *D6*, and *D7*) using 6 pain parameters *(P3*, *P4*, *P7*, *P8*, *P9*, *P11*). Sensitivity, specificity and accuracy of the developed classifier have been calculated to validate the performance of the LBC using Eqs. 6, 7 and 8, respectively. Table 4 shows the individual as well as the average sensitivity, specificity, and accuracy values.

Conclusions and future work

Dental pain is the most common symptom in dentistry and highly subjective in nature. Thus, diagnosing a dental

Table 4 Sensitivity, Specificity, Accuracy measures of six significant diseases (D1–D4, D6, D7) with nine sets of test cases

Sheet No.	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
	D1			D2			D3			D4			D6			D7		
Data sheet 2	61	88	83	75	77	76	86	82	83	49	85	74	71	94	69	71	89	67
Data sheet 3	66	65	64	87	47	73	85	68	71	61	55	63	79	73	76	88	48	59
Data sheet 4	44	81	59	57	76	52	68	94	71	31	93	67	45	97	64	47	91	54
Data sheet 5	69	96	82	81	92	65	84	91	85	53	94	76	69	95	81	70	95	73
Data sheet 6	83	98	79	84	96	69	93	98	87	79	97	79	87	96	82	81	94	80
Data sheet 7	65	94	83	70	92	76	76	88	83	42	97	74	66	89	71	59	95	77
Data sheet 8	46	93	54	40	84	64	43	91	74	37	89	68	47	92	61	51	85	56
Data sheet 9	71	88	75	89	82	79	93	87	85	83	89	77	82	88	84	92	84	76
Data sheet 10	32	91	64	54	79	71	58	75	82	31	83	75	30	81	82	34	85	64
Average	58	81	71	71	73	74	78	88	81	48	93	78	64	96	64	68	87	69

disease based on the pain parameters *(P)* is a challenging task and mandates many painful procedures (e.g., percussion, probing etc.) and X-Ray exposure to the patients. This paper discusses a detailed methodology for designing a Bayesian classifier for the automatic detection of dental diseases using exclusively pain-related parameters. Statistical data analysis with regression studies on the real-world dental data show that P3 (Ability to reproduce pain during examinations) has a significant association (i.e., $p<0.05$) of D6 (Acute alveolar abscess); P4 (Quality of pain) indicates a significant association with D1 (Dentinal pain), D2 (Acute pulpitis), and D3 (Apical periodontitis); P7 (tenderness on percussion) is a significant association of D2 and D4 (Chronic pulpitis); P8 (Drifting of teeth) is significantly associated with D6 and D7 (Gingivitis); P9 (Facial swelling) is significantly present with D6; and finally P11 (Bleeding gums) is significantly associated with D7. In the next step, the above-mentioned information is used to design the LBC using Hill climbing algorithm. The optimum learning rate (l) has been engineered after careful parametric studies and the best 'l' (which is 0.7 in this case) has been selected based on the best updating of the weight values for all the diseases.

Finally, the sensitivities, specificities, and accuracies of the developed LBC are measured for each disease given all test datasheets. It is able to diagnose D1–D4, D6, and D7 with the average accuracy of 72%, which is an encouraging result as per the human experts.

The contributions of the work are three-fold—(i) the research methodology, (ii) construction of the Bayes' model on a set of subjective dental data, and (iii) the average diagnostic accuracy of dental diseases exclusively by the 'pain'-related parameters, which is novel in dental healthcare research.

In the end the authors also propose that such a classifier might be tested in dental clinics, in view of assisting novice dentists in diagnosing dental illnesses based on the pain symptoms as it learns and matures. It on the other hand may also act as a teacher by familiarizing them with various cases so that they may be able to diagnose similar cases in future independently. However, such assumptions need careful examinations in future. It will also be much of research interest to note whether establishing such a tool in dental Outpatient Door (OPD) could reduce the load of X-Ray exposure and painful clinical tests.

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Appendix 1

Table 5 Generated matrix as a questionnaire template

S.NO	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
1	0.70	0.6	0.1	0	0.4	0.1	0.8	0.9	0.5	0.7	0	0	0	0										
2	0.30	0.6	0.3	0.1	0.6	0.8	0	0	0	0	0	0	0.1	0.1										
3	0.60	0.4	0.9	0.8	0.2	0.7	0	0	0	0	0	0	0.3	0.3										
4	0.50	0.4	0.8	0.6	0.8	0.7	1	0.1	0	0	0	0	0.5	0.5										
5	0.40	0.4	0.8	0.2	0.3	0.6	0.5	0	0	0	0	0	0.1	0.1										
6	0.30	0.1	0.2	0.3	0.2	0.1	0.4	0.8	0	0.6	0.9	0.5	0.3	0.3										
7	0.80	0.9	0.7	1	0.9	0.8	1	0.5	0.6	0.5	0	0.6	0.5	0.5										
8	0.00	0.1	0	0.1	0	0	0	0	0	0.5	1	0	0	0										
9	0.80	0	0.6	0.7	0.7	0.6	0.6	0.2	0.3	0.3	0.4	0.7	0.5	0.7										
10	0.60	0.8	0.7	0.8	0.8	0.9	0.5	0.1	0	0	0	0	0.7	0.7										
11	0.10	0.4	0.3	0.1	0.6	0.5	0	0	0	0	0	0	0.1	0										
12	0.20	0.5	0.8	0.8	0.2	0.6	0	0	0	0	0	0	0.3	0										
13	0.20	0.5	0.9	0.5	0.7	0.4	1	0	0	0	0	0	0.4	0.4										
14	0.80	0.5	0.7	0.1	0.2	0.6	0.4	0	0	0	0	0	0.2	0.2										
15	0.90	0.2	0.6	0.2	0.1	0.1	0.6	0.8	0	0.4	0.8	0.4	0.4	0.4										

Table 5 (continued)

S.NO	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
16	0.20	0.9	0	0.9	0.8	0.8	1	0.2	0.7	0.6	0	0.3	0.6	0.6										
17	0.10	0.1	0	0.2	0	0	0	0	0	0.4	0.4	0	0	0										
18	0.50	0	0.6	0.5	0.7	0.5	0.7	0.2	0.4	0.7	0.4	0.6	0.3	0.3										
19	0.20	0	0.8	0.6	0.6	0.6	0.7	0.1	0	0.6	0.4	0.5	0.6	0.6										
20	0.10	0.7	0.4	0.8	0.7	0.9	0.6	0	0	0	0	0	0.6	0.6										
21	0.10	1	0.7	0.7	0.5	0.8	0	0	0	0	0	0	0.1	0										
22	0.50	1	0.5	0.9	0.2	0.9	0	0	0	0	0	0	0.7	0										
23	0.60	1	0.9	0.7	0.4	0.7	1	0	0	0	0	0	0.7	0										
24	0.70	1	0.5	0.7	0.1	0.7	0	0	0	0	0	0	0.2	0										
25	0.20	0	0.5	0.6	0.6	0	0	0	0	0.5	0	0	0.4	0.6										
26	0.70	1	0.8	0.8	0.1	0.7	0	0.7	0	0.7	0.7	0	0.7	0.5										
27	0.10	0	0.1	0.1	0.4	0	0	0	0	0.4	0.7	0	0	0										
28	0.80	0	0.6	0.5	0.8	0	0.7	0.5	0	0	0.3	0.7	0.1	0										
29	0.80	0	0.8	0.7	0.7	0	0	0	0	0.7	0.1	0.5	0	0.7										
30	0.40	1	0.8	0.7	0.5	0.4	0.7	0	0	0	0	0	1	0										
31	0.20	0.5	0.2	0	0.5	0.8	0	0	0	0	0	0	0.5	0										
32	0.50	0.3	0.8	0.9	0.1	0.6	0	0	0	0	0	0	0.5	0										
33	0.40	0.5	0.7	0.6	0.9	0.5	0.9	0	0	0	0	0	0.8	0										
34	0.40	0.5	0.7	0.5	0.2	0.3	0.2	0	0	0	0	0	0	0										
35	0.20	0	0.1	0.2	0.1	0	0.3	0.6	0	0.2	0.8	0.5	0.5	0										
36	0.70	0.8	0.9	1	0.8	0.8	0.9	0.9	0.9	0.9	0.3	0.5	0.8	0.7										
37	0.00	0	0	0	0	0	0	0	0.5	0.9	0	0	0	0										
38	0.50	0	0.5	0.5	0.8	0.7	0.6	0.5	0	0.8	0.5	0.8	0.7	0										
39	0.70	0	0.5	0.6	0.8	0.6	0	0.2	0.7	0.9	0.9	0.7	0.9	0.8										
40	0.50	0.7	0.8	0.9	0.7	0.8	0.8	0	0	0	0	0	0.9	0.2										

Appendix 2

Table 6 Filled-up questionnaire: a sample

S.NO	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
1	0.70	0.6	0.1	0	0.4	0.1	0.8	0.9	0.5	0.7	0	0	0	0	0	0	0	0	0.5	0	0	0.5	0	0
2	0.30	0.6	0.3	0.1	0.6	0.8	0	0	0	0	0	0	0.1	0.1	0	0	0	0.8	0	0	0	0	0.2	0
3	0.60	0.4	0.9	0.8	0.2	0.7	0	0	0	0	0	0	0.3	0.3	0	0.8	0	0	0	0	0	0	0.2	0
4	0.50	0.4	0.8	0.6	0.8	0.7	1	0.1	0	0	0	0	0.5	0.5	0	0	0.9	0	0	0	0	0	0.1	0
5	0.40	0.4	0.8	0.2	0.3	0.6	0.5	0	0	0	0	0	0.1	0.1	0	0	0.5	0	0.5	0	0	0	0	0
6	0.30	0.1	0.2	0.3	0.2	0.1	0.4	0.8	0	0.6	0.9	0.5	0.3	0.3	0	0	0	0	0	0.2	0	0.2	0.6	0
7	0.8	0.9	0.7	1	0.9	0.8	1	0.5	0.6	0.5	0	0.6	0.5	0.5	0	0.1	0.9	0	0	0	0	0	0	0
8	0.00	0.1	0	0.1	0	0	0	0	0	0.5	1	0	0	0	0	0	0	0	0	0	1	0	0	0
9	0.80	0	0.6	0.7	0.7	0.6	0.6	0.2	0.3	0.3	0.4	0.7	0.5	0.7	0	0	0	0	0	0	0	0	1	0
10	0.60	0.8	0.7	0.8	0.8	0.9	0.5	0.1	0	0	0	0	0.7	0.7	0	0.9	0	0	0	0	0	0	0.1	0
11	0.10	0.4	0.3	0.1	0.6	0.5	0	0	0	0	0	0	0.1	0	0	0	0	1	0	0	0	0	0	0
12	0.20	0.5	0.8	0.8	0.2	0.6	0	0	0	0	0	0	0.3	0	0	1	0	0	0	0	0	0	0	0
13	0.20	0.5	0.9	0.5	0.7	0.4	1	0	0	0	0	0	0.4	0.4	0	0	1	0	0	0	0	0	0	0
14	0.80	0.5	0.7	0.1	0.2	0.6	0.4	0	0	0	0	0	0.2	0.2	0	0	0	0.9	0.1	0	0	0	0	0
15	0.90	0.2	0.6	0.2	0.1	0.1	0.6	0.8	0	0.4	0.8	0.4	0.4	0.4	0	0	0	0	0.1	0	0	0.9	0	0
16	0.20	0.9	0	0.9	0.8	0.8	1	0.2	0.7	0.6	0	0.3	0.6	0.6	0	0	0	0	1	0	0	0	0	0

Table 6 (continued)

S.NO	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
17	0.10	0.1	0	0.2	0	0	0	0	0	0.4	0.4	0	0	0	0	0	0	0	0	0	1	0	0	0
18	0.50	0	0.9	0.5	0.7	0.5	0.7	0.2	0.4	0.7	0.4	0.6	0.3	0.3	0	0	0	0	0	0	0	0.5	0.5	0
19	0.20	0	0.8	0.6	0.6	0.6	0.7	0.1	0	0.6	0.4	0.5	0.6	0.6	0	0	0	0	0	0	0	0.2	0.8	0
20	0.10	0.7	0.4	0.8	0.7	0.9	0.6	0	0	0	0	0	0.6	0.6	0	0.2	0.8	0	0	0	0	0	0	0
21	0.10	1	0.7	0.7	0.5	0.8	0	0	0	0	0	0	0.1	0	0	0.9	0.1	0	0	0	0	0	0	0
22	0.50	1	0.5	0.9	0.2	0.9	0	0	0	0	0	0	0.7	0	0	0.5	0	0	0	0	0	0	0	0.5
23	0.60	1	0.9	0.7	0.4	0.7	1	0	0	0	0	0	0.7	0	0	0	0.5	0	0	0	0	0	0	0.5
24	0.70	1	0.5	0.7	0.1	0.7	0	0	0	0	0	0	0.2	0	0.4	0.6	0	0	0	0	0	0	0	0
25	0.20	0	0.5	0.6	0.6	0	0	0	0	0.5	0	0	0.4	0.6	0	0	0	0	0	0	0	0.2	0.8	0
26	0.70	1	0.8	0.8	0.1	0.7	0	0.7	0	0.7	0.7	0	0.7	0.5	0	0.6	0	0	0.2	0	0	0	0.2	0
27	0.10	0	0.1	0.1	0.4	0	0	0	0	0.4	0.7	0	0	0	0	0	0	0	0	0	1	0	0	0
28	0.80	0	0.6	0.5	0.8	0	0.7	0.5	0	0	0.3	0.7	0.1	0	0	0	0	0	1	0	0	0	0	0
29	0.80	0	0.8	0.7	0.7	0	0	0	0	0.7	0.1	0.5	0	0.7	0	0	0	0	0	0	0.2	0	0.8	0
30	0.40	1	0.8	0.7	0.5	0.4	0.7	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
31	0.20	0.5	0.2	0	0.5	0.8	0	0	0	0	0	0	0.5	0	0	0	0	1	0	0	0	0	0	0
32	0.50	0.3	0.8	0.9	0.1	0.6	0	0	0	0	0	0	0.5	0	0.8	0.2	0	0	0	0	0	0	0	0
33	0.40	0.5	0.7	0.6	0.9	0.5	0.9	0	0	0	0	0	0.8	0	0	0.2	0.8	0	0	0	0	0	0	0
34	0.40	0.5	0.7	0.5	0.2	0.3	0.2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
35	0.20	0	0.1	0.2	0.1	0	0.3	0.6	0	0.2	0.8	0.5	0.5	0	0	0	0	0	0.5	0	0.5	0	0	0
36	0.70	0.8	0.9	1	0.8	0.8	0.9	0.9	0.9	0.9	0.3	0.5	0.8	0.7	0	0	0	0	0	1	0	0	0	0
37	0.00	0	0	0	0	0	0	0	0.5	0.9	0	0	0	0	0	0	0	0	0	0	1	0	0	0
38	0.50	0	0.5	0.5	0.8	0.7	0.6	0.5	0	0.8	0.5	0.8	0.7	0	0	0	0	0	1	0	0	0	0	0
39	0.70	0	0.5	0.6	0.8	0.6	0	0.2	0.7	0.9	0.9	0.7	0.9	0.8	0	0	0	0	0	0	0	0	1	0
40	0.50	0.7	0.8	0.9	0.7	0.8	0.8	0	0	0	0	0	0.9	0.2	0	0.5	0	0	0	0	0	0	0	0.5

Appendix 3

Table 7 Regression results of ten datasheets: italicized values indicate significant diseases (D) that are used to develop the Bayesian classifier

	Beta	Sig.	C.I		Beta	Sig.	C.I		Beta	Sig.	C.I		Beta	Sig.	C.I		Beta	Sig.	C.I	
			L.B	U.B			L.B	U.B			L.B	U.B			L.B	U.B			L.B	U.B
	D1				D2				D3				D4				D5			
Const.		0.45	−0.1	0.26		0.54	−0.4	0.22		0.45	−0.1	0.26		0.02	0.09	0.8		0.44	−0.2	0.51
P1	0.32	0.2	−0.1	0.44	0	0.91	−0.5	0.42	0.32	0.2	−0.1	0.44	−0.1	0.77	−0.6	0.43	0.11	0.65	−0.4	0.64
P2	−0.7	0.06	−0.5	0.01	−0.1	0.75	−0.5	0.38	−0.7	0.06	−0.5	0.01	0.31	0.31	−0.3	0.78	−0.1	0.71	−0.6	0.44
P3	−0.2	0.42	−0.4	0.16	0.05	0.82	−0.4	0.48	−0.2	0.42	−0.4	0.16	0.18	0.43	−0.3	0.69	−0.5	0.07	−1	0.03
P4	0.7	***0.03***	0.03	0.59	0.68	***0.01***	0.21	1.11	0.7	***0.03***	0.03	0.59	−1	0	−1.5	−0.5	0.22	0.44	−0.3	0.74
P5	−0.3	0.26	−0.4	0.12	0.07	0.75	−0.4	0.51	−0.3	0.26	−0.4	0.12	0.1	0.67	−0.4	0.61	0.09	0.74	−0.4	0.61
P6	0.29	0.33	−0.1	0.39	0.37	0.1	−0.1	0.78	0.29	0.33	−0.1	0.39	0.17	0.49	−0.3	0.66	0.16	0.57	−0.4	0.65
P7	−0.1	0.76	−0.2	0.15	−0.4	***0.05***	−0.6	0	−0.1	0.76	−0.2	0.15	−0.5	***0.03***	−0.7	0	0.28	0.24	−0.1	0.55
P8	0.11	0.69	−0.2	0.33	0.34	0.11	−0.1	0.79	0.11	0.69	−0.2	0.33	0.02	0.94	−0.5	0.52	0.32	0.24	−0.2	0.84
P9	0.14	0.61	−0.2	0.41	−0.1	0.61	−0.7	0.39	0.14	0.61	−0.2	0.41	0.12	0.62	−0.5	0.75	−0.3	0.24	−1	0.26
P10	−0.1	0.64	−0.3	0.21	−0.1	0.65	−0.5	0.34	−0.1	0.64	−0.3	0.21	−0.3	0.19	−0.8	0.18	0.15	0.62	−0.4	0.65
P11	−0.1	0.68	−0.3	0.21	0.14	0.55	−0.3	0.55	−0.1	0.68	−0.3	0.21	−0.3	0.22	−0.8	0.19	−0.3	0.32	−0.8	0.26
P12	−0.4	0.34	−0.6	0.2	−0.4	0.16	−1.1	0.18	−0.4	0.34	−0.6	0.2	0.38	0.23	−0.3	1.14	0.34	0.33	−0.4	1.1
P13	0	0.99	−0.2	0.24	−0.2	0.21	−0.6	0.15	0	0.99	−0.2	0.24	0.07	0.76	−0.4	0.52	−0.1	0.67	−0.6	0.37
P14	−0.3	0.17	−0.4	0.08	−0.1	0.5	−0.5	0.27	−0.3	0.17	−0.4	0.08	0.15	0.46	−0.3	0.64	−0.3	0.15	−0.8	0.14
R-sq	0.386				0.653				0.598				0.578				0.456			

Table 7 (continued)

	Beta	Sig.	C.I		Beta	Sig.	C.I		Beta	Sig.	C.I		Beta	Sig.	C.I		Beta	Sig.	C.I	
			L.B	U.B			L.B	U.B			L.B	U.B			L.B	U.B			L.B	U.B
	D6				D7				D8				D9				D10			
Const.		0.39	−0.3	0.11		0	0.16	0.68		0.46	−0.2	0.33		0.51	−0.2	0.37		0.47	−0.2	0.12
P1	−0.4	0.08	−0.5	0.04	0	0.95	−0.4	0.36	0.19	0.43	−0.2	0.48	0.07	0.7	−0.3	0.48	0.36	0.16	−0.1	0.44
P2	0	0.94	−0.3	0.28	−0.1	0.65	−0.5	0.3	−0.2	0.6	−0.4	0.26	−0.1	0.68	−0.5	0.33	0.1	0.78	−0.2	0.3
P3	0.55	***0.03***	0.02	0.58	−0.3	0.08	−0.7	0.05	0.01	0.98	−0.3	0.34	0.11	0.56	−0.3	0.51	−0.3	0.34	−0.4	0.13
P4	0.01	0.99	−0.3	0.29	0.23	0.23	−0.2	0.61	−0.3	0.4	−0.5	0.21	−0.2	0.44	−0.6	0.26	0.28	0.36	−0.1	0.38
P5	0.08	0.74	−0.2	0.32	−0.1	0.54	−0.5	0.26	−0.2	0.39	−0.5	0.2	0.02	0.93	−0.4	0.41	−0.2	0.54	−0.3	0.18
P6	0	0.97	−0.3	0.27	−0.2	0.19	−0.6	0.13	0	0.98	−0.3	0.33	−0.2	0.42	−0.5	0.23	0.06	0.83	−0.2	0.27
P7	−0.2	0.35	−0.3	0.1	0.2	0.2	−0.1	0.41	0.29	0.23	−0.1	0.36	−0.3	0.07	−0.5	0.02	0.31	0.22	−0.1	0.27
P8	0.62	***0.02***	0.06	0.62	−0.5	***0.01***	−0.9	−0.1	0.36	0.19	−0.1	0.57	−0.3	0.12	−0.7	0.09	−0.4	0.15	−0.4	0.07
P9	0.63	***0.02***	0.07	0.74	0.16	0.35	−0.2	0.65	−0.2	0.55	−0.5	0.29	−0.1	0.54	−0.6	0.33	−0.2	0.46	−0.4	0.19
P10	−0.2	0.55	−0.4	0.2	0.25	0.2	−0.1	0.61	0.18	0.55	−0.2	0.44	0.18	0.39	−0.2	0.57	0.25	0.43	−0.2	0.36
P11	0.1	0.7	−0.2	0.32	0.48	***0.01***	0.1	0.82	−0.1	0.71	−0.4	0.27	−0.1	0.7	−0.5	0.31	0.06	0.83	−0.2	0.27
P12	−0.2	0.62	−0.5	0.3	−0.3	0.14	−0.9	0.14	−0.1	0.68	−0.6	0.39	0.39	0.13	−0.1	1	−0.1	0.77	−0.4	0.31
P13	0	0.97	−0.3	0.24	−0.2	0.26	−0.5	0.15	0	0.94	−0.3	0.29	0.16	0.36	−0.2	0.52	0.31	0.22	−0.1	0.37
P14	0	1	−0.3	0.26	−0.2	0.21	−0.6	0.13	0.18	0.47	−0.2	0.43	0.58	0	0.26	1.01	−0.4	0.14	−0.4	0.06
R-sq	0.504				0.766				0.414				0.722				0.402			

Appendix 4

Table 8 ANOVA results

Model	D1					D2					D3					D4	
	Sum of squares	df	Mean square	F	Sig.	Sum of squares	df	Mean square	F	Sig.	Sum of squares	df	Mean square	F	Sig.	Sum of squares	df
Regression	0.295	14	0.021	1.123	.386[a]	2.319	14	0.166	3.355	.004[a]	2.604	14	0.186	2.657	.016[a]	2.213	14
Residual	0.469	25	0.019			1.235	25	0.049			1.75	25	0.07			1.618	25
Total	0.764	39				3.554	39				4.354	39				3.832	39

Model	D4			D5					D6					D7			
	Mean square	F	Sig.	Sum of squares	df	Mean square	F	Sig.	Sum of squares	df	Mean square	F	Sig.	Sum of squares	df	Mean square	F
Regression	0.158	2.442	.025[a]	1.462	14	0.104	1.494	.185[a]	0.506	14	0.036	1.816	.094[a]	2.862	14	0.204	5.84
Residual	0.065			1.747	25	0.07			0.498	25	0.02			0.875	25	0.035	
Total				3.21	39				1.004	39				3.738	39		

Model	D7	D8					D9					D10				
	Sig.	Sum of squares	df	Mean square	F	Sig.	Sum of squares	df	Mean square	F	Sig.	Sum of squares	df	Mean square	F	Sig.
Regression	.000[a]	0.527	14	0.038	1.259	.298[a]	2.654	14	0.19	4.627	.000[a]	0.279	14	0.02	1.203	.332[a]
Residual		0.747	25	0.03			1.024	25	0.041			0.415	25	0.017		
Total		1.274	39				3.678	39				0.694	39			

Appendix 5

Table 9 CPT of significant pain parameters and dental diseases obtained from regressions

	P3	$\overline{P3}$	P3	P3	P3	P3	P3	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	P3	P3	P3	P3
	P4	P4	$\overline{P4}$	P4	P4	P4	P4	$\overline{P4}$	P4	P4	P4	P4	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$
	P7	P7	P7	$\overline{P7}$	P7	P7	P7	P7	$\overline{P7}$	P7	P7	P7	$\overline{P7}$	P7	P7	P7
	P8	P8	P8	P8	$\overline{P8}$	P8	P8	P8	P8	$\overline{P8}$	P8	P8	P8	$\overline{P8}$	P8	P8
	P9	P9	P9	P9	P9	$\overline{P9}$	P9	P9	P9	P9	$\overline{P9}$	P9	P9	P9	$\overline{P9}$	P9
	P11	P11	P11	P11	P11	P11	$\overline{P11}$	P11	P11	P11	P11	$\overline{P11}$	P11	P11	P11	$\overline{P11}$
D1	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1
D2	0.4	0.4	0.2	0.2	0.4	0.4	0.4	0.2	0.2	0.4	0.4	0.4	0.1	0.2	0.2	0.2
D3	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1
D4	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0	0.2	0.2	0.2	0.1	0.2	0.2	0.2
D6	0.6	0.4	0.6	0.6	0.4	0.4	0.6	0.4	0.4	0.2	0.2	0.4	0.6	0.4	0.4	0.6
D7	0.4	0.4	0.4	0.4	0.2	0.4	0.2	0.4	0.4	0.2	0.4	0.2	0.4	0.2	0.4	0.2
	P3	P3	P3	P3	P3	P3	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	P3	P3	P3	P3	P3	P3
	P4	P4	P4	P4	P4	P4	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	P4	P4	P4
	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$	P7	P7	P7	$\overline{P7}$	P7	P7	P7	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$	P7
	$\overline{P8}$	P8	P8	$\overline{P8}$	$\overline{P8}$	P8	P8	$\overline{P8}$	P8	P8	$\overline{P8}$	P8	P8	$\overline{P8}$	$\overline{P8}$	$\overline{P8}$
	P9	$\overline{P9}$	P9	$\overline{P9}$	P9	$\overline{P9}$	P9	P9	$\overline{P9}$	P9	P9	$\overline{P9}$	P9	$\overline{P9}$	P9	$\overline{P9}$
	P11	P11	$\overline{P11}$	P11	$\overline{P11}$	$\overline{P11}$	P11	P11	P11	$\overline{P11}$	P11	P11	$\overline{P11}$	P11	$\overline{P11}$	$\overline{P11}$
D1	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2
D2	0.2	0.2	0.2	0.4	0.4	0.4	0.1	0.2	0.2	0.2	0.1	0.1	0.1	0.2	0.2	0.4
D3	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2
D4	0.1	0.1	0.1	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.2
D6	0.4	0.4	0.6	0.2	0.4	0.4	0.4	0.2	0.2	0.4	0.4	0.4	0.6	0.2	0.4	0.2
D7	0.4	0.4	0.2	0.2	0.1	0.2	0.4	0.2	0.4	0.2	0.2	0.4	0.2	0.2	0.1	0.1
	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	P3	P3	P3	P3	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	P3	P3	P3
	P4	P4	P4	P4	P4	P4	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	P4	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	P4
	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$	P7	P7	P7	P7	P7	P7	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$
	$\overline{P8}$	P8	P8	$\overline{P8}$	$\overline{P8}$	P8	$\overline{P8}$	$\overline{P8}$	P8	P8	$\overline{P8}$	P8	P8	$\overline{P8}$	$\overline{P8}$	$\overline{P8}$
	P9	$\overline{P9}$	P9	$\overline{P9}$	P9	$\overline{P9}$	$\overline{P9}$	P9	$\overline{P9}$	$\overline{P9}$	P9	$\overline{P9}$	P9	$\overline{P9}$	P9	$\overline{P9}$
	P11	P11	$\overline{P11}$	P11	$\overline{P11}$	$\overline{P11}$	P11	$\overline{P11}$	$\overline{P11}$	$\overline{P11}$	P11	P11	$\overline{P11}$	P11	$\overline{P11}$	$\overline{P11}$
D1	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.2
D2	0.2	0.2	0.2	0.4	0.4	0.4	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.2
D3	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.2
D4	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1
D6	0.2	0.2	0.4	0.1	0.2	0.2	0.2	0.4	0.4	0.4	0.2	0.2	0.4	0.2	0.4	0.2
D7	0.2	0.4	0.2	0.2	0.1	0.2	0.2	0.1	0.2	0.2	0.4	0.4	0.2	0.2	0.2	0.1
	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	P3	$\overline{P3}$	$\overline{P3}$	P3	$\overline{P3}$	$\overline{P3}$	P3	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$	$\overline{P3}$
	P4	P4	P4	$\overline{P4}$	P4	$\overline{P4}$	$\overline{P4}$	P4	$\overline{P4}$	$\overline{P4}$	P4	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$	$\overline{P4}$
	$\overline{P7}$	$\overline{P7}$	P7	P7	P7	P7	$\overline{P7}$	$\overline{P7}$	P7	$\overline{P7}$	$\overline{P7}$	P7	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$	$\overline{P7}$
	$\overline{P8}$	P8	$\overline{P8}$	$\overline{P8}$	$\overline{P8}$	P8	P8	$\overline{P8}$	$\overline{P8}$	$\overline{P8}$	$\overline{P8}$	$\overline{P8}$	P8	$\overline{P8}$	$\overline{P8}$	$\overline{P8}$
	P9	$\overline{P9}$	$\overline{P9}$	$\overline{P9}$	$\overline{P9}$	$\overline{P9}$	$\overline{P9}$	$\overline{P9}$	P9	$\overline{P9}$	$\overline{P9}$	$\overline{P9}$	$\overline{P9}$	P9	$\overline{P9}$	$\overline{P9}$
	$\overline{P11}$	$\overline{P11}$	$\overline{P11}$	$\overline{P11}$	$\overline{P11}$	$\overline{P11}$	$\overline{P11}$	P11	$\overline{P11}$	$\overline{P11}$	$\overline{P11}$	$\overline{P11}$	$\overline{P11}$	$\overline{P11}$	P11	$\overline{P11}$
D1	0.2	0.2	0.2	0.1	0.2	0.1	0.1	0.2	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1
D2	0.2	0.2	0.4	0.2	0.4	0.2	0.1	0.2	0.2	0.1	0.2	0.2	0.1	0.1	0.1	0.1
D3	0.2	0.2	0.2	0.1	0.2	0.1	0.1	0.2	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1
D4	0	0.1	0.2	0.2	0.2	0.2	0.1	0.1	0.2	0.1	0.1	0.2	0.1	0.1	0.1	0.1
D6	0.2	0.2	0.1	0.2	0.1	0.2	0.4	0.1	0.2	0.2	0.1	0.1	0.2	0.2	0.1	0.1
D7	0	0.2	0.1	0.1	0.1	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.2	0.1	0.2	0.1

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