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Using Bayesian Belief Networks for Prognosis & Diagnosis of Breast Cancer

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Abstract: Today in field of Medicine there is a bulk collections and sets of data in hand about the patients, diagnosis, treatment procedures etc .Using data mining techniques in those cases endow with a statistical and logical analysis of the data looking for patterns that can aid by decision making and prediction. In this paper we presents study of using Bayesian network (BN) in the domain of cancer specially breast cancer where BN are especially appropriate because of their symbolic representation, handling of uncertainty, where different scenarios are possible by given evidences. The objective of this paper is to survey the utility of a Bayesian Belief Network for an automated breast cancer detection support tool. We conclude that Bayesian networks provide a potentially useful technique for mammographic decision support.

Keywords: Data mining, Machine learning, Bayesian Belief networks, Breast cancer, Computer-aided detection, Diagnosis, Prognosis. Mammography, Markov Blanket Estimation, Tree Augmented Naive Bayes.

I. INTRODUCTION

Data mining focuses on sorting through large amounts of data and picking out relevant information[6].In this paper we presents a study of using Bayesian network as data mining tool for decision support system for predicting in the domain of emergency medicine for Breast cancer.

Breast cancer is a very common and serious cancer for women. It is the second largest cause of cancer deaths among women .Breast cancer accounts for approximately 40,000 deaths of American women annually; 120000 to 180000 new cases of the disease are detected each year [13]

Mammography is one of the most used methods to detect this kind of cancer [10], [8]. And other method is Fine Needle Aspiration Cytology (FNAC) but the average correct identification rate of FNAC is only 90% [9] but suspicious mammographic finding can lead to perform biopsy which is very costly and discomfort. Thus it is necessary to develop better identification method to recognize the breast cancer. Computer aided diagnosis can help to reduce the number of false positives and therefore reduce the number of unnecessary biopsies .Several classification problems like statistical techniques and artificial intelligence methods have been successfully used to predict the breast cancer by several researchers[11]. The principle of these identification techniques is to assign a patient to either a benign group that does not have breast cancer or a malignant group who has strong evidence of having breast cancer. The goal of this study is to summarize various review and technical articles on diagnosis and prognosis of breast cancer. In this paper we provide a general idea of the current research being carried out on various breast cancer datasets using Bayesian Belief Network to enhance breast cancer diagnosis and prognosis.

A probability estimation classifier estimates the conditional probability distribution of the values of the class attribute given the values of the predictive attributes. Such classification models which represent conditional distribution will be concise and easy to comprehend. They include Naive Bayes, logistic regression, decision tree and Bayesian network. Naive Bayes and logistic regression models can only represent simple distributions, whereas decision tree models can represent arbitrary distributions, but they fragment the training dataset into smaller and smaller pieces, which unavoidably yield less reliable probability estimates. Bayesian Network (BN) is the best-known classifier that able to provide the probability distributions concisely and comprehensibly (Witten and Frank, 2005). BN is a probabilistic model that consists of dependency structure and local probability. BN is drawn as a network of nodes, one for each attribute, connected by directed edges in such a way that there are no cycles; a directed acyclic graph. The major advantage of BN is the ability to represent and hence understand knowledge. Recently, there is increasing attention regarding the application of BN in medical contexts (Linda *et al*., 2008),and to discuss the current role of Bayesian networks in diagnosis & prognosis of Breast cancer .

II. MATERIALS AND METHODS

A. Bayesian Network

A Bayesian network is a probabilistic graphical model that represents a set of variables and their probabilistic independences [7]. For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can

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be used to compute the probabilities of the presence of various diseases. Formally, Bayesian networks are directed acyclic graphs whose nodes represent variables, and whose arcs encode conditional independences between the variables. Nodes can represent any kind of variable, be it a measured parameter, a latent variable or a hypothesis.. Efficient algorithms exist that perform inference and learning in Bayesian networks.

III. USING BAYESIAN NETWORK FOR DIAGNOSIS & PROGNOSIS OF BREAST CANCER

In [1] authors (Linda m.Roberts,Charles), implemented Mammonet as a knowledge base of rules and this problem –specific networks are constructed using a Bayesian Network construction algorithm. In this paper authors describe design, implementation, and preliminary evaluation of Bayesian networks to detect the presence and absence of breast cancer based on demographic risk factors, mammographic signs and physical findings. The Network is implemented using Bayesian Network Generator (BNG)[12]. The BNG system generates Bayesian problem specific networks from probability logic knowledge bases. Given a query and a evidence, BNG generates the structural minimal network to compute the posterior probability of the query. The network is then passed to the IDEAL system for evaluation. The Mammonet shown generated by backward chaining on the query and the given evidence shown in Fig.1.

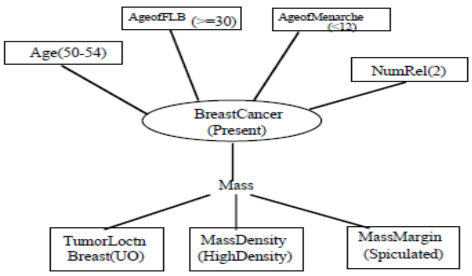

Fig.1. Network generated for query BreastCancer(Present)

Then to test the ability of Mammonet to detect breast cancer, authors ran the network against several text book cases. Examples of Test cases in Table.1.

TABLE I
MAMMONET TEST CASES

Age	Mammographic Analysis	Radiologist's Analysis	Histology	MammoNet Coding	MammoNet Result
65	no halo sign, circumscribed, irregular, low density	although circumscribed tumor and low-density, it is irregular and there is no halo sign	mucinous carcinoma; no axillary metastases	MassMargin = irregular; HaloSign = absent; MassDensity = low; Calcification = none	.9960
40	small group of calcification in LO quadrant; casting-type; irregular, varying	cancer	invasive ductal carcinoma; no lymph node metastases	TumorLctnBreast = UO; CalcArrangement = scattered&clustered; CalcShape = LinearBranching	.9659
52	small tumor, UO quadrant, circumscribed, sharply outlined, low density	probably benign	benign	MassMargin = rwdefined; TumorLctnBreast = UO; MassDensity = low	.0020

RESULT:
The performance of the model was assessed using Receiver Operating Characteristic (ROC) analysis[14] , MammoNet's performance — as measured by the very high Az value of 0.9585 —compares very favorably with that of artificial neural network models[15] and expert mammographers.

In [2] the authors presented Bayesian networks as a highly practical framework for working with a kind of classification problem. Authors intended to demonstrate how the BayesiaLab software can extremely quickly, and relatively simply, create Bayesian network models that achieve the performance of the best custom-developed models, while only requiring a fraction of the development time. Authors wishes to illustrate how Bayesian networks can help researchers and practitioners generate a deeper understanding of the underlying problem domain.

BayesiaLab's speed of model building, its excellent classification performance, plus the ease of interpretation provide researchers with a powerful new tool. Bayesian networks and BayesiaLab have thus become a driver in accelerating research.

DATASETS used in [2]:
Wisconsin Breast Cancer Database
In this paper authors had used Wisconsin breast cancer Database consisting of 699 instances of patient consisting of two classes: 458 benign cases (65.5%) and 241 malignant cases (34.5%).The Wisconsin Breast Cancer Database is available to any interested researcher from the UC Irvine Machine Learning Repository
The following eleven attributes2 are included in the database:
1. Sample code number
2. Clump Thickness (1 - 10)
3. Uniformity of Cell Size (1 - 10)
4. Uniformity of Cell Shape (1 - 10)
5. Marginal Adhesion (1 - 10)
6. Single Epithelial Cell Size (1 - 10)
7. Bare Nuclei (1 - 10)
8. Bland Chromatin (1 - 10)
9. Normal Nucleoli (1 - 10)
10. Mitoses (1 - 10)
11. Class (benign/malignant)

In this paper a tool known as Bayesialab is used to generate a Bayesian network.

RESULT:
By using Bayesian networks as the framework and BayesiaLab as the tool, authors have shown a practical new modeling and analysis approach based on the widely studied Wisconsin Breast Cancer Database .BayesiaLab can rapidly machine-learn reliable models, even without prior domain knowledge and without hypothesis. The classification performance of the BayesiaLab-generated Bayesian network models is on equivalence with all research based on this topic. Beyond the predictive performance, BayesiaLab enables a range of analysis and interpretation functions, which can help the researcher gain deeper domain knowledge and perform inference more efficiently.

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In [3] the authors evaluated two different Bayesian classifiers; tree augmented Naive Bayes and Markov blanket estimation networks in order to build an ensemble model for predicting the severity of breast masses. The objective of their proposed algorithm was to help physicians in their decisions to perform a breast biopsy on a suspicious lesion seen in a mammogram image or to perform a short term follow-up examination. They applied the approach ensemble Bayesian classifiers to predict the severity of breast masses. Bayesian classifiers had been selected as they were able to produce probability estimates rather than predictions. These estimated allow predictions to be ranked and their expected costs to be minimized.

Bayesian Network (BN) is the best-known classifier that enable us to provide the probability distributions concisely and comprehensibly.BN classifiers have been evaluated as potential tools for the diagnosis of breast cancer using two real-world databases in [18][19]. In their study, two different implementations of BN have been investigated for the prediction of severity of breast masses; Tree Augmented Naive Bayes (TAN) and Markov Blanket Estimation (MBE) learning algorithms. Both algorithms use Naive Bayes classifier as a starting point for the learning procedure.

DATA SETS used in [3]:

The mammographic mass dataset used here has been collected at the Institute of Radiology of the University Erlangen-Nuremberg between 2003 and 2006 [16].BI-RADS stands for the Breast Imaging and Reporting Data System and was developed by the American College of Radiology (ACR). The data set is available by http access of the University of California at Irvine (UCI) machine learning repository. Table.2 shows the mammographic mass dataset which contains the BIRADS assessment, the patient's age and three BIRADS attributes together with the ground truth (the severity attribute) for 516 benign and 445 malignant masses that have been identified on full field digital mammograms.

TABLE II.
ATTRIBUTES OF MAMMOGRAPHIC MASS DATASET

Attribute	Type	Values and labels: Value	Values and labels: Label	No. of missing values
BI-RADS assessment (non-predictive)	Ordinal	0	Assessment incomplete	2
		1	Negative	
		2	Benign findings	
		3	Probably benign	
		4	Suspicious abnormality	
		5	Highly suggestive of malignancy	
Ages	Integer		Patient's age in years	5
Mass shape	Nominal	1	Round	31
		2	Oval	
		3	Lobular	
		4	Irregular	
Mass margin	Nominal	1	Circumscribed	48
		2	Microlobulated	
		3	Obscured	
		4	Ill-defined	
		5	Speculated	
Mass density	Ordinal	1	High	76
		2	Iso	
		3	Low	
		4	Fat-containing	
Severity (target class)	Binominal	0	Benign	
		1	Malignant	

The Naive Bayes (NB) classifier is one of the most effective methods to build BNs (Friedman *et al.*, 1997).But it works well only for simple distributions. Usually, NB network is used as a starting point for the search. In their study, two learning algorithms have been used to build the BN classifiers starting NB network; Tree Augmented Naïve Bayes (TAN) and Markov Blanket Estimation (MBE) learning algorithms.

Markov Blanket Estimation (MBE): MBE is a learning algorithm to create BN model by identifying the conditional independence relationships among the attributes. This algorithm ensures that every attribute in the dataset is in the Markov blanket of the node that represents the class attribute (Witten and Frank, 2005).

Tree Augmented Naive Bayes (TAN): TAN is an improvement over the naive Bayes model as it allows for each attribute to depend on another attribute in addition to the target attribute.

RESULT:

The prediction accuracies of Bayesian ensemble was benchmarked against the well-known multilayer perceptron neural network and the ensemble had achieved a remarkable performance with 91.83% accuracy on training subset and 90.63% of test one and outperformed the neural network model. And Authors concluded that experimental results show that the Bayesian classifiers are competitive techniques in the problem of prediction the severity of breast masses.

In [4] authors discussed how to develop and use a Bayesian belief network in Medicine Field. This paper is more dealt with how BBNs can be applied to specific problems and describing how calculations can be performed .As the important characteristics of an expert system is the ability to make diagnosis decisions.In this paper authors states that construction of BBN begins with defining diagnostic problem i.e distinction between benign and malignant .In their work they developed and used a BBN for grading of Breast cancer according Bloom and Richardson scheme.

For creating a BBN, authors included four steps:
STEP 1.Define the DECISION NODE.
STEP 2. Define the EVIDENCE NODE.
STEP 3.Defining the relationship between the evidence and the decision.
STEP 4.Initialisation of the network.

Then in order to use BBN to make a decision in the diagnostic outcomes authors had entered evidence about specific case into the network. This process of how evidence modifies the diagnostic belief performs certain steps.
STEP 1.Entering the evidence into the EVIDENCE NODE.

RESULT:

A BBN designed in the work done is a computer program which accept evidence and process it to arrive at a final decision node .A suitable software program known as DIAGSOFT, is used (kleselstrasse 14a,D-

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8099,Munich,Germany) for development and investigation of BBN's in pathology.BBN has been created and applied to microscopic diagnosis and prognostic grading of breast lesions. And It is proving easy for the experts to define the diagnostic or prognostic outcomes for the various killing disease.

IV. AVAILABLE COMPUTATIONAL TOOLS

In [5] the authors have discussed various tools available to implement inference algorithms in the context of a Bayesian Network.

A. Bayesware Discoverer

Bayesware Discoverer is an automated modeling tool that transforms a database into a network of dependencies, by searching for the most probable model responsible for the observed data. Bayesware Dis-coverer also provides sophisticated visualization tools, flexible connectivity capabilities and easy to use wizard interfaces to execute common tasks.

B. Bayesware classifier

Bayesware Classifier is a fast supervised classification. program that is able to handle missing data. Based on a novel analytical methodology, Bayesware Classifier is able to trade-off the risk of various hypotheses about the patterns of missing data and provides both accurate analysis of your incomplete database and principled decisions about the predictions from the data.

C. BN PowerConstructor

A system that learns Bayesian belief network structures and parameters from data.

D. BN PowerPredictor

A data mining system for datamodeling/classification/ prediction. It extends BN PowerConstructor to BN based classifier learning.

E. DataPreprocessor

A tool used with BN PowerConstructor and BN PowerPredictor for preprocessing the training data.

F. BNT tool box

BNT supports many types of conditional probability distributions (nodes), decision and utility nodes, as well as chance nodes, that is, influence diagrams as well as Bayes nets. BNT supports static and dynamic Bayesian Networks (useful for modeling dynamical systems and sequence data). BNT supports many different inference algorithms, several methods for parameter learning and several methods for regularization. The source code is extensively documented, object-oriented, and free, making it an available tool for teaching, research and rapid prototyping.

G. Elvira

The Elvira is an available tool for the implementation of Bayesian expert systems. Elvira can operate in three modes, (1) Edit, to create and modify Bayesian networks and Influence Diagrams whose variables are only discrete. (2) Inference, to do evidence propagation and abduction. Most of the explanation capabilities of Elvira are offered only in this mode. (3) The learning mode allows the building of Bayesian networks from databases. Elvirais implemented to be run in several languages. And, as other graphical tools, the user can open different windows simultaneously in order to perform different tasks.

H. Esthauge

The LIMID software system from Esthauge Decision Knowledge is a full Java software tool for construction and manipulation of graphical models in the form of Bayesian networks and decision graphs. It consists of an application programming interface for embedding with other Java software tools and a graphical user interface for visual construction, editing and maintenance of models.

I. Hugin

The Hugin Development Environment provides a set of tools for constructing model-based decision support systems in domains characterized by inherent uncertainty. The models supported are Bayesian networks and their extension influence diagrams. The Hugin Development Environment allows to define both discrete domain variables and to some extent continuous domain variables in your models. The Hugin Decision Engine can be used through the Hugin Graphical User Interface. The Hugin Development Environment can also be used through one of several APIs (Application Program Interfaces), which come as libraries for C, C++, NET and Java, and as an ActiveX server. The Hugin Development Environment can be used to construct models as components in applications for decision support, data mining and expert systems. The application communicates with the constructed component models through one of the Hugin APIs.

J. JavaBayes

JavaBayes is a system that handles Bayesian networks: It calculates marginal probabilities and expectations, produces explanations, performs robustness analysis, and allows the user to import, create, modify and export . the idea of graphical model, a complex system consists of simple parts, which are bound together with probability theory. For the application of computer aided detection in mammography, the researchers intend to design an interface between the project's Bayesian network learning algorithm and the radiologists, So that the radiologists can have interaction with the system by labeling only a small number of informative images presented by the active learning algorithm. In this way, the project's system only requires very little labeling effort from radiologists, while significant improvements of classifiers are achieved. The ease with which such systems can be embedded in clinical information systems, which are now starting to emerge in most critical care units, renders this at least an attractive possibility.

V. CONCLUSION

Bayesian network classifiers have three major advantages; It have the ability to deal with missing values, It explicitly provide the conditional *p*robability distributions of the values of the class attribute given the values of the other

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input attributes and finally they are easy to comprehend. For these fine proprieties, the awareness to apply and use Bayesian network classifiers in the medical context is increasing.The main goal of this study is to show the effectiveness of these classifiers and their ensemble in the prediction of breast mass severity. Two different implementations of Bayesian network have been applied on the mammographic mass dataset; tree augmented Naive Bayes and Markov blanket estimation learning algorithms.. Bayesian network classifiers outperformed the multilayer perceptron neural network on the prediction of the severity of breast masses and they provide an elegant way to rank the attributes that most significantly indicate the likelihood of default.On the basis of these results we concluded that Bayesian network classifiers may be a competitive alternative to other techniques in medical applications.

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