Bayesian Network Model for Diagnosis of Psychiatric Diseases

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Abstract. *Because of numerous possible causes involved, it isn't easy for general physicians to identify the precise reason of the psychiatric diseases and to decide the correct treatment. Bayesian networks are recognized as efficient graphical models with significant capabilities for investigating biomedical data either to obtain relationships between variables, either for medical predictions. Our paper provides a Bayesian network-based analysis of psychiatric patient data, which have been gathered from a Romanian specialized clinic during a couple of years. The development of this Bayesian network led us to the identification of most significant factors that affect some important diseases and their correlations.*

Keywords. Bayesian networks, psychiatric diseases, decision making, reasoning.

1. Introduction

Diagnosis has a very important role in all medical procedures, being the first step from a set of therapeutic actions that are developed in order to save the patients life or to improve their health. An error at this level can have dramatic consequences. Nowadays physicians can use a lot of systems (informatics tools) that are made to suggest a diagnosis or to give a prognostic about the health level of a patient. These tools are broadly utilized in medical activity because of their relevant advantages: pragmatism, repeatability, efficiency and immunity toward perturbation factors that are specific to human beings (fatigue, stress, diminished attention). It is obvious that technology cannot replace human expertise in this point of medical assistance; it only gives support through the medical systems that are able to select or to generate relevant data for the physicians.

The tremendous progress related to the artificial intelligence research area has been the source for numerous techniques efficiently applied in the implementation of medical diagnosis systems [1]-[3]. One of these methods is based on Bayesian networks (also called belief networks) and represents a step forward in computer assisted medical diagnosis. Bayesian networks are graphical models that contain a set of variables together with their probabilistic independences, being used to represent and handle uncertain knowledge. In other words, a Bayesian network is a mechanism that automatically applies Bayes theorem to complex problems.

In this paper, Bayesian networks (BN) are involved in a medical decision making process. In particular, in a psychiatric diagnosis procedure, predicting the probability of a patient to suffer from a certain psychiatric disease based on detected symptoms represents a crucial issue. Hereinafter we describe the steps in formalizing and constructing the Bayesian network and, in the end, we present case studies based on datasets recorded in the division of Psychiatry from Lugoj Municipal Hospital.

2. Related Work

In this section we briefly present some significant researches in the field of Bayesian network applications, relevant for our investigation. As described in [4], Bayesian networks arose as a research topic in the '80s and are successfully used in medical decision making since the '90s. They have a large applicability in medical domain, from the possibility to predict the evolution of a disease to the opportunity to find out if a treatment has benefits to a specified patient or not.

Bayesian networks can be used to implement decisional systems, which also give solutions for other types of problems connected with medical domain. In this sense, Bayesian networks are implemented based on different learning algorithms [5] and used to represent health-care systems for patients that arrive to the emergency department of a hospital. This kind of system can make predictions about some variables of interest

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or can offer support in decision-making regarding the actions that must be performed. Using this type of systems, the general activity from a hospital and the medical care can be improved.

The main efficiency of medical Bayesian networks remains in the diagnosis field. Bayesian networks are used to represent knowledge and, on the other hand, they are used as method of reasoning. For this, a learning process is required. In [6] it is presented an automatic learning method that optimizes the Bayesian networks applied to classification, using a hybrid method of learning. It combines the advantages of the decision trees with those of the Bayesian networks. Therefore, recent researches prove that decisional systems implemented by Bayesian networks represent an efficient tool for medical and non-medical healthcare practitioners.

3. The Bayesian Network modeling of psychiatric diseases

Bayesian networks are complex probabilistic diagrams that systematize a mixture of domain expert knowledge and observed datasets by mapping out cause-and-effect relationships between key variables and encoding them with numbers that signify the amount in which one variable is probable to influence another. In conjunction with Bayesian inference methods, the Bayesian network modeling proves to be an efficient instrument in the decision making process for a variety of medical domains. Our research is focused on the use of BN in assisting psychiatric diagnosis and confirms the efficiency of such an approach.

Psychiatry is a medical specialty devoted to the treatment, study and prevention of mental disorders. Whatever the circumstance of a person's referral, a psychiatrist first assesses the person's mental and physical condition. This usually involves interviewing the person and often obtaining information from other sources such as health and social care professionals, relatives, associates, law enforcement, emergency medical personnel and psychiatric rating scales. A mental status examination is carried out, and a physical examination is usually performed to establish or exclude certain illnesses such as thyroid dysfunction or brain tumors, or identify any signs of self-harm.

With the precise objective of helping physicians in the final stage of their decisional process of diagnosis and treatment planning, we developed a BN model for analyzing the psychiatric diseases, based on observed symptoms and a priori known causal relationships.

In Fig. 1 we presented a BN model of four major psychiatric diseases: schizophrenia (simple and paranoid), mixed dementia (Alzheimer disease included), depressive disorder and maniac depressive psychosis. Each of them has a genetic influence along with distinctive other factors like patients age or educational level. The problem is to decide, based on current medical symptoms and BN statistical knowledge, what disease the diagnosed patient is more likely to have.

In order to understand the philosophy applied in the development of the mentioned Bayesian network we considered as a starting point the Bayes theorem [7]-[9], expressing the conditional and marginal probabilities of two events α and β, where β has a non-vanishing probability:

$$P(\alpha/\beta) = \frac{P(\beta/\alpha)P(\alpha)}{P(\beta)} \qquad (1)$$

The meaning of every term in the theorem is described below:

1. $P(\alpha)$ is the prior probability (marginal probability) of the event α, without any information about the event β,
2. $P(\alpha/\beta)$ is the conditional probability of the event α, given the event β,
3. $P(\beta/\alpha)$ is the conditional probability of the event β, given the event α,
4. $P(\beta)$ is the marginal probability of the event β, acting like a normalizing constant.

A BN architecture, suited for setting relationships among a large number of nodes/variables, is graphically represented by a directed acyclic graph that efficiently encodes the joint probability distribution (2) for a large set of variables (3).

$$P(X) = \prod_{i=1}^{n} P(X_i|Parents(X_i)) \qquad (2)$$

$$X = \{X_1, ..., X_n\}, \qquad (3)$$

where:

- n represents the number of nodes included in BN,
- $Parents(X_i), i = \overline{1,n}$ represents the set of parents of the node X_i.

After the modeling stage, the Bayesian inference[10] is used to update the network statistical knowledge based on current observations and the Bayes theorem.

As follows, we will describe the formalization of the BN graphical model presented in Fig. 1, focusing on the diagnosis of the schizophrenia disease (enclosed by dashed line in the figure). Observing the network structure and the number of nodes, the full joint distribution is defined in the following equation:

$$P(X_1, X_2, ..., X_{29}) = \prod_{i=1}^{n} P(X_i | Parents(X_i)). \quad (4)$$

In other words, the BN is a pair $(G(X, E), P(X))$, where $G(X, E)$ is the directed acyclic graph presented in Fig. 1 (X is the set of variables and E is the set of directed edges), and $P(X)$ is the joint distribution of the model. Based on parent dependencies of each node, we obtained the following expression of the joint distribution:

$$P(X_1, ..., X_{29}) = P(X_{29} | X_{28}, ..., X_1)$$
$$P(X_{28} | X_{27}, ..., X_1) ... P(X_2 | X_1) P(X_1). \quad (5)$$

In the Table 1 we present the marginal and conditional probabilities of the BN nodes involved in the diagnosis of the schizophrenia disease. The values are obtained both from medical statistics from the division of Psychiatry from Lugoj Municipal Hospital and from physician expert knowledge.

TABLE 1. The probability distribution statistical data for schizophrenia disease

	Probability Distribution per Node		
X_{14}	X_{11}	X_{12}	**Result**
	T	*T*	25 %
	T	*F*	15 %
	F	*T*	8 %
	F	*F*	1 %
X_{11}	X_1	X_2	**Result**
	M	*Z*	1 %
	M	*O*	5 %
	M	*B*	30 %
	F	*Z*	1 %
	F	*O*	6 %
	F	*B*	46 %
X_{12}	**Component**		**Result**
	True		12 %
	False		88 %
X_1	**Component**		**Result**
	Male		50 %
	Female		50 %
X_2	**Component**		**Result**
	Zero		88 %
	One		11.9 %
	Both		0.1 %
X_{19}	X_{14}		**Result**
	Present		85 %
	Absent		3 %
X_{20}	X_{14}		**Result**
	Present		88 %
	Absent		10 %
X_{27}	X_{14}	X_{16}	**Result**
	Present	Present	100 %
	Present	Absent	87 %
	Absent	Present	95 %
	Absent	Absent	5 %

Analyzing the structure presented in Fig. 1, we can observe a large number of input nodes having a significant influence inside the network. Some of them are described below.

Two important variables involved in obtaining the probability of a disease is the genetic influence: patients' sex and number of relatives diagnosed with the illness. It is known that women are more liable to have or to develop a psychiatric disease than men. Also there is a chance of schizophrenia for those whose mothers had some kind of virosis during pregnancy. One factor with great effect on developing a sort of mental disease is the environment of the patient and the educational level. Age is another coefficient in this medical equation; statistically, people less than 40 years old being more exposed to develop schizophrenia.

Based on the model described above, in the following section we will present the results obtained using the BN model in the diagnosis of the psychiatric diseases.

4. Case Study

In this section we will present: a) the detailed mathematical dependencies of the schizophrenia diagnosis using the Bayesian network described above; and b) the results obtained in given case studies implemented over datasets recorded in the division of Psychiatry from Lugoj Municipal Hospital. In order to obtain the BN for diagnosing psychiatric diseases, we chose the Netica Software from Norsys [11], because of the simplicity and high performance.

The probability of diagnosing a patient with simple schizophrenia disease is given by the full joint distribution of the X_{14} node from Fig. 1. Having multiple parents, the probability of the X_{14} node of the BN is given bellow:

$$\begin{aligned} P(X_{14}) = {} & P(X_{14} | X_{12}, X_{11}) P(X_{12}) P(X_{11}) + \\ & P(X_{14} | X_{12}, -X_{11}) P(X_{12}) P(-X_{11}) + \\ & P(X_{14} | -X_{12}, X_{11}) P(-X_{12}) P(X_{11}) + \\ & P(X_{14} | -X_{12}, -X_{11}) P(-X_{12}) P(-X_{11}) + \end{aligned} \quad (6)$$

where:

$$P(X_{12}) = P(-X_{12})$$
$$P(X_1) = P(-X_1)$$
$$P(X_2) = \begin{cases} P(X_{2,1}) \\ P(X_{2,2}) \\ P(X_{2,3}) \end{cases},$$
$$P(-X_2) = \begin{cases} P(-X_{2,1}) \\ P(-X_{2,2}) \\ P(-X_{2,3}) \end{cases} \tag{7}$$

and $X_1 = male$, $-X_1 = female$, $X_{2,1} = none$, $X_{2,2} = one$, $X_{2,3} = both$, $X_{11} = true$, $-X_{11} = false$, $X_{12} = true$, $-X_{12} = false$, $X_{14} = true$, $-X_{14} = false$.

The joint distribution of the genetic influence (node X_{11}) over simple schizophrenia disease is depicted below:

$$\begin{aligned} P(X_{11}) = P(X_{11}|X_{2,2}, X_1)P(X_{2,1})P(X_1) + \\ P(X_{11}|X_{2,1}, -X_1)P(X_{2,1})P(-X_1) + \\ P(X_{11}|X_{2,2}, X_1)P(X_{2,2})P(X_1) + \\ P(X_{11}|X_{2,2}, -X_1)P(X_{2,2})P(-X_1) + \\ \\ P(X_{11}|X_{2,3}, X_1)P(X_{2,3})P(X_1) + \\ P(X_{11}|X_{2,3}, -X_1)P(X_{2,3})P(-X_1) + \end{aligned} \tag{8}$$

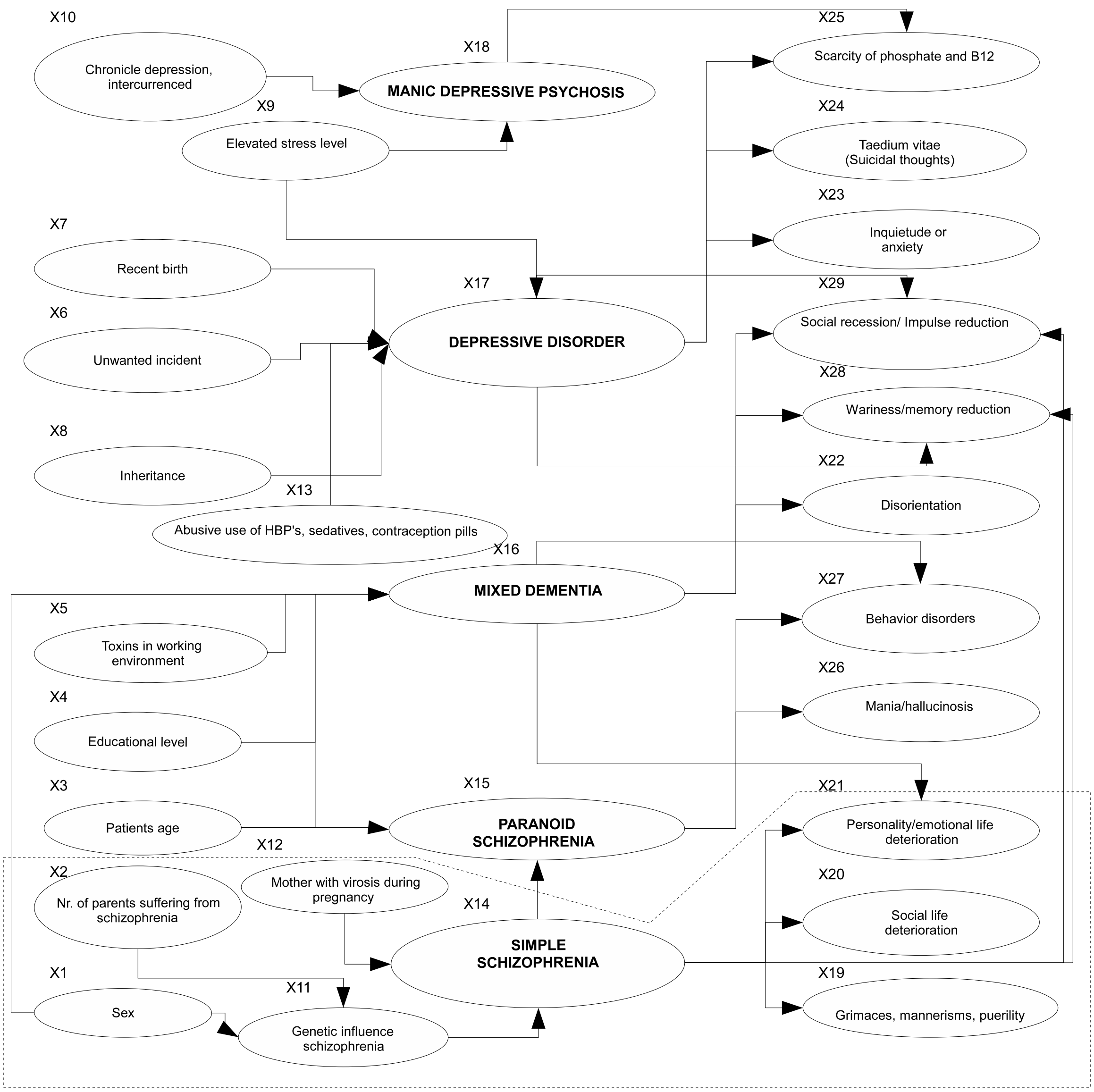

Figure 1. The Bayesian Network graphical model of Schizophrenia and mixed dementia diagnosis

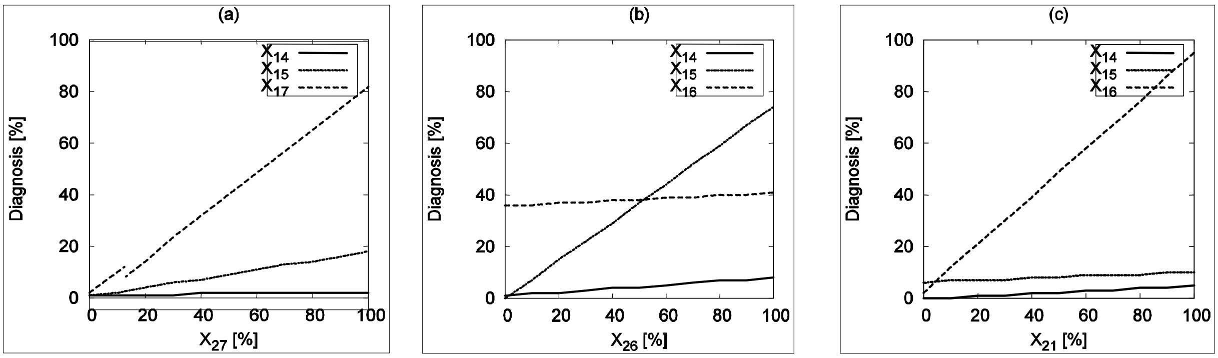

Figure 2. The probability of diagnosing a certain patient with psychiatric diseases (simple schizophrenia, paranoid schizophrenia and mixed dementia) taking in consideration only one evidence at a time: a) behavior disorders, b) mania/hallucinosis, c) personality/emotional life deterioration

Using the BN information presented in Fig. 1 and Table 1, and the mathematical relations (6), (7), (8), we obtained the following results:

$$\begin{aligned} P(X_{11}) = 0.01*0.88*0.5+ \\ 0.01*0.88*0.5+ \\ 0.05*0.119*0.5+ \\ 0.06*0.119*0.5+ \\ 0.3*0.001*0.5+ \\ 0.46*0.001*0.5 \simeq 0.01 \end{aligned} \tag{9}$$

$$P(-X_{11}) = 100 - P(X_{11}) = 0.99$$

$$P(X_{12}) = 0.12,$$

$$P(-X_{12}) = 100 - P(X_{12}) = 0.88 \tag{10}$$

$$\begin{aligned} P(X_{14}) = 0.25*0.12*0.01+ \\ 0.08*0.12*0.99+ \\ 0.15*0.88*0.01+ \\ 0.01*0.88*0.99 \simeq 0.02 \end{aligned} \tag{11}$$

$$P(-X_{14}) = 100 - P(X_{14}) = 0.98$$

From equation (11) we can observe that the probability of a certain patient to be diagnosed with simple schizophrenia, depending on no evidence, is approximately 2%. Certainly, the result obtained from the BN inference will be changing, depending on every evidence node involved in the decision process.

For evaluating the BN model presented above, we imagined four case studies, based on statistical data recorded during the period of four months in the division of Psychiatry from Lugoj Municipal Hospital.

The first three case studies have the same goal: observing the influence of changing the values of only one evidence node at a time over the probability of diagnosing a certain patient with psychiatric diseases (simple schizophrenia, paranoid schizophrenia and mixed dementia). The graphical results are presented in Fig. 2.

The last case study presents the statistical data over a period of four months, obtained from the usage of the BN in the process of diagnosing patients with possible psychiatric diseases. In other words, we present the evolution in time of the psychiatric diseases diagnosis, based on the BN model and using recorded data symptoms of diagnosed patients. The graphical results are presented in Fig. 3.

Mixed dementia (X_{16}) (Alzheimer disease included) is a complex illness, so the effects on humans are easier to be observed. As presented in the Fig. 2 a), the influence of mixed dementia on the persons behavior (X_{27}) is higher then other studied diseases. Paranoid schizophrenia (X_{15}) is also relatively high, using the behavior disorders symptoms as evidence node in the modeled BN.

Identifying mania or/and hallucinosis symptoms on a certain patient, gives the specialist the diagnosis direction of paranoid schizophrenia. The probabilities of the other two diseases, in the case of detecting mania or/and hallucinosis symptoms, are much lower, as shown in Fig. 2 b).

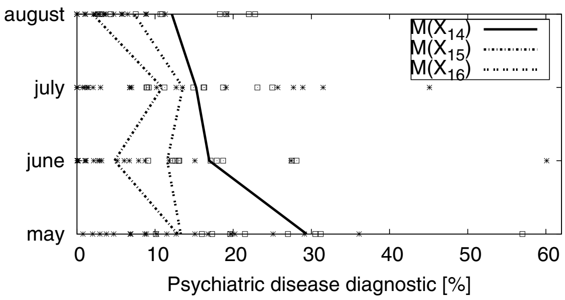

Figure 3. The evolution in time of the average probability of the psychiatric diseases diagnosis

Similar with Fig. 2 a), in Fig. 2 c) by interpreting the graphical dependency of mixed dementia disease on personality and emotional life of the patient, can be observed a higher grade of influence than in the case of the other two diseases, simple and paranoid schizophrenia.

In the Fig. 3 we can observe the graphical representation of the evolution in time of the average diagnose probability for three psychiatric diseases: simple schizophrenia (X_{14}), paranoid schizophrenia (X_{15}) and mixed dementia (X_{16}). Based on the statistical data recorded in the Lugoj Municipal Hospital over the period of four months, we can conclude that the probability of patient diagnose with the specified psychiatric diseases fluctuates in the case of the mixed dementia and paranoid schizophrenia disease and drops with 50% in the case of the simple schizophrenia disease.

5. Conclusions

In this paper we presented the BN modeling of a medical decision making process applied to the diagnosis of psychiatric diseases. Based on recorded medical evidence and statistics in the Division of Psychiatry from Lugoj Municipal Hospital we developed the BN model in the scope of improving the diagnose process made by physicians. We developed four case studies for observing the influence of certain symptoms over the probability of psychiatric diseases, and also for presenting the evolution in time of the modeled psychiatric diseases.

For the medical domain, the Bayesian Networks are once again proved to be an efficient instrument for the physicians involved in prediction and treatment of certain diseases. With minor adjustments (including supplementary nodes and links and modifying the table of marginal and conditional probabilities) the BN can be improved to satisfy all requirements. Like any other decisional system, the Bayesian Networks represent useful tools for measuring the probability of events, being an ideal representation of both causal prior knowledge and observed data.

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