AN APPROACH FOR THE DIAGNOSIS OF TYPE 2 DIABETES: A HYBRID MODEL IN DECISION MAKING

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ABSTRACT

Diabetes is a disease that affects over 371 million people worldwide and this number continues to grow. In 2012, there were 4.8 million deaths and 471 billion dollars spent. The diagnosis when performed early, associated with the correct treatment, may delay the onset of chronic complications providing better living conditions for patients and reducing the impact on our society, bringing substantial gains in economic growth of countries. This work was developed with the goal to improve the diagnosis process, focusing on the diagnosis of type 2 diabetes. We present a hybrid model to create an Expert System, structured in probability rules by applying Bayesian Networks, Multiple Criteria Decision Analysis and representation of knowledge structured in production rules and probability (Artificial Intelligence). The proposed model was applied to a Canadian dataset with 4,611 diabetic patients and a Brazilian dataset with 1,222 diabetic patients [12] [13] [25].

KEYWORDS. Automated diagnosis. Bayesian Network. Diabetes. Early diagnosis. Expert Systems. Multi-criteria.

Multicriteria Decision Support, Operational Research in Health.

1. Introduction

This paper presents a hybrid methodology aiming to support health professionals in decision making for the early diagnosis of type 2 diabetes consistently, combining probability rules, by applying Bayesian Networks and Multiple Criteria Decision Analysis (MCDA) to select the parameters which has the greatest impact on the diagnosis to compose the knowledge base of the Expert System. The methodology will support the early diagnosis of type 2 diabetes, allowing measures to be taken to control the disease at an early stage. The focus of this work is in the diagnosis of type 2 diabetes, using non-invasive procedures. Once identified the high risk of the disease, the person should have their blood glucose levels measured by a health professional to confirm the diagnosis. Hybrid models have been used to support decision making and search for disease diagnosis, such as Alzheimer's diagnosis [7] [8] [9] [24] and Psychological Disorders [20].

2. Diabetes

Diabetes is a group of metabolic diseases characterized by hyperglycemia (high blood glucose), which may result from defects in production and/or action of insulin (a hormone produced by the pancreas to control blood glucose). The chronic hyperglycemia of diabetes is associated with long-term damage, dysfunction and failure of different organs, especially the eyes, kidneys, nerves, heart and blood vessels [1].

2.1. A public health problem

Diabetes set today as a global epidemic and now affects some 371 million people worldwide. It is also estimated that most people who have diabetes don’t know their condition. There are 4 million deaths per year related to diabetes and its complications, representing 9% of world mortality. The main consequence of this fact is the large economic and social impact for both the individual and society. Their high costs are mainly related to a high frequency of acute and chronic complications, such as higher incidence of cardiovascular and cerebrovascular diseases, blindness, kidney failure and non-traumatic amputations of lower limbs, which are causes of hospitalization, greater needs for medical care, disability, lost productivity and premature death. The correct and early diagnosis of diabetes associated with the appropriate treatment can decrease the chance of developing the complications of diabetes.

2.2. Classification

There are three major types of diabetes, which causes and risk factors are different for each type:

- Type 1 diabetes can occur at any age, but it is most often diagnosed in children, teens, or young adults, affects some 10% of cases and is caused by the reduction of pancreatic beta cells which results in deficiency of insulin production, and often the person needs to receive daily injections of insulin;
- Type 2 diabetes, which affects 90% of cases and the person has almost normal levels of insulin in the blood, but suffers a reduction in the number of receptors of this hormone in target cells, reducing the ability of these cells to absorb glucose in the blood. It most often occurs in adulthood, but teens and young adults are now being diagnosed with it because of high obesity rates. Many people with type 2 diabetes do not know they have it.
- Gestational diabetes is a preclinical stage of diabetes. A woman develops signs of hyperglycemia of varying intensity, first diagnosed during pregnancy and usually resolves in the postpartum period, but in most cases women who have gestational diabetes are at high risk of their developing diabetes after.

The type 2 will be addressed in this work because it is the most common type.

2.3. Parameter for the diagnosis

The parameters for the diagnosis are classified as risk factors for developing the disease, symptoms which can appear and laboratory tests that are commonly used in the diagnosis. These parameters were obtained from literature review and direct interviews with a panel of experts in the area.

3. Hybrid application

The methodology proposed in this paper aims to build a hybrid model to create an Expert System, structured in probability rules using Bayesian Networks, Decision Support Methodologies (Multiple Criteria Decision Analysis - MCDA) and structured representations of knowledge in production rules and probability (Artificial Intelligence), as shown in Figure 1. This model will be applied to the diagnosis of type 2 diabetes in order to support healthcare professionals in early diagnosis [15] [16] [17].

Figure 1 Hybrid methodology

The hybrid application will follow five steps:

1. Identify the parameters for the diagnosis of the disease;
2. Apply Bayesian Networks to represent the relationship between the parameters for the diagnosis and establish the probability of each one occurs;
3. Apply the methodology MCDA to select which of these parameters has a greater impact on the diagnosis, based on probabilities defined in the Bayesian Network;
4. Build the knowledge base of the Expert System which will be composed by the selected parameters as the greatest impact on diagnosis;
5. Update the database with the results obtained by the Expert System to recalculate the probabilities.

Aiming to facilitate the application of the proposed methodology, we developed a computational tool, SDD (*Sistema de Diagnóstico de Diabetes* or System to Diagnose Diabetes), in platform Java Web to automate the process of generating Bayesian Networks using the Netica-J API and the construction of the Judgment Value Matrix.

Step 1. The first step is to identify the parameters for the diagnosis of diabetes and then conducting a survey of available databases and the parameters that are presented in each database. Two groups were defined, one group of patients and a control group, and the system seeks to determine if the new patient is in the patient group. The hybrid model proposed seeks to diagnose new cases structured from the history of patients with diabetes.

For this study we first considered the Statistics Canada database consisting of 108,177 people, where 4,611 were classified as having diabetes, according to Table 1, and then we considered the CAMED database consisting of 1,222 diabetic patients of a total of 1,726 people, according to Table 2. The CAMED is a Brazilian company with over 30 years in the market that provides medical, hospital and dental care [18].

These databases must be registered in the tool SDD. For each database is necessary to inform the total amount of people present in the database, the amount of people who have the disease, the parameters for the diagnostic and their values (alternatives).

Table 1 Statistics Canada database

Parameter for the diagnosis	Alternatives of the decision problem	Amount of people Diabetic	Amount of people Total	Value function PVF1	Value function PVF2
A: Age	A1: 12 to 44	433	54,216	0.52	0.09
	A2: 45 to 64	1,789	30,022	0.27	0.39
	A3: 65 or older	2,389	23,939	0.21	0.52
B: Chronic conditions	B1: Yes	3,568	66,499	0.61	0.77
	B2: No	1,043	41,678	0.39	0.23
C: Body Mass Index (BMI)	C1: Underweight	124	11,619	0.11	0.03
	C2: Normal	1,011	42,678	0.40	0.22
	C3: Overweight	1,709	33,510	0.31	0.37
	C4: Obese	1,637	17,053	0.15	0.36
	C5: Missing	130	3,317	0.03	0.03
D: Physical activity	D1: Active	638	24,339	0.23	0.14
	D2: Moderate	879	23,697	0.22	0.19
	D3: Inactive	2,826	53,255	0.49	0.61
	D4: Missing	268	6,886	0.06	0.06
E: Smoking	E1: Never	1,243	36,473	0.34	0.27
	E2: Former	2,504	42,571	0.39	0.54
	E3: Current	856	28,912	0.27	0.19
	E4: Missing	6	221	0.00	0.00
F: Alcohol consumption	F1: Regular	1,543	56,112	0.53	0.33
	F2: Occasional	1,099	23,106	0.21	0.24
	F3: Former/Never drank	1,961	28,641	0.26	0.43
	F4: Missing	8	318	0.00	0.00
G: Daily fruit/vegetable consumption	G1: Fewer than 5 times	2,767	68,915	0.64	0.60
	G2: 5 times or more	1,757	37,554	0.35	0.38
	G3: Missing	87	1,708	0.02	0.02
	Total	4,611	108,177		

Step 2. According to the registered database, the SDD tool calculates the probability of each parameter occurs and generates the Bayesian Network using the Netica-J API (www.norsys.com). The Bayesian Network for the Statistics Canada database can be visualized in Figure 2.

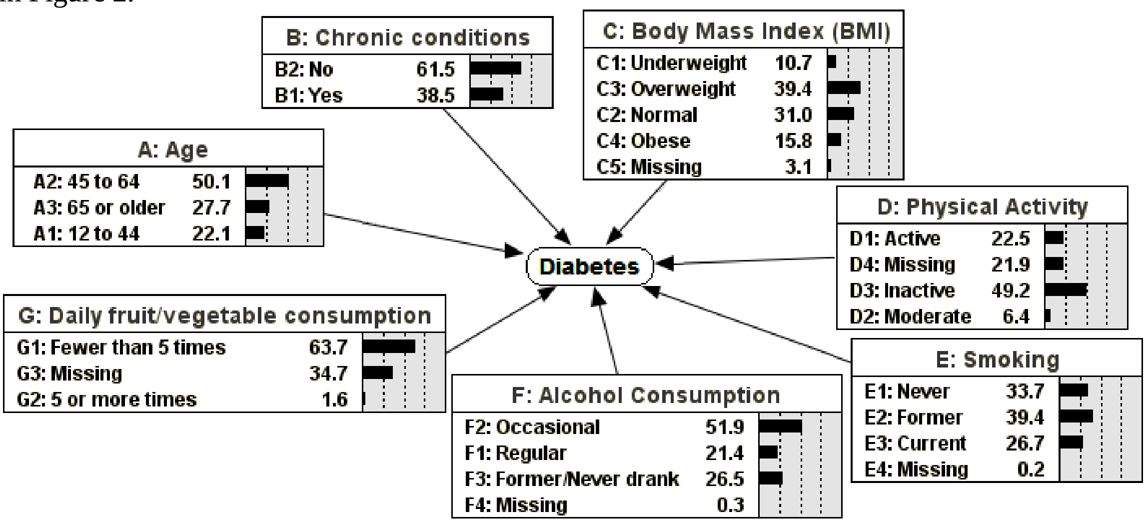


Figure 2 Bayesian Network extracted from the tool SDD

Table 2 CAMED database

Parameter for the diagnosis	Alternatives of the decision problem	Amount of people		Value function	
		Diabetic	Total	PVF1	PVF2
A: Age	A1: 12 to 44	79	119	0.08	0.06
	A2: 45 to 64	538	787	0.49	0.44
	A3: 65 or older	605	820	0.43	0.50
B: Family history	B1: Yes	729	729	0.00	0.60
	B2: No	328	328	0.00	0.27
	B3: Missing	165	669	1.00	0.14
C: Waist circumference	C1: Normal	89	138	0.10	0.07
	C2: High	150	225	0.15	0.12
	C3: Very high	279	417	0.27	0.23
	C5: Missing	704	946	0.48	0.58
D: Physical activity	D1: Active	558	783	0.45	0.46
	D2: Inactive	546	628	0.16	0.45
	D3: Missing	118	315	0.39	0.10
E: Smoking	E1: Yes	97	113	0.03	0.08
	E2: No	983	1,348	0.72	0.80
	E3: Missing	142	265	0.24	0.12
F: Alcohol consumption	F1: Yes	325	440	0.23	0.27
	F2: No	755	1,021	0.53	0.62
	F3: Missing	142	265	0.24	0.12
G: Health eating habits	G1: Yes	908	1,204	0.59	0.74
	G2: No	191	201	0.02	0.16
	G3: Missing	123	321	0.39	0.10
H: Hypertension	H1: Yes	724	724	0.00	0.59
	H2: No	365	365	0.00	0.30
	H3: Missing	133	637	1.00	0.11
	Total	1,222	1, 726		

The Netica-J provides the complete Netica API (Application Programmer Interface) in Java. The Netica APIs are a set of powerful toolkits for working with Bayesian Networks. They allow you to build your own Bayesian Networks and influence diagrams, do probabilistic inference, learn nets from data, modify nets, and save and restore nets. It allows direct connection to most database software. Netica is a powerful tool for building Bayesian Network, simple, intuitive, reliable and high performance.

Bayesian Networks is a good strategy to deal with problems involving uncertainty in complex domains, very common in the medical field, where prior knowledge about the problem is not enough to draw conclusions. It allows representing and manipulating uncertainty based on well-founded probabilistic principles. Bayesian Network offers an approach to probabilistic reasoning, which includes graph theory for the establishment of relations between sentences and probability theory, for assigning levels of reliability [10] [14].

Bayesian Networks have shown high performance when used in the medical field. Prognosis of head injuries [23], pneumonia [2] and diagnosis of breast cancer [6] are some examples of successful applications of Bayesian Network.

Step 3. From the probabilities defined above, the decision support model will assess which parameters for diagnosis are more attractive, for each level of influence (little influence or much influence), to define the diagnosis of the disease.

The Methodology Multiple Criteria Decision Analysis (MCDA) has much to add to the process of diagnosis, by providing techniques and tools that allows the decision maker to structure the parameters for the diagnosis and prioritize in order of degree of importance of each one in the decision process of search for the diagnosis [11] [21].

The methodology MACBETH was chosen among the available methodologies MCDA. The MACBETH (Measuring Attractiveness by a Category-Based Evaluation Technique) is a decision-aid approach to multicriteria value measurement, which uses only qualitative judgments, facilitating the elicitation of preferences of the decision maker [3] [4] [5].

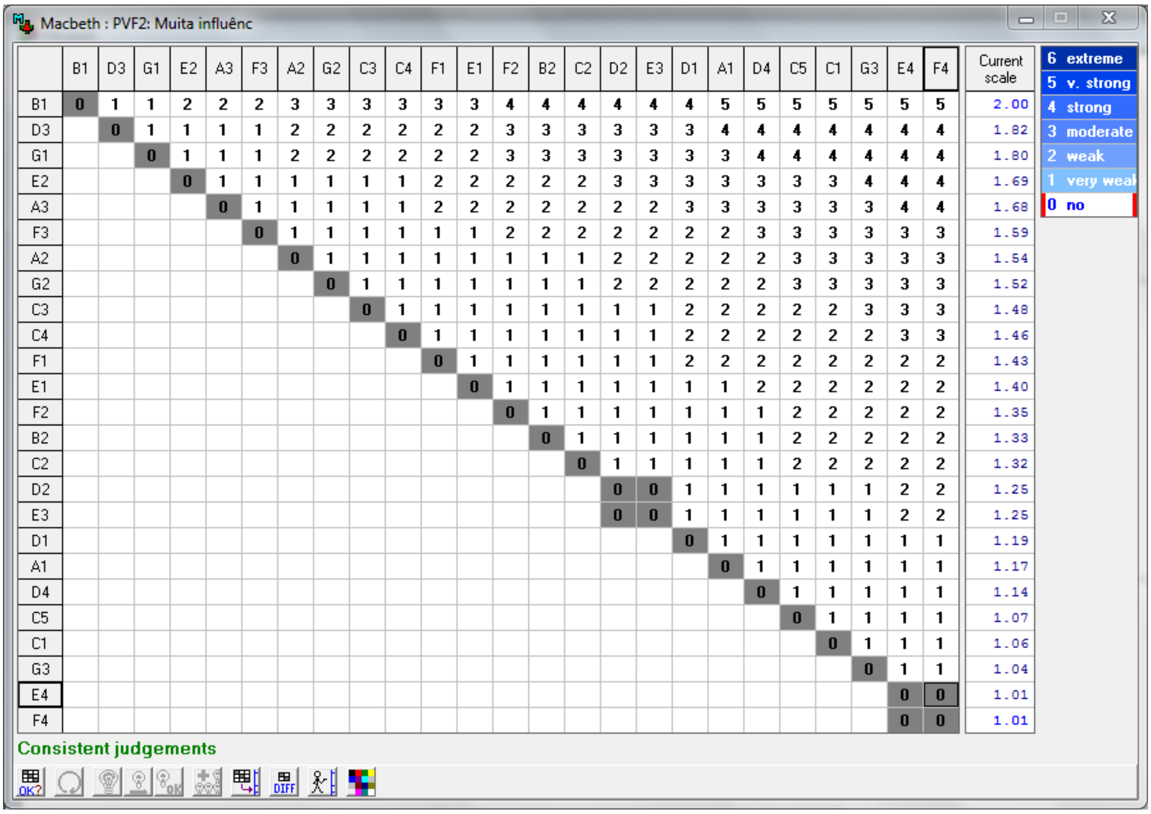
The level of influence of each parameter in the diagnosis of disease was defined based on the cases of people present in the database. For each alternative has defined a value function, which can be seen in Tables 1 and 2. For the Fundamental Point of View (FPV)1: Little influence in the diagnosis, the value function of each alternative has been obtained from the division between the number of people without diabetes who presented a specific value for a parameter for diagnosis by the total amount of people in the database without diabetes. For the FPV2: Much influence, the value function was defined as the conditional probability of a person being in a certain range of value considering that she has Diabetes. For example, according to Statistics Canada database the number of people with diabetes who is obese (C4) is 1,637 between the 4,611 people in the database who have Diabetes, then the value function of this alternative is equal to 0.36.

The difference in attractiveness between two alternatives was judged as the difference of their value functions, and then equivalence is made between the differences in attractiveness present in MACBETH, as shown on Table 3.

Table 3 Difference in attractiveness on MACBETH

Difference in attractiveness on MACBETH	Results obtained in the model application
0 No	0,00
1 Very weak	0,01 to 0,18
2 Weak	0,19 to 0,34
3 Moderate	0,35 to 0,51
4 Strong	0,52 to 0,67
5 Very strong	0,68 to 0,84
6 Extreme	0,85 to 1,00

The Judgment Value Matrices are generated by the tool SDD for each Fundamental Point of View and then are inserted in software Hiview. The Judgment Value Matrix for the FPV2: Much influence in the diagnosis and the scale generated by MACBETH can be seen in Figure 3. The Hiview (www.catalyze.co.uk) is a computational tool that has the option to runs MACBETH method in their functionalities. As decisions are entered into the software, it automatically checks the consistence of the information in order to compose a robust judgment matrix. Finally, when the matrix is complete, a numerical scale of preference is generated.



	B1	D3	G1	E2	A3	F3	A2	G2	C3	C4	F1	E1	F2	B2	C2	D2	E3	D1	A1	D4	C5	C1	G3	E4	F4	Current scale
B1	0	1	1	2	2	2	3	3	3	3	3	3	4	4	4	4	4	4	5	5	5	5	5	5	5	2.00
D3		0	1	1	1	1	2	2	2	2	2	2	3	3	3	3	3	3	4	4	4	4	4	4	4	1.82
G1			0	1	1	1	2	2	2	2	2	2	3	3	3	3	3	3	3	4	4	4	4	4	4	1.80
E2				0	1	1	1	1	1	1	2	2	2	2	2	3	3	3	3	3	3	3	4	4	4	1.69
A3					0	1	1	1	1	1	2	2	2	2	2	2	2	3	3	3	3	3	3	4	4	1.68
F3						0	1	1	1	1	1	1	2	2	2	2	2	2	2	3	3	3	3	3	3	1.59
A2							0	1	1	1	1	1	1	1	1	2	2	2	2	2	3	3	3	3	3	1.54
G2								0	1	1	1	1	1	1	1	2	2	2	2	2	3	3	3	3	3	1.52
C3									0	1	1	1	1	1	1	1	1	2	2	2	2	2	3	3	3	1.48
C4										0	1	1	1	1	1	1	1	2	2	2	2	2	2	3	3	1.46
F1											0	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1.43
E1												0	1	1	1	1	1	1	1	2	2	2	2	2	2	1.40
F2													0	1	1	1	1	1	1	1	2	2	2	2	2	1.35
B2														0	1	1	1	1	1	1	2	2	2	2	2	1.33
C2															0	1	1	1	1	1	2	2	2	2	2	1.32
D2																0	0	1	1	1	1	1	1	2	2	1.25
E3																0	0	1	1	1	1	1	1	2	2	1.25
D1																		0	1	1	1	1	1	1	1	1.19
A1																			0	1	1	1	1	1	1	1.17
D4																				0	1	1	1	1	1	1.14
C5																					0	1	1	1	1	1.07
C1																						0	1	1	1	1.06
G3																							0	1	1	1.04
E4																								0	0	1.01
F4																								0	0	1.01

Figure 3 The Judgment Value Matrix for the FPV2: Much influence in the diagnosis and the scale generated by MACBETH from software Hiview for the Statistics Canada database

According to the analysis of the numerical scale of preference generated by Hiview we can identify which parameters are most attractive to include in the knowledge base of the Expert System to diagnose diabetes. For example, According to the analysis of the Statistics Canada database's graph, in Figure 4 we can see that the five parameters with the greatest impact in defining the diagnosis of diabetes are: presence of chronic complications (B1), physical inactivity (D3), low consumption of fruits/vegetables (G1), smoked (E2) and has 65 years or more (A3). With this result, it can be said that these five parameters are best suited to assess whether a person has diabetes.

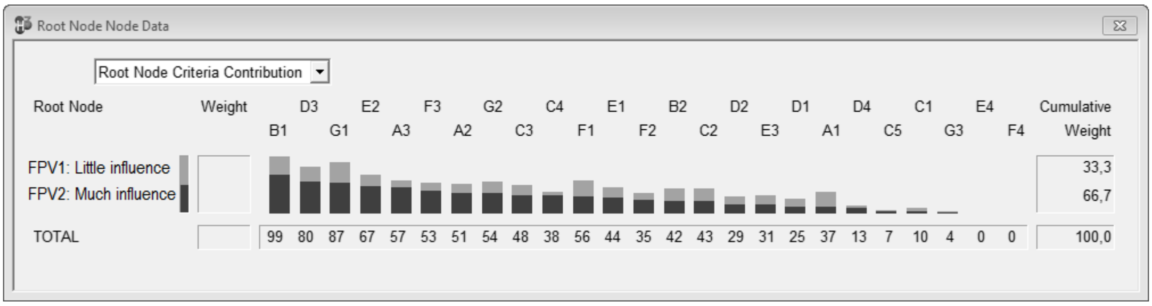


Figure 4 MACBETH scale from software Hiview for the Statistics Canada database

According to the graph in Figure 5 it can be seen that in the CAMED database, most patients with diabetes do not smoke (E2) have healthy eating habits (G1) and do not consume alcohol (F2) but have a family history (B1) and are hypertensive (H1). Regarding the waist circumference (B), for the majority of patients, this information is not contained in its database (C4), but in patients who have this information, most have very high waist circumference (C3) followed by high waist circumference (C2) and the minority have normal circumference (C1).

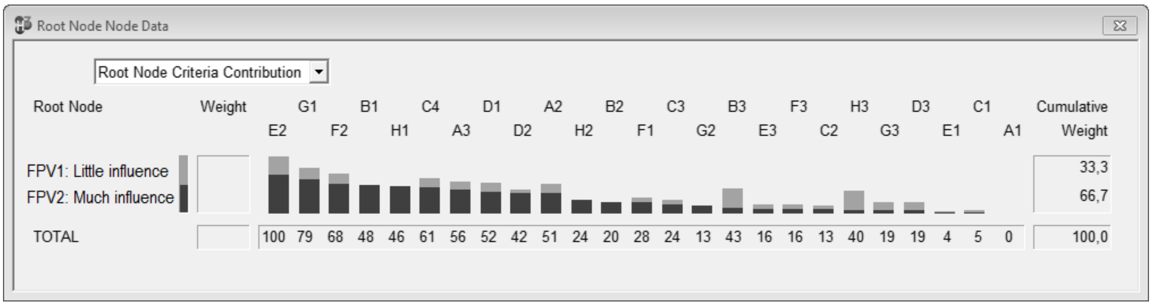


Figure 5 MACBETH scale from software Hiview for the CAMED database

Step 4. Expert Systems are computer programs that use Artificial Intelligence to solve specific problems in a given domain, simulating or emulating the performance of human experts. However, despite presenting a performance sometimes comparable to human experts in solving specific problems, the Expert System does not have learning capacity, then, they have not really intelligent behavior. Expert Systems are often employed as assistants or consultants to human users. They may have use in solving routine problems, freeing the human experts for unusual problems. They can also bring expertise to places where human experts are not available or makes it accessible when specialized services are very expensive [22].

The software Expert SINTA (www.lia.ufc.br) applies Artificial Intelligence techniques to automatically generate Expert Systems, simplifying the steps of creating a complete Expert System. This tool allows only concerned with the representation of knowledge and interpret this knowledge is your responsibility. The Expert SINTA was created by a group of scholars at the Federal University of Ceará (UFC) and the State University of Ceará (UECE), called Group SINTA (*Sistemas INTeligentes Aplicados* or Applied Intelligent Systems). This tool uses a model of knowledge representation based on production rules, with conditions in the style IF... THEN..., with the possibility of including logical connectives relating the attributes in the scope of knowledge and the use of probabilities, using an inference engine shared and probabilistic treatment of the production rules [19]. The Expert SINTA use the architecture described in Figure 6.

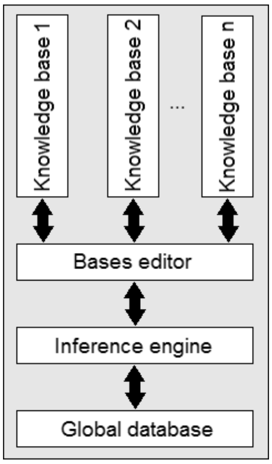


Figure 6 Architecture of ExpertSINTA

For the creation of the knowledge base of the Expert System, our first step was defining the variables and their values according to the value of the parameters for diagnosis and the objective, which is having diabetes or not. Then the questions were registered to be performed by the system to the user, regarding the given attribute. The next step was to define the rules to model the human knowledge, according to the results obtained by MACBETH. The rules lead the user of the Expert System to a diagnostic and their order can have a vital influence on the functioning of the system. For example, applying Statistics Canada database, the number one rule, as in the worst case, if the user has chronic complications, does not practice physical activity, has a daily consumption of fruit/vegetable fewer than 5 times, smoked and your age is 65 years or more, his probability of having diabetes is too high. These steps can be seen in Figure 7.

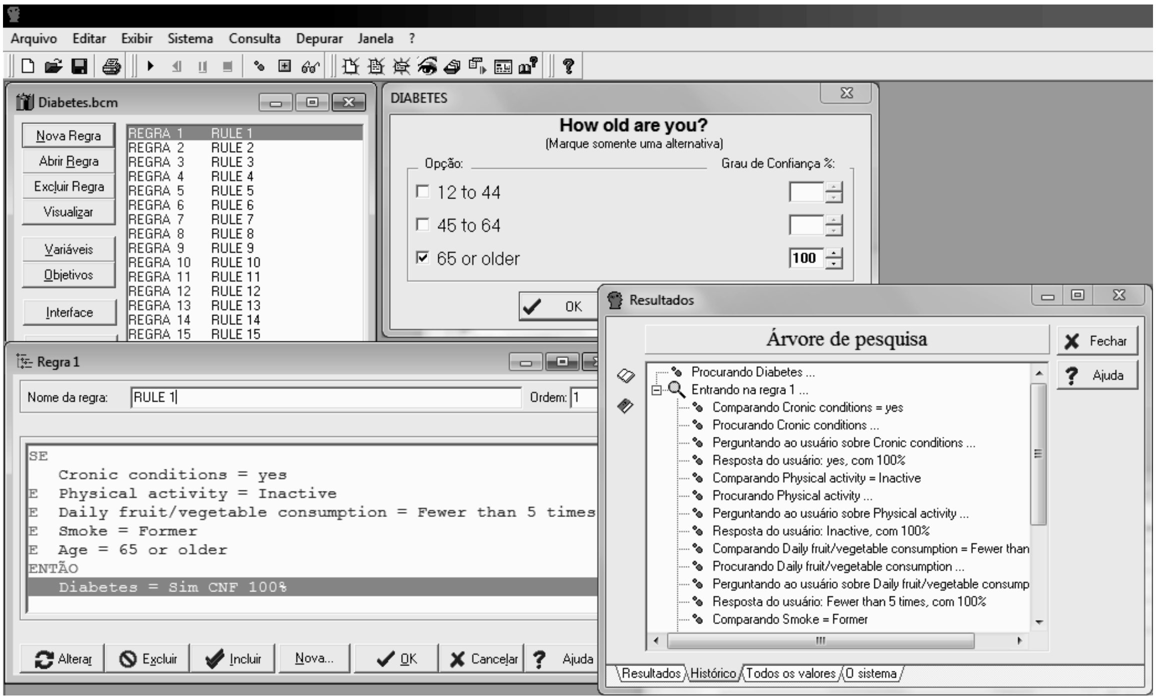


Figure 7 Expert SINTA

The Expert SINTA seeks to achieve conclusions for certain objectives asking questions to the user. Whenever one of these objectives is reached, or when they exhaust all the possibilities, the Expert SINTA display a window with the results, and how they came to that conclusion. In the history is presented a search tree that is a path of logical reasoning conducted by Expert System. The history of how the Expert System achieves a particular conclusion aims to assist in the analysis of the results obtained after diagnosis, increasing the reliability of the answers found.

Step 5. The diagnoses made by the Expert SINTA will be entered into the software database so that the probabilities are recalculated for the computational tool SDD.

4. Comparison of databases

Analyzing the graphs extracted from Hiview for the Canadian database, shown in Figure 4, and the Brazilian database, shown in Figure 5, we can make a comparison between the values of the parameters more presented by patients, as shown in Table 4.

In Table 4 we can observe that in both databases, the predominant age among patients is over 65 years. In Canadian database, most patients do not practice physical activities, while in Brazilian the probability of a patient practice or not physical activity is almost the same. The eating habits presented by Brazilians are healthy, different from the Canadians that had a low consumption of fruits and vegetables.

Table 4 Comparison between the applied databases

Parameter for the diagnosis	Database	
	Statistics Canada	**CAMED**
Age	65 or older	65 or older
Physical activity	Inactive	Inactive and Active
Smoking	Former	No
Alcohol consumption	Former/Never drank	No
Daily fruit/vegetable consumption	Fewer than 5 times	-
Health eating habits	-	Yes
Body Mass Index (BMI)	Obese and Overweight	-
Waist circumference	-	Very high
Chronic conditions	Yes	-
Family history	-	Yes
Hypertension	-	Yes

5. Conclusion and future work

Early diagnosis is the first step to successful treatment. The main causes of chronic diseases are known and these risk factors can be eliminated. There is no justification for not using the available knowledge about the prevention and control of chronic diseases, representing an unnecessary risk to future generations and high costs. The utilization of Expert Systems applied in the medical field improves the quality of medical services, in addition to spreading knowledge of specific areas of medicine. This article is part of a study with the proposal to contribute to the development of automated diagnosis with quality. The present study demonstrates that the probability rules and the degrees of confidence defined in the software Hiview can be useful to compose the knowledge base that will be processed by the machine inference of the Expert System, which uses this information to make the diagnosis. The methodology described in this paper can be applied to another disease.

As future work, the tool SDD will implement the methodology MACBETH to check the consistency of the Judgment Value Matrix and generate a numerical scale of preference and integrate with Expert SINTA enabling the entire process is done automatically and made available on the Web

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