Chapter 8
DAS-Autism: A Rule-Based System to Diagnose Autism Within Multi-valued Logic

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Abstract In front of the continued growth of autistics number in the world, intelligent systems can be used by non-specialists such as educators or general physicians in autism screening. Moreover, it can assist psychiatrists in the diagnosis of autism to detect it as early as possible for early intervention. We propose in this chapter a tool for the diagnosis of autism: DAS-Autism. It is a knowledge-based system that handles qualitative knowledge in the multi-valued context. For this, we use our knowledge-based system shell RAMOLI, and its inference engine executes an approximate reasoning based on linguistic modifiers that we have introduced in a previous work. We have built a knowledge base that represents the domain expertise, in collaboration with a child psychiatry department of Razi hospital, the public psychiatric hospital in Tunisia. We have then conducted an experimental study in which we compared the system results to expert's diagnoses. The results of this study were very satisfactory and promising.

8.1 Introduction

Researchers are increasingly confronted with the need to support imperfect data in intelligent systems. In addition to the need to take account of this imperfection, one of the objectives of this work is to design systems that act as human behavior. Indeed, human mind uses imperfect knowledge that can be uncertain, vague, imprecise, etc.

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H. Idoudi and T. Val (eds.), *Smart Systems for E-Health*, Advanced Information and Knowledge Processing, https://doi.org/10.1007/978-3-030-14939-0_8

Fuzzy logic was introduced by Zadeh [1] to handle these types of knowledge. It has attracted a lot of interest and has been used in several fields of application [2–5]. However, according to some authors [6–8], using fuzzy logic to represent abstract terms from natural language, such as *ugly*, *beautiful*, *intelligent*, is complicated and artificial to realize. Indeed, in fuzzy logic context, every term is modeled by a fuzzy set, which is based on a numerical domain. Nevertheless, abstract terms do not refer to numerical scales, which makes their modeling with fuzzy logic difficult and artificial. Symbolic multi-valued logic [6–9] is another logic that allows a symbolic representation of terms, and it is based on multi-set theory.

We have built in [10] a knowledge-based system shell in the multi-valued framework, called Raisonnement Approximatif basé sur les MOdificateurs LInguistiques (RAMOLI). It includes a data manager to introduce symbolic knowledge and an inference engine to reason with this knowledge. The inference engine uses an approximate reasoning based on linguistic modifiers that we proposed in [11, 12]. We propose in this work to use our approach of approximate reasoning through a practical application. Thus, our goal is to construct a knowledge-based system using RAMOLI and then evaluate its performance.

Knowledge-based systems are used in various fields to solve various problems: diagnosis (diseases, failures, etc.), decision on treatment, prognosis, etc. [13–16]. RAMOLI works in the context of multi-valued logic. All data are therefore represented symbolically. Its use is thus advantageous in applications which handle symbolic data. This is the case of medicine. Each medical specialty has its own way to define and establish diagnosis. It is done by collecting symptoms drawn from the patient's state. A symptom may have either a numeric value or a symbolic value. The doctor obtains symptoms with numerical values through measuring equipments (blood pressure monitor, glucose meter, blood test, etc.), whereas for symbolic information, he refers to the patient interrogation or to his own observation.

We chose in this work to build a knowledge-based system for medical diagnosis, more precisely for autism diagnosis. We chose psychiatry because its symptoms are mostly qualitative. Thus, it is easy to represent and manipulate them in our work environment.

Cases of autism are increasing worldwide. Zablotsky et al. [17] estimate that in 2016, 2.76% of American children are autistic, against 2% in 2012 [18] and 1.16% in 2007 [19]. The most serious problem is that the diagnosis is often made too late. This is because there are not enough specialists knowledgeable about various ways in which autism can appear [20]. This consequently causes a delay in the treatment of autism. Thus, it is necessary to detect autism as early as possible for early intervention. The aim of our work, as we initiated it in [21], is to help non-specialists such as educators or general physicians in autism screening. Also it will allow assisting psychiatrists in the diagnosis of autism. We call this system diagnosis aid system of autism (DAS-Autism) [22].

This chapter is organized as follows. In Sect. 8.2, we present autism, and we specify the limits of the tools already proposed in the literature for the diagnosis of this disease. Section 8.3 is devoted to knowledge representation in symbolic way, and we briefly describe the basic concepts of multi-valued logic, the context of our work.

We also present our approximate reasoning which is based on linguistic modifiers. Then in Sect. 8.4, we describe the design of the knowledge base and the development of the knowledge-based system DAS-Autism. An experimental study is presented in Sect. 8.5, for that we use real cases and compare the system results to experts diagnoses. Finally, Sect. 8.6 concludes the work.

8.2 Autism Diagnosis

We begin in this section by presenting autism. We also cite some diagnosis systems for autism that we found in the literature.

8.2.1 Description of the Domain

Autism usually begins in the early years of childhood (before age three) [23]. It is defined as a pervasive developmental disorder (PDD), which is characterized by severe development alterations in three areas [24]:

- Verbal and nonverbal communication;
- Social interaction;
- Behavior, interests and activities that are restricted and stereotyped.

Specialists make the diagnosis by observing the behavior of the patient and by questioning parents, referring to some standard protocols. The most widely used manual in psychiatry is diagnostic and statistical manual of mental disorders (DSM-IV-TR) [24], Published by the American Psychiatric Association (APA). It provides diagnostic criteria and classifications of mental disorders. We can also cite the ICD-10 (International Statistical Classification of Diseases and Related Health Problems) [25], published by the World Health Organization (WHO). It is a medical disease classification that includes a chapter devoted to mental and behavioral disorders.

Specialists also use evaluation questionnaires designed for the diagnosis of autism. They specify the intensity at which a child is autistic and allow monitoring of the disorders evolution. These questionnaires do not provide an entirely correct assessment in all cases, but help physicians to validate their opinions and to detect fragility signs of the child. The most used assessment instrument of autism diagnosis is childhood autism rating scale (CARS) [26]. It determines if a child is autistic and assesses the severity of the syndrome. It is a questionnaire of 14 symptoms of autism. For each symptom, a score is assigned on a scale expressing its severity. Despite its performance, CARS does not meet all the criteria of DSM-IV-TR and ICD-10. Autism Diagnostic Interview-Revised (ADI-R) [27] is another questionnaire. It is a tool of semi-structured interview with parents. ADI-R is based on the diagnostic criteria of DSM-IV-TR, ICD-10 and the latest knowledge in autism. It determines the diagnosis with a threshold obtained by an algorithm. However, this instrument takes a long time (at least two hours).

In our work, we choose to refer to DSM-IV-TR. Indeed, this manual provides a fairly detailed description of autism and gives an algorithm for diagnosis aid. We also use CARS for the description of some symptoms. We will detail this idea later in this chapter.

8.2.2 Autism Diagnosis Tools

In computer science, researchers continue to make intelligent systems for medicine [28, 29], using various technologies: such as neural networks, genetic algorithms…, or combinations of these techniques. Some researchers were interested in some psychiatric diseases [30–33].

In the literature, some systems focus on autism diagnosis [20, 34–37]. These systems are based on data mining. Cohen et al. [20] use neural networks to differentiate children with autism and children with mental retardation. For this, 128 cases were used for learning and ten cases for the test. The average classification of the system is 92%. In the work of Arthi and Tamilarasi [34], the authors use fuzzy neural networks. Forty cases (patients) were collected for learning and for testing. The performance of this model is between 85 and 90%. Sunsirikul and Achalakul [35] use association-based classification to find behavior models for autistic and children with pervasive developmental disorder not otherwise specified. The clinical data in this study correspond to 140 patients and are operated by cross-validation. The average rate of correct classification is 85.27%. Kannappan et al. [36, 37] enforced the technique of fuzzy cognitive maps (FCM) on 40 cases. They had an accuracy percentage of 89.41%.

The disadvantage of neural network techniques is that they do not provide explanation of the diagnosis result. On the other hand, knowledge-based systems are able to give a trace of reasoning from inputs, triggered rules and chaining to attend the deduced result. Thus, the user can have an idea on the process covered by the system to achieve the provided result.

Another disadvantage of the systems described above is that they detect autistic children in a group which does not have a variety of associated pathologies. For example, the cases used in the system of Sunsirikul and Achalakul [35] are either autistic or suffering from pervasive developmental disorders. However, a system of autism diagnosis should be able to distinguish between autistic and normal children and children with other mental disorders. Indeed, some disorders have similar symptoms to those of autism.

8.3 Symbolic Knowledge-Based System

The context of our work is the multi-valued logic. We present in this section how to represent and manipulate imprecise knowledge to construct multi-valued knowledge-based systems in that context.

8.3.1 *Knowledge Representation*

Multi-valued logic introduces symbolic truth degrees which are intermediate between true and false [9]. According to this logic, every linguistic term is modeled by a multi-set. It generalizes classic set theory: The notion of belonging or not to a set is replaced by a partial belonging to a multi-set. The set of possible truth degrees is $\mathcal{L}_M = \{\tau_0, \ldots, \tau_i, \ldots, \tau_{M-1}\}$[1] with the total order relation: $\tau_i \leq \tau_j \Leftrightarrow i \leq j$, its smallest element is τ_0 (false), and the greatest is τ_{M-1} (true) [9, 38]. A possible list of truth degrees for $M = 7$ is $\mathcal{L}_7$ = {*not-at-all, very-mildly, mildly, mildly-to-moderately, moderately, moderately-to-severely, severely*}.

On the scale of truth degrees $\mathcal{L}_M$, operators can be defined to aggregate degrees as implications, T-norms and T-conorms. In multi-valued logic, the aggregation functions of Lukasiewicz are often preferred [9, 39].

These qualitative degrees can be considered as membership degrees of multi-sets. Indeed, "*X is* $\upsilon_\alpha A$" means that υ_α is the degree to which X satisfies the multi-set A.[2] In other words, the predicate A is satisfiable to a certain degree expressed through the scalar adverb υ_α associated with the truth degree τ_α of $\mathcal{L}_M$.

Multi-valued logic is based on the following interpretation:

$$\begin{aligned} X \text{ is } \upsilon_\alpha A &\Leftrightarrow X \text{ is } \upsilon_\alpha A \text{ is true} \\ &\Leftrightarrow \text{"}X \text{ is } A\text{" is } \tau_\alpha\text{-true} \end{aligned}$$

For example, the statement "John is rather tall" means that John satisfies the predicate *tall* with the degree *rather*.

8.3.2 *Approximate Reasoning Based on Linguistic Modifiers*

In order to manage imperfect knowledge in intelligent systems, Zadeh has introduced the concept of *approximate reasoning* [40]. It is based on a generalization of *modus ponens* (MP) known as *generalized modus ponens* (GMP). This rule can be expressed in its standard form as follows:

[1] With M a positive integer not null, which represents the number of truth-degrees in the scale $\mathcal{L}_M$.

[2] Denoted mathematically by "$X \in A$": the object X belongs with a degree to the multi-set A.

$$\frac{\begin{array}{l}\text{If } X \text{ is } A \text{ then } Y \text{ is } B\\ X \text{ is } A'\end{array}}{Y \text{ is } B'} \tag{8.1}$$

where X and Y are linguistic variables and A, A', B and B*'* are fuzzy sets. GMP serves to infer not only with an observation exactly equal to the rule premise ("X is A"), but also with an observation which is different but approximately equal to it ("X is A'"). This allows handling imprecise knowledge in the inference process.

To determine the inference conclusion ("Y is B'"), a set of axioms is taken into account in order to have a logical and coherent result in concordance with human reasoning [41, 42]. In [11], we have proposed the generalization (8.2) of criteria appeared in [42]:

$$\left|\begin{array}{ll}\textbf{C I} & A' = A \Rightarrow B' = B\\ \textbf{C II-1} & A' \text{ is a reinforcement of } A \Rightarrow \text{ the more } A' \text{ is a reinforcement of } A\\ & \text{the more } B' \text{ is a reinforcement of } B\\ \textbf{C II-2} & A' \text{ is a reinforcement of } A \Rightarrow B' = B\\ \textbf{C III} & A' \text{ is a weakening of } A \Rightarrow \text{ the more } A' \text{ is a weakening of } A\\ & \text{the more } B' \text{ is a weakening of } B\end{array}\right| \tag{8.2}$$

Existing works in multi-valued framework of Akdag et al. [9] do not respect these axioms (see [11]). We introduced in a previous work [11, 43] an approximate reasoning that checks this axiomatics more precisely, criteria I, II-1 and III. These criteria allow having a gradual reasoning, which is adequate for our application of autism. Indeed, the severity of autism is proportional to the severity of the observed symptoms.

The proposed approximate reasoning is based on linguistic modifiers. A linguistic modifier is a function that expresses the modification that a predicate must undergo to become another predicate. In the multi-valued framework, modification of predicates is performed by dilation or erosion of the scales, and/or increasing or decreasing of the truth degrees. Akdag et al. [44] introduced linguistic modifiers in the multi-valued context and called them *generalized symbolic modifiers*. An example of these modifiers is the conserved reinforcing (CR) operator, which reinforces the degree by ρ and conserves the base:

$$CR_\rho = \begin{cases} \tau_{i'} = \tau_{min(i+\rho, M-1)} \\ \mathcal{L}_{M'} = \mathcal{L}_M \end{cases}$$

with ρ is the radius. The GMP of our approximate reasoning based on linguistic modifiers is the following:

$$\frac{\begin{array}{l}\text{If } X \text{ is } \upsilon_\alpha A \quad \text{then } Y \text{ is } \upsilon_\alpha B \\ X \text{ is } m(\upsilon_\alpha A)\end{array}}{Y \text{ is } m(\upsilon_\alpha B)} \tag{8.3}$$

where X and Y are linguistic variables, A and B are multi-sets, and υ_α and υ_β are linguistic degrees associated to the truth degrees υ_α and υ_β in $\mathcal{L}_M$. For the GMP (8.3), the observation is modeled by a modification of the rule premise $m(\upsilon_\alpha\ A)$, where m represents a linguistic [44].

In addition to check axiomatics, our approximate reasoning is very advantageous when knowledge is qualitative. Indeed, this type of knowledge is represented and managed easily by symbolic multi-valued logic. We recall that in fuzzy logic, knowledge, even the qualitative ones, is modeled by fuzzy sets. They are represented by a fuzzy membership functions on a numerical and continuous universe. So, reasoning with qualitative knowledge in fuzzy logic necessitates a complex matrix calculation. However, this is avoided with our approximate reasoning.

We extended this approximate reasoning in [45] to handle with heterogeneous knowledge. We mean by this heterogeneity that the multi-set in the observation is not necessarily the same as that of the rule premise, and/or the multi-set in the inferred conclusion is not necessarily the same as that of the rule conclusion. This offers more flexibility in the inference process.

Moreover, sometimes expert knowledge must be modeled by complex rules, i.e., rules whose premises are conjunction or disjunction of propositions. For this reason, we improved our approximate reasoning in [12] to deal with complex rules. We introduced for that new operators that aggregate linguistic modifiers: M-norm and M-conorm. M-norm, denoted by A_T, allows aggregating linguistic modifiers in a conjunction of propositions and is associated to a T-norm T. M-conorm, denoted by A_S, is for the disjunction case and is associated to a T-conorm S. We have proved that these aggregators verify logical connectives properties. For example, the aggregation of two modifiers $CR_{\rho 1}$ and $CR_{\rho 2}$ for the conjunction case is

$$A_T(\mathrm{CR}_{\rho 1}, \mathrm{CR}_{\rho 2}) = \mathrm{CR}_{\rho 3} \text{with } \tau_{\rho 3} = T(\tau_{\rho 1}, \tau_{\rho 2})$$

8.3.3 Knowledge-Based System Shell

A knowledge-based system shell is a generic tool that allows the construction of knowledge-based systems. It provides a software platform for building a knowledge base and provides a generic inference engine that allows the deduction of new knowledge.

In previous work [10], we have developed a knowledge-based system shell for symbolic multi-valued knowledge, we called it RAMOLI. This shell is a generic tool that can be used in any field. Domain expertise is represented by multi-valued production rules and facts by multi-valued propositions. The inference engine implements exact reasoning as well as approximate reasoning. We have integrated our approximate reasoning based on linguistic modifiers that we had proposed in [11, 12, 43, 45]. The system is interactive and has GUIs that allow introducing knowledge base and triggering inference engine.

The construction of a knowledge base in RAMOLI is made by a set of stages. First, the user must introduce the basis that he will use, with their sizes and linguistic degrees terms. After, he specifies the manipulated multi-sets and associates to each of them a base. He must also add the linguistic variables that he will use. Once done, facts and rules can be constructed by doing combinations of linguistic variables, multi-sets and truth degrees. The inference engine can be executed after the filling of the knowledge base. It performs a forward chaining while considering imprecision and adds new facts to the knowledge base.

RAMOLI was developed in Java programming language. Thus, it provides platform portability, extensibility and easy integration with other Java code or applications.

8.4 Construction of DAS-Autism

Our goal is to build a knowledge-based system to aid diagnosis of autism: DAS-Autism. In what follows, we explain the steps that we followed for the development of this system: design of the knowledge base and system implementation.

8.4.1 Design of the Knowledge Base

Knowledge acquisition consists in acquiring knowledge from experts and in formalizing it. The formalization requires identifying involved concepts. These concepts are represented in our system by predicates, while expert knowledge will be represented by rules. We chose the formalism of rules because, in the autism domain, expert knowledge is easily translated into rules.

In this stage, our goal is to determine the set of predicates and rules that represent expert knowledge about autism. This is done by interviewing experts of the considered domain. However, in medicine, particularly in psychiatry, diagnosis strategies may vary from a doctor to another. Thus, the expertise of the interviewed doctors will influence the system result. System performance will not only depend on our approaches of inferences implementation, but more strongly on the quality of the knowledge acquisition phase, i.e., the involved doctors' expertise and its translation to a knowledge base.

Initially, to facilitate knowledge acquisition, our work is based on DSM-IV-TR [24]. Indeed, it provides an algorithm for decision making. An extract of the algorithm is given in Appendix A. From this algorithm, we have first extracted autism symptoms, and we have defined their linguistic variables and predicates in order to represent them. Then we built our rules base using these symptoms. But the symptoms shown in the DSM-IV are not nuanced, i.e., only their presence or absence in children is considered. However, our discussions with the psychiatrists have shown that they nuanced the symptoms. We recall that in our RAMOLI system predicates are multi-valued and can have several degrees. We therefore enriched extracted predicates by assigning a scale of ordered symbolic degrees. In a second step, we validated this knowledge base by domain experts, namely child psychiatrists from Razi hospital, the public psychiatric hospital in Tunisia.

We have extracted a total of 15 symptoms from the DSM-IV-TR algorithm. Identified symptoms are shown in Table 8.1. We note that autism may manifest many other symptoms. But these last symptoms may not characterize autism or are correlated with other symptoms. Their integration into the diagnosis is delicate, without warranty of betterment.

The used multi-sets for symptoms are *impaired* and *present*. Indeed, autism manifests some characters which are not present in a normal child. For these symptoms, we use the multi-set *present* to express the degree of presence of this character. Other characters are present in a normal child, and their presence in an autistic occurs in an altered way. For this reason, we use for these symptoms the multi-set *impaired*. As in the case of CARS, intensity of identified symptoms is qualified by degrees belonging to a scale of seven degrees:

Table 8.1 Symptoms list of autism

1	Nonverbal behaviors are impaired
2	Ability to develop peer relationships is impaired
3	Willingness to share is impaired
4	Social reciprocity is impaired
5	Emotional reciprocity is impaired
6	Development of spoken language is impaired
7	Conversation is impaired
8	Stereotyped or idiosyncratic language is present
9	Imitative play is impaired
10	Stereotyped patterns of interest are present
11	Patterns of interest abnormal in intensity are present
12	Patterns of interest abnormal in focus are present
13	Inflexible or ritual, non-functional adherence is present
14	Stereotyped and repetitive motor mannerisms are present
15	Persistent preoccupation with parts of objects is present

$$\begin{aligned}\mathcal{L}_7 = \{ & \upsilon_0 = \text{not-at-all},\\ & \upsilon_1 = \text{very-mildly},\\ & \upsilon_2 = \text{mildly},\\ & \upsilon_3 = \text{mildly-to-moderately},\\ & \upsilon_4 = \text{moderately},\\ & \upsilon_5 = \text{moderately-to-severely},\\ & \upsilon_6 = \text{severely}\}.\end{aligned}$$

Recall that the system is intended not only to psychiatrists, but also to non-specialists. To have accurate and efficient facts, it is necessary to provide the most help to the user without taking into account their pre-knowledge about the disease.

In the CARS questionnaire, a manual is provided to the user. It explains each symptom and its degrees. It indicates the status of the child for whom a degree is chosen.

Similarly, we have associated with each degree of each symptom an explanation of the patient status. Some of these explanations are extracted from CARS, and others are provided from child psychiatrists of Razi hospital.[3] We give the user an explanation of degrees υ_0, υ_2, υ_4 and υ_6 of the base $\mathcal{L}_7$. The other degrees are considered intermediate degrees between these latter.

The final result is also in the form of a multi-set. The objective is the diagnosis of autism, so the chosen multi-set is *autistic*. It is represented by a base of four degrees:

$$\begin{aligned}\mathcal{L}_4 = \{ & \upsilon_0 = \text{not-at-all},\\ & \upsilon_1 = \text{mildly},\\ & \upsilon_2 = \text{moderately},\\ & \upsilon_3 = \text{severely}\}.\end{aligned}$$

Thus, the diagnosis result can have various degrees. Thus, the system not only indicates whether the child is autistic or not. As do child psychiatrists, it is able to indicate the severity of impairment of the child with the disease. We have also integrated other symbolic predicates, which are global symptoms deducted from symptoms entered by the user, such as *social interaction* or *communication*. These predicates will be used in chaining process.

Once the predicates are defined, the next step is to build the rule base which represents expert knowledge. We used for this the diagnosis algorithm of autism in the DSM-IV-TR [24]. For each symptom, we associated a rule whose premise is that symptom. Other rules were added and used for the deduction of intermediate global symptoms. Our rule base comprises a total of 23 rules. We give in appendix an extract from the rule base.

[3]Our set of symptoms, which is extracted from the DSM-IV, is not equivalent to that of CARS. Common symptoms between DSM-IV-TR and CARS are listed in Table 8.1 with the numbers 1, 3, 5, 6, 9, 13, 14 and 15.

Fig. 8.1 Principal menu of DAS-Autism

8.4.2 Development of DAS-Autism

In order to provide an appropriate system for autism diagnosis, we have developed specific GUI. Packages dedicated to the generation of knowledge-based systems in RAMOLI are included in DAS-Autism. Moreover, the necessary knowledge for the construction of the knowledge base and their characteristics, namely linguistic variables, predicates, scales degrees and rules are already introduced in the source code. The main window of the system is shown in Fig. 8.1.

"Open a diagnosis" and "List of diagnoses" buttons allow viewing the diagnoses already registered in the system. The "Option" button allows the setting of the KBS. It gives the possibility to change the T-norm and/or the T-conorm used for aggregation of modifiers.

When the user creates a new diagnosis, a first window appears, to enter information about the child. Then, a chain of windows occurs successively, each one for a symptom. Each interface provides the ability to choose the level of the corresponding symptoms. Figure 8.2 shows as an example the interface of the symptom *Willingness to share*. As we can see in the figure, the symptom name and its degrees have help buttons at the left. These buttons give descriptions and explanations in order to help the user in choosing the appropriate intensity of the symptom. For example, the description of *moderately altered* is shown in Fig. 8.3.

At the end of the questionnaire, a window displaying the result of the diagnosis appears (see Fig. 8.4). It specifies the severity of impairment of the child, i.e., the intensity of autism. Similarly, a button provides the ability to see the trace of reasoning. The trace specifies all the steps taken to arrive, from the introduced symptoms, to the deducted result of diagnosis.

Fig. 8.2 Window of the symptom “Willingness to share”

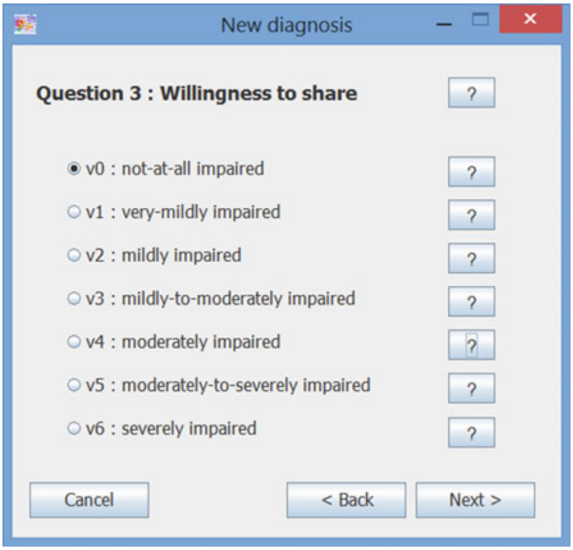


Fig. 8.3 Description dialog of “Willingness to share moderately altered”

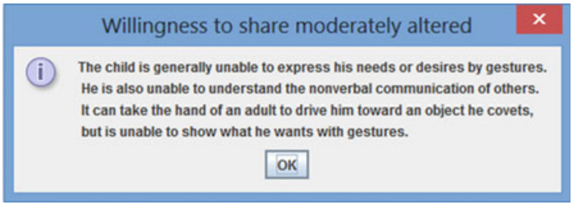
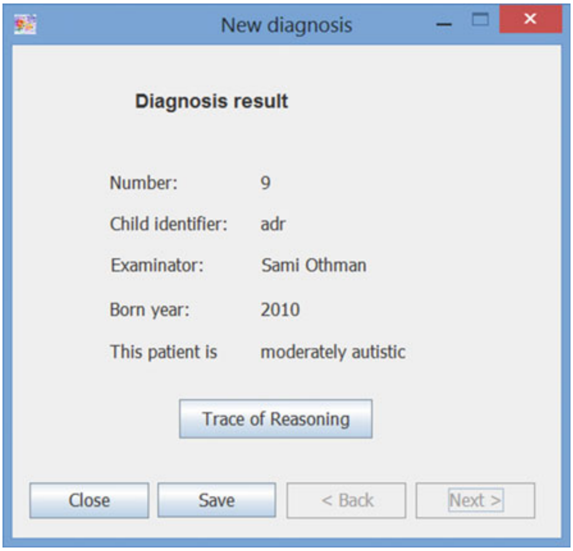


Fig. 8.4 Window of diagnosis result



8.5 Experimental Study

After constructing the DAS-Autism system, it is important to evaluate it. The objective is to determine whether it is effective enough to make valid diagnoses. To do so, the system result is compared with the diagnosis of expert to verify if they agree on their diagnoses and on the degree associated with their diagnosis. We also consider positive diagnosis for non-autistic cases (i.e., false-positive cases) and negative diagnoses for autism (i.e., false-negative cases) in order to detect potential errors of the system.

There is no common data set or benchmark for the diagnosis of autism. Every related work (see Sect. 8.2.2) has used its own testing set, which does not have the same attributes as the other works. In order to perform this experimental study, we used real cases with associated diagnoses of experts from child psychiatry department of Razi hospital. The given diagnoses are the synthesis of agreement after meeting and discussion of the child psychiatrists. The service has provided us a set of 40 cases [22]. Among these cases, 29 are autistic, with various degrees of severity. These cases allow us to see if the system gives true-positive diagnoses and/or false-negative diagnoses. Similarly, they allow comparing the severity degrees of system diagnoses with those given by the experts. The other 11 cases correspond to a set of children who are not autistic, but contain healthy children and other patients with other pathologies such as depression, mental retardation and infantile psychosis. This set is considered to check if the system provides true-negative diagnoses and/or false-positive diagnoses. Table 8.2 shows the partitioning of the test set according to the decisions of experts.

DAS-Autism has two parameters: T-norm and T-conorm. They are used in approximate reasoning to aggregate linguistic modifiers with M-norm and M-conorm. In this experimental study, we chose to use the T-norm and T-conorm of Zadeh *min* and *max*.

Table 8.3 shows the results of this study. We noticed from this experimental study that it does not provide false-positive and false-negative diagnoses. Therefore, the correct classification rate (CCR) is 100%. We then compared the severity degree of diagnoses. We found that for 29 autistics, the system gives the same severity degree as the expert for 23 cases. For the remaining six cases, the difference of severity degrees is of a unit for each case. The CCR becomes then 85% when considering

Table 8.2 Partitioning of the test set

Intensity	Cases number
Not-at-all autistic	11
Mildly autistic	7
Moderately autistic	15
Severely autistic	7
Total	40

Table 8.3 Result of the experimental study of DAS-Autism

Result	Cases number
True-positive	29
True-negative	11
False-positive	0
False-negative	0
Total	**40**
Correct severity degree	34
Incorrect severity degree	6 (gap = 1 degree)
Total	**40**

classification degrees, with a mean squared error (MSE) of 0.02. Therefore, the overall performance of the system is estimated at 93%.

These results are very satisfactory and promising. Immediate perspective would be to continue the experimental tests. It would be more interesting to compare our results with those obtained by other systems in the literature on common databases. For now, if we compare other systems to DAS-Autism (Sect. 2.2), we see that DAS-Autism provides better results. This comparison is of course to be qualified to the extent that the test base is different.

8.6 Conclusion

Imperfection becomes an inherent aspect of knowledge in knowledge-based systems. Its management allows getting as close as possible to the opinion of the expert. In this context, we chose to use symbolic multi-valued logic to handle such type of knowledge. We have proposed in this chapter a symbolic knowledge-based system for the diagnosis of autism, called DAS-Autism. We were based for the construction of this system on a knowledge-based system shell for symbolic multi-valued data, called RAMOLI [10]. More precisely, we used a package that allows introducing knowledge (rules and symptoms) and to perform an inference engine for deducing new facts (the diagnosis). We also implemented a specific GUI for this application to make easier the symptoms' entry. Then, a knowledge acquisition was necessary in order to model the expertise of the autism diagnosis. For that, we built a rule base in collaboration with psychiatrists in Razi hospital, and we were also based on DSM and CARS. We finally conducted an experimental study of DAS-Autism with real cases from Razi hospital. The obtained results are very satisfactory and enable a first validation of our work, both practically and theoretically. In this particular context, our approximate reasoning provides good results. The next step will be to deploy our diagnosis aid tool of autism among general practitioners.

Acknowledgements Authors would like to thank the psychiatrist Dr. Zied Choubani and the child psychiatrists Pr. Mohamed Bechir Hlaiem and Pr. Ahlem Belhadj for their help to elaborate this work. They particularly opened for us the child psychiatry service of Razi hospital and provided us access to anonymous patient records.

Appendix 1. Extract from the Diagnosis Algorithm of DSM-IV-TR

A. A total of six (or more) items from (1), (2) and (3), with at least two from (1), and one each from (2) and (3):

  1. Qualitative impairment in social interaction, as manifested by at least two of the following:
     a. Marked impairment in the use of multiple nonverbal behaviors such as eye to-eye gaze, facial expression, body postures and gestures to regulate social interaction;
     b. Failure to develop peer relationships appropriate to developmental level;
     c. A lack of spontaneous seeking to share enjoyment, interests, or achievements with other people (e.g., by a lack of showing, bringing or pointing out objects of interest);
     d. Lack of social or emotional reciprocity.
  2. Qualitative impairments in communication as manifested by at least one of the following:
     a. Delay in, or total lack of, the development of spoken language (not accompanied by an attempt to compensate through alternative modes of communication such as gestures or mime);
     b. In individuals with adequate speech, marked impairment in the ability to initiate or sustain a conversation with others.
     c ….

Appendix 2. Extract from the Knowledge Base of DAS-Autism

A. If social interaction is impaired and communication is impaired and restricted/repetitive/stereotyped behavior is present, then patient is autistic

  1. Social interaction:
     a. If nonverbal behaviors are impaired, then social interaction is impaired.
     b. If ability to develop peer relationships is impaired, then social interaction is impaired.
     c. If willingness to share is impaired, then social interaction is impaired.
     d. If reciprocity is impaired, then social interaction is impaired.

i. If social reciprocity is impaired, then reciprocity is impaired.
ii. If emotional reciprocity is impaired, then reciprocity is impaired.

2. Communication:
   a. If development of spoken language is impaired, then communication is impaired.
   b. If conversation is impaired, then communication is impaired.
   c. …

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