A Belief Rule Based Expert System to Assess Autism under Uncertainty

Saad Talal Alharbi, Mohammad Shahadat Hossain and Ahmed Afif Monrat

***Abstract*- Autism is one of the most common neurological disorders found in children, resulting disabilities, which continue until adulthood. The accurate assessment of autism is considered as a challenging clinical decision making problem because of the presence of various types of uncertainties that exist with its factors such as social interaction, communication and behavior. These factors cannot be measured with 100% certainty since they are associated with various types of uncertainty such as vagueness, imprecision, randomness, ignorance and incompleteness. Consequently, traditional autism diagnosis procedures such as DSM-IV Criteria, Childhood Autism Rating Scale (CARS), Autistic behavior Interview (ABI) and Childhood Autism checklist for Toddlers (CHAT), which is carried out by a physician, is unable to deliver accurate result. Therefore, this paper presents the design, development and application of an expert system to assess autism under uncertainty. The Belief Rule Based Inference Methodology using the Evidential Reasoning (RIMER) approach, employed to develop this expert system. The knowledge base of this system constructed by using the real patient data as well as by taking expert opinion. Practical case studies were used to validate the expert system. The results generated from the expert system have been compared with the expert opinion as well as with the fuzzy rule based system. It has been observed that expert system's generated results are more effective and reliable than that of fuzzy rule based system and expert opinion.**

Index Terms- Belief Rule Base; Uncertainty; Autism; Inference

I. I NTRODUCTION

Autism is a neurological disorder characterized by impaired social interaction, verbal and non-verbal communication, and restricted and aggressive behavior. Parents usually notice signs in the first two years of their child's life [1]. The signs develop gradually, but some children with autism will reach their developmental milestones at a normal pace and then regress [2]. Autism appears in infancy and early childhood, which cause delays in many basic areas of development such as learning to communicate, play and interact with others. Autism is highly heritable, but the cause includes both environmental factors and genetic susceptibility [3] [4] [5]. With recent studies, it has been development and language; and pervasive developmental disorder, not otherwise specified (commonly abbreviated as PDD-NOS), which is diagnosed when the full set of criteria for autism or Asperger syndrome are not met [7]. In this paper, the entire three spectrums, including classical ASD, Asperger syndrome and pervasive development disorder, have taken under consideration to assess the degree of autism within an autistic child. Fig. 1 represents a child with the above three ASDs.

Fig. 1. Children with Autism Spectrum Disorder

As of 2010 the rate of autism is estimated at about 1-2 per 1,000 people worldwide, and it occurs four to five times more often in boys than girls. About 1.5% of children in the United States (one in 68) are diagnosed with ASD as of 2014, a 30% increase from one in 88 in 2012 [7]. The rate of autism among adults aged 18 years and over in the United Kingdom is 1.1% [8]. The number of people diagnosed is increasing dramatically since the 1980s. The question of whether actual rates have increased is unresolved.

The children who are affected by autism are called autistic children. Life becomes very difficult and challenging for them as they face problems with social

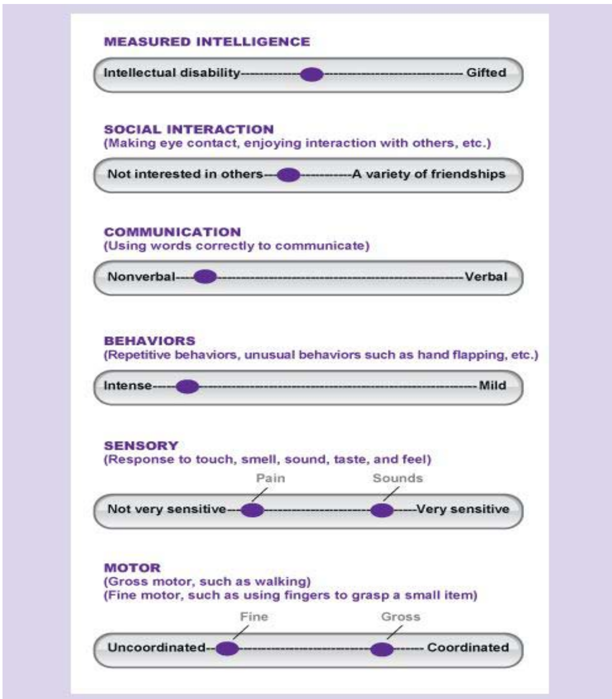

Fig. 2. Factors to Assess Autism

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interaction and communication. Moreover, the treatment process is very complex as uncertainty prevails in almost every stage of autism detection process. Sources of uncertainties may include that patients or their parents cannot describe exactly what has happened to them, doctors and nurses cannot tell exactly what they observe and laboratory report results may be with some degrees of error. The degree or level of autism is measured by assessing the factors as illustrated in Fig. 2. Uncertainty is a term indicated the inherent deficiencies of values, functions, manifestations or states that are not concrete and certain in their existence. The types of uncertainties are noticed with the factors in assessing autism consists of randomness, ambiguity, ignorance, incompleteness, vagueness and imprecision, which are illustrated in Table I.

Table I Types of Uncertainty with Autism Factors

Autism Factors	Uncertainty Type	Discussion
Social Interaction	Ignorance, vagueness	The information from the parents of the patients often contains inadequate facts which is the clear indication of their ignorance about autism and also found inconsistency in terms of describing the symptoms in similar cases with different patients.
Communication	Incompleteness	Expert assessment is incomplete
Behavior	Ignorance	Sometimes patients are unable to say what happened to them.
Sensory	Preciseness	It is difficult to measure with accuracy the degree of smell, sound, taste and feeling.
Motor	Ambiguity, Inconsistency	Similar unknown factors found as input parameter as well as final results which lacks lucidity for instance information on Gross motor, such as walking and Fine motor that enable us to grasp a small item using fingers are often proves too difficult to assess as these contains high degree of inconsistent and ambiguous data.
Measured Intelligence	Vagueness	The results of different types of activity may have vague information. For example, autistic children’s intelligence are tested with different sorts of activities such as puzzles, sports, drawing. However the results inexplicable in some manner.

II. LITERATURE REVIEW

Autism can be assessed with some conventional disease diagnostic tools such as DSM-IV Criteria, Childhood Autism Rating Scale (CARS), Autistic behavior Interview (ABI) and Childhood Autism checklist for Toddlers (CHAT). However, these systems are unable to assess autism with 100% certainty as they are not equipped to handle various uncertainties with the factors as illustrated in Table I. However, some expert systems for assessing autism have been reported in the literature [9] [10] [11] [12]. The traditional procedure of the medical diagnosis of autism employed by a physician is analyzed using the neuro-fuzzy inference procedure proposed by [9] was a self-learning and adaptive system that is able to handle the uncertainties often associated with the diagnosis and analysis of autism. Prediction of autistic disorder by applying ANN technique developed by [10] [11] demonstrated that the method works better in putting the borderline between autistic grades in terms of accuracy. Development and evaluation of an expert system for the diagnosis of child autism developed by [12], based on a diagnostic algorithm supported by a developmental scale (PEDS) and a diagnostic tool of autism (CARS). However, these systems cannot handle different types of uncertainty associated with the autism factors.

The assessment of autism is an example of a complex problem because it consists of multiple autism factors as shown in Fig. 2. Problem of this nature usually cannot be handled by an algorithmic approach rather expert systems are considered as suitable. An expert system has two components: the knowledgebase and the inference engine. The knowledge base can be constructed using various languages such as proportional logic (PL), first-order logic (FOL) or fuzzy logic (FL). Reasoning mechanisms such as forward chaining (FC) and backward chaining (BC) are used to develop the inference engine. PL and FOL are not equipped to capture uncertainty. However, FL can handle uncertainty due to vagueness and ambiguity. However, FL cannot handle other types of uncertainty such as ignorance and incompleteness that may exist with the factors of autism. Therefore, a knowledge representation schema is required that can handle all types of uncertainty that exist with the autism factors. Since FC and BC are not equipped to handle all types of uncertainty, new inference mechanism needs to be deployed.

A recently developed Belief Rule-Based Inference Methodology using the Evidential Reasoning (RIMER) approach [13] [14] [15] was used to design and develop the belief rule based expert system (BRBES) presented in this paper. Uncertainty can be addressed by this methodology. Belief rule base (BRB) is used to construct knowledge base while Evidential Reasoning (ER) works as an inference mechanism in this methodology. Here, a rule base is designed with belief degrees embedded in all the possible consequents of a rule. Inference in such a rule base is implemented using the evidential reasoning approach that can handle different types and degrees of uncertainty associated with the autism factors.

The rest of the paper is organized as follows. The next section provides an overview of the RIMER methodology. Then the system architecture, design and implementation of the proposed BRBES are discussed. Experimental results and discussions are then presented. A conclusion is included to summarize the contribution.

III. OVERVIEW OF RIMER METHODOLOGY

The Belief Rule-based inference methodology using the evidential reasoning approach (RIMER) [13] consists of Belief Rule Base (BRB) to represent domain knowledge under uncertainty and an inference procedure consisting of input transformation, rule activation weight calculation belief update and rule aggregation using Evidential Reasoning (ER). This will be discussed below.

A. Domain Knowledge Representation using BRB

A belief rule base is an extension of traditional IF THEN rule base, which is capable of representing more complicated non-linear causal relationships under uncertainty. The antecedent part of BRB contains referential value of the antecedent attribute. For example, the referential value of the antecedent attribute "behavior" is "aggressive" as shown in Eq.(1). The consequent attribute of the consequent part of the BRB is associated with belief degree with its different referential values. For example, in Eq. (1) the referential values of the consequent attribute "Autism Assessment" is embedded with belief degrees. Eq. (1) illustrates an example of a belief rule.

$$R_k : \begin{cases} IF(\text{Interaction is poor})\, and\, (\text{behaviour is aggressive})\, and \\ (\text{Communication is moderate})\, and\, (\text{Sensory is hypersensi tive})\, and \\ (\text{Measured IQ is moderate}) \\ THEN \\ \text{Autism Assessment is} \\ \{(Severe,(0.6)),(Moderate,(0.4)),(Mild,(0.0))\} \end{cases} \quad (1)$$

Where $\{(Severe,(0.6)),(Moderate,(0.4)),(Mild,(0.0))\}$ is a belief distribution of referential values such as "Severe", "Moderate" and "Mild" associated with "Autism Assessment". The belief distribution states that the degree of belief associated with severe is 60%, 40% with moderate while, 0% with mild. In this belief rule, the total degree of belief is (0.6+0.4+0+0) =1, and hence, the assessment is complete.

B. Inference Procedures in BRB

The inference procedure in BRB consists of input transformation, rule activation weight calculation, belief degree update and rule aggregation using ER as mentioned earlier.

The input transformation is equivalent to the transforming an input into a distribution of the referential values of an antecedent attribute [15]. At an instant point in time, the *i*-th value of an antecedent attribute P_i can equivalently be transformed into a distribution over the referential values of that antecedent attribute. The *i*-th input value P_i, which is the *i*-th antecedent attribute along with its belief degree ε_i of a rule is shown below by Eq. 2. The belief degree is assigned to the input value by the experts.

$$H(P_i,\varepsilon_i) = \{(A_{ij},\alpha_{ij}), j = 1,......, j_i\}, i = 1,........, T_k \quad (2)$$

Here, H is used to show the assessment of the belief degree assigned to the input value of the antecedent attributes. In this equation, A_{ij} (*i*-th value) is the *j*-th referential value of the input P_i. α_{ij} is the belief degree to the referential value, A_{ij} with $\alpha_{ij} \geq 0$. $\sum_{j=1}^{j_i} \alpha_{ij} \leq 1, (i = 1,......, T_k)$, and j_i is the number of the referential values.

The input value of an antecedent attribute is usually collected from the autistic children or from the physician in terms of linguistic values such as severe, moderate and mild. These linguistic values are assigned a degree of belief ε_i using expert judgment. This assigned degree of belief is then distributed in terms of belief degree α_{ij} of the different referential values A_{ij}. To assess autism six antecedents are considered by taking account of Fig. 1, including Social Interaction (A_1), Behavior (A_2), Communication (A_3), Motor (A_4), Sensory (A_5) and Measured Intelligence (A_6). The referential values of these antecedent attributes consist of severe (S), moderate (Mo) and mild (M). Eq. (3), (4) and (5) below illustrate how to distribute the input value of an antecedent attribute to its referential values.

$$IF(S\ value \geq input\ value \geq Mo\ value)\, THEN$$
$$Moderate = \frac{S\ value - input\ value}{S\ value - Mo\ value}, Severe = 1 - Moderate, Mild = 0.0, Normal = 0.0 \quad (3)$$

$$IF(Mo\ value \geq input\ value \geq M\ value)\, THEN$$
$$Mild = \frac{Mo\ value - input\ value}{Mo\ value - M\ value}, Moderate = 1 - Mild, Severe = 0.0, Normal = 0.0 \quad (4)$$

$$IF(M\ value \geq input\ value \geq N\ value)\, THEN$$
$$Normal = \frac{Mo\ value - input\ value}{Mo\ value - M\ value}, Mild = 1 - Normal, Severe = 0.0, Moderate = 0.0 \quad (5)$$

In the *k*-th rule, it is assumed that α_i^k is the belief degree of one of the referential values A_i^k (which is the element of A_{ij}) of the ith input P_i. This is called the individual matching degree. α_{ij} can be calculated by using Eq. (3), (4) and (5). When the *k*-th rule is activated, the weight of activation of the *k*-th rule, *ωk*, is calculated by using the flowing formula [13] [14] [15].

$$\omega_k = \frac{\theta_k \alpha_k}{\sum_{j=1}^{L} \theta_j \alpha_j} = \frac{\theta_k \prod_{i=1}^{T_k} (\alpha_i^k)^{\bar{\delta}_{ki}}}{\sum_{j=1}^{L} \theta_j \left[\prod_{i=1}^{T_k} (\alpha_i^j)^{\bar{\delta}_{ji}}\right]}, \delta_{ki}' = \frac{\delta_{ki}}{\max_{i=1,....,T_k}\{\delta_{ki}\}} \quad (6)$$

Here, δ_{ki} is the relative weight of P_i, which is used in the *k*-th rule and is calculated by dividing the weight of P_i by the maximum weight of all antecedent attributes of the *k*-th rule to normalize the value of δ_{ki} meaning its value should be within the range of 0 and 1.

There may be a case that input value of all the antecedent attributes may not be calculated, which is an example of ignorance. In that case the original belief degree of a rule needs to be updated and this can be achieved by using Eq. (7) [12][13][15].

$$\beta_{ik} = \overline{\beta_{ik}} \frac{\sum_{t=1}^{T_k} \left(\tau(t,k) \sum_{j=1}^{J_t} \alpha_{tj}\right)}{\sum_{t=1}^{T_k} \tau(t,k)} \quad (7)$$

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Where $(t,k) = \begin{cases} 1, if\ P_i\ is\ used\ in\ defining\ R_k\ (t = 1,\ldots,T_k) \\ 0, otherwise \end{cases}$

Here, $\overline{\beta_{ik}}$ is the original belief degree, and β_{ik} is the updated belief degree. Usually, when ignorance occurs then the belief degrees of a rule get updated. For example, if the input value of antecedent "interaction" is ignored, then the initial belief degrees of the BRB are updated. An example of the updated belief degrees from initial is shown in Table II.

Table II - Belief degree update

Rule Id		Severe D1	Moderate D2	Mild D3
1	Initial	0.6	0	0.4
	Update	0.48	0	0.32

In order to obtain the consequent referential values of the consequent attribute based on the input data of the antecedent attributes, ER approach is used. The ER approach is used to aggregate the activated rules of the BRB and it has two forms recursive [12] and analytical [16]. However, the rule aggregation is carried out by using an analytical approach, which has been considered computationally efficient than that of recursive approach [15]. Hence, Eq (8) [15][16] is used for the rule aggregation.

$$\beta_j = \frac{\mu \times \left[\prod_{k=1}^{L}\left(\omega_k\beta_{jk} + 1 - \omega_k\sum_{j=1}^{N}\beta_{jk}\right) - \prod_{k=1}^{L}\left(1 - \omega_k\sum_{j=1}^{N}\beta_{jk}\right)\right]}{1 - \mu \times \left[\prod_{k=1}^{L} 1 - \omega_k\right]} \quad (8)$$

with

$$\mu = \left[\sum_{j=1}^{N}\prod_{k=1}^{L}\left(\omega_k\beta_{jk} + 1 - \omega_k\sum_{j=1}^{N}\beta_{jk}\right) - (N-1)\times\prod_{k=1}^{L}\left(1 - \omega_k\sum_{j=1}^{N}\beta_{jk}\right)\right]^{-1}$$

The final output generated by ER is represented by $\{(C_1,\beta_1),(C_2,\beta_2),(C_3,\beta_3),\ldots\ldots,(C_N,\beta_N)\}$, where β_j is the final belief degree attached to the *j*-th referential value C_j of the consequent attribute, which is obtained after all activated rules in the BRB are combined by using ER. This output can be converted into a crisp/numerical value by assigning a utility score to each referential value of the consequent attribute [13][15], as shown in Eq. (9).

$$H(A^*) = \sum_{j=1}^{N} u(C_j)\beta_j \quad (9)$$

Where $H(A^*)$ is the expected score expressed as a numerical value and $u(C_j)$ is the utility score of each referential value.

IV. BRBES FOR ASSESSING AUTISM

This section discusses the architecture, design and implementation of the Belief Rule Based Expert System. In addition, the procedure of knowledgebase construction along with the system interface is also presented.

A. *Architecture, Design and Implementation of the BRBES*

The system architecture represents how its components, consisting of inputs, process, and outputs are organized. It also considers the pattern of the system organization, known as an architectural style. The BRBES adopts three-layer architectural style as shown in Fig. 3.

i) Interface layer – It is used to get the input value of the antecedent attributes as well as to display the results of the system.

ii) Application layer – Input transformation, rule activation weight calculation, belief rule update and finally the aggregation of the rules are carried out in this layer.

iii) Data management layer – The initial belief rule base as well as the facts are managed and stored in this layer.

PHP has been employed to implement the inference procedures. It has been considered for its simplicity and shorter development cycles. Moreover, it allows the system to be accessible through online. The system interface developed using other web based languages such as HTML, CSS, Javascript and JQuery. MYSQL, which is a relational database used at the back-end to store and manipulate the initial BRB, which is flexible and user friendly. MySQL also ensures the security as needed by the BRBES and it allows the faster access of data.

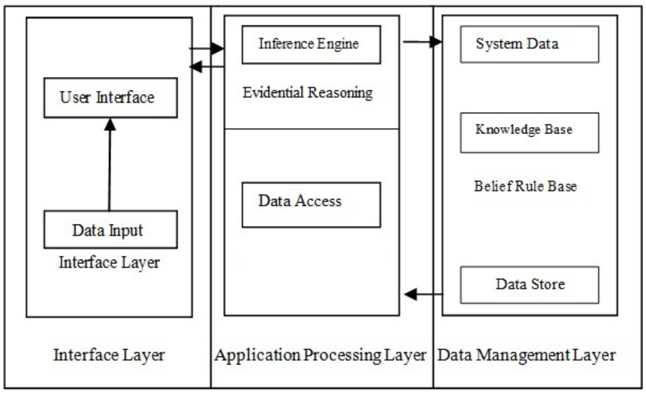

Fig. 3 BRBES Architecture

B. *Knowledge Base Construction*

In order to construct the knowledgebase for the BRBES, a BRB framework as shown Fig 4. has been developed by taking account of the autism factors of Fig 2. In this framework, the mid nodes contain the autism factors such as social interaction, behavior, communication, motor, sensory and measured intelligence. It can be seen from Fig. 4 that mid-level nodes have their child nodes, which are the leaf nodes of the tree. For example, "behavior" autism factor depends upon three elements such as "Aggressive", "Destructive" and "Odd". Hence, to assess the behavior of an autistics child the data on these three elements are required. In this way, a multilevel and nonlinear framework to assess autism has been developed.

The BRB consists of seven sub-rule bases. The autism assessment sub rule base involves six attributes, each with different referential values. The total number of rules in this sub-rule base can be calculated by using Eq (10). J_i denotes the number of referential values of an attribute while L denotes the number of rules.

$$L = \prod_{i=1}^{T} J_i \quad (10)$$

Here J_1 = 2, J_2 = 3, J_3 = 2, J_4 = 2, J_5 = 2, J_6=2 so L = (2*3*2*2*2*2) = 96. Thus, this sub-rule base consists of 96

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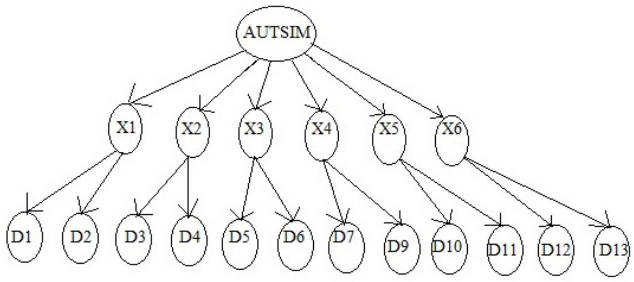
rules. In this way, the number of rules for the other six sub-rule bases can be calculated. It is assumed that all rules have equal rule weight and all antecedent attributes have equal weight. The initial sub rule base for "Communication" autism factor shown in Table III, where D6 (Non-verbal) and D7(High-verbal) are the antecedent attributes and X3 (Communication) is the consequent attribute. A BRB can be established in the following four ways [17]- (1) Extracting belief rules from expert knowledge (2) Extracting belief rules by examining historical data; (3) Using the previous rule bases if available, and (4) Random rules without any pre-knowledge. In this paper, we constructed initial BRB by the domain expert knowledge.



X1	Social Interaction
X2	Behavior
X3	Communication
X4	Motor
X5	Sensory
X6	Measured IQ
D1	Self-Absorbed
D2	Quirky
D3	Aggressive
D4	Destructive
D5	Odd
D6	Non-verbal
D7	Highly-verbal
D8	Awkward
D9	Agile
D10	Hyposensitive
D11	Hypersensitive
D12	Profound Intellectual Disabilities
D13	Gifted

Fig.4. The BRB Framework for Autism Assessment

Table III. Communication Sub-rule Base

Rule ID	Rule Weight	IF		THEN		
		D6	D7	X3		
R1	1	High	High	1.0	0.0	0.0
R2	1	High	Medium	0.6	0.4	0.0
R3	1	High	Low	0.8	0.0	0.2
R4	1	Medium	High	0.6	0.4	0.0
R5	1	Medium	Medium	0.0	1.0	0.0
R6	1	Medium	Low	0.0	0.8	0.2
R7	1	Low	High	0.8	0.0	0.2
R8	1	Low	Medium	0.0	0.6	0.4
R9	1	Low	Low	0.0	0.0	1.0

An example of a belief rule taken from Table III is illustrated below.

R1: IF Non-verbal is High AND High-verbal is High THEN Communication is{(High,l,0),(Medium,0.0),(Low,0.0)}.

In the above belief rule, the belief degrees are attached to the three referential values.

C. BRBES Interface

A system interface can be defined as the medium that enables the interaction between the users and the system. Fig. 5 iIllustrates the interface of the BRBES. By using this interface the leaf nodes data of the BRB framework (Fig. 4) can be collected from the autistic children, their parents or the person who involves in their take care. This interface also facilitates the displaying of the assessment result not only at the aggregated level or top level but also at the mid level, for example, what is the communication level of the autistic child under certain input data. In this way, the BRBES can be used to perceive the different scenarios of the autistic child, based on the autism factors mentioned in Fig 2.

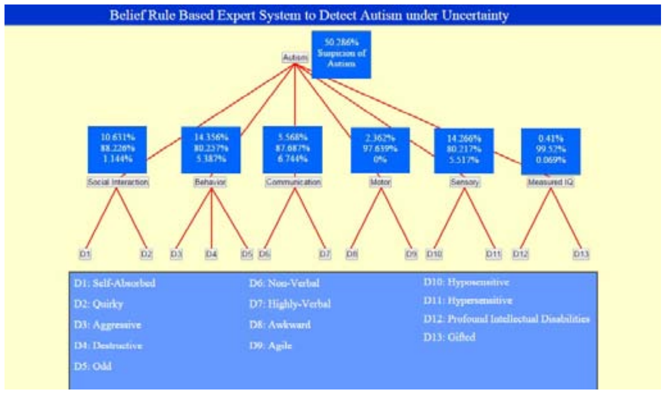


Fig.5. BRBES Interface

This will allow the physician to determine the areas (such as communication, social interaction etc.) in which the autistic child is very weak or strong. This phenomenon can be understood from Fig 5, where degree of belief for the mid level node of the BRB tree calculated in terms of fuzzy value. For example, the level of "communication" for a certain input data of an autistic child is (High, 5.568%), (Medium,87.687%) and (Low, 6.744%). The belief degree attached with the referential values of the "communication" attribute has been calculated by using Eq. (8). These fuzzy values can be converted into numerical or crisp value by using Eq. (9), where utility value need to be considered against each referential value. Following the above way, the overall assessment of the autism of a child has been obtained in terms of crisp value, which is 50.286% as shown in Fig 5.

V. RESULTS AND DISCUSSION

The BRBES presented in this paper has been used to assess the level of autism of the children of an autistic school (Fig 6.) located in Chittagong city of Bangladesh. The school has highly trained teachers who have the ability to assess the level of autism of children by considering six autism factors mentioned in Fig 2. However, during our experiment we have noticed that the teachers are not aware of the different types of uncertainty associated with the autism factors as shown in Table I. Therefore, there is a high risk that teacher's assessment level of autism may not be accurate. In this research teachers have considered as the experts. The BRBES used to experiment on hundred students of the school by collecting data of the leaf nodes of the BRB framework as shown in Fig 4 and Fig 5.

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Table IV Autism Assessment both by BRBES and Experts

Student ID	Signs & Symptoms						BRBES output	Expert Opinion
	Social Interaction	Behavior	Communication	Motor	Sensor	Measured IQ		
1	Good	Aggressive	Highly-verbal	Awkward	Hyposensitive	Gifted	64.71%	65%
2	Fair	Normal	Nonverbal	Agle	Hyposensitive	Poor	77.49%	76%
3	Poor	Normal	Verbal	Agle	Hyposensitive	Normal	64.12%	60%
4	Poor	Calm	Highly-verbal	Awkward	Hyposensitive	Poor	73.34%	72%
5	Good	Aggressive	Verbal	Awkward	Hyposensitive	Normal	38.32%	40%
6	Fair	Normal	Nonverbal	Agle	Hyposensitive	Gifted	65.2%	67%
7	Poor	Calm	Highly-verbal	Awkward	Hyposensitive	Normal	74.75%	75%
8	Fair	Calm	Nonverbal	Agle	Hyposensitive	Normal	26.98%	30%
9	Good	Normal	Verbal	Agle	Hyposensitive	Gifted	65.67%	60%
10	Good	Calm	Highly-verbal	Awkward	Hyposensitive	Gifted	76.89%	78%

Table IV shows the assessment of autism of the students of the school, generated by the BRBES and the opinion given by the experts by taking account of the six autism factors. For simplicity the table shows the data of ten students. Now it is necessary to prove whether BRBES's generated results are reliable than that of expert opinion.

The Receiver Operating Characteristic (ROC) curve is widely used to analyze the effectiveness of assessment having ordinal or continuous results [18]. Therefore, it has been considered in this research to test the accuracy of the BRBES' output against expert opinion by taking account of benchmark data. If the expert's opinion or perception on the level of autism is greater than 50% , then outcome is considered as one otherwise zero and this data have been considered as the baseline as shown in Column 5 of Table V. The accuracy or performance of the BRBES in assessing the autism level can be measured by calculating the Area Under Curve (AUC) [18][19][20][21] [22]. IF AUC of BRBES output is larger than the expert opinion then it can be inferred that BRBES produces more accurate and reliable results.

Table V. Autism Assessment by BRBES, Fuzzy System and Experts

Student ID	BRBES output	Experts Assumption	Fuzzy Logic	Benchmark Data
1	64.71	65	52.76	1
2	77.49	76	65.00	1
3	64.12	60	45.98	1
4	73.34	72	58.00	1
5	38.32	40	31.25	0
6	65.2	67	53.00	1
7	74.75	75	67.45	1
8	26.98	30	35.77	0
9	65.67	60	54.89	1
10	76.89	78	80.25	1
11	81.45	80	62.12	1
12	27.34	30	40.78	0
13	67.11	69	72.13	1
14	76.89	75	66.45	1
15	21.50	22	24.55	0
16	92.23	90	83.59	1
17	45.67	44	48.00	0

Fig. 6. Autistic School at Chittagong, Bangladesh

Fig 7 shows the two ROC curves, one represent the performance of the BRBES and the other expert opinion. The ROC curve with blue line in Fig 7 illustrates the expert opinion while the curve with green line illustrates the BEBES result. The AUC for BRBES is 0.974 (95% confidence intervals 0.960 – 1.012), and the AUC for expert opinion is 0.907(95% confidence intervals 0.939 – 1.014). From the AUC of the BRBES' and expert opinion, it can be observed that AUC of BRBES is greater than the AUC of expert opinion. This implies that results generated from BRBES are better than the results generated by the expert opinion, which uses traditional rule without taking account of uncertainty. The SPSS 16.0 has been used to construct the ROC curve and to calculate the AUC of these curves.

In addition to the expert opinion, a Fuzzy Logic Based Expert System has also been developed in MATLAB environment to compare its result with the BRBES presented in this paper. Column 4 of Table V shows the results generated by the fuzzy based system, which has been applied with the same hundred students of the school. Fig 8 shows the ROC curves which compare the performance of the BRBES, Fuzzy based system and expert opinion. ROC curve with blue line illustrates the Fuzzy based system result while the curve with green line illustrates the BRBES result. In addition ROC curve with gray line represents expert opinion. The AUC for fuzzy based system is 0.907 (95%

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confidence intervals 0.842 – 0.976). Hence, the relaibility of the BRBES is also better than that of fuzzy based system. The reason for this is that fuzzy logic only considers uncertainties due to vagueness, imprecision and ambiguity while BRBES in addition to these uncertainties considers uncertainty due to randomness and ignorance. In addition, the inference procedures of BRBES consists of input transformation, rule activation weight calculation, belief update and rule aggregation using evidential reasoning approach. Evidential reasoning is capable of processing various types of uncertainties, which is not the case with the fuzzy based inference engine such as Mamdani and Takagi–Sugeno (TS). Table VI shows the comparison of the reliability of the results among BRBES, fuzzy based system and expert opinion.

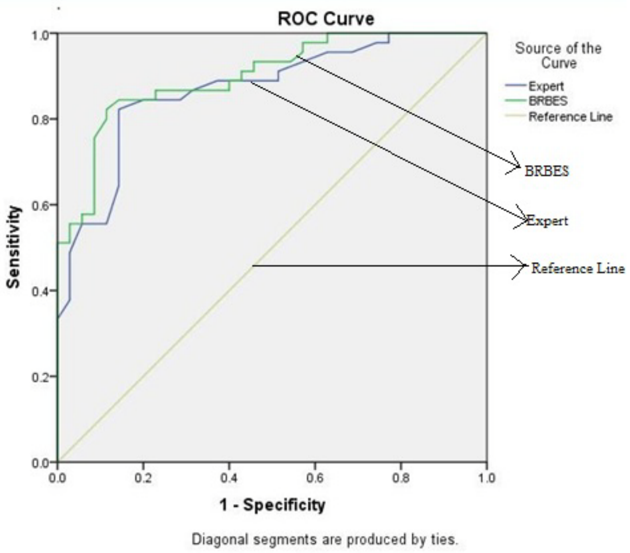

Fig.7. ROC curve comparing BRBES's result and Expert's opinion

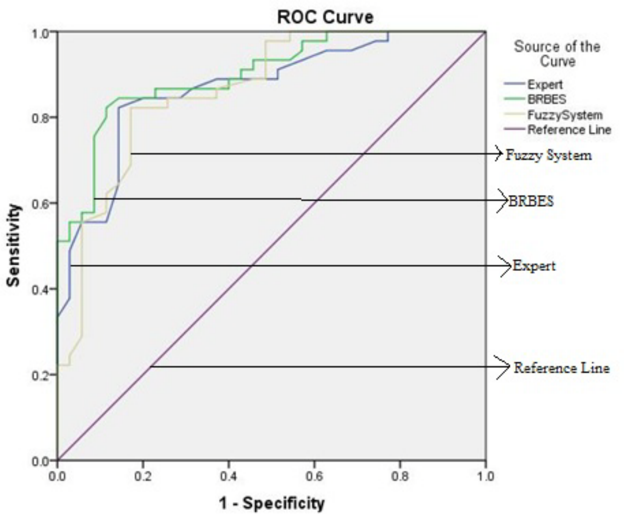

Fig. 8. ROC curve comparing BRBES result, Expert's opinion and Fuzzy system's resul

Table VI. Realibility Comparision among three systyems

Test Result	AUCa	Asymptotic 95% Confidence Interval
BRBES	0.974	0.853-0.999
Expert	0.907	0.851-0.999
Fuzzy	0.953	0.842-0.976

VI. CONCLUSION

The BRBES presented in this paper uses belief rule base as the knowledge representation schema, which has the capability to handle different types of uncertainty that exist with the autism factors as shown in Fig 2. It also considers knowledge representation parameters such as rule weight, attribute weight and belief degrees, which play an important role in increasing the reliability of the system results. The BRBES can be considered as a robust and reliable tool since it's performance is better than that of expert option and fuzzy based system as demonstrated in the earlier section. In addition, the system allows the generation of various 'what if' scenarios which can be used to develop an appropriate treatment plan for the autistics children. Hence, this system can be used to evaluate the state of the autistics children over time.

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