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Interval Valued Data Enhanced Fuzzy Cognitive Maps: Torwards an Appraoch for Autism Deduction in Toddlers

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Abstract— **Fuzzy Cognitive Maps (FCMs) are a soft computing technique characterized by robust properties that make them an effective technique for medical decision support systems. Making decisions within a medical domain is difficult due to the existence of high levels of uncertainty. The sources of this uncertainty can be due to the variation of physicians' opinions and experiences. The structure of existing FCMs is based on type -1 fuzzy sets in order to represent the causal relations among concepts of the modeled system. Therefore, the ability of the FCM to handle high levels of uncertainties and deliver accurate results can be hindered. In this paper, we propose using the Interval Agreement Approach to model the weights of links in FCMs to capture high level uncertainties in the presence of imprecise data acquired from different medical experts to enhance its decision modelling and reasoning capability. The proposed model is used in identifying if a child is diagnosed with an Autism Spectrum Disorder (ASD) where the Modified Checklist for Autism in Toddlers is used as a standard tool to derive the inputs for the FCMs. Initial results demonstrate that the proposed method outperforms conventional FCMs in classifying ASD based on a dataset of diagnosed cases.**

Keywords—Autism; Interval computation; MCHAT; medical decision support sytem; type-2 fuzzy set; fuzzy cognitive map.

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder that appears in early life stages. As described in [1] it is characterized by communication deficiency and impairments in social interaction. Children with autism tend to have abnormalities represented by repetitive behavior and limited interests. Their understanding capacity of non-verbal activities is comparatively lower than neurotypical children and affects their communication and interaction with other children and adults. This can be manifested in the form of maintaining eye contacts and expressing emotions. Early diagnosis and treatment of Autism can help Autistics to reach their full developmental potential, engage with others, and integrate into society to lead normal lives. The process of diagnosing ASD is challenging due to the existence of different qualitative and quantitative data sources that need to be elicited and analyzed in order to diagnose the severity of the condition. Moreover, different opinions of different stakeholders such as teachers, parents, and physicians may vary and need to be taken into account.

The aforementioned reasons suggest the necessity to create a decision model based on combining key indicators contributing to a diagnosis, which can be used to identify early signs, type and severity of the Autism. FCMs have been used in combination with learning techniques for the identification of ASD. Previous works [2-4], were based on knowledge elicited by physicians for evaluating abilities of trained FCM models for classifying ASD.

One limitation of current FCMs is its ability to handle uncertain information and aggregate information from different sources [5]. In previous research, fuzzy values associated with the FCM concepts and links between them have normally been represented using type-1 fuzzy sets, which do not have the ability to handle various sources of uncertainty associated with real world knowledge, human subjective opinion and noisy data sources. Recent work [6] has investigated the use of triangular fuzzy numbers to represent the uncertain relations between the concepts. Extending type-1 to Interval and General Type-2 Fuzzy Sets (GT2FS) [7-8] has the potential to improve the efficiency of modelling higher orders of uncertainty associated with the elicited domain data. Using general type-2 Fuzzy sets also enables the combination of inter and intra uncertainties from multiple experts thus representing different users' perceptions, and levels of hesitancy in their working knowledge.

The ability to generate type-2 fuzzy sets from observed and aggregated data also offers the means to represent true possibility and uncertainty distributions of the data that more accurately resembles real world information [9]. The use of type-2 fuzzy sets can therefore be combined with the modelling and reasoning abilities of FCMs to improve its reasoning capability. This paper aims to enhance the FCM through introducing GT2FS into the weights of directed edges of the

FCM. The GT2FS are generated by Interval Agreement Approach (IAA) [9] based on the aggregated opinions of different physicians to capture higher order uncertainties related to Autism diagnosis and prognosis.

The Modified Checklist for Autism in Toddlers (MCHAT) is recognized by the American Academy of Pediatrics as a screening tool for indicating if a child between 16 months and 30 months of age is at risk of developing Autism [1]. The existing MCHAT questionnaire considers the crisp inputs namely yes/no for answering each of 20 questions pertaining to unique skills and difficulties of a toddler. Based on the responses of parents on the MCHAT, the physician follows subsequent evaluation flow charts to reach a decision on diagnosis. This decision can be imprecise and intuitive in nature based on the perception and expertise of a given physician. These procedures can also be time consuming with a high degree of information loss in the assessment procedure due to its dependents on crisp inputs. The proposed approach extends on previous work that uses FCMs for modeling MCHAT based decision making process [2] by using GT2FS generated from interval valued data obtained from the doctors to represent the FCM weights.

This paper is structured as follows: Section II provides background knowledge on the use of FCM in medical domains, and discusses the use of Interval Agreement Approach. Section III proposes an enhanced FCM combined with IAA for decision-making. Section IV illustrates the computational steps used in the proposed method for computing the weights between the C_1 input and C_{21} decision concept of the generated FCM. In section V, the experimental results are presented. In section VI the advantages of the proposed method, limitations and future works are discussed.

II. Background

A. *Fuzzy Cognitive Map in medical domain*

FCMs are a strong computational tool for representing and analyzing the behavior of people and systems [10]. FCM can be used in order to model complex environments by utilizing diverse data sources, including the knowledge and experience of human experts. FCM is a fuzzy weighted directed graph with feedback and it is able to exploit the benefits of fuzzy logic and causal maps. Compared to conventional rule based reasoning approaches, FCM is based on a strong mathematical structure that helps systematic causal propagation.

In the graph-based structure of the FCM, knowledge is represented as nodes, and causal connections. The FCM graph consists of n nodes which stand for concepts C_i : $i = 1,2,3,\ldots n$. These nodes represent the most important factors influencing a decisional environment. The weighted and directed edges of the FCM connecting the aforementioned nodes represent the relationships between those factors. Each edge e_{ij}, represents the causal relation from causal concept C_i to the effect or decision concept C_j. The strength of the causal relation between the concepts C_i and C_j is represented by the weight W_{ij} of the edge e_{ij}, where $W_{ij} \in [-1,1]$. The weights of the edges between n concepts are associated in an nxn matrix, called connection matrix (weight matrix). In the process of designing an FCM, the number of concepts and the causal relations among them, can be defined by subject experts. FCMs provide excellent mechanisms to develop forecasting exercises, especially what-if analysis. Therefore, the inference process of the FCM can be performed to draw knowledge, analyze, assess the influence of parameters, and predict outcomes in complex decision-making scenarios [11].

The inherent computational and decision-making properties of the FCM, have led to the development of a large number of FCM based applications in diverse application areas [12]. One of the most prominent application areas is the development of Medical Decision Support System (MDSS). Due to their capabilities for resembling the human decision making process, FCMs have played a significant role in developing MDSS for diagnosis and prognosis. The methods for constructing the FCM of an MDSS can be divided into two main categories: the expert based FCM that utilize experiences and knowledge of experts in order to develop a model; and the computational FCM, which uses historical data to develop a model around a specific problem. The process of constructing an FCM for medical decision support system comprises of two main steps: the identification of the key concepts that can be used for diagnosis (e.g. symptoms, test results, or physician observations); and the identification of the causal relationships among those concepts. After the FCM is constructed, it can receive data from input concepts, and implement reasoning. Hence, the medical decisions are inferred as values of output or decision concepts.

In previous literature, several FCM structures have been used to model MDSS. In [13] a data driven nonlinear Hebbian learning method was presented. This method used historical data and was able to achieve improved performance compared to previous methods [13]. In [14] an FCM based method for characterizing brain tumors was presented. The FCM was used to represent and model subject experts' knowledge, and its performance was enhanced by using the Activation Hebbian Algorithm. The experimental results demonstrated that the FCM model had a satisfactory accuracy compared to other machine learning techniques, while at the same time retained a high degree of transparency and interpretability [14]. In the work by Stylios et al., three types of FCM architectures for MDSS were presented [15]. These architectures included: the competitive FCM, which was suitable when a single diagnosis was required; the distributed m-FCM which was suitable for complex problems that included a large number of factors; and a hierarchical m-FCM architecture which collected information from the other subsystems in order to provide intelligent decisions [15]. A recent example of FCM-based medical research includes the work of Subramanian et al. [16]. The researchers proposed a model that combined demographic risk factors, with the results of screening mammograms to elicit hidden and impeding risk of developing breast cancer [16]. In a study in [17] the team presented a decision support tool for urinary tract infection diagnosis. This tool was based on the use of an FCM based soft computing technique implemented in a Semantic Web approach [17]. In [5] the researchers proposed a novel design of the FCM methodology, which was based on intuitionistic fuzzy sets. The team applied and tested their design in two experiments. The first was an industrial chemical process control problem, and the second an MDS problem concerning pneumonia risk assessment. The proposed FCM model was able to address the limited ability of previous FCM designs to model the hesitancy, due to various reasons such as: deficient facts, missing info, and indecision [5].

B. *Interval Agreement Approach*

Computing with words (CW) is a methodology, where the main objects of computation are natural language words. It is inspired by the human ability to exploit perceptions in order to perform mental and physical tasks and delivers the promise of providing machines with the same ability [18]. In order to utilize the Computing with Words paradigm, several techniques have been proposed with the ability to capture the user's perceptions of concepts expressed through the use of survey data. Demonstrative examples are: the Interval Approach (IA), the Enhanced Interval Approach (EIA) and the Interval Agreement Approach (IAA) [9]. The main role of the aforementioned approaches is to generate fuzzy models from data for words or concepts, in order to implement the required process of computation and reasoning.

IAA, which is the basic technique used in this research paper, was introduced in [9]. IAA's main aim is to construct fuzzy sets to accurately represent the information captured in the responses of an individual to interval valued survey questions. IAA can be used in order to generate different types of fuzzy sets. Based on the nature of the collected data, IAA can generate Type-1, Interval Type-2, or General Type-2 fuzzy sets [19]. IAA is able to deliver fuzzy sets that account for two types of uncertainty contained in survey data. Inter-source uncertainty representing the variation in the answers provided by a group of individuals (e.g. different subject experts may provide different opinions on the same question) and intra-source uncertainty which can be considered as the variation in the answers of a specific participant (e.g. an individual's responses may vary over time). Many experimental survey designs, as the one described in this paper, are based on the participants expressing their views through providing interval values. It can be considered, that the width of the interval specifies the level of uncertainty in the individual's response. For example, a “narrow interval” represents less uncertainty and a “wider interval” represents more uncertainty. IAA is able to model these innate uncertainties, through the different dimensions of the generated fuzzy sets [8]. Moreover, as demonstrated in [8], IAA is able to generate models that efficiently exploit the knowledge contained in data. This is due to the minimal requirements of the method concern with: distributions within the data; data preprocessing; and outlier removal. It is logical to claim that the performance of a computational model can be hindered, when outliers are included in the training of the model. However, these outliers may contain rich information, which are not necessarily false or insignificant. IAA is able to account for this information. Therefore, the resulting fuzzy sets are extremely useful in applications that require complex reasoning and decision-making.

IAA has been used successfully in recent research in order to extract and exploit the knowledge contained within interval valued survey answers in practical medical contexts. The studies in [19] and [20] have illustrated the ability of IAA to produce type -1 fuzzy sets, and analyze the similarity and difference in the meaning of words and terms to different stakeholders in a specific medical domain. The studies in [19] and [20] have explored this problem since discrepancies in the concept of meaning for a word by different individuals such as patients/doctors/physiotherapists etc. may affect the medical assessment and proposed treatment plan. Their results demonstrate that the IAA can be a powerful tool for analyzing the vocabulary used in a medical context, and promote effective communication between patient and medical practitioners [19].

III. PROPOSED FUZZY COGNITIVE MAP

In this study the concepts used to model the proposed FCM are extracted from the Fuzzy MCHAT (F-MCHAT) where the answer of each question is modified to three options represented by fuzzy sets as in [2], to overcome the shortcomings of the existing MCHAT. The extracted concepts are listed in Table I. A questionnaire with 20 questions has been designed for the purpose of this study to collect data from the experts about the weight of interrelations among these concepts and a decision on the risk of developing ASD. The proposed FCM has 20 causal nodes and one decision node. From the questionnaire, experts' opinions are collected on a Likert Scale [21], which ranges from 0 to 100. In Fig. 1 an example question is shown. The experts draw ellipses to represent their opinion about the interrelation between the causal and the decision concept as shown in Fig.2. Based on their input data the weight of interrelation between these two concepts are calculated. The novelty of this method is that instead of providing a yes/ no option, the experts can express the fuzzy nature of each option. The answers from each expert is in the form of interval valued data as shown in Fig.1. The motivation behind collecting the data as intervals, is to allow greater chance to capture uncertainty due to imperfect information and hesitation. The interval valued data is then collected and aggregated using the IAA approach.

TABLE I. CONCEPTS OF FUZZY COGNITIVE MAP

C1	Enjoy being swung
C2	Take an interest in other children
C3	Climbing on things
C4	Pretend other things
C5	Pointing index finger
C6	Indication of interest
C7	Bringing objects to parents
C8	Eye contact
C9	Oversensitive to noise
C10	Smile in response to parents face
C11	Imitate
C12	Response to the name
C13	Looking at a toy when pointing
C14	Walking
C15	Look at things you are looking at
C16	Unusual finger movement near his/her face
C17	Attract your attention
C18	Deafness
C19	Understanding what others say
C20	Look to your face to check reaction

This paper uses IAA to produce GT2FS based on z slices [9] to capture uncertainties around assigning the weights of edges that link the nodes of the FCM. The implementation of IAA in this work includes the following two phases:

- Representing intra- response/option uncertainty by Type-1 fuzzy sets.
- Generating GT2FS based on *z* slices from the Type-1 fuzzy sets generated in the first phase for each expert where the resulting *z*-GT2FS contain intra and inter response/option uncertainty.

It is to be noted that the second dimension of the resulting fuzzy sets in the first phase, represents the level of agreement among each of the doctors across each option (intra-option). The third dimension of the resulting *z* slices in the second phase, represents the overall agreement among all doctors, across all the responses of the three options (inter-options) of a question in the MCHAT questionnaire.

In this study, three doctors D_1, D_2, D_3 from Sultan Qaboos University Hospital participated to determine the influence weight of each casual FCM concept on the decision concept by providing their responses to the questionnaire that was designed for this purpose. For every interrelation between a causal concept and the decision concept, each doctor provided three responses as an interval on a Likert scale to determine the weights based on parents' response concepts which resulted in three fuzzy values. After gathering the information, we extracted interval-valued data. By following the aforementioned procedure, each interrelation between an input concept and the output concept is represented by nine intervals. Across each option 'a', 'b', and 'c', a type-1 fuzzy set M is generated using the first phase of IAA. Hence, three fuzzy sets are produced, namely M_a, M_b and M_c. Here option 'a' means "certainly not", 'b' means "at some times" and 'c' means "always" for question 1.

To find the overall agreement (weight), M_a, M_b and M_c are aggregated by employing IAA to generate *z*-GT2FS and use the third dimension *z* to represent the level of agreement among the type-1 fuzzy sets M_a, M_b and M_c.

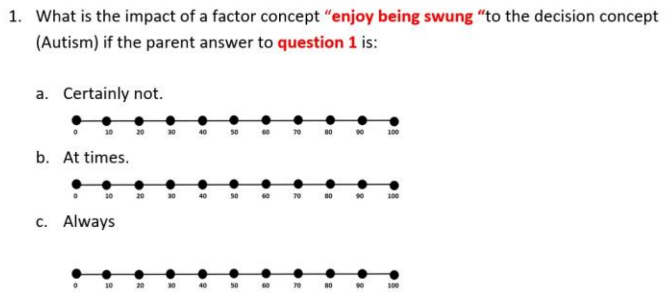

Fig. 1. Sample Questionnaire

Therefore, three slices Z_a, Z_b and Z_c are produced, where:

$$Z_a = \tfrac{1}{3}/(M_a \cup M_b \cup M_c) \qquad (1)$$

$$Z_b = \tfrac{2}{3}/(M_a \cap M_b) \cup (M_a \cap M_c) \cup (M_b \cap M_c) \qquad (2)$$

and

$$Z_c = 1/(M_a \cap M_b \cap M_c) \qquad (3)$$

The overall fuzzy agreement on weights of *z*-GT2FSs is given by (4) which is defuzzified by the centroid method in [8] to get the weight between the cause and decision concepts.

$$\mathbf{Z} = (Z_a \cup Z_b \cup Z_c) \qquad (4)$$

Finally, all the weights are collected to form a weight matrix, and they are used by the FCM to predict Autistic disorder as follows:

At each step, the value of C_i of a concept is calculated by computing the influence of the causal concepts to the decision concepts, according to the following equation.

$$C_i^{(k+1)} = f\left(C_i^{(k)} + \sum_{\substack{j \neq i \\ j=i}}^{N} C_i^{(k)} * W_{ji}^{(k)} \right) \qquad (5)$$

Where $C_i^{(k+1)}$ denotes the value of concept C_i at simulation step (k+1), $W_{ji}^{(k)}$ is the weight of concept C_j and concept C_i and *f* is the sigmoid threshold function which is calculated as given in (6).

$$f(x) = \frac{1}{1+e^{-mx}}. \qquad (6)$$

Here *m* is a positive constant, which takes values as 1 or 5 and *f(x)* lies between 0 and 1.

IV. ILLUSTRATION

In this section, the numerical calculations are illustrated for the method proposed in the previous section. The inputs are collected from the three doctors D_1, D_2, D_3. For example, for question 1 the weight given by the three doctors for the edge connecting causal concept C_1 (enjoy being swung) and the decision concept C_{21} (Autism) is shown in Table II. By using the Likert Scale for each option for question 1, the resulting interval values are computed and shown in Table II.

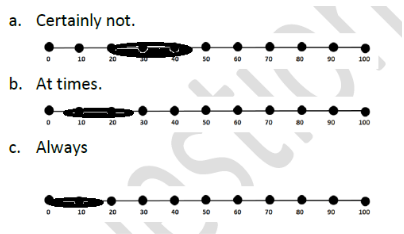

Fig. 2. Sample Answer of D_1 for Q_1

TABLE II. RELATION BETWEEN C_1 AND C_{21}

Option for C_1	D_1	D_2	D_3
a	[0.2-0.45]	[0.15-0.35]	[0.05-0.25]
b	[0.05-0.25]	[0.35-0.60]	[0.40-0.70]
c	[0-0.15]	[0.50-0.70]	[0.65-0.85]

Table III shows the fuzzy sets produced for the aforementioned relation through the implementation of the first phase of the IAA.

Fig. 3 depicts the generated type-1 fuzzy sets M_a, M_b and M_c (intra-option) agreement and also shows that there is an area of agreement among the generated sets.

After performing the calculations in the second phase of the IAA, by using equations (1), (2) and (3), the results are given in Table IV where ϕ indicates the empty intersections of intervals.

TABLE III. RELATION OF C_1

M_a	[0.05 0.45]	1/3
	[0.15 0.35]	2/3
	[0.2 0.25]	1
M_b	[0.05 0.7]	1/3
	[0.4 0.6]	2/3
	ϕ	1
M_c	[0 0.85]	1/3
	[0.65 0.7]	2/3
	ϕ	1

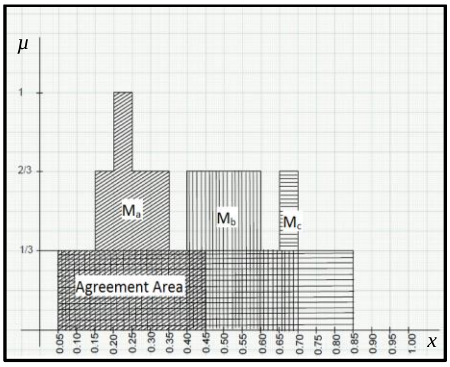

Fig. 3. Intra Option Type-1 Fuzzy Sets

TABLE IV. IAA RESULTS

	$Z_a = 1/3$	$Z_b = 2/3$	$Z_c = 1$
Option for C_1	Interval in x	Interval in x	Interval in x
	[0 0.85]	[0.05 0.7]	[0.05 0.45]
	[0.15 0.7]	ϕ	ϕ
	[0 0.25]	ϕ	ϕ
Centroid	0.275	0.0625	0.04166
Z Centroid		$W_1 = 0.0875$	

Therefore, weight W_1 of the interrelation between C_1 and C_{21} is 0.0875, which is the overall defuzzified value of produced z-GT2FS. By following the same procedure for all C_i to C_{21}; $i = 1, 2, 3\ldots, 20$ the weights of C_i on C_{21} is calculated and shown in Table V.

The proposed FCM based on the concepts listed in Table I is shown in Fig. 4 along with its computed weights from Table V. The proposed FCM is a competitive FCM with no cyclic relations. The rationale behind this is that the models focus is to emphasize the influence between each cause concept and diagnosis concept [15]. Future work will investigate the application of this approach to other FCM topologies.

TABLE V. WEIGHTS BETWEEN CAUSE AND DECISION CONCEPT

W1	0.0875	W6	0.1854	W11	0.1319	W16	0.0681
W2	0.0847	W7	0.1306	W12	0.1063	W17	0.1271
W3	0.1271	W8	0.209	W13	0.1	W18	0.1458
W4	0.1	W9	0.1028	W14	0.2708	W19	0.1478
W5	0.0917	W10	0.1083	W15	0.2215	W20	0.0938

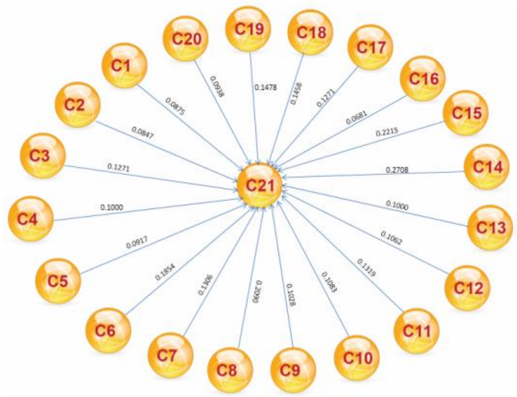

Fig. 4. Proposed FCM

TABLE VI. VALUES OF CONCEPTS

Iteration	1	2	3	4	5	6	7
C_1	0.3	0.5744	0.6398	0.6547	0.6581	0.6588	0.659
C_2	0.55	0.6341	0.6534	0.6578	0.6588	0.659	0.659
C_3	0.6	0.6457	0.656	0.6584	0.6589	0.659	0.659
C_4	0.2	0.5498	0.6341	0.6534	0.6578	0.6588	0.659
C_5	0.69	0.666	0.6606	0.6594	0.6591	0.6591	0.6591
C_6	0.73	0.6748	0.6626	0.6598	0.6592	0.6591	0.6591
C_7	0.86	0.7027	0.6688	0.6612	0.6595	0.6592	0.6591
C_8	0.1	0.525	0.6283	0.6521	0.6575	0.6587	0.659
C_9	0.57	0.6388	0.6545	0.658	0.6588	0.659	0.659
C_{10}	0.4	0.5987	0.6454	0.656	0.6584	0.6589	0.659
C_{11}	0.5	0.6225	0.6508	0.6572	0.6586	0.659	0.659
C_{12}	0.62	0.6502	0.6571	0.6586	0.6589	0.659	0.659
C_{13}	0.6	0.6457	0.656	0.6584	0.6589	0.659	0.659
C_{14}	0.71	0.6704	0.6616	0.6596	0.6592	0.6591	0.6591
C_{15}	0.9	0.7109	0.6706	0.6616	0.6596	0.6592	0.6591
C_{16}	0.15	0.5374	0.6312	0.6528	0.6576	0.6587	0.659
C_{17}	0.25	0.5622	0.637	0.6541	0.6579	0.6588	0.659
C_{18}	0.45	0.6106	0.6481	0.6566	0.6585	0.6589	0.659
C_{19}	0.49	0.6201	0.6502	0.6571	0.6586	0.6589	0.659
C_{20}	0.62	0.6502	0.6571	0.6586	0.6589	0.659	0.659
C_{21}	0.6591	0.659	0.659	0.659	0.659	0.659	0.935552

V. EXPERIMENT AND RESULT

After calculating the weights among the concepts using IAA, the effectiveness of proposed FCM is compared with FCM available in [2] that was used for same purpose. The results of similar diagnosis cases resulted in the same domain of decision either: definitely Autism, probable Autism or not Autism. For example, initial values for the concepts of one case (diagnosed as definite Autism) used in the prediction evaluation in [2] are used with the proposed FCM. The values of the concepts are derived by iterating the initial values using equation (5). The concepts reached equilibrium after seven iterations. The initial and iterated values for the concepts for this case are shown in Table. VI. The decision concept of the proposed FCM resulted in a final value of 0.935552 which lies in definitely Autism and is comparable to the result of original approach in [2]. The advantage of the proposed method compared to the method discussed in [2] is that we are not tuning the FCM through the learning algorithm to obtain the desire result. Thus, the processing complexity is reduced. In addition, using the proposed FCM approach with the dataset of 40 diagnosed cases in [2] we found that of the 23 cases diagnosed as definite Autism, 13 cases diagnosed as probable Autism and 4 cases diagnosed as not Autism, the proposed approach correctly classified 22/23, 11/13, and 3/4 giving an accuracy of 85.04% which is higher compared to the 79% accuracy achieved by the FCM used in [2] on the same data.

VI. CONCLUSION AND FUTURE WORKS

This paper proposed a fuzzy method for evaluating the weights between causal and decision concepts of an FCM applied to the process of diagnosing ASD. The existing flow chart of MCHAT is limited to the consideration of crisp inputs provided by the parents, or caretakers of the child for making a decision on the risk of developing Autism. The proposed method has both increased the expressivity and reduced the complexity of the MCHAT, and improved the accuracy of the FCM weights, by adopting interval agreement method, which is the novelty of this paper. The illustration section provides the reader with a step by step implementation of the proposed method to facilitate understanding. Weights between the casual concepts are generated using IAA. The results produced in this paper are compared with previous results and are shown to be better and more consistent. Our current work is in the process of developing formal descriptions to explain these results more fully. Future work will further validate the approach based on a more extensive set of user studies. We also plan to address improvements of the proposed FCM through introducing IAA to evaluate the concepts values.

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