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Interpretable Fuzzy System for Early Detection Autism Spectrum Disorder

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Abstract: Autism spectrum disorder (ASD) is a chronic developmental impairment that impairs a person's ability to communicate and connect with others. In people with ASD, social contact and reciprocal communication are continually jeopardized. People with ASD may require varying degrees of psychological aid in order to gain greater independence, or they may require ongoing supervision and care. Early discovery of ASD results in more time allocated to individual rehabilitation. In this study, we proposed the fuzzy classifier for ASD classification and tested its interpretability with the fuzzy index and Nauck's index to ensure its reliability. Then, the rule base is created with the Gauje tool. The fuzzy rules were then applied to the fuzzy neural network to predict autism. The suggested model is built on the Mamdani rule set and optimized using the backpropagation algorithm. The proposed model uses a heuristic function and pattern evolution to classify dataset. The model is evaluated using the benchmark metrics accuracy and F-measure, and Nauck's index and fuzzy index are employed to quantify interpretability. The proposed model is superior in its ability to accurately detect ASD, with an average accuracy rate of 91% compared to other classifiers.

Index Terms: Autism Spectrum Disorder, Fuzzy Neural Network, Pattern Classification.

1. Introduction

Autism spectrum disorder (ASD) is a lifelong diagnosis. However, with the right care and support, those living with an ASD can improve their quality of life significantly. This includes improved social and physical health, increased learning and development of new skills, as well as the potential to work. Recent US government statistics suggest that at least 1% of the population is affected by autism, though it is more frequently seen in men. Interestingly, a recent study shows that women with autism may be going undiagnosed due to their ability to mask their difficulties [1]. Individuals with autism often have other conditions, like depression, anxiety, epilepsy, and loss of attention. Autism can range from having a considerable disability to displaying incredible intelligence. It has been estimated that it is present in three to six out of every 1,000 children. Furthermore, there is an observable four-to-one male-to-female ratio in its occurrence. Three main behaviours are associated with autism, which can range from mild to severely debilitating [2,3]. Persons with high-functioning autism frequently struggle to communicate, especially in social circumstances, due to compulsive hobbies and repetitive body language. In order to detect ASD, a comprehensive examination and several tests will be conducted by psychiatrists for children and other qualified specialists. ADI-R (Autism Diagnostic Interview-Revised) and ADOS-R (Autism Diagnostic Observation Schedule Revised) are the default methods for diagnosing ASD. The ADOS-R and ADI-R are lengthy and time-consuming tests that necessitate a substantial amount of effort and time [4,5]. Autism appears to run in families, despite the fact that research into its aetiology is still in progress. Autism is often referred to as a "hidden handicap" because most autistic people appear to have the same characteristics as everyone else. Spectrum disorders, like autism, affect People differ and change over time. [6,7]. As a result of their lack of social skills, Autistic people may have seemed disconnected or uninterested in other people at

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times and may have trouble making friends [8,9].

Artificial Intelligence is revolutionizing decision making and predictions by leveraging interpretable fuzzy systems [10, 11, 12]. This technology has the potential to make decisions that are more accurate, robust and reliable than ever before. It is being used to automate tasks such as financial forecasting, risk management, fraud detection and customer segmentation. The interpretable fuzzy system uses a combination of algorithms and data-driven models to make decisions based on fuzzy logic[13]. This allows for greater accuracy in predicting outcomes as it takes into account multiple variables at once. Additionally, this technology provides insights into the decision-making process which can be used to improve decision accuracy over time.

Existing classification methods are intended to identify whether a person (child, adolescent, or adult) has ASD. There is a lack of standard classifier that can classify all three types and suffer from accuracy and interpretability. By increasing field observations and data analysis, we can gain a deeper understanding of the lives of autistic people. The main disadvantage of machine learning models is their box-like nature. The goal of this study is to develop a trustful standard fuzzy logic based autism diagnosis technique and turn it into a machine learning model. The prime objective of this work is to improve the accuracy and describe the causes behind its decision.

The article is divided in six sections, section 2, present the literature survey. Section 3 presented the proposed model for autism spectrum disorder classification. Section 4, present the experimental and results. Section 5, presented the brief discussion of the outcomes and comparison with others models. Section 6, presented the conclusion and future research detections.

2. Literature Survey

This section presents the relevant and latest literature review of fuzzy system, interpretable fuzzy system and the pattern classification techniques

2.1. Fuzzy System

It was prof. Zadeh, who first introduced fuzzy sets in 1965 [14,15,]. Researchers have discovered several methods to apply this theory to expand current approaches and develop new theories, tools and techniques for decision making and pattern recognition since then [16]. According to Bezdek [17], fuzzy logic concepts could be applied to input vectors to produce more interesting and useful results. The aim of Bezdek's research is to integrate fuzzy set techniques into classic k-NN decision-making algorithms. In fuzzy k-NN, fuzzy memberships are used to classify patterns. Additionally, a number of fuzzy logic-based classification algorithms have been published in the literature. Using fuzzy logic concepts in neural networks with projection layer is the novelty of this study.

2.2. Interpretable Fuzzy System

This section describes the fuzzy system; it is intended to demonstrate features of developing interpretable fuzzy systems [18,19]. Fuzzy system could have several input variables and output variables and the mapping of the system is projected by the Eq. (1)

$$X \rightarrow Y \tag{1}$$

Here, $\mathbf{X} = \mathbf{x_1}, \mathbf{x_2}, \dots, \mathbf{x_n} \subset \mathbf{R^n}$, $\mathbf{Y} = \mathbf{y_1}, \mathbf{y_2}, \dots, \mathbf{y_n} \subset \mathbf{R^m}$ denotes the set of relation of input and output vectors

The structures of fuzzy system consist of four blocks: First, fuzzification provides a conversion of crisp sets $\mathbf{X} \subset \mathbf{R^n}$ to fuzzy sets specified in X; as a result of fuzzification, numeric values can be given at system inputs. The fuzzification operation maps $\bar{\mathbf{x}} = [\bar{\mathbf{x}}_\mathbf{1}, \bar{\mathbf{x}}_\mathbf{2}, \dots, \bar{\mathbf{x}}_\mathbf{n}] \in \mathbf{X}$ to fuzzy set $\mathbf{A'} \subseteq \mathbf{X}$ by using Eq. (2) both singleton and non-singleton fuzzification act as filter in fuzzy system.

$$\boldsymbol{\mu}_{\mathbf{A'}}\ (\mathbf{x}) = \begin{cases} \mathbf{1} & \textbf{if } \mathbf{x} = \bar{\mathbf{x}} \\ \mathbf{0} & \textbf{if } \mathbf{x} \neq \bar{\mathbf{x}} \end{cases} \tag{2}$$

A fuzzy rule-base is a group of n numbers of fuzzy-rules and these rules are presented in the form of relation in the set $X \times Y$. As demonstrated in Eq. (3)

$$R^k\colon \begin{pmatrix} \text{if}\left(x_1 \text{ is } A_1^k\right) \text{AND...AND}\left(x_n \text{ is } A_n^k\right) \\ \text{then}\left(y_1 \text{ is } B_1^k\right),\dots,\left(y_m \text{ is } B_m^k\right) \end{pmatrix} \tag{3}$$

Here, m indicates number of system inputs, outputs respectively, $x = [x_1, x_2, \dots, x_n] \in X$, $y = [y_1, y_2, \dots, y_m] \in Y$ represents the vector of linguistic value of inputs and outputs.

$A_1^k, A_2^k, \dots, A_n^k (k = 1, \dots, n)$, $B_1^k, B_2^k, \dots, B_m^k (k = 1, \dots, m)$ are representing the input and output linguistic variables, where as $\mu_{A_1^k}(A_i)$, $\mu_{B_1^k}(B_i)$ are indicates input and output membership functions. These groups are denoted by phrases such as "low," "medium," and "high," among others. Artificial neural networks are incapable of handling certain verbal terms.

Second, the inference block uses fuzzy input values to produce fuzzy output. Initially, fuzzy results have been obtained from the fuzzy inference block denoted as fuzzy sets $\overline{B}_j^k$ independently.

The fuzzy set $\overline{B}_j^k$ can be represented as:

$$\overline{B}_j^k = A' \circ \left(A^k \longrightarrow B_j^k\right)$$

Here, $A^k \longrightarrow B_j^k$ indicates the fuzzy relation in fuzzy-rule R^k and $A^k = A_1^k \times A_2^k \times \ldots \times A_n^k$ is a Cartesian product of fuzzy sets $A_1^k, \ldots, A_n^k$,

Membership values of the B_j^k is calculated by Eq. (4)

$$\mu_{\overline{B}_j^k}(y_i) = \sup_{x\in X}\left\{T\left\{\mu_{A'}(X), \mu_{A^k\to B_j^k}\left(X, y_j\right)\right\}\right\} \tag{4}$$

Here, t-norm $T\{\cdot\}$ is a conjunction operator.

Singleton defuzzification and a t-norm boundary condition can be used to minimize the dependency, as shown by Eq. (5).

$$\mu_{\overline{B}_j^k}(y_i) = \mu_{A^k} \to B_j^k\left(\overline{x}, y_j\right) = I\left(\mu_{A^k}(\overline{x}), \mu_{B_j^k}\left(y_j\right)\right) \tag{5}$$

Here, $I(\cdot)$ is a type of reasoning operator. For improving the accuracy of the inference operator employed in Eq. (6) play key role for influencing interpretability.

Notation A^k is known as an activityxlevel of rule R^k and computed as follows:

$$\mu_{A^k}(\overline{X}) = \underset{i=1}{\overset{n}{T}}\left\{\mu_{A^k}(\overline{x}_i)\right\} = \tau_k(\overline{x}) \tag{6}$$

The investigation of rule activity with the precision of the aggregate operator has a substantial impact on interpretability.

Third, the fuzzy results from the inferences block's fuzzy rules $\overline{B}_j^k$ are aggregated to provide the entire rules base's fuzzy result.

The function of the defuzzification block is to transform fuzzy values to crisp values. In fact, several defuzzification operators exist. For the purpose of clarity, we've used centre of area method for the defuzzification in this study as show in Eq. (7)

$$\overline{y}_j = \frac{\sum_{r=1}^{N} \overline{y}_{j,r}^B \cdot \mu_{B_j'}\left(\overline{y}_{j,r}^B\right)}{\sum_{r=1}^{N} \mu_{B_j'}\left(\overline{y}_{j,r}^B\right)} \tag{7}$$

Here, $\overline{y}_{j,r}^B$ represent discretizationxpoints of fuzzy set B_j', it should be emphasized, therefore, the majority of defuzzification approaches are dependentxon the number N of systemxrules, it represents an inverse correlation between defuzzification operators and the total number of fuzzy rules. An examination of this dilemma is a crucial component of affectingxinterpretability.

2.3. Pattern Classification

Pattern classification is a major component of AI and is essential to the development of intelligent systems. It is used to identify patterns in data and classify them accordingly. Pattern classification is used for various tasks such as object recognition [20], speech identification [21], and natural language processing (NLP) [22]. The most common techniques used for pattern classification are neural networks [23], support vector machines [24], fuzzy systems [25,26], and hybrid systems [27,28]. Neural networks are the most commonly used technique as they can learn from data and make predictions based on it [29]. Support vector machines are also popular as they can be applied to a wide range of problems. Fuzzy systems are useful when there is uncertainty in the data while hybrid systems combine multiple techniques to increase accuracy and efficiency [30]. Classification is the process of assigning items to distinct groups in order to ensure that elements within one group are similar and distinct from those in other groups. The more information we have about the subject, the better our classification algorithms can be adapted to the actual situation. For instance, when a priori probability and dependent density for all classes in an established set are known, Bayes decision theory produces optimal results by minimizing expected classification error. Traditional Backpropagation techniques [31] have long been known to be computationally expensive and often find them settling down at local minima, making them inefficient for complex tasks. Furthermore, due to their nature, they require a large number of hidden nodes to complete these difficult tasks which can become an additional challenge in itself. One major advantage of using this technique is that it helps minimize errors. By training the system on a large sample dataset, it is possible to achieve results that are close to a Bayesian distribution [32], thus greatly reducing the error using the feedback system.

3. Proposed Model

In this section, we describe the architecture of suggested model (see fig.1) module by module. Thinking about the inherent benefits of neural networks against statistical approaches, the major goal of this research is to empirically determine how well this strategy works as a classifier for early identification of autism. The architecture of model described module by module.

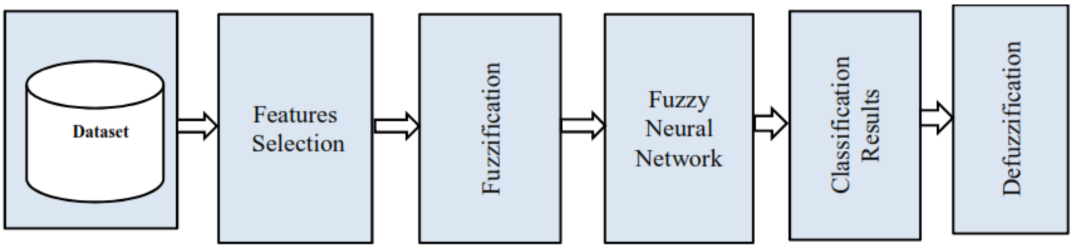

Fig.1. Process of autism spectrum disorder classification

3.1. Feature Selection

Filter-based feature selection [33] is a type of feature selection method that uses statistical measures to evaluate the importance of each feature in the dataset. This method is used to identify the most relevant features for a given problem. It is fast and efficient, but it does not consider the interactions between features. Examples of filter-based feature selection methods include correlation-based feature selection [34], mutual information-based feature selection [35], and chi-squared feature selection [36]. In this study, we used correlation-based feature selection method to select the appropriate inputs.

3.2. Fuzzification

Have you ever wondered how fuzzy logic can be applied to real-world situations? Fuzzification is a powerful method that enables us to take imprecise, uncertain, and partial data and turn it into a more exact and reliable form. In this article, we used three (triangular [37], trapezoidal [38] and Gaussian [39] membership functions to express the fuzzy phenomena as depicted in fig.2.

3.3. Fuzzy Neural Network(FNN)

This module consists of three layers: input, hidden, and output. As depicted in Fig. 2. A standard fuzzy neural network is used in this module. In this study, we used type three fuzzy neural networks [40] (fuzzy input and fuzzy output). For the improving the interpretability, the hierarchical architecture is used for the classification. The inaccuracy is employed to figure out the number of neurons in the input, output, and hidden layers. A log-sigmoid transfer function is used by the output neuron. For faster convergence, updated Backpropagation training rules are used.

3.4. Linguistic Term Representations

A neural network undergoes two steps in general: training and testing. The supervised learning approach is used to train the model during the training phase. Instead of picking the node with the greatest activation value, every network output might be allocated a membership that is higher than zero. It enables the modelling of fuzzy data when the feature space contains spanning pattern classes. Each inaccuracy in membership assignment is recycled instantly during training, and the network's connection weights are adjusted accordingly. The back propagated error, which is a membership value indicating how much the input vector belongs to a certain class, is calculated for each intended output. The testing phase of a fuzzy network is comparable to that of a regular neural network.

Assume, M_{kj} and μ_{jk} specify the mean and standard deviation for the j^{th} input of the k^{th} training data sample. In the case of an m-class problem with an n-dimensional feature set. The weighted distance of the i^{th} training sequence vector F_i from the k^{th} class is given by Z_{ik}.

$$Z_{ik} = \sqrt{\sum_{j=1}^{n} \left[\frac{F_{ij}-M_{kj}}{\mu_{kj}}\right]^2 \quad for\ k = 1,2, \ldots m\ and\ j = 1,2, \ldots n} \tag{8}$$

The weight $1/\mu_{kj}$ compensates for class variance, thus a trait with a greater variance has less relevance.

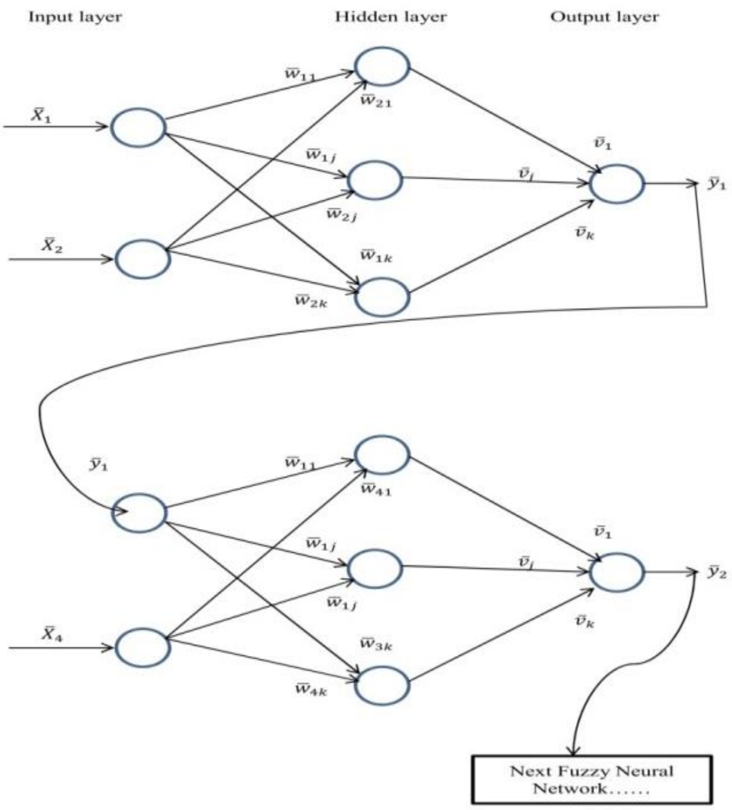

Fig.2. Proposed Model

3.5. *Classification of Results*

Defining a class, the membership of the $\boldsymbol{i^{th}}$ pattern to class $\boldsymbol{C_k}$ is defined in Eq. (9)

$$\boldsymbol{\mu_k(F_i) = \left(\frac{Z_{ik}-min_k(Z_{ik})}{max_k(Z_{ik})-min_k(Z_{ik})}\right)\ for\ k = 1, \dots, m} \tag{9}$$

$\boldsymbol{\mu_k(F_i)}$ is obviously in the interval [0,1]. The training process and network structure are identical to those of the artificial neural network classifier, except for the fuzzy membership values in the output layer.

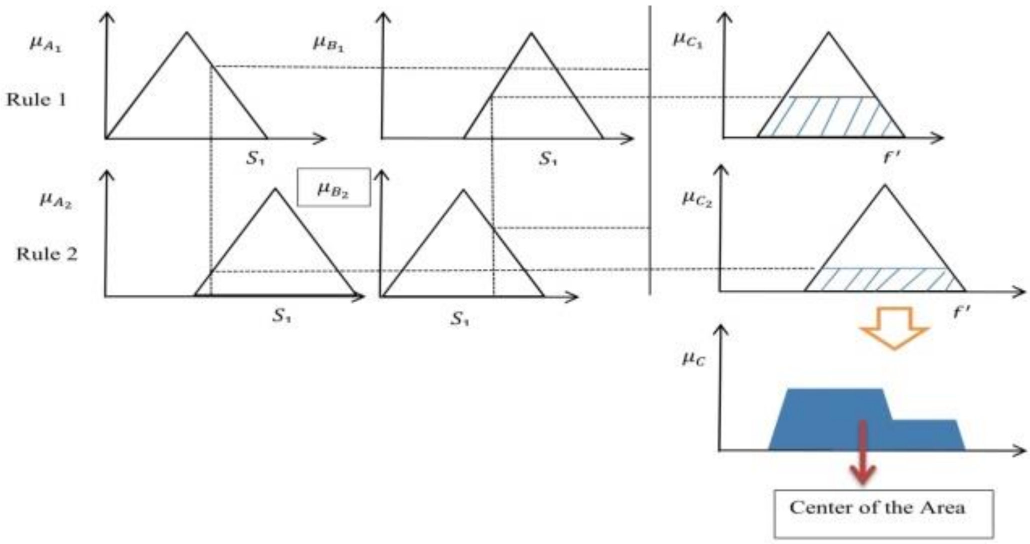

Fig.3. Process of defuzzification

3.6. *Defuzzification*

The main objective of the defuzzification process is to convert fuzzy value in to crisp. Let us consider the two input fuzzy rules as discuss the mechanism of defuzzification.

Rule-1: if S_1 is A_1 and S_2 is A_2 then F' is C_1

Rule-1: if S_1 is A_1 and S_2 is A_2 then F' is C_2

As demonstrated in fig. (3), the crisp value can be obtained from the fuzzy output by using the center of sums method (see Eq. (10)) as given bellows:

$$\mu'_{f'} = \frac{\sum_{j=0}^{n} A(\alpha_j) \times f_j}{\sum_{j=0}^{n} A(\alpha_j)} \tag{10}$$

Where, $A(\alpha_j)$: denotes the firing area of j^{th} fuzzy rule, f_j indicate the center of area and n is number of fuzzy rules

4. Experiment

This section presents the methods and materials of the experiments, the experiments performed with different methods.

4.1. Classification of Autism Spectrum Disorders (ASD)

There is no known single cause of autism spectrum disorders (ASD), it is characterized by difficulties in social interaction and communication, abnormal patterns of habit and practice, and unexpected reactions to senses. There is no single known cause for autism spectrum disorders; scientists do not know the precise origins of their development, and it is believed that a combination of factors contributes to their development. The present study was conducted with 703 cases diagnosed with any of the subclasses of autism established. The observed people's age belongs between 18 months and four years old, to determine the main elements to which they were exposed to determine possible common groups of causal factors of the disease. Based on the analysis, three prominent casual factors were determined in the group, and a number of recommendations were formulated as a result. It is essential to identify and treat autism spectrum disorders early if we want to decrease the symptoms and improve the quality of life. It is not possible to detect autism with a medical test. Symptoms of autism are usually recognized by observation. When older and adolescents go to school, their parents and teachers usually identify their symptoms. A special education team at the school then evaluates their symptoms. The observation team suggested that these children undergo necessary testing with their health care provider. ASD symptoms are more difficult to identify in adults than in older children and adolescents because some of the symptoms may overlap with other mental health conditions. Autism specific brain imaging is much easier to identify after 2 years of age than identifying behavioral changes in a child by observation because they can be seen early on in the child's life.

For the experimental purpose, we analyzed the dataset .The dataset contains 703 observations. Fig.4 depicted the sample observations.

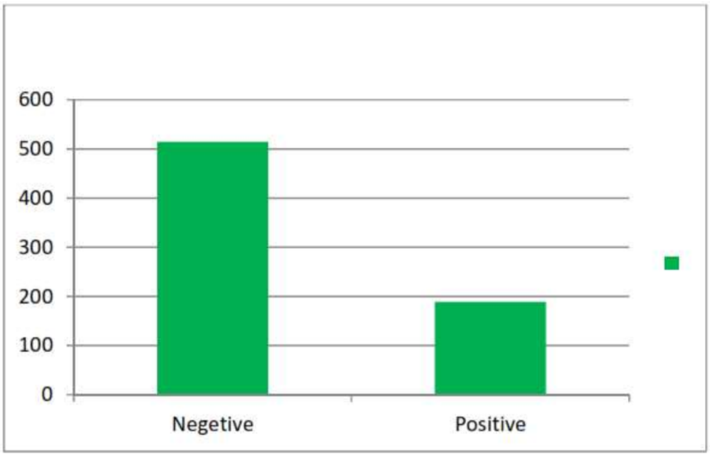

Fig.4. Histogram of the sample observations

In this study, we applied 14 input features such as: A1Score, A2Score, A3Score, A4Score, A5Score, A6Score, A7Score, A8Score, A9Score, A10Score, age, jaundice, autism, result, and ASD is the class level. After that, the dataset is divided into two parts: 70% of the data was used for training the classifiers, and the remaining 30% was utilized to test the classifiers. A training set of 70% samples is chosen at random from each class (positive and negative). Furthermore, we obtain fuzzy value by using the three different membership's functions. The linguistic terms are applied to the inputs values of the model. The neural module of the model allowed to maps of input linguistic terms to projection network. Backpropagation algorithms are used to optimization of fuzzy rule. Finally, in the output module we obtained the classification outcomes. For the implementation of the model we used python programming language (version 2.7). The performance of the model is depicted in fig.5. As seen the ROC is cover value is 0.91 area of the whole area, it means the model achieved accuracy is 91%. The study's findings on four classification algorithms demonstrate the size of the classification accuracy difference when compared to expert classification.

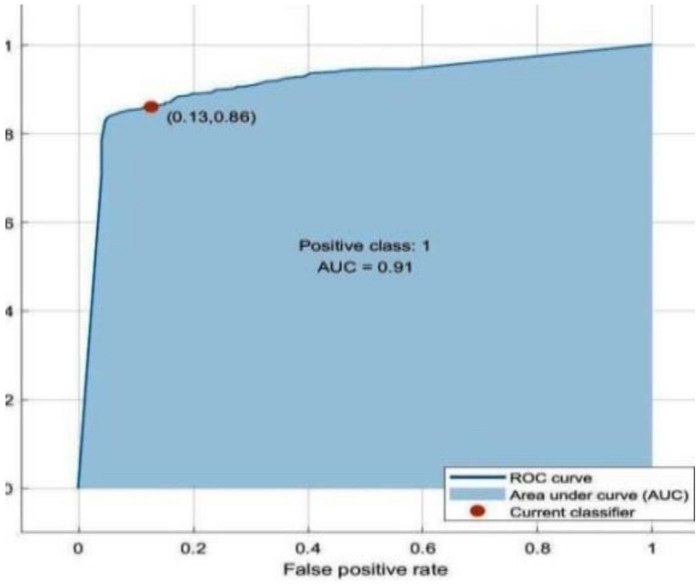

Fig.5. ROC curve of neuro-fuzzy system

4.2. *Interpretability Analysis*

The interpretability of a fuzzy system reflects how easily it can be perceived by individuals [41]. Several scholars have expressed an interest in developing highly interpretable fuzzy models in recent years [42]. However, due to its subjectivity and the tremendous number of components involved, the choice of a suitable interpretability measure is still unknown. Significant research on interpretability metrics has provided interpretability indices for fuzzy systems [43]. The Nauck index and the Fuzzy index are the most commonly used interpretability indices.

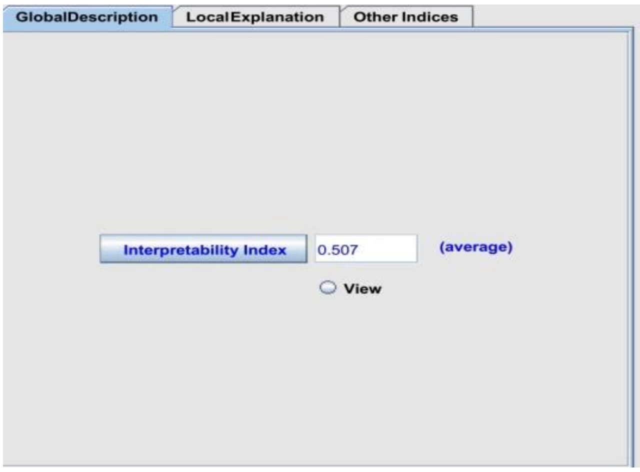

Fig.6. Global interpretability

- Nauck index

Nauck introduced a numerical index called the "Nauck Index." It is employed in order to assess the interpretability of the fuzzy system. In this work, we use it to assess the interpretability of the suggested model.

It is a multiplication of three terms as shown in Eq. (11)

$$\text{Nauck index} = \text{comp} \times \overline{\text{cov}} \times \overline{\text{part}} \tag{11}$$

Where, comp represent the complexity of the fuzzy system. It is computed as the following Eq. (12)

$$\mathrm{comp} = \frac{m}{\sum_{i=1}^{r} n_i} \tag{12}$$

Here, m indicates total number of MFs in consequences, r and n_i represents the total number of rules and number of input variables used in the i^{th} rule.

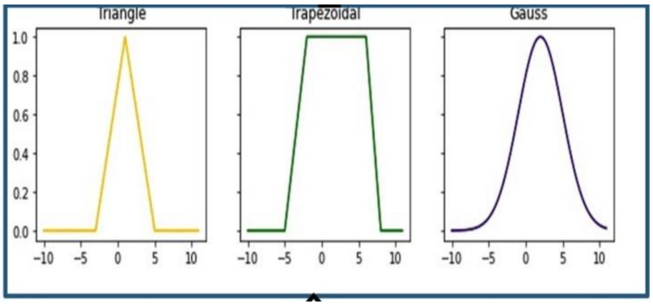

Fig.7. Membership function showing the full membership values

cov: is a fuzzy partition coverage degree. Suppose that if Z_l is represent the domain of l^{th} input variable which is partitioned by d_l membership function $\{\mu_l^1, \dots, \mu_l^{d_l}\}$, the coverage degree can be computed as:

$$cov_l = \frac{\int_{Z_l} \hat{h}_l(z)dx}{N_l} \tag{13}$$

$$\hat{h}_l(z) = \begin{cases} h_l(z) & if\ 0 < h_l(z) > 1 \\ \frac{d_l - h_l(z)}{d_l - 1} & otherwise \end{cases} \tag{14}$$

$$h_l(z) = \sum_{k=1}^{d_l} \mu_l^k(z) \tag{15}$$

Where $h_l(z)$ are the total MFs of l^{th} input variable with $N_i = |X|$, and the coverage $\overline{cov} = \sum_{i=1}^{r} \frac{cov_i}{n_i}$, indicates the normalized value of all input variables. Fig.7 showed the coverage of input membership functions.

Part: indicates the index partition, it can be computed (see Eq. (16)) by taking the inverse of Membership functions and subtracted by one for each input variable;

$$part_i = 1/(p_i - 1) \tag{16}$$

Where p_l indicates number of Membership Functions in the l^{th} input variable.

A fuzzy model is less interpretable if the Nauck index is closer to zero; when the Nauck index value is closer to 1, the fuzzy system is more interpretable. Fig. 7 shows the Nauck indicator.

Fig.8. Nauck indicator

Table 1. Outcome of the models

Model	Case 1		Case 2	
	Accuracy	interpretability	Accuracy	interpretability
k-NN	82.32	0	68	0
Fuzzy k-NN	84.67	0.381	87	0.395
Backpropagation network	87.50	0	74	0
Fuzzy neural network	**91**	**0.507**	**89**	**0.612**

Using the above nauck components, we computed the nauck index of the proposed model. Similarly, we can calculate the nauck index of fuzzy-kNN model that is used for the classification of malicious domains. The nature of non-fuzzy models is block-box, so that the nauck index value is 0. The final results based on accuracy and interpretability is presents in the table.1

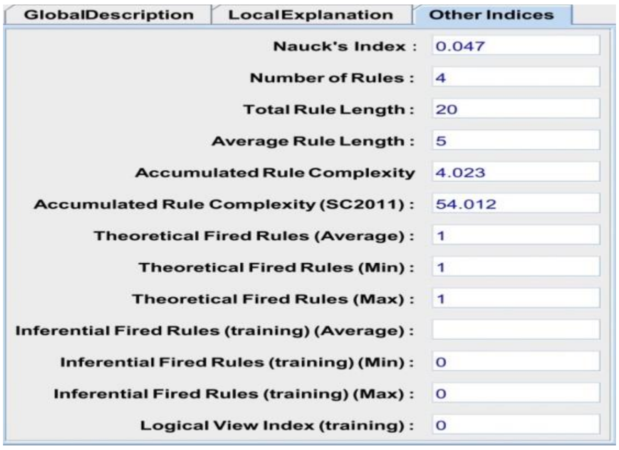

Fig.9. Finding of Nuack's Index

5. Result Analysis

Let us now discuss in more detail's internal computations of a hierarchical Fuzzy Neural network, A bar symbol over a symbol indicates fuzzy sets, and all fuzzy sets are real numbers. In a FNN the input $\bar{X}_1$, $\bar{X}_2$, the weights $\bar{w}_{ij}$, $\bar{v}_j$ and the output $\bar{y}$ will all be fuzzy. The architecture of fuzzy NN is shown in fig.2. The outputxfrom input neuron 1 and 2 is $X_1(X_2)$. So thexinputxtoxhidden neuron k is

$$\bar{I}_j = \bar{X}_1\bar{w}_{1j} + \bar{X}_2\bar{w}_{2j}, \quad 1 \le j \le k \tag{17}$$

Where, wexusexstandardxfuzzyxarithmetic to compute $\bar{I}_j$. The output from the j^{th} hidden neuron will be

$$\bar{z}_j = f(\bar{I}_j), 1 \le j \le k \tag{18}$$

Forxsigmoidal f, wherexthe extensionxprinciple is used toxobtain $\bar{z}_j$. It followsxthat thexinput toxthe output neuron is

$$\bar{I}_o = \bar{z}_1\bar{v}_1 + \cdots + \bar{z}_j\bar{v}_j \tag{19}$$

And the final output will be

$$\bar{y} = f(\bar{I}_o) \tag{20}$$

Usingxregularxfuzzyxarithmetic in Eq. (7) and thexextensionxprinciple in Eq. (8). Whenxwe doxnot need $\bar{y}$ to be fuzzy subset of [0, 1] wexomit f in Eq. (8) and set

$$\bar{y} = (\bar{I}_o) \tag{21}$$

As demonstrated in table1. The outcome of Fuzzy Neural Network achieved the highest Accuracy and Interpretability as compared to, k-NN, Fuzzy k-NN and Conventional Neural Network. The suggested model is able to classify vague, uncertain and imprecise data.

Drawback of the model: The performancexof model is degraded in the following cases:

Case 1: *if we apply high numbers of features as input then Accuracy is increased, But Interpretability is decreased.*
Case 2: *if we apply less numbers of input features then Interpretability increased, but Accuracy is decreased.*

6. Conclusions

Interpretable fuzzy neural networks used in hierarchical manner this article to classify the neurological disorder more accurately than traditional classifiers, the fuzzy sets are used as inputs to the model and output is also a fuzzy set. The interpretability analysis of model is novelty and make it more trust full, it explore the behaviour of the model. In order to train the proposed network more effectively, thextriangular, trapezoidal andxGaussian membership functions are used to express the fuzzy phenomena of input features. Based on accuracy and interpretability parameters, we compared the proposed model to k-NN, fuzzy k-NN, and traditional neural network. The simulation result shows that the proposed classification method outperforms. The comparison findings demonstrate that the proposed model is a better in accuracy and self-explanatory (having the ability to explain the outcome) tool for early prediction of autism disease. Further, the model may be improve in terms of the accuracy and interpretability by applying intuitionistic fuzzy set theory or neutrosophic set theory, as well as different types of membership functions.

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