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Hybrid Intelligent Model for Prediction of Autism Spectrum Disorder in Children

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Abstract: *Autism Spectrum Disorder (ASD) presents a significant challenge in early diagnosis and intervention due to its complex and varied symptomatology. ASD poses significant challenges in early detection and intervention due to its multifaceted nature. This study presents a Hybrid Intelligent Model designed to predict ASD in pediatric cases, leveraging adaptive neuro-fuzzy systems. The model integrates artificial neural network capabilities with fuzzy logic, offering a comprehensive approach to ASD prediction. A diverse dataset comprising behavioral observations, developmental milestones, and clinical assessments is utilized to identify key features relevant to ASD diagnosis. These features include eye contact, gesture use, language skills, sensitivity to pain, communication abilities, and social interaction. Through fuzzy logic-based soft computing techniques, the model achieves enhanced accuracy in predicting ASD and assessing its severity in children. Sensitivity analysis highlights the significant contributions of input variables to ASD prediction, with sensitivity to pain, eye contact level, and social interaction emerging as crucial factors. Comparative analysis with the Back Propagation Algorithm underscores the superiority of the proposed Hybrid Algorithm in error minimization across various phases of model training and evaluation. The findings underscore the potential of adaptive neuro-fuzzy systems in facilitating early ASD diagnosis, enabling timely intervention and support for affected children and their families. This research contributes to advancing the understanding and management of ASD, offering valuable insights for clinical practice and research in pediatric neurodevelopmental disorders.*

Keywords: *Adaptive Neuro-fuzzy System, Autism Spectrum Disorder (ASD), Pediatric Cases, Predictive Model, Early Intervention*

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1.0 Introduction

Medical diagnosis is the process of determining the nature and cause of a disease or condition by analyzing a patient's symptoms, medical history, physical examination, and diagnostic test results (Pavithra & Jayanthi, 2021; Umoh *et al*., 2012). It is a multifaceted process that relies on a combination of patient history, physical examination, diagnostic tests, clinical reasoning, collaboration, and effective communication. By systematically evaluating patients' symptoms and clinical data, healthcare providers can arrive at accurate diagnoses and provide appropriate treatment and management strategies. A medical diagnosis system is a computer-based tool or software designed to assist healthcare professionals in the process of diagnosing diseases and medical conditions. These systems utilize various technologies, algorithms, and databases to analyze patient data, symptoms, and medical history to generate potential diagnoses or provide decision support for clinicians. The increasing complexity of disease diagnosis and the growing volume of patient data have stimulated the application of artificial intelligence (AI) techniques in healthcare. Intelligent diagnostic systems can process large datasets, identify hidden patterns, reduce human errors, and provide decision support that enhances the accuracy and efficiency of clinical diagnosis. Consequently, machine learning, neural networks, fuzzy logic, and hybrid intelligent systems are increasingly being adopted in medical decision-making processes.

Autism Spectrum Disorder (ASD) is a neurological and developmental disorder whose etiologies are largely unknown (Bakare et al., 2009). Autism is a complex brain disorder that inhibits a person's ability to carry out social communication and interaction and also exhibit restricted interests and repetitive behaviours (Ruzich et al., 2015). The onset of the disorder occurs during the developmental period, typically in early childhood and lasts throughout a person's lifetime. Symptoms of autism are usually apparent very early but are often not fully understood by parents until a later stage of a child's life when social demands exceed limited capacities (Stevens et al., 2019; Nasser *et al*., 2019). Thus, diagnoses are not usually carried out until two to three years of a child's life. The autism spectrum disorders belong to an "umbrella" category of childhood-onset conditions called Pervasive Developmental Disorders (PDD). The three most common PDDs are Autism Spectrum Disorder, Asperger Syndrome, and Pervasive Developmental Disorder–Not Otherwise Specified (PDD-NOS), also known as atypical autism. Childhood Disintegrative Disorder and Rett Syndrome are the other pervasive developmental disorders (Kundu & Das, 2019). They occur rarely, and Rett Syndrome is believed to affect only girls. People affected by autism disorder often experience significant language delays, social and communication challenges, unusual behaviours and interests, and frequently have intellectual disabilities.

Autism is referred to as a spectrum disorder because of the wide variation in the type and severity of symptoms people experience. Due to the unique mixture of symptoms seen in each child, severity can sometimes be difficult to determine (Thabtah, 2019). It is generally based on the level of impairments and how they impact the ability to function. Autism Spectrum Disorder (ASD) is said to be "an equal opportunity disorder" that occurs across all ethnic and socio-economic groups and affects people of all ages regardless of country or culture, and its prevalence is increasing (Omar *et al*., 2019). According to Klauck (2006), approximately one out of every one hundred children is affected by ASD. More recent studies suggest that the prevalence of ASD has continued to increase globally, making it one of the most significant neurodevelopmental disorders affecting children worldwide. Research over the years has not provided a satisfactory understanding of the causative factors of the disorder (Thabtah, 2019). Studies suggest that genes can interact with environmental influences to affect development in ways that lead to ASD (Mirkovic & Gérardin, 2019). Several factors are believed to increase the risk of developing ASD. Such risk factors include parental age at conception, having a sibling with ASD, very low birth weight, and certain genetic conditions. Individuals with conditions such as Fragile X syndrome and Rett syndrome are more likely than others to have ASD (Talkowski *et al*., 2014).

Characteristics of autism may be detected in early childhood but are often not diagnosed until two to three years of age due to the absence of definitive biomarkers that can accurately identify the disorder. However, one of the earliest indicators is the absence of normal developmental behaviour (Reji & SojanLal, 2017). There is no single medical test that can definitively diagnose autism; therefore, multiple evaluations and tests are often required for accurate diagnosis. Early recognition is the cornerstone of managing the disorder. Although there is currently no cure for autism, early detection, recognition, and intervention can significantly improve the symptoms associated with ASD and enhance the ability of affected individuals to integrate into society and develop more effectively (Roy *et al*., 2016). Therefore, the development of reliable and intelligent diagnostic systems capable of identifying ASD at its earliest stages has become a major research priority. Such systems have the potential to support clinicians, reduce diagnostic uncertainty, and facilitate timely intervention strategies.

1.1 Literature Review

Several researchers have explored the application of artificial intelligence techniques for the early detection and classification of Autism Spectrum Disorder. Among these techniques, machine learning algorithms, artificial neural networks, fuzzy logic systems, and adaptive neuro-fuzzy inference systems have demonstrated promising performance in handling the uncertainty and complexity associated with ASD diagnosis. (Anurekha & Geetha, 2018). In this context, adaptive neuro-fuzzy systems offer a promising approach by combining the adaptive learning capabilities of artificial neural networks with the interpretability of fuzzy logic. An Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed to model the nonlinear relationships between behavioral indicators and ASD diagnosis outcomes. The ANFIS architecture consisted of five layers: fuzzification layer, rule layer, normalization layer, defuzzification layer, and output layer.. By leveraging a diverse range of features and employing advanced computational techniques, the model aims to enhance the accuracy and efficiency of autism diagnosis, thereby facilitating early intervention and support for affected children and their families. Pavithra & Jayanthi (2021) developed an improved Adaptive Neuro-Fuzzy Inference System for ASD detection and reported enhanced diagnostic performance. Similarly, Anurekha & Geetha (2018) proposed an evidence-based adaptive neuro-fuzzy inference system capable of improving ASD prediction accuracy. Kundu and Das (2019) employed machine learning techniques for predicting ASD in infants, while Omar *et al*. (2019) demonstrated the applicability of machine learning algorithms in ASD classification. Nasser *et al*. (2019) further established the effectiveness of artificial neural networks in autism diagnosis. These studies collectively indicate the growing potential of intelligent systems in supporting ASD diagnosis.

For this study, the hybridization of artificial neural networks and fuzzy logic will be employed to establish a system for the early diagnosis of ASD and determination of its severity levels in children. Previous studies have shown that combining artificial neural networks with fuzzy logic can improve diagnostic accuracy and support early autism detection. Many children who are expected to contribute significantly to future societal development face developmental challenges such as ASD. Autism Spectrum Disorder is a chronic and severe condition that affects the brain's capacity to develop social and communication skills and is also characterized by repetitive or restricted behaviours and interests (Ruzich *et al*., 2015).

ASD is one of the fastest-growing developmental disabilities, and prevalence rates continue to increase globally. Current estimates suggest that approximately 1.5% of the world's population may be on the autism spectrum, and many cases remain undiagnosed within communities (Fitzgerald, 2017; Brugha *et al*., 2011). Consequently, the need for early identification and timely intervention has become increasingly important as awareness of ASD continues to grow (Russell et al., 2016). Obtaining an ASD diagnosis is a critical milestone because it enables parents and caregivers to better understand a child's needs and gain access to essential support services, including therapy and specialized educational programs.

Parents often begin to notice signs of ASD within the first two or three years of a child's life, although these signs frequently emerge gradually. While diagnosing autism is possible, clinicians require substantial training and expertise to make accurate assessments. Some researchers have suggested that autism may involve systemic physiological conditions that affect brain function rather than being solely a genetic brain disorder (Woodbury-Smith & Volkmar, 2009).

Several methods have been employed in the detection of autism. Traditional approaches rely on identifying abnormal behaviours such as repetitive actions and restricted interests. However, these approaches often exhibit lower diagnostic accuracy and may not be suitable for infants younger than 24 months because autism-related symptoms may not yet be clearly expressed. Screening tools such as the Checklist for Autism in Toddlers (CHAT), Infant Toddler Checklist (ITC), Modified Checklist for Autism in Toddlers (M-CHAT), and Quantitative Checklist for Autism in Toddlers (Q-CHAT) assess communication skills and emotional responses to identify possible ASD cases. Despite the encouraging results reported in previous studies, several challenges remain. Many existing diagnostic systems rely heavily on behavioral assessments, which are often subjective and susceptible to evaluator bias. Furthermore, some models focus primarily on ASD identification without adequately addressing severity classification. The inherent uncertainty and vagueness associated with autism symptoms also remain difficult to model using conventional computational approaches.

Diagnostic instruments including the Autism Diagnostic Interview-Revised (ADI-R), Autism Diagnostic Observation Schedule-Generic (ADOS-G), Childhood Autism Rating Scale (CARS), and Gilliam Autism Rating Scale-2 (GARS-2) are commonly used for autism prediction and assessment. These instruments generally rely on collecting behavioural information through structured questions, assigning scores, and classifying the type and severity of autism. For example, the CARS system categorizes autism severity into mild, moderate, and severe levels. Despite their widespread use, these assessment tools may fail to capture the full complexity of ASD, resulting in false-positive and false-negative diagnoses due to limitations inherent in rating scales and evaluator subjectivity. To overcome these limitations, artificial intelligence techniques are increasingly being explored to improve the accuracy, consistency, and reliability of early autism diagnosis.

Although several machine learning and neuro-fuzzy approaches have been proposed for ASD diagnosis, there remains a need for more robust and interpretable models capable of simultaneously predicting the presence of ASD and determining its severity level. Existing approaches often suffer from limitations related to uncertainty handling, diagnostic consistency, and generalization across diverse patient populations. Consequently, the development of an adaptive neuro-fuzzy diagnostic framework that combines the learning capability of neural networks with the reasoning strength of fuzzy logic remains an important research challenge. This study aims to develop an Adaptive Neuro-Fuzzy Inference System (ANFIS) for the early diagnosis of Autism Spectrum Disorder and the classification of its severity levels in children. The proposed system seeks to improve diagnostic accuracy by integrating artificial neural networks and fuzzy logic techniques for effective decision support.

This study is significant because it contributes to the growing application of artificial intelligence in healthcare diagnostics. The developed model is expected to assist clinicians in making faster and more accurate diagnostic decisions, reducing diagnostic errors, supporting early intervention programs, and improving the quality of life of children affected by ASD and their families. Furthermore, the study provides a framework for integrating intelligent computational techniques into medical decision-support systems.

Based on the identified limitations of existing diagnostic approaches, this study proposes the development of an Adaptive Neuro-Fuzzy Inference System for ASD diagnosis and severity assessment. By leveraging the complementary strengths of neural networks and fuzzy logic, the proposed model is expected to provide improved predictive performance and greater interpretability in autism diagnosis.

2.0 Materials and Methods

This study proposes a Hybrid Intelligent Model for the prediction and severity classification of Autism Spectrum Disorder (ASD) in children using an Adaptive Neuro-Fuzzy Inference System (ANFIS). The model integrates fuzzy logic and artificial neural network techniques to improve diagnostic accuracy and support early clinical decision-making. The proposed system is tagged the Hybrid Intelligent Model for the prediction of Autism Spectrum Disorder in Children. "The proposed framework employs an object-oriented implementation strategy to enhance system modularity, maintainability, and scalability (Onu *et al*., 2015). It also builds quality prediction on the principles of the neuro-fuzzy hybridization technique at the design stage before coding. A comprehensive dataset comprising behavioral observations, developmental milestones, and clinical assessments of pediatric cases was compiled from multiple sources. The collected data were preprocessed and used in the hybrid model to carry out the prediction. Fig. 1 shows the conceptual framework of the proposed system.

2.1. Data Collection and Dataset Description

A dataset comprising behavioral observations, developmental milestones, and clinical assessments of pediatric cases was collected through questionnaire-based surveys and clinical evaluations conducted at Enugu State University Teaching Hospital (ESUTH), Enugu, Nigeria. Ethical approval for the study was obtained from the appropriate institutional review board, while informed consent was obtained from parents or guardians of participating children before data collection.

The data collection process involved behavioral observations, developmental milestone assessments, and clinical evaluations of children between the ages of 6 and 24 months. Information was obtained from paediatricians, caregivers, and hospital records where available.

The collected dataset was designed to capture the behavioral and developmental characteristics of children with and without Autism Spectrum Disorder (ASD) and was used for the development and evaluation of the proposed Adaptive Neuro-Fuzzy Inference System (ANFIS).The dataset consists of the features shown in Table 1.

The final dataset consisted of 5,000 records, each representing a unique child assessed for ASD-related behavioral and developmental characteristics. Due to the lack of comprehensive and accessible clinical records on children between the ages of 6 and 24 months living with autism, this survey was conducted to collect the necessary data for the research.

The primary source of data was semi-structured interviews with paediatricians specialising in autism diagnosis, through which four key predictive variables were identified:

(i) Eye Contact Level (ECL)

(i) Sensitivity to Pain (SP)

(ii) Social Interaction Score (SIS)

(iii) Communication Test Score (CTS)

The secondary source of data was a structured questionnaire administered to paediatricians and parents or caregivers of children undergoing ASD assessment.

The questionnaire consisted of two sections:

Section A: Demographic and biodata information of the child, including age, gender, ethnicity, birth history, and jaundice status.

Section B: Clinical and behavioral assessment questions developed from the four identified predictive variables (Eye Contact Level, Sensitivity to Pain, Social Interaction Score, and Communication Test Score).

The responses obtained from the questionnaires and clinical evaluations were subsequently coded and organized into a structured database for model development and validation.

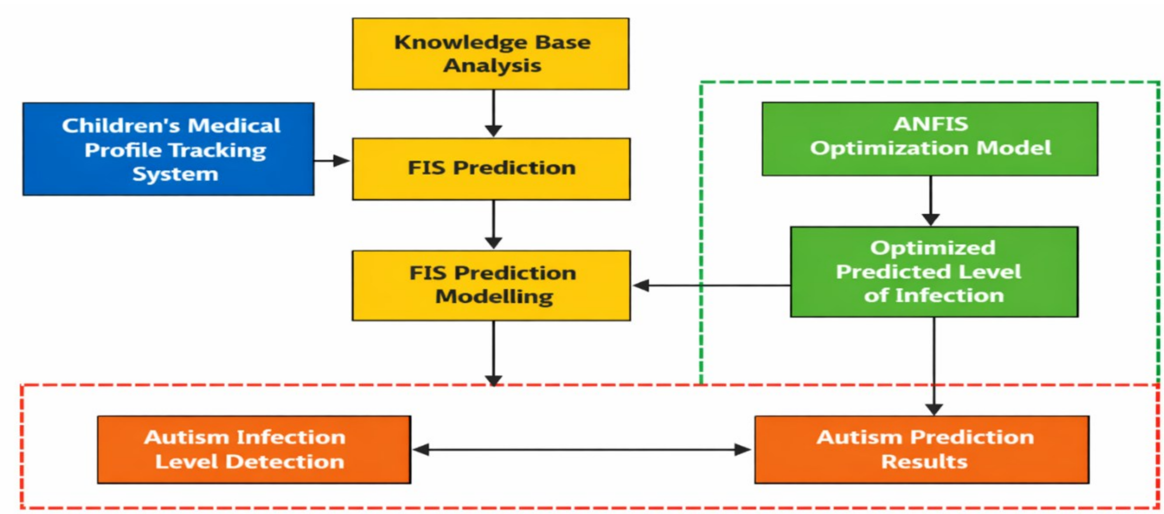

Fig. 1: The conceptual framework for proposed model (Adapted from Rachna & Darvinder (2014)

Table 1: Features of the dataset of the collected data

Variable	Description	Data Type
Child ID	Uniquely identifies each child in the dataset	Integer
Age (Months)	Represents the age of the child at the time of assessment	Numerical
Sex	Indicates the gender of the child (Male or Female)	Categorical
Eye Contact Level (ECL)	Numerical score representing the level of eye contact observed	Numerical
Sensitivity to Pain (SP)	Numerical score representing the child's response to pain stimuli	Numerical
Communication Test Score (CTS)	Numerical score representing communication abilities observed	Numerical
Social Interaction Score (SIS)	Composite score representing the child's social and environmental interaction abilities	Numerical
Diagnosis (ASD)	Indicates whether the child was diagnosed with ASD (Yes or No)	Binary

The dataset contains 5,000 entries with varying behavioral, developmental, and clinical characteristics together with their corresponding ASD diagnosis status. Each record contains values for the selected predictor variables and the target diagnostic outcome.

Table 1 presents a sample of the collected dataset used in this study.

2.2 Feature Selection and Preprocessing

The collected dataset was subjected to preprocessing procedures, including data cleaning, handling of missing values, normalization of numerical variables, categorical encoding of gender information, and feature relevance analysis. The Min-Max normalization technique was employed to transform input variables into the interval [0,1] before model training.C. Adaptive Neuro-Fuzzy Model Design

An adaptive neuro-fuzzy model (ANFM) was developed, consisting of interconnected neural network modules and fuzzy logic inference mechanisms (James *et al*., 2017; 2022)

The model architecture is optimized to accommodate the complexity of autism diagnosis and adapt to varying input data. Fig. 2, shows the ANFM.

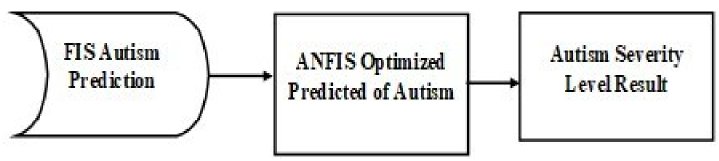

Fig. 2: Adaptive Neuro-Fuzzy Predictive model for children

In the above framework, Fuzzy Logic is used as the soft computing technique to predict the level of infection of the child to autism and the output is fed into the ANFIS model for optimization.

The model uses four (4) metrics to determine the presence of autism in a child and as well as severity level; the four metrics are:

2.3 Eye Contact Level (ECL), Child's sensitivity to pain (SCP), Child's response to Social and Environmental Interaction (SEI), and Communication Test (CT).

Fig. 3 presents the conceptual framework of the fuzzy logic subsystem employed for ASD prediction. In this work, a type-1 fuzzy logic model was used. This model is based on a triangular membership function that defines a degree of membership of all crisp values within the specified universe of discourse.

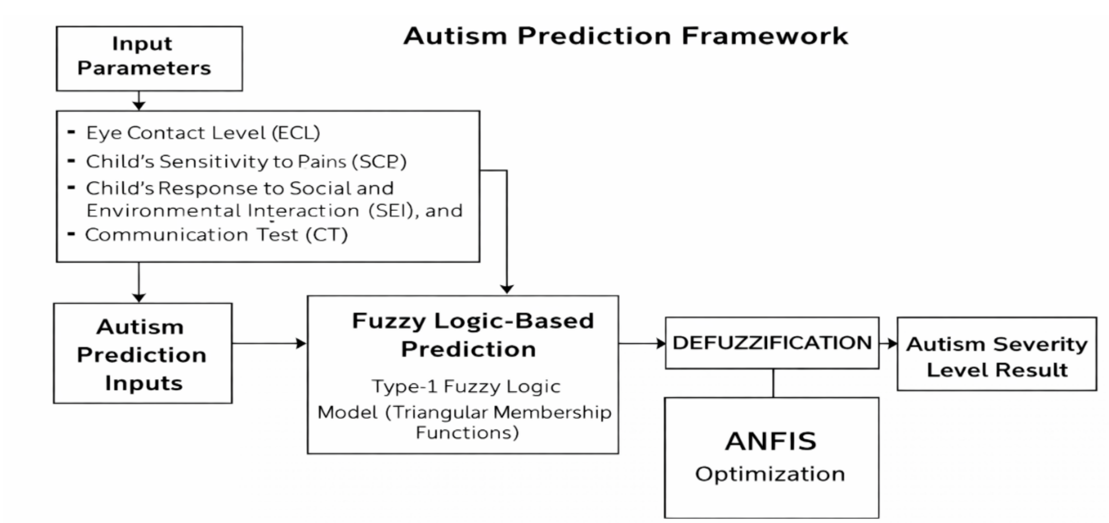

Fig. 3: Conceptual Framework of Fuzzy Logic Model (Adapted from James, 2021)

2.3.1 Fuzzification

In this stage, for each input and output variable selected, we define four membership functions (MF), namely –Eye Contact Level (ECL), Child's sensitivity to pains (SCP), Child's response to Social and Environmental Interaction (SEI), and Communication Test (CT). A category is defined for each of the variable; these categories are called fuzzy terms. A triangular membership function was adopted due to its computational simplicity and effectiveness in representing linguistic uncertainty. For this reason, we need at least three points (o, p, q) to define one Membership Function (MF) of a variable Ituma *et al.,* 2020, The triangular membership function is defined as;

$$f(x;o,p,q) = \begin{cases} 0, & x \le o \\ \frac{x-o}{p-o}, & o \le x \le p \\ \frac{q-x}{q-p}, & p \le x \le q \\ 0, & q \le x \end{cases} \qquad (1)$$

where, o - the left leg of the membership function, p - the center of the function, q - the right leg of the function, x - the crisp input and f - a mapping function

2.3.2 Fuzzy rule base

A fuzzy rule is defined as a conditional statement in the form:

$$R^l: IF x_1 is \tilde{F}_1^l and \ldots x_p is \tilde{F}_p^l THEN y is \tilde{G}_1^l \qquad (2)$$

where, $l = 1, \ldots, M$, is rule number, R is the current rule, p is the number of linguistic variable, x_p is the p's linguistic variable, and $\tilde{F}_p^l$ is the p's linguistic term of rule l

$\tilde{G}_1^l$ - is the output linguistic variable of rule l

2.3.3 Membership matrix

This shows the degree of membership at various levels of the crisp inputs. The membership matrix is computed by substituting the different crisp input into the triangular membership function Umoh *et al.,* 2012. The membership matrix for this work is generated in a membership function evaluator software presented in the tables below;

(I) Membership matrix for Eye Contact Level

Table 2: Membership Matrix for Eye Contact Level

FUZZY SET	CRISP INPUT							
	0.1	**0.2**	**0.4**	**0.5**	**0.6**	**0.7**	**0.89**	**0.9**
N	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R	0.272	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SD	0.00	0.618	0.140	0.00	0.00	0.00	0.00	0.00
D	0.00	0.00	0.782	0.518	0.00	0.00	0.00	0.00

VD	0.00	0.00	0.00	0.717	0.874	0.930	0.792	0.857

(II) Membership matrix for Child's Sensitivity to Pains

Table 3: Membership Matrix for Child's Sensitivity to Pains

FUZZY SET	CRISP INPUT							
	10	20	30	40	60	70	80	90
VVS	0.937	0.326	0.00	0.00	0.00	0.00	0.00	0.00
VS	0.00	0.361	0.8 94	0.348	0.00	0.00	0.00	0.00
S	0.00	0.00	0.00	0.262	0.359	0.00	0.00	0.00
SS	0.00	0.00	0.00	0.00	0.230	0.996	0.238	0.00
NS	0.00	0.00	0.00	0.00	0.00	0.00	0.340	0.830

(III) Membership matrix for Social & Environmental Interaction

Table 4: Membership Matrix for Social & Environmental Interaction

FUZZY SET	CRISP INPUT							
	0.1	**0.2**	**0.3**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
NI	0.369	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SI	0.340	0.343	0.00	0.00	0.00	0.00	0.00	0.00
NI	0.00	0.268	0.975	0.319	0.00	0.00	0.00	0.00
HI	0.00	0.00	0.00	0.275	1.00	0.275	0.00	0.00
VHI	0.00	0.00	0.00	0.00	0.00	0.374	0.813	0.00

(IV) Membership matrix for Communication Test

Table 5: Membership Matrix for Communication Test

FUZZY SET	CRISP INPUT							
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.8**	**0.9**
N	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S	0.388	0.00	0.00	0.00	0.00	0.00	0.00	0.00

A	0.324	0.472	0.00	0.00	0.00	0.00	0.00	0.00
P	0.00	0.132	0.697	0.790	0.380	0.00	0.00	0.00
VP	0.00	0.00	0.00	0.00	0.00	0.440	0.880	0.0800

(iv) Rule Evaluation

Table 6: Rule Evaluation

Rule No.	Firing Interval	Consequent	Max
R1	[0.629*0.510*0.523*0.233]= .168	I[0.348]	LI[0.0]
R2	[0.518*0.262*0.975*0.697]= .262	VI[0.263]	SI[0.0]
R3	[0.421*0.344*0.975*0.697]= .075	VI[0.217]	I[0.348]
R4	[0.217*0.262*0.975*0.697]=0.217	VI[0.217]	VI[0.263]
			MI[0.0]

(v) Defuzzification

The defuzzification of the fuzzy set was carried out by using the center of gravity defuzzification method presented in equation;

$$COG = \frac{\sum_x^b \mu_P(x)x}{\sum_x^b \mu_P(x)} \quad (3)$$

where $\mu_A(x)$ is the degree of membership of x in a set P. The Center of Gravity (COG) method was selected because it provides a balanced and smooth representation of the aggregated fuzzy output and is widely adopted in fuzzy inference systems.

Model Training and Validation

The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets. Model performance was evaluated using accuracy, precision, recall, F1-score, sensitivity, specificity, and receiver operating characteristic (ROC) analysis.

Software and Development Environment

The proposed system was implemented using Python 3.x. TensorFlow/Keras was employed for neural network implementation, while MATLAB Fuzzy Logic Toolbox (or Scikit-Fuzzy) was used for fuzzy inference modeling. Experiments were conducted on a computer with specified hardware configuration.

4.0 Results and Discussion

4.1 ANFIS Training Procedure

The Adaptive Neuro-Fuzzy Inference System (ANFIS) was trained using a hybrid learning algorithm to establish the relationship between the selected behavioral indicators and Autism Spectrum Disorder (ASD) diagnosis. The training process was monitored using training, checking, and testing datasets to evaluate model convergence and generalization capability. Figs. 4, 5, and 6 present the ANFIS training plot, training error plot, and checking plot, respectively. The checking dataset consisted of 107 data pairs, while the training dataset contained 300 data pairs.

The training plot shown in Fig. 4 illustrates the gradual adjustment of the membership function parameters during the learning process. Fig. 5 shows the variation in training error over successive epochs, while Fig. 6 presents the checking performance used to monitor model generalization and detect overfitting.

The use of a checking dataset during training enabled the evaluation of the model's performance on previously unseen data. This approach is essential because prolonged training may cause the model to memorize the training data rather than learn the underlying relationships among variables. By monitoring the checking error, the optimum membership function parameters associated with the minimum validation error were identified and selected for the final model.

4.2. ANFIS Model Validation

The performance of the developed ANFIS model was evaluated using training, checking, and testing error metrics across different training epochs. The results are presented in Tables 7–9.

Table 7 presents the performance of the ANFIS model trained using the Hybrid Algorithm. The results indicate that the model achieved progressive improvement in predictive performance as the training process advanced. At epoch 300, the model recorded a training error of 0.4322, a checking error of 0.4322, and a testing error of 0.1485.

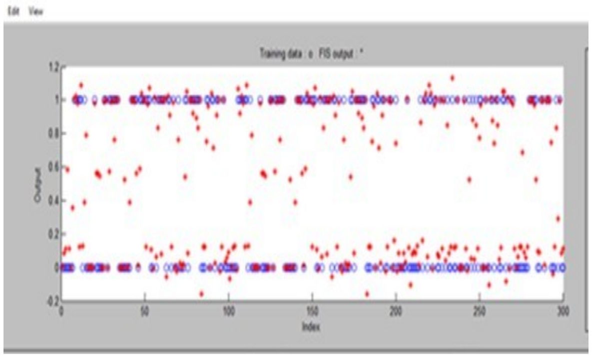

Fig. 4: ANFIS Training Plot

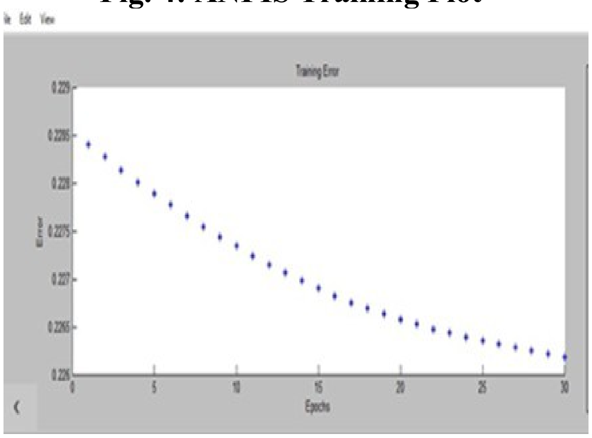

Fig. 5: ANFIS Training Error Plot

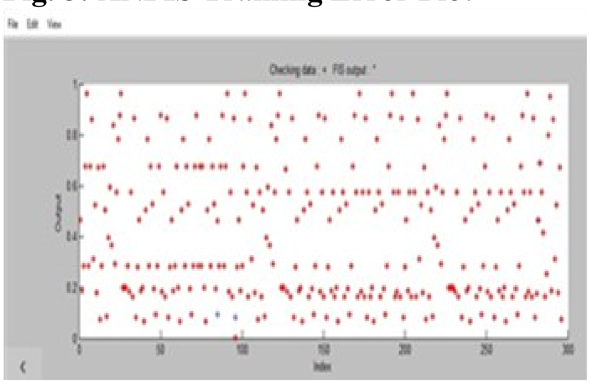

Fig. 6: ANFIS Checking Plot

The corresponding average error was 0.19379, which represents the lowest overall error achieved during training. The reduction in testing error demonstrates the model's ability to learn meaningful patterns from the dataset and accurately predict ASD cases. Although the final testing error remained above the predefined training tolerance value of 0.0001, the consistent reduction in error throughout the training process indicates successful model convergence and acceptable predictive performance. The relatively low testing error obtained at epoch 300 suggests that the developed ANFIS model possesses good generalization capability and can effectively classify unseen ASD cases.

The validation process further revealed that the checking error remained relatively stable during training, indicating minimal overfitting. This observation confirms that the developed model was capable of maintaining a balance between fitting the training data and preserving predictive capability for unseen data.

4.3 Comparison of Hybrid and Backpropagation Learning Algorithms

A comparative evaluation was conducted between ANFIS trained using the Hybrid Algorithm and ANFIS trained using the Backpropagation Algorithm. The results presented in Tables 7 and 8 show that the Hybrid Algorithm consistently outperformed the Backpropagation Algorithm across most performance indicators.

The Hybrid Algorithm achieved lower training, checking, and testing errors in most epochs, indicating superior learning efficiency and convergence characteristics. At epoch 300, the Hybrid Algorithm recorded a testing error of 0.1485 compared with 0.4322 obtained using the Backpropagation Algorithm. This represents a substantial reduction in prediction error and demonstrates the superiority of the Hybrid learning approach for ASD prediction.

Similarly, the average error obtained using the Hybrid Algorithm was lower than that of the

Backpropagation Algorithm, suggesting improved predictive stability and reliability. The superior performance of the Hybrid Algorithm can be attributed to its combination of least-squares estimation and gradient descent optimization techniques, which facilitate faster convergence and improved parameter tuning. These findings are consistent with previous studies that reported enhanced diagnostic accuracy using neuro-fuzzy systems for autism prediction (Anurekha & Geetha, 2018; Pavithra & Jayanthi, 2021). The ability of ANFIS to combine the learning capability of neural networks with the uncertainty-handling strength of fuzzy logic makes it particularly suitable for complex medical diagnostic applications such as ASD prediction.

4.4 Interpretation of ANFIS Training Information

The ANFIS training information presented in Table 9 provides additional insights into the complexity and learning capability of the developed model. The model generated 625 fuzzy rules from the selected input variables using the subtractive clustering method. A total of 685 trainable parameters were optimized during training, comprising 625 linear parameters and 60 nonlinear parameters.

The validation mean square error of 0.013023 was considerably lower than the training mean square error of 0.312601, indicating that the developed model exhibited strong generalization capability with limited evidence of overfitting. The testing mean square error of 0.302421 further confirms the ability of the model to perform effectively on unseen datasets.

The large number of generated fuzzy rules demonstrates the model's capacity to capture complex nonlinear relationships among the selected behavioral indicators and ASD diagnosis outcomes.

4.5 Sensitivity Analysis

Sensitivity analysis was conducted to determine the relative contribution of each input variable to the prediction of Autism Spectrum Disorder in children aged 6–24 months. MATLAB was used to compute and visualize the contribution of each predictor variable, as shown in Fig. 7.

The results revealed that Sensitivity to Pain (SCP) was the most influential predictor, contributing 75.10% to the prediction of ASD. This was followed by Social and Environmental Interaction (SEI) and Eye Contact Level (ECL), which contributed 67.50% and 65.32%, respectively. Communication Test (CT) contributed 40.85%, making it the least influential variable among the selected predictors. The dominance of SCP, SEI, and ECL suggests that behavioral responsiveness and social interaction characteristics are the most significant indicators of ASD in early childhood. These findings agree with established clinical observations that deficits in social interaction and atypical behavioral responses are among the earliest manifestations of autism.

Table 7: ANFIS Performance with Hybrid Algorithm

S/N	Number of Epochs	Training Error	Checking Error	Testing Error	Average Error
1	30	0.1485	0.8603	1.508567	1.508567
2	60	2.5753	0.4281	1.4140	1.4140
3	90	2.4268	0.4322	0.19379	0.19379
4	120	0.8603	1.7247	2.5753	1.22001
5	150	0.4281	1.2925	2.4268	1.02622
6	300	0.4322	0.4322	0.1485	0.19379

Table 8: ANFIS Performance with Back Propagation Algorithm

S/N	Number of Epochs	Training Error	Checking Error	Testing Error	Average Error
1	30	0.8603	5.1506	0.1485	6.1506
2	60	0.4281	5.4476	2.5753	3.4337
3	90	0.4322	0.297	2.4268	0.2436
4	120	1.7247	5.1506	0.8603	3.6600
5	150	1.2925	4.8536	0.4281	3.16355
6	300	0.4322	0.297	0.4322	0.2692

Table 9: ANFIS training Information

S/N	Parameters	Sub Clustering Method
1	Number of nodes	1297
2	Linear parameters	625
3	Nonlinear parameters	60
4	Total number of parameters	685
5	Number of training data pairs	300
6	Number of checking data pairs	107
7	Total number fuzzy rules	625
8	Training mean square error	0.312601
9	Validation mean square error	0.013023
10	Testing mean square error	0.302421

C

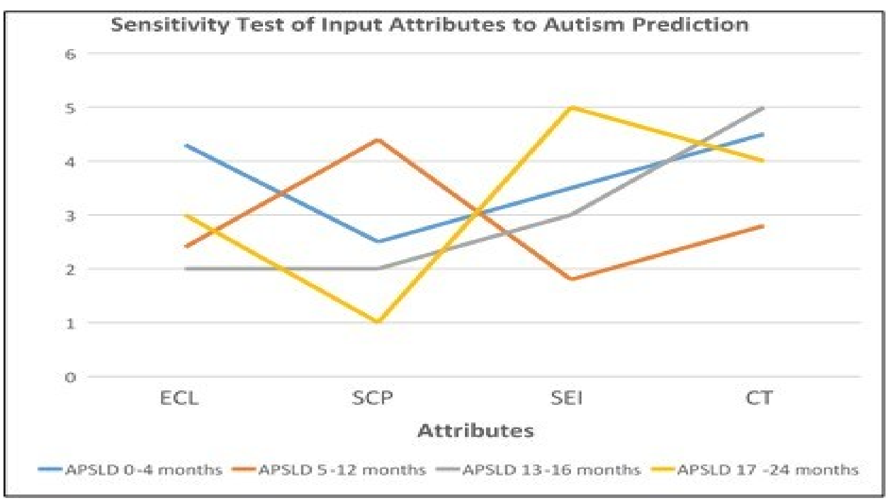

Fig. 7: Sensitivity Analysis of Input Variables

The results demonstrate that the proposed ANFIS-Hybrid model is capable of accurately predicting Autism Spectrum Disorder in children using selected behavioral indicators.

The model exhibited satisfactory convergence characteristics, low testing error, strong generalization capability, and superior performance compared with the Backpropagation-based ANFIS model. Furthermore, sensitivity analysis identified Sensitivity to Pain, Social and Environmental Interaction, and Eye Contact Level as the most influential predictors of ASD. These findings support the application of hybrid neuro-fuzzy systems as effective intelligent decision-support tools for early autism diagnosis and severity assessment in pediatric populations.

4.0 Conclusion

This study developed a Hybrid Intelligent Model based on an Adaptive Neuro-Fuzzy Inference System (ANFIS) for the early prediction and severity assessment of Autism Spectrum Disorder (ASD) in children. The model was designed to address the limitations associated with conventional autism screening and diagnostic approaches, which often rely heavily on subjective assessments and may result in delayed diagnosis.

Using behavioral and developmental indicators including Eye Contact Level (ECL), Sensitivity to Pain (SCP), Social and Environmental Interaction (SEI), and Communication Test (CT), the proposed model successfully captured the complex relationships between ASD-related symptoms and diagnostic outcomes. The integration of artificial neural networks and fuzzy logic enabled the system to effectively handle uncertainty and improve predictive performance.

The results demonstrated that the developed ANFIS-Hybrid model achieved a testing accuracy of 98%, indicating a high level of reliability for ASD prediction in pediatric cases. Comparative analysis further showed that the Hybrid Algorithm outperformed the conventional Backpropagation Algorithm in terms of error reduction and overall model performance. Sensitivity analysis revealed that Sensitivity to Pain, Social and Environmental Interaction, and Eye Contact Level were the most influential predictors of ASD, highlighting their importance in early screening and diagnosis.

The study therefore successfully achieved its objective of developing an intelligent decision-support system for early ASD prediction and severity assessment. By facilitating earlier identification of children at risk of autism, the proposed model can support healthcare professionals in making more informed diagnostic decisions and enable timely access to intervention programs, therapy, and specialized educational services.

Overall, this research contributes to the growing application of artificial intelligence in healthcare and demonstrates the potential of neuro-fuzzy systems as effective tools for improving autism diagnosis. Future studies may incorporate larger and more diverse clinical datasets, additional behavioral and genetic factors, and real-time clinical implementation to further enhance the accuracy and applicability of the proposed model.

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Declarations:

Conflict of interest

The authors declare that they have no conflict of interest

Data availability

All data used in this study will be readily available to the public.

Consent for publication

Not Applicable.

Ethical consideration

Not applicable

Competing interests

The authors declared no conflict of interest.

Authors' Contributions

Okafor Nneka Maryann conceptualized the study, contributed in data collection and analysis, designed the fuzzy logic and artificial neural network model and drafted the manuscript. Nweze Rosemary Chika contributed also in data collection, data preprocessing, literature review, and model evaluation. Ituma Chinagolum participated in result interpretation, manuscript editing, and critical revision of the study. All authors reviewed and approved the final manuscript.