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Game Theory Enhanced Deep Neuroimaging for Advanced Autism Spectrum Disorder Diagnosis

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Abstract: Autism spectrum disease (ASD) is a neuro-developmental disorder that is complicated and degenerative. The majority of current approaches use functional MRI to diagnose autism spectrum disorder (ASD), but they have several drawbacks. In order to address these issues, a novel framework for diagnosing ASD is presented by the suggested approach, which combines deep learning, sophisticated neuroimaging, and game theory. Using an optimized Deep Neuro Fuzzy Network (DNFN) through Feedback-Henry Gas Optimization (FHGO) and functional connectivity data, this study builds upon a novel approach and applies game theory to model the complex interactions within neural networks and improve the automated autism diagnosis model's performance. The proposed Game Theory Optimized DNFN-FHGO shows better accuracy and yield an accuracy of 98.63 % which is 17.54% higher when compared with DNN, SVM and DANN and establishing a new standard in the area by fusing the strategic insights of game theory, the adaptability of deep learning, and the predictive potential of neuroimaging.

Keywords: *Autism Spectrum Disorder Diagnosis, Deep Fuzzy Neural Network, Feedback Henry Gas Optimization, Game Theory Optimization*

1. Introduction

A spectrum of neurodevelopmental problems spanning a lifetime, autism spectrum disorder (ASD) is typified by limited and repeated patterns of behaviour as well as challenges with social interaction and communication [1]. The WHO estimated that 1 in 160 children worldwide suffers with ASD [2]. ASD is an intellectual disabilities; many people with ASD have remarkable skills and abilities[3]. About 40% possess above-average intelligence and a special ability to view the world from a distinct angle. The most recent Canadian prevalence rate for autism spectrum disorder is 1 in 66 children and youth (ages 5–17) according to NASS[4] . NIHM states that while the precise origin of autism is unknown, certain evidence points to the involvement of genetic and environmental factors. A low birth weight is one of the probable risk factors for ASD, along with having an older parent, a sibling with ASD, and pre-existing genetic disorders like Rett disorder, fragility X syndrome, and Down syndrome [5]. It's also important to note that studies have revealed structural variations in the brains of infants before 27 weeks [4], meaning that extremely premature babies have an increased chance of having ASD. People on the autistic spectrum do far better when diagnosed early in their initial few years of life, yet diagnosis and recognition of ASD are frequently delayed. More kids would benefit from early treatment if health services were more adept at spotting kids who are at increased risk for ASD and getting them in sooner for a thorough evaluation. For many classifiers, the most major hurdles are the needed computational time and the accuracy of the classification while constructing an automatic diagnosis system. Even though these techniques are extremely accurate, they are also clearly comprehensive, time-overriding, and require professional knowledge that may not be available in many healthcare facilities. As a result of recent technological advancements, a sizable number of research are exploring the possibility of automating computer-aided identification of autism[6] and creating interactive tools to support the recovery and therapy of individuals with autism [7]. Numerous studies utilizing neuroimaging methods, like as positron emission tomography or Magnetic Resonance Imaging, have shed light on the neurodevelopmental traits that underlie ASD [8]. The majority of these imaging studies' conclusions are predicated on a single analytical method that assumes the independence of every voxel[9]. ML models may distinguish between an afflicted and control group and recommend an appropriate course of action for each patient. MRIs, or magnetic resonance imaging, are useful in the detection of neuropsychiatric and neurodegenerative conditions [10]. Patients with ASD have behavioral and social interaction issues. The term "spectrum" in the nomenclature of ASDs refers to the wide range of behavioral abnormalities that patients have displayed, including attention deficit, poor social skills, and nonsensical speech and actions. Early diagnosis, however, can assist medical professionals and caregivers in implementing preventative measures and taking first action to ensure a certain degree of normalcy in the lives of their patients. Following many years of intensive investigation, it has been established that early diagnosis is not a simple undertaking. Conventional questionnaire-based diagnostic techniques, involve assessing patients' interview responses and observing their behaviours to make the diagnosis. Unfortunately, because there are no certain identifiable behaviours that can be objectively classified as ASD, these diagnosis techniques are subjective, ineffective, and occasionally deceptive[11]. Therefore, developing trustworthy techniques that go beyond simply using behavioral questions to diagnose ASD more effectively and precisely in a quantitative or partially quantitative manner is essential. As artificial intelligence and neuroimaging technology

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progress, neuroimages are increasingly being used to study neurological conditions through functional and/or structural research[12].

Our understanding of the fundamentally disrupted brain systems underlying neuro-disorders has improved significantly because to neuroimaging[13]. On the other hand, the limited adoption of brain imaging methods in clinical settings can be partly ascribed to the ongoing debate on the diagnostic precision of these instruments. Making a diagnosis based solely on behavioral signs can be a laborious and imprecise process[14]. By utilizing machine learning, automated diagnostics could become more accurate in their predictions and consume less time than they already do. Brain imaging sample sets are frequently linked to a high number of characteristics and small dataset sizes [15]. As a result, a number of machine learning techniques are designed to minimize dimensionality and avoid issues with data fitting. Further, machine learning classifiers may be taught to forecast the severity of the condition and correctly differentiate affected controls from healthy ones. Therefore, the combination of accurate illness diagnosis with brain imaging could be made possible by machine learning algorithms[16].

Fuzzy systems are information processing-focused structures built on fuzzy approaches. They are mostly utilized in systems where using classical binary logic is impractical or challenging. Fuzzy conditional IF-THEN rules, which express symbolic knowledge, are their primary characteristic. As a result, the innovative DNN and fuzzy systems have shown how to use fuzzy rules to effectively reduce uncertainty. The use of DNFN has become incredibly widespread in the last five to six years within AI research circles[17]. Thus, there has been a noticeable increase in the application of this paradigm in a number of fields, including healthcare. A novel method for identifying ASD from brain scans of autistic people is developed. The pre-trained DNFN is used to identify patients with autism spectrum disorders. Using the suggested FHGO-based DNFN, a novel ASD classification technique is created. The goal is to calculate the accuracy of the detection efficiency and produce an FHGO-DNFN for the purpose of identifying the ASD biomarker through image analysis. Finding ASD will help clinicians diagnose ASD, which is the aim. The previously trained DNFN is employed to identify ASD patients. Accurate calculations of the model efficiency are made using the training DNFN model's output. The suggested FHGO is used to adjust the DNFN weights. In this case, the FAT algorithm and Henry Gas Solubility Optimization (HGSO) are combined to produce the FHGO. The creation of game theory into the diagnostic process is a unique element of our technique. Game concept lets in us to conceptualize the interactions between exceptional brain regions as strategic moves, shedding light at the hidden patterns and complexities of ASD-associated neural dynamics. This integration not best complements the diagnostic accuracy but also opens new avenues for exploring healing interventions tailored to the specific neurobiological profiles of individuals with ASD.

1.1 This study's key contributions are as follows:

- The framework integrates various superior techniques, inclusive of rs-fMRI statistics collection, Deep Neuro Fuzzy Network, and hybrid optimization algorithms, to address the complexities of ASD analysis comprehensively.
- By leveraging the Learning capabilities of DNN and the interpretability of Fuzzy Inference Systems inside the DNFN framework, the method pursuits to improve the accurateness of ASD analysis.
- The incorporation of FHGO, a hybrid optimization algorithm combining FAT and HGSO, facilitates the convergence in the direction of optimal solutions for various optimization demanding situations encountered in ASD evaluation. This enhances the efficiency of the overall technique through effectively addressing optimization difficulties
- The inclusion of Game theory optimization in the DNFN framework promotes strategically determine the weight assigned to local versus global performance in the diagnostic interpretation process. This fosters a cooperative environments work together to improve segmentation accuracy and overall ASD diagnosis development, leading to extra effective results.

The following is the arrangement of the remained sections in this article: A summary of relevant studies is given in Section 2. The problem statement for the current system is given in Section 3. In Section 4 of the paper, the methodology of Deep Neuro Fuzzy Network with Feedback-Henry Gas Optimization for advanced Autism Spectrum Disorder diagnosis is described. The results of the research and the discussion that followed are presented in Section5. Section 6 discusses the conclusion of the suggested model and its future application

2. Related Works

ASD recognition model employing functional connectivity aspects of resting-state fMRI data was proposed by Subah et al. [18]. To complete the classification task, DNN classifier is employed. According to simulation data, the suggested model performs more accurately than cutting-edge techniques. While the state-of-the-art approaches' mean accuracy ranged from 67% to 85%, the proposed model's mean accuracy was 88%. The suggested model's sensitivity, F1-score, and area under the AUC score were, in that order, 90%, 87%, and 96%. The effective application of this technique could lead to a variety of uses, including the identification of the neuronal activity patterns that cause autism and the visual assessment of the functioning features of the autistic brain. It is also possible to uncover and establish the underlying neuronal or biological foundation of ASD by comparing the brains of autistic and control individuals. One potential limitation of the approach is that its excellent performance on simulation data might not transfer well to different populations or real-world situations.

Yin et al.[19] developed a deep learning techniques to diagnose ASD using functional brain networks built from brain functional magnetic resonance imaging, or fMRI, data. The complete ABIDE 1 collection of information to examine the effectiveness of the techniques. Using brain fMRI scans, we first build brain networks and then define raw features from these brain networks. In order to extract sophisticated characteristics from the raw data, we secondly use an auto encoder. Next the enhanced features to train DNN, which achieves a 76.2% classification accuracy and a 79.7% AUC. In contrast, a number of conventional machine learning algorithms were trained using the same sophisticated features in order to evaluate the classification performance. Lastly, to train the DNN with the raw features after combining it with the pre trained AE. This results in an AUC of 82.4% and a classification accuracy of 79.2%. These findings demonstrate that deep learning techniques perform better than cutting-edge techniques.

Ke et al. [20] used 14 distinct model types, including CNN, to develop a deep learning model for examining the strategic and structural underpinnings of ASD. We illustrated that deep neural networks may be utilized as tools for detecting and assessing psychiatric diseases using an open-source autism dataset that included over 1000 MRI scan pictures and an excellent quality structural MRI dataset. In order to show combinations of brain areas and represent the most often referenced regions used by the model during image classification, a 3D convolutional neural networks. RNN were also used to effectively classify the order of brain regions. Strong evidence in both structure and strategy, were discovered which the model largely depends upon for classification. The subcortical regions such as the basal ganglia (BG) are frequently linked to the structural and strategic evidence. In order to assure a cost-effective and timely diagnostic procedure, our work streamlines the deductive reasoning that physicians can employ to identify the unique brain structures that define a complicated psychiatric condition. It may be more difficult for academics and clinicians to use the model to gain significant insights into the neurobiological mechanisms behind ASD if they are unable to understand exactly particular brain regions or traits are emphasized by the model.

A deep learning algorithm for automatic ASD diagnosis was created by Niu et al.[22]. 809 participants, were used to test the multichannel DANN model using the ABIDE repository. By combining three levels of brain functioning connectives and personal characteristic data, the model was able to obtain an outstanding accuracy of 0.732 on ASD classification, surpassing several peer machine learning methods in a k-fold cross authentication experiment. Further experiments were carried out to evaluate the robustness and generalizability of the suggested multichannel DANN model using k-fold and leave-one-site-out crossover validation. The findings indicate that deep learning models may be useful in supporting automated clinical diagnosis of ASD in the future. The chosen cohort for the study is comprised of adolescents and young adults, which restricts the model's generalizability because the ASD diagnosis was made much earlier in life**.**

Mayor Torres et al.[23] classified facial emotions perceived by people with and without ASD (N = 88) using concurrently logged electroencephalography signals using a discriminative and modern machine learning technique called DCNN . Despite the fact that people with ASD did worse on the concurrent FER task, CNN successfully identified facial emotions for both the ASD and non-ASD groups. Convolutional neural networks in the ASD group actually had higher accuracy, and this difference was unrelated to behavioural performance. Three separate participant samples showed the same pattern of results. Furthermore, feature significance studies revealed that facial emotion categorization for people with ASD may benefit particularly from a late temporal window of brain activity (1000–1500 ms). The findings show that emotion-related facial data is encoded in the brain signals of people with (and without) ASD for the first time. Therefore, it is likely that issues in deploying or decoding facial expression information within the brain signal cause reported behavioural FER impairments linked to ASD. One limitation of the research is that the strategies ought to concentrate on leveraging this intact encoding instead of advocating for FER prosthesis.

The limitations across the reviewed studies on system studying models for Autism Spectrum Disorder prognosis include concerns approximately generalizability and transferability. Several models showcase wonderful performance on simulation or unique datasets, however their effectiveness in numerous populations or real-international scenarios remains uncertain. Interpretability is every other not unusual task, as the complexity of deep learning models may also avoid clinicians' information of the specific mind regions or trends emphasized all through class. Additionally, the age specificity of a few models, which include the ones targeted on teens and young adults, limits their applicability to a broader age range of ASD prognosis. Moreover, troubles like lack of interpretability and capability resistance from healthcare specialists to rely upon diagnostic tools without clean understanding ought to hinder the practical attractiveness of those models. Furthermore, over fitting is recognized as a subject in one examine, emphasizing the need for robustness in device getting to know models to avoid learning noise and random oscillations inside the training facts.

3. Problem Statement

Despite tremendous advancements inside the area of Autism Spectrum Disorder (ASD) research, the accurate and early analysis of ASD stays a difficult assignment. These limitations recognized in previous studies underscore the necessity for improved generalizability, interpretability, and robustness in models designed for predicting ASD analysis [25]. Addressing these challenges is pivotal for enhancing the practical utility and attractiveness of such models in clinical settings throughout numerous populations and age groups. This paper addresses these demanding situations via offering a novel framework that integrates game theory, advanced neuroimaging, and DNFN-FHGO algorithm to improve the accurateness and depth of ASD analysis. By leveraging the strategic insights supplied with the aid of recreation principle, the adaptability of deep mastering, and the predictive power of neuroimaging, we goal to triumph over the restrictions of current diagnostic methods and offer an extra complete information of the neurobiological underpinnings of ASD.

4. Proposed Game theory optimized Deep Neuro Fuzzy Network with Feedback-Henry Gas Optimization Advanced Autism Spectrum Disorder Diagnosis

The proposed methodology involves the mixing of diverse superior techniques to enhance autism spectrum disease (ASD) analysis. It starts with data collection of rs-fMRI data following information pre-processing, followed by the integration of a DNFN for advanced ASD prognosis. DNFN integrates fuzzy inference structures and DNN to address high-dimensional information efficiently. DNN's ability to learn complex functions from massive datasets, are mixed with FIS, which affords a rule-based totally structure for obvious decision-making. This integration pursuits to harness the getting to know capability of DNNs at the same time as preserving the interpretability of FIS. Furthermore, the study consists of FHGO, a hybrid optimization algorithm that combines FAT and HGSO. FHGO leverages the adaptability of FAT and the efficient mechanism of HGSO to converge in the direction of optimal solutions for various optimization difficulties. Additionally, the combination of recreation principle optimization into the DNFN framework introduces strategic collaboration among decentralized establishments concerned in ASD analysis. This strategic interplay fosters a cooperative surroundings in which establishments purpose to enhance segmentation accuracy and the overall improvement of ASD diagnosis. Figure 1 represents the conceptual diagram of the proposed method.

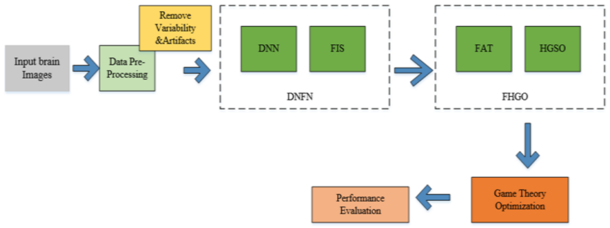

Fig. 1. Overall Conceptual Block Diagram of the Proposed Methodology.

4.1 Data Collection

The dataset is engaged from the secondary source[26]. The Autism Imaging Data Exchange (ABIDE I) provided the rs-fMRI data used in this investigation. ABIDE is a consortium that shares rs-fMRI ASD and identical control data that has been previously gathered for the goal of data exchange in the scientific community. Data from 530 identical controls and 505 ASD people were included in the study. The 17 distinct imaging sites where the ABIDE dataset were gathered comprise rs-fMRI images, brain structure images, and patient phenotypic data.

4.2 Data Pre-Processing

To remove between-subjects variability caused by data capture, different detectors, artifacts, or partial volume effects, pre-processing is an essential prerequisite. Furthermore, non-brain tissues are typically detected in brain MRI studies. To extract morphological characteristics from each sMRI volume it undergoes surface inflation and spherical atlas registration, brain separation and skull stripping, brain segmentation and region labelling, and tessellation of the grey white matter boundary. Magnetic susceptibility artifacts and RF-field in homogeneities are usually the cause of the differences in both intensity and contrast across sMRI images, which lead to the degradation of the sMRI images. Any segmentation process that uses intensity information to categorize voxel data into distinct tissue types should avoid this contamination.

The technique of automatically removing the skull and any non-brain tissue from an intensity-normalized image is known as "brain extraction" or "skull stripping." A tessellated ellipsoidal template is distorted into the shape of the inner surface of the skull in order to eliminate the skull and any non-brain tissue. The deformation process is driven by two types of forces: (i) a curvature-reducing force and (ii) an MRI-based force. The force derived from MRI is intended to push the template away from the brain. It is computed using nonlocal information that is gleaned from sampling the MRI data perpendicular to every vertex of the template tessellation along its surface.

4.3 Deep Neuro Fuzzy Network (DNFN) for Advanced ASD Diagnosis

Deep neuro-fuzzy Network (DNFN) are considered unique methodologies that integrate FL (fuzzy inference systems) and DNNs to handle high-dimensional data in various real-world problem solving scenarios. Thus, before elucidating the idea behind the creation of DNFNs, this part provides an overview of DNNs and FIS. Multi-layered artificial neural networks (DNNs) are an improved form of ANNs that were first developed in 2006. Two important elements are taken into account by the network: supervised or unsupervised learning, and nonlinear processing in various layers or stages [27]. A single perceptron's fundamental components are as follows: the input layer multiplies the number of inputs $(y_1, y_2, ..., y_n)$ by the weight connections $(w_1, w_2, ..., w_n)$ [20].

The f is used to introduce nonlinearity into the function's parameters and the output x, while the bias b is used to calculate the threshold value. The DNN's design is an expansion of the fundamental ANN, which has one hidden layer, one input, and one output. DNN, on the other hand, automatically derives features from the data, enabling more abstract unsupervised training. This DNN benefit makes it easier for the model to learn complex nonlinear functions from a given input, hence reducing error. The DNN model consists of an input layer processing input data, multiple hidden layers processing information in a forward pass, and an output layer computing the error cost.

In order to maximize a cost function, these two variables are adjusted periodically. The network is given a training set of $y^{(i)}$ inputs and $x^{(i)}$ outputs, and on the output layer that comes before it, a transformation using a nonlinear function f is applied. In addition to helping to link each layer using the w and b parameters, this transformation also produces the activation values of the neuron using the subsequent Eqns. (1) & (2)

$$hl_n(y^{(i)}) = f(w_{n-1}{}^{n}\, hl_{n-1}(y^{(i)}) + b_n), \qquad j = 2, \dots \dots, N-1 \tag{1}$$

$$hl_1(y^{(i)}) = f(w_0^1 y^{(i)} + b_1 \tag{2}$$

$$PL(tc|hl(y)) = \frac{e(w_{final}^{tc} hl_{final(y)} + b_{final}^{tc})}{\sum_{j=1}^{TC} e(w_{final}^{k} hl_{final(y)} + b_{final}^{k})} \tag{3}$$

where $hl_{final(y)}$ is the definition of the final layer that is hidden activation for input y. The outcome for target class tc is connected to the last hidden layer by using the weighted matrix w_{final}^{tc} and the bias vector b_{final}^{tc}; After the output is produced, the parameters are adjusted iteratively using the Stochastic Gradient Descent (SGD) method in Eqn. (4) until the anticipated output for the effective data classification matches the intended output.

$$(w_n, b_{n)} \leftarrow (w_n, b_{n)} + \eta \frac{\partial L}{\partial(w_n, b_n)} \tag{4}$$

The rate of learning g dictates the degree of alteration in each iteration. In each iteration, the SGD algorithm meets minimum and produces the optimal value for the weight parameter.

In 1965, Zadeh introduced FL [28]. Any problem that is dependent on ambiguous, inaccurate, or insufficient data can be solved using FL. FIS was first established using fuzzy sets, where each object's membership function determines its partial (fuzzy) belongingness to the relevant fuzzy sets.

A fuzzy function of membership that yields a level of truth and membership is used to express the inputs in FL. The fuzzy version of the IF-THEN rules given in the below Eqn. (5) defines the relationship between inputs and outputs. According to the criterion in Eqn. (5), the output value of q corresponds to fuzzy set S IF the value of p is inside the acceptable limits of fuzzy set R. The parameters in this rule's IF section are referred to as antecedent parameters because they justify or offer proof for the conclusion, while the parameters in the THEN section are referred to as consequence constraints because they allow judgments to be made based on one or more IF statements.

$$IF_p \in \{R\}\ THEN_q \in \{s\} \tag{5}$$

A system that maps inputs into outputs using FL is called a FIS. The FIS structure consists of four primary parts: (i) fuzzification; (ii) reasoning (rule-based); (iii) the inference engine; and (iv)defuzzification. The fuzzification process uses the value of the input membership functions to change the system's input values from 0 to 1. FIS creates a list of fuzzy IF–THEN rules to categorize fuzzy outputs utilizing fuzzy inputs and membership function. Generally speaking, a rule is represented by the logic implication p $\rightarrow$q, where p stands for the rule's premise and q for its conclusion. By utilizing the output membership function and the defuzzification formula, the defuzzification process transforms fuzzier data into crisp output values. Research employing deep learning methods, like DNN, has garnered a lot of interest thus far, and a number of intriguing findings have been published in academic journals. Recent years have seen a notable advancement in DNN thanks to its effective applications in numerous scientific, commercial, and technical fields. DNN is regarded as a cutting-edge method that can handle large or complicated amounts of data. Because of its deep design, this approach also calculates and optimizes millions of parameters. As a result, the DNN model is frequently criticized for lacking transparency and for being a "black box," making it impossible for people to track the predictions it makes. As a result, the disadvantage of lack of transparency has recently presented researchers with a chance to apply the idea of fusing DNNs with the understandable FIS to create a model known as the DNFN.

In a sequential model, information flows by layers, with each layer's output depending on the layer before it. The FIS can be positioned in front of the neural network in this configuration to transform clear data into fuzzy linguistic values that the DNN classifier can analyse. As an alternative, FIS can be used to assist the network in producing a final, comprehensible result following the DNN classifier. The FIS and DNN models each send out information individually, which is eventually combined to provide the final result. Lastly, the FIS model's defuzzification component produces the result in the same clear format. Deep learning approaches can be used by the potent DNFN method to process massive amounts of data. The DNNs' learning technique and mechanism are used to train the membership function parameters in the DNFN model's FIS. Because of this, DNFN are not only more computationally capable than other conventional classifiers, but the model is also more adaptive. Parametric optimization involves optimizing and adjusting the fuzzification part's parameters, such as the kind and quantity of membership functions. Structural optimization involves to increase the network's performance with the fewest possible rules by

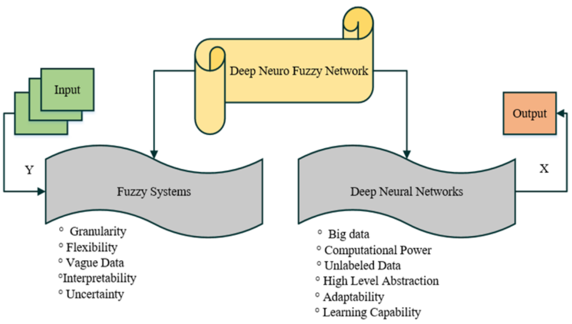

Fig. 2. Representation of Deep Neuro Fuzzy Network

4.4 Feedback-Henry Gas Optimization (FHGO)

In this case, the FAT algorithm and Henry Gas Solubility Optimization (HGSO) are combined to produce the FHGO.

The FAT (Feedback Artificial Tree) algorithm represents an evolution of the original Artificial Tree (AT) set of rules, drawing idea from organic matter transport and branch update theories. Building upon AT's basis, FAT introduces several upgrades for enhanced performance. It keeps the concept of moving organic remember between nodes, similar to AT, but augments this with a remarks mechanism for moisture level within the tree shape. Eqn. (6) represents

$$OM_{i,j} = i, j + \alpha \cdot OM_{parent} \tag{6}$$

In FAT, a comments mechanism for moisture is introduced. This may want to involve a mechanism wherein moisture degrees are adjusted based on the nation of the tree and its surroundings. An Eqn. (7) governing this remarks mechanism is given by

$$M_{i,j} = M_{i,j} + \beta \cdot (M_{external} - M_{i,j}) \tag{7}$$

The Self-Propagating Operator in the FAT (Feedback Artificial Tree) algorithm ensures self-replication and dissemination of statistics inside the tree structure, using rules or mechanisms governing node reproduction and unfold. Similarly, the Dispersive Propagation Operator helps the dissemination of records throughout the tree, doubtlessly utilizing diffusion-like procedures or spreading guidelines. FAT's overall performance superiority is established through benchmark trying out on regular issues, showcasing its effectiveness in comparison to the unique AT algorithm and different heuristic tactics. This evaluation entails choosing appropriate benchmark troubles, running FAT, and comparing its performance throughout metrics together with solution exceptional and convergence velocity. Furthermore, parameter sensitivity analysis validates FAT's robustness by means of analysing how parameter variations affect its conduct and overall performance on various hassle times. These enhancements together increase FAT's performance, distinguishing it from both its predecessor and other heuristic algorithms.

Henry's law, a gas law that describes the state of a gas that dissolved in a liquid at a stable temperature, was developed in the 1800s. This law, which states that the volume of any gas that dissolved in any liquid with any volume is proportionate to the part pressure of the provided gas and liquid in an equilibrium condition, essentially characterizes the interaction between gas and fluid in terms of the ability to dissolve property of gas. As a result, one crucial factor on which Henry's law depends is temperature. Henry's law states that the following represents the link between a gas's solubility and partial pressure.

$$S_g = \mathrm{H} \times P_g \tag{8}$$

where S_g, P_g, and H stand for Henry's constant, partial pressure, and gas solubility, respectively. Since Henry's constant is heavily reliant on temperature and must be taken into consideration, temperature differences in any gas-liquid system result in a change in the constant. Eqn. (8) can be used to characterize this

$$\frac{d \ln H}{d(\frac{1}{T})} = \frac{-\nabla_{sol} E}{R} \tag{9}$$

The variables ∇_{sol}E, R, and T in Eqn. (9) stand for the temperature dependence, the constant of gas, and the dissolution enthalpy, respectively. Eqn. (10) can be achieved in the following ways.

$$H(T) = e^{C/T} \times B \tag{10}$$

where T's parameters are A and B. An alternative way to express 298.15 K as a temperature is as follows.

$$H(T) = e^{\left(-D \times \left(1 \backslash T - \frac{1}{T^{\theta}}\right)\right)} \times H^{\theta} \tag{11}$$

The solubility of gases in liquid media can be evaluated using Eqns. (11) through (12), which highlight the significance of temperature and pressure as two key factors influencing solubility. The HGSO was inspired by the essential behaviour of Henry's law. Because it includes stages for exploration and exploitation, the HGSO is regarded as an algorithm for global optimization. Eight phases were reported for the HGSO mathematical model. The initialization procedure (stage 1) for the number and placements of gases is given by the following equation, where t is the iteration period and r is a random value between 0 and 1.

$$Y_j(t+1) = Y_{min} + r \times (Y_{max} - Y_{min}) \quad (12)$$

Y_{max} *and* Y_{min} – Bounds of problems

$$H_i(t) = l_1 \times rand(0,1)$$
$$P_{j,i} = l_2 \times rand(0,1)$$
$$C_i = l_3 \times rand(0,1) \quad (13)$$

In Eqn. (13) l_1 , l_2 *and* l_3 are constants with values of 5×10^{-2} , 100, 10^{-2} . Since identical gases form each particular cluster, H_i is the same for all of them. In the stage 3 of the evaluation process, each cluster's i best gas is identified by obtaining the highest equilibrium. This step also includes performing a ranking stage in the entire swarm to obtain the ideal gas. In the fourth stage, Eqn. (14) is used to update the Henry's coefficient:

$$H_i(t+1) = H_i(t) \times e^{\left(-D_i \times \left(1 \backslash T(t) - \frac{1}{T^\theta}\right)\right)} \quad (14)$$

$$T(t) = e^{\left(-\frac{t}{iter}\right)} \quad (15)$$

The following Eqn. (16) is used to update the solubility in stage 5.

$$S_{j,i(t)} = K \times H_i(t+1) \times P_{j,i}(t) \quad (16)$$

Eqn. (10) illustrates how the position update is completed in stage 6. Then Eqn.18) and (19) represents

$$Y_{j,i}(t+1) = Y_{j,i}(t) + F \times r \times \gamma \times \left(Y_{j,best(t)} - Y_{j,i}(t)\right) + F \times r \times \alpha \times \left(S_{j,i(t)} \times Y_{best}(t) - Y_{j,i}(t)\right) \quad (17)$$

$$\gamma = \beta \times e^{-\left(\frac{F_{best}(t)+\varepsilon}{F_{j,i}(t)+\varepsilon}\right)}, \varepsilon = 0.05 \quad (18)$$

In order to escape from the local optimum, the number of worst agents (N_w) is ranked and chosen in stage 7 with the aid of Eqn. (19).

$$N_w = N \times (rand(c_2 - c_1) + c_1), \quad (19)$$

$c_1 = 0.1$ and $c_2 = 0.2$

The position of the lowest agents is updated in the stage 8, which is as follows in Eqn. (20)

$$G_{j,i} = G_{\min(j,i)} + r \times (G_{\max(j,i)} - G_{\min(j,i)}) \quad (20)$$

Where, $G_{j,i}$ represents the position of gas j in cluster I and r is random number, the bounds are G_{min} and G_{max}.

4.5 Integration of Game Theory Optimization for Improving Accuracy into DNFN

Game theory is employed to strategically determine the weight assigned to local versus global performance in the diagnostic interpretation process, optimizing collaboration among decentralized institutions. Additionally, it is utilized to dynamically adjust weights based on strategic contributions, enhancing convergence speed and overall model performance. In ASD diagnostics, the combination of game proposition principle ideas into DNFN introduces a strategic layer that optimizes the collaboration amongst decentralized institutions all through the training system. The ideal is to align character pursuits with the collaborative aim of enhancing segmentation delicacy while considering sequestration constraints. The cooperative literacy technique is modelled as a cooperative game, where every taking part institution is considered a player. The mileage characteristic for party p is strategically designed to stability near performance enhancement with contributions to the worldwide diagnostic interpretation

$$U_p = \beta.Local\ Performance_p + (1-\beta).Global\ Performance \quad (21)$$

Here, the weight assigned to local versus global performance is a parameter β

Each group strategically makes a decision the significance and course of its model updates to maximize its utility. This strategic interplay fosters a cooperative environment, in which establishment's goal to proportion precious facts without compromising their aggressive benefit. The model updates $\Delta\theta_p$ calculated through thinking about the gradients of the loss function with appreciate to the model parameters:

$$\Delta\theta_p = -\eta.\nabla_\theta L_p\theta \quad (22)$$

Where, η-Learning rate

∇_θ-Gradient

$L_p\theta$-Local Loss Function at institution p

Dynamic learning rate adjustment is added based totally on the strategic behaviour of institutions. Institutions dynamically modify their learning rates $\eta_p(t)$ primarily based on their strategic contributions, adapting to the collaborative gaining knowledge of environment. This dynamic adjustment guarantees responsiveness to strategic interactions given in Eqn. (23), optimizing the convergence speed and standard overall performance of the model.

$$\eta_p(t+1) = \eta_p(t) + \lambda.U_p(t) \quad (23)$$

Where, t-Iteration

λ-Parameter governing the rate of adjustment

$U_p(t)$- Utility of player p

Institutions incorporate privacy-preserving strategies into the game formulation. Differential privacy principles are introduced, where noise or perturbations (ϵ) are added to the model updates to prevent inference of sensitive patient information during the collaborative training process:

$$\Delta\theta_p = -\eta.\nabla_\theta L_p\theta_{+\epsilon} \quad (24)$$

The parameter ϵ controls the extent of privacy renovation, and its strategic tuning guarantees a stability among privacy and the application of contributions. In summary, integrating game theory principles right into a DNFN for advanced autism spectrum disorder diagnosis entails formulating the collaborative learning process as a cooperative game, strategically updating models, dynamically adjusting mastering charges, and incorporating privacy-maintaining strategies. This strategic integration optimizes the collaboration among decentralized establishments, enhancing segmentation accuracy while keeping privacy in dermatological image analysis.

5. Results and Discussion

The results section gives a thorough review of the conclusions and findings from the experimental evaluation of ASD diagnosis. For diagnosing ASD combines deep learning, sophisticated neuroimaging, and game theory the novel framework proposed. Utilizing a Game theory optimized Deep Neuro Fuzzy Network through Feedback-Henry Gas Optimization and functional connectivity data, the study achieves significant improvements in the automated ASD diagnosis model's performance. The study is implemented in Windows 10 operating system, MATLAB and SPM programming language.

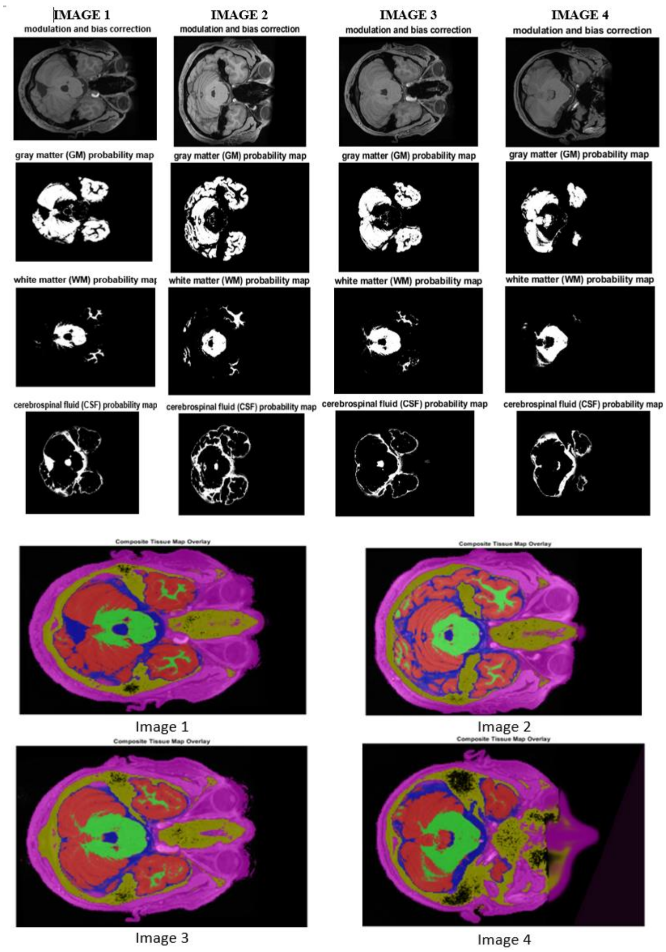

Fig.3. Multi-Model Brain Tissue Segmentation and Bias corrected Images

Figure 3 indicates the grey matter (GM) and white matter (WM) probability map. It shows the likelihood of each voxel being grey matter and white matter. Also represents the cerebrospinal fluid (CSF) probability map, indicating the likelihood of each voxel being CSF. It represent edge probabilities or other non-brain structures, depending on the specific segmentation process used. Edge probabilities typically indicate the likelihood or confidence of a pixel belonging to an edge or boundary between different regions in the image. Other tissues such as the skull or soft tissue outside of the brain. In modalities like MRI or CT in medical imaging, the captured images often encompass not only the specific organ or region of interest and also the bias-corrected and modulated version of the original T1-weighted image are also presented in the figure.

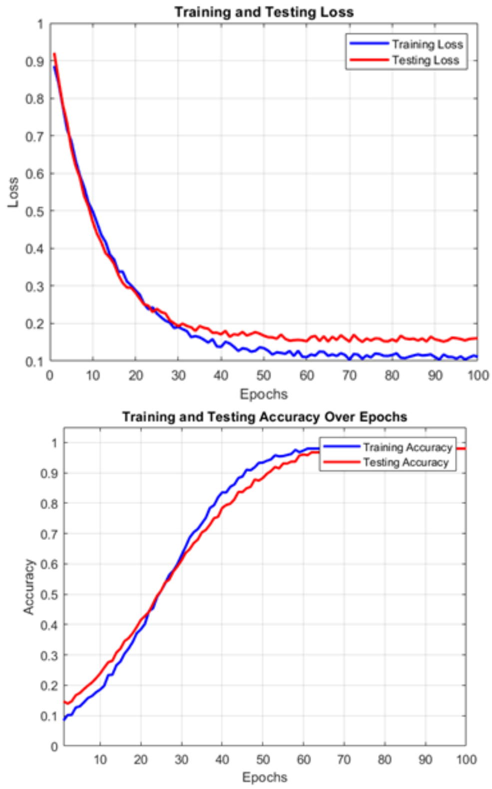

Fig.4. Training and Testing Loss and Accuracy of the proposed Game Theory Optimized DNFN+FHGO

Figure 4 presents the proposed Game Theory Optimized DNFN+FHGO model's training and testing loss and accuracy, providing understandings into its convergence behaviour and generalization performance. The curve offers a visualization of the model's learning process and its ability to minimize loss while maximizing accuracy on both training and unseen testing data.

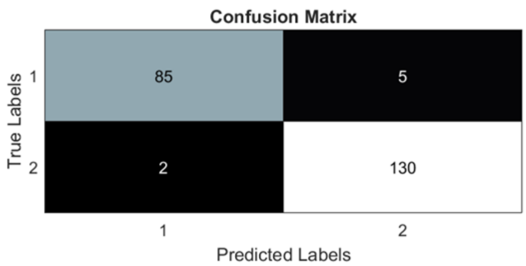

Fig.5. Confusion Matric for ASD

Figure 5 displays the confusion matrix for ASD offering a concise summary of the model's classification performance by depicting the true positive, true negative, false positive, and false negative predictions to precisely classify individuals with ASD and those without, emphasizing potential areas for improvement in classification accuracy or error analysis.

Figure 6 illustrates the weights assigned to the classifiers in the proposed Game theory optimized DNFN combined with FHGO. These weights play a crucial role in the model's decision-making process, determining the significance of each classifier's contribution to the overall classification task.

The word “data” is plural, not singular. The subscript for the permeability of vacuum μ_0 is zero, not a lowercase letter “o.” The term for residual magnetization is “remanence”; the adjective is “remanent”; do not write “remnance” or “remnant.” Use the word “micrometer” instead of “micron.” A graph within a graph is an “inset,” not an “insert.” The word “alternatively” is preferred to the word “alternately” (unless you really mean something that alternates). Use the word “whereas” instead of “while” (unless you are referring to simultaneous events). Do not use the word “essentially” to mean “approximately” or “effectively.” Do not use the word “issue” as a euphemism for “problem.” When compositions are not specified, separate chemical symbols by en-dashes; for example, “NiMn” indicates the intermetallic compound.

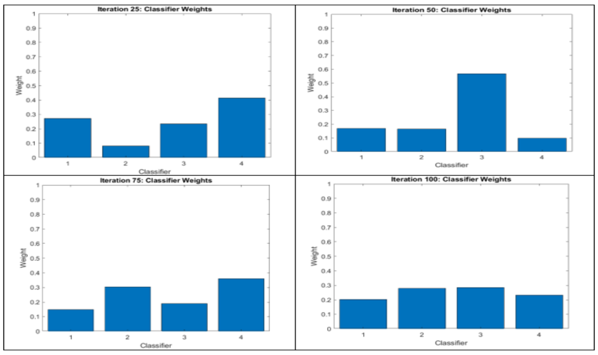

Fig. 6. Weights of Classifiers of the Proposed Game Theory Optimized DNFN+FHGO Model

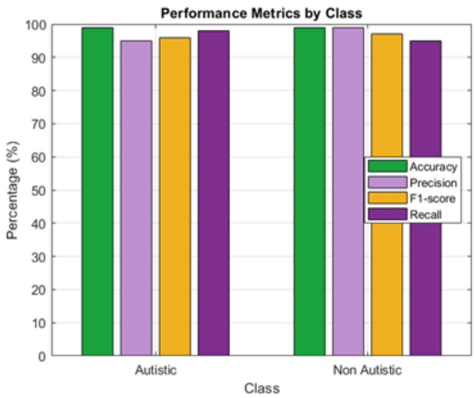

Fig. 7. Performance Metric by Class for Autistic and Non-Autistic

Figure 7 provides a detailed understanding of the model's classification performance, offering insights into its ability to correctly identify individuals with autism and those without for each class, thus aiding in the evaluation of the model's discriminative skills

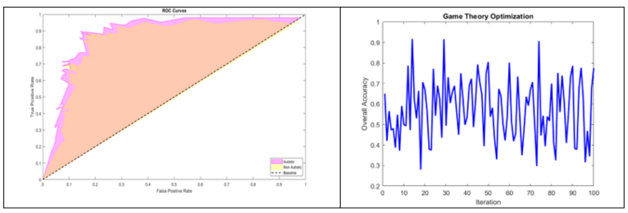

Fig. 8. Roc Curve and the Fitness Curve of the proposed Game Theory Optimized DNFN+FHGO

Figure 8 curve is a graphical representation of the system’s performance in binary category obligations and the fitness curve of the proposed Game theory optimization, illustrating the change-off among its true positive rates and false positive rates across numerous threshold values. A higher AUC suggests better discriminative ability of the model.

5.1 Performance Evaluation

5.1.1 Accuracy

Comparing the ground truth (actual) labels for your test dataset with the predicted class labels produced by the DNFN in order to determine the accuracy. If the projected label matches the actual label for an image in the test dataset, increase the "Number of Correct Predictions." then divide this count by the "Total Number of Predictions" after processing all the test photos to determine the accuracy.

5.1.2 Precision

Precision is a frequently measured parameter, mainly in machine learning and statistics. It evaluates the way a model predicts the future in the positive. Precision is defined as the ratio of accurate forecasts to all reliable forecasts.

5.1.3 Recall

Recall in effective object detection refers to the model's capacity to accurately identify each pertinent instance of a given class present in the dataset. Out of all real positive occurrences for a given class, it calculates the percentage of true positive predictions (properly detected instances of that class).

5.1.4 F1-Score

The F1 score is a commonly used statistic to estimate the performance of sorting models, especially those that are effective at object detection and tracking tasks. The F1 score is particularly useful in datasets that are unbalanced meaning that one class significantly outnumbers the other.

Table 1: The Suggested Method's Performance Metrics are Compared to those of Existing Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1Score (%)
DNN[18]	90	87	96	88
SVM[24]	88.75	88.71	83.76	88.13
DANN[22]	73	82.4	81.56	79
Proposed Game Theory Optimized DNFN+FHGO	98.63	98.44	97.89	95.72

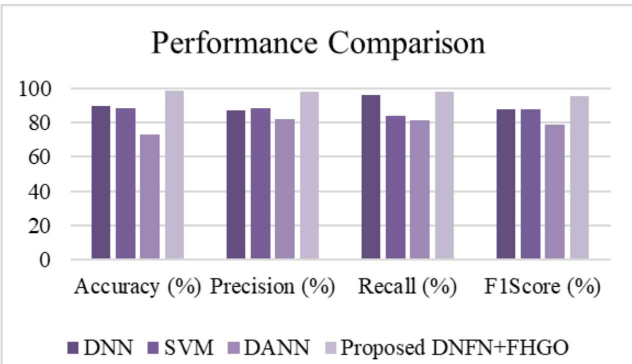

Fig. 9. Visual Representation of the Performance Measures of the Suggested Game Theory Optimized DNFN+FHGO Using Traditional Methods

The suggested model's accuracy is displayed in Table 1 and the graphical representation is illustrated in Figure 9. It shows the Accuracy (98.63%), Recall (97.89%), Precision (98.44%) and F1-

score (95.72%) of the proposed approach with traditional methods. The accuracy of the suggested method Game Theory Optimized DNFN+FHGO (98.63%) is greater than the traditional approaches DNN, SVM and DANN.

5.2 Discussion

The results demonstrate that the proposed framework, integrating deep learning with neuroimaging and Game theory optimized DNFN+ FHGO model, significantly outperforms conventional methods in ASD diagnosis. Achieving an accuracy of 98.63%, precision of 98.44%, consider of 97.89%, and an F1-score of 95.72%, the model reveals remarkable efficacy in classification responsibilities. The figures illustrate the Game Theory Optimized DNFN+FHGO model's superior overall performance over conventional techniques, with high accuracy, sturdy gaining knowledge of dynamics, and effective class demonstrated through ROC curves and confusion matrices, indicating its capacity for reliable ASD analysis. These findings underscore the capability of leveraging advanced computational techniques for reinforcing diagnostic accuracy in ASD, highlighting the promise of integrating multiple modalities for complete assessments. Overall, these figures collectively provide a comprehensive understanding of the proposed Game Theory Optimized DNFN+FHGO model's performance, convergence behaviour, classification accuracy, and discriminative ability, crucial for evaluating its effectiveness in ASD diagnosis and neuroimaging applications. Further validation and integration of this method may want to significantly impact ASD diagnosis and intervention strategies, contributing to progressed results for individuals and families laid low with the disorder.

6. Conclusion and Future Scope

In conclusion, the proposed technique affords a holistic approach to enhancing Autism Spectrum Diagnosis (ASD) analysis by integrating superior strategies such as rs-fMRI data collection, Deep Neuro Fuzzy Network (DNFN), and hybrid optimization algorithms (FHGO). Through the synergistic combination of those methodologies, the studies ambitions to enhance the accuracy of ASD diagnosis even as fostering strategic collaboration amongst decentralized establishments concerned in ASD evaluation. The complete conceptual framework provided serves as a roadmap for enforcing the method successfully. In future, further validation and refinement of the technique using large datasets and medical trials should beautify its applicability and impact in ASD analysis and remedy. Additionally, exploring the ability integration of rising technologies inclusive of machine getting to know interpretability techniques and multi-modal records fusion should further develop the competencies and scope of ASD analysis methodologies.

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Author contributions

Kavitha Nair R: Conceptualization, Methodol ogy, Software, Validation, Formal analysis, Investigation, Resources, Data curation.

P Ranjana: Writing – original draft, Writing – re view & editing, Project administration, Supervision.

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