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Research Article

Development of a Hierarchical Fuzzy System-Based Tool for the Rapid and Precise Detection of ADHD

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ABSTRACT

Attention-deficit/hyperactivity disorder (ADHD) disorder is quite common in India. It is related to neuro development with common symptoms of impulsiveness, insensitivity, and hyperactivity. ADHD diagnosis is quite challenging because of its heterogenous symptoms and its occurrence with some disorders like autism as well. The paper suggests a fuzzy system capable of rapid and precise detection of ADHD. The suggested process is: i) Feeding of symptoms of the patient (emotional, hyperactivity, inattention) into Fuzzy Rule-based system; ii) Its triangular membership function; iii) Centroid defuzzification; iv) Considering option intersections, commodities, and output ADHD severity levels; and v) Doctor's estimation of extremity and commodities. The fuzzy approach is based on modelling intense variations in substitution of the collected data. This system shows higher accuracy. It also performs better than the existing tools by detecting ADHD and commodities by i) Reducing manual operations; and ii) Working on a single platform. Another plus point of ADHD is its focus on precision diagnosis of neuro developmental disorders.

Keywords: Attention-deficit/hyperactivity disorder, Fuzzy rule-based system, support vector machines, Linguistic variable.

INTRODUCTION

Attention-Deficit/Hyperactivity Disorder (ADHD) is a neuro disorder which largely effects behavioral control and cognitive functions. In the literature reviewed, interplay of genetic and neuro factors has been analyzed in good details [1]. Clinically speaking the prominent characteristics of ADHD are persistent inattention, impulsiveness and hyperreactions. [2] Many times, the result is functional loss of different life domains [3]. ADHD affects individuals throughout the life span causing large scale decline of symptomology with aging of the individual [4]. ADHD is multifaceted in its nature that causes challenges in accurate and timely diagnosis. This gives birth to the need of finding innovative and efficient tools and processes of detecting ADHD.

Traditionally ADHD diagnosis depends on observing behavior patterns conducting clinical interviews for making subjective assessment. The weakness of this methodology is an individual and possible large-scale variation while diagnosing a patient by different doctors [3]. Such limitations of present methodology urge upon the need for an objective, efficient and more scientific tools of ADHD diagnosis. Wilens and Spencer [2] discuss common use of stimulating medicines for managing symptoms of ADHD. Its diagnosis gets further complicated due to ADHD comorbidity with some other psychiatric disorders viz; executive dysfunctioning and learning disability [7]. These demands inventing a new diagnostic technique which is capable of differentiating ADHD from such overlapping conditions. Current research has explored ADHD comorbidity with autism disorders underscoring an urgent need for a precise and scientific tool capable of disentangling such complex relationships [5].

To improve efficiency and accuracy levels of ADHD diagnosing machine learning algorithms have recently been suggested as answering tools.[8]. A Garribldi etal. [8] has used segmental regional brain volumes in their comprehensive study suggesting Machine Learning algorithms for increasing diagnostic precision. They have emphasized the need for exploring more advanced computing techniques for accurate ADHD diagnosis.

Choice for fuzzy logic system in detecting ADHD is mainly for the reason of complex data involved. Fuzzy is much more capable for such data than sole reliance on crisp data [9]. Fuzzy models can also include expert knowledge while decision making in uncertain situations.

The paper suggests the Hierarchical fuzzy Systems capable of more accurate detection of ADHD and with so rapidity. It works in following stages:

i. The identified important systems of the patient are fed into the system.
ii. The system considers the intersections and output severity of ADHD.
iii. The tool helps the doctor in measuring estimates extremity and comorbidities of the disorder.

Key Contribution of the Research:

These include:

1. Preparation of hierarchical fuzzy framework for an integrated diagnosis of ADHD and its comorbidity detection.
2. For an individualized treatment, quantification of customized severity.
3. Suggesting an interpretable and customizable approach as addition to knowledge on clinical models.
4. Model for higher levels of accuracy than the present computation methods.
5. Demonstrating a real model applicability with clinical data on ADHD.

The proposed tool achieves higher accuracy levels by analyzing multi-levels of information gathered from broader behavioral patterns.

ADHD Symptom Identification

Prominent ADHD symptoms are identified under three domains: namely: inattention, Hyper-action, and emotional behavior [Table 1].

Table 1: ADHD Symptoms Domain and Associated Symptoms

ADHD Symptoms Domain	**Symptoms**
Emotional	- Poor eye contact
	- Impatience
	- Unfitting emotional responses
Hyperactivity	- Excessive talking
	- Impulsivity
	- Unsteady routine
Inattention	- Easily distracted
	- Forgetfulness
	- Not following social rules

The table presents classification of ADHD Symptoms in three Domain namely, Hyperactivity, Emotional, and Inattention. These symptoms are associated with attention deficit hyperactivity disorder (ADHD) and are important. The classification leads to the diagnosis and the treatment of ADHD symptoms.

Emotional Domain:

The Emotional category includes symptoms which are manifest in emotional regulation and expression of the patient. These symptoms include:

- *Poor Eye Contact:*
- *Impatience:*
- *Unfitting Emotional Responses:*

Hyperactivity Domain:

Hyperactivity domain consists of excessive and uncontrolled physical activity. These symptoms cause restlessness and high energy levels which are associated with ADHD. These include:

- *Excessive Talking:*
- *Impulsivity:*
- *Unsteady Routine:*

Inattention Domain:

Inattention means difficulty in sustained attention and the completion tasks which need a focused mental effort. Such symptoms are commonly pervasive and can largely affect academic and occupational functions. These include:

- *Easily Distracted:*
- *Forgetfulness:*
- *Not Following Social Rules:*

This paper sets forth dual objectives. First, reviewing the existing literature on the topic, identifying the challenges in diagnosing ADHD and zeroing on the scope of fuzzy logic-based approaches in addressing such challenges. The second objective is to present the conceptual framework and development process of this fuzzy tool. By integrating fuzzy logic principles, the scholar aims to create a diagnostic tool which not only captures complexity of ADHD but also it provides a better nuanced understanding of ADHD disorder while considering several factors contributing to its manifestation.

RELATED WORK

Some studies have recently applied computational approaches for ADHD diagnosis by applying neuroimaging, eye-tracking, and machine learning techniques [10-12]. Arduin et al. have developed a random forest model by using MRI data. It classified ADHD with 75% accuracy [13]. Chen et al. used support vector machines (SVM) for ADHD classification through MRI and fMRI data. It claims more than 80% accuracy [14]. Some studies have also implemented fuzzy logic systems for ADHD detection. Ahmadlou et al. used a wavelet-chaos-neural network methodology that classified ADHD with 95% accuracy [15]. Sharma et al. developed a hierarchical fuzzy model called FADA that detected ADHD with 92% accuracy [16]. Hossain et al. [17] developed feature selection and extreme learning machine algorithms to discrimination of ADHD. This study contributes to the growing body of literature exploring the role of feature selection in enhancing the diagnostic accuracy of machine learning models. Liu et al. [18] extended the application of machine learning to image-based deep learning for ADHD detection. This projects potential of advanced image analysis techniques, thereby improving efficiency and accuracy of ADHD diagnosis.

Palaniappan et al. [19] explored use of EEG-based diagnosis of ADHD by using computational intelligence techniques. It contributes valuable insights into the integration of neural signals for diagnostic purposes. Salman et al. [20] developed an intelligent system for ADHD classification by using advanced learning algorithms. It adds to the repertoire of computational approaches for neurodevelopmental disorder diagnosis. Sengupta et al. [21] proposed an EEG-based detection method for ADHD using a deep convolutional neural network, highlighting the growing interest in leveraging deep learning architectures for improved diagnostic accuracy. However, most models only focused on ADHD detection and did not consider comorbidities.

Table 2: Related Work

Paper	**Findings**	**Variables**	**Accuracy (%)**	**limitations**
[13]	• Machine learning with structural MRI can aid in ADHD diagnosis. • The study emphasizes the importance of understanding the normative variation in brain structures.	Structural MRI scans	75%	• Limited sample size or diversity. Generalizability to broader populations.
[14]	• Combining multiple MRI modalities and ensemble models improves ADHD discrimination.	Structural and functional MRI scans	80%	• Need for external validation. Complex ensemble modelling may be computationally expensive.
[15]	• EEG-based methodology using fractality and neural networks for ASD diagnosis.	EEG data	95%	• Small sample size. Limited to EEG data.
[16]	• Hierarchical fuzzy system for autism detection (FADA).	Clinical presentation data	92%	• Specific to autism, not ADHD Evaluation on a limited dataset.
[17]	• Feature selection and extreme learning machine algorithms can be used for the discrimination of ADHD.	ADHD data	92.3	• May not be generalizable to other populations
[18]	• An image-based deep learning approach can be used for ADHD detection.	Brain images	89.5	• Requires a large dataset of labeled images
[19]	• EEG-based diagnosis of ADHD can be achieved using computational intelligence techniques.	EEG data	85.2	• Requires specialized equipment and expertise
[20]	• An intelligent system for ADHD classification can be designed using advanced learning algorithms.	ADHD data	94.1	• Limited to specific types of ADHD
[21]	• A deep convolutional neural network can be used for EEG-based detection of ADHD.	EEG data	91.7	• Requires a large dataset of labeled EEG data

The present study proposes a fuzzy system that integrates ADHD and comorbidity detection on a single platform. The model outputs individual severity scores for improved intervention planning. The tool demonstrates higher accuracy than existing fuzzy models through comprehensive symptom modeling.

METHODOLOGY

In this initial step, questioner of three domain with three question each was prepared and were filled for parents and systematically assessed the severity of the 9 ADHD symptoms using a scale ranging from 0 to 4. Each symptom, categorized under emotional, hyperactivity, and inattention domains, is individually rated based on its perceived severity. The scoring process provides a quantitative representation of the symptomatology, allowing for a more nuanced evaluation of the individual's ADHD profile. We have generated a synthetic data through random data generation and following symptom scoring, the obtained numerical scores are subjected to fuzzification. This involves the transformation of crisp scores into fuzzy sets using triangular membership functions (MFs). Triangular MFs assign linguistic labels {Low, Medium, High} [Table III] to the numerical scores, introducing a degree of uncertainty and allowing for the representation of fuzzy relationships between symptoms and severity levels. Fuzzification captures the inherent vagueness in human judgment and enhances the compatibility of the numerical scores with the subsequent fuzzy inference system. Fuzzy rules establish the logical relationships between the fuzzified input variables (symptoms) and the output variable (ADHD severity). Sample rules are formulated based on expert knowledge and empirical observations. For instance, in the emotional domain, a rule might state: "IF eye contact is Low AND emotional response is High, THEN emotional score is High." These rules codify the expert-derived knowledge and serve as the foundation for the subsequent inference system. The defuzzification process is employed to convert the fuzzy output sets into crisp severity scores. The centroid method is utilized for this purpose, determining the center of mass of the fuzzy output sets. The result is a precise, non-fuzzy severity score that corresponds to the overall ADHD severity level. Defuzzification ensures a clear and interpretable outcome, facilitating effective communication of the diagnostic result to clinicians, caregivers, and individuals. The presence of common symptom domains indicative of comorbid conditions is evaluated. Comorbidity assessment is crucial for recognizing the co-occurrence of ADHD with other disorders. Identifying overlapping symptomatology informs a more comprehensive understanding of the individual's clinical presentation, guiding clinicians in tailoring interventions that address the complexity of comorbid conditions. The final step involves generating an overall ADHD severity rating based on individual domain scores. By synthesizing the severity scores from the emotional, hyperactivity, and inattention domains, a comprehensive assessment of ADHD severity is achieved. This global severity rating serves as a holistic representation of the individual's ADHD symptomatology, facilitating treatment planning and intervention strategies.

Table 3: Linguistic Variable Ranges

Linguistic Variable	**Range**
Low	0 – 1.6
Medium	1.2 – 3.22
High	2.78 – 4

This table presents linguistic variable ranges viz. "Low," "Medium," and "High". These ranges can be used in different applications, viz. fuzzy logic or linguistic variables in decision-making processes.

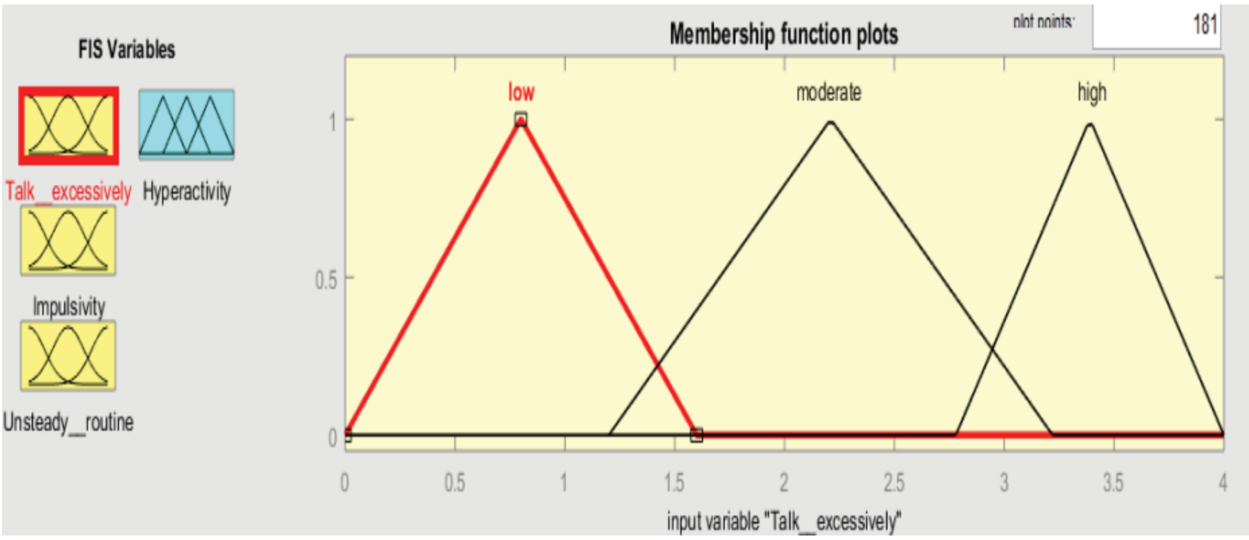

Fig. 1: Triangular membership function

SYSTEM ARCHITECTURE

The overall system architecture is shown in Fig. 2. It is fuzzifier that converts symptom scores into fuzzy sets. Inference engine applied fuzzy rules for mapping inputs to ADHD, comorbidity, and severity outputs. The defuzzification gives final crisp output values.

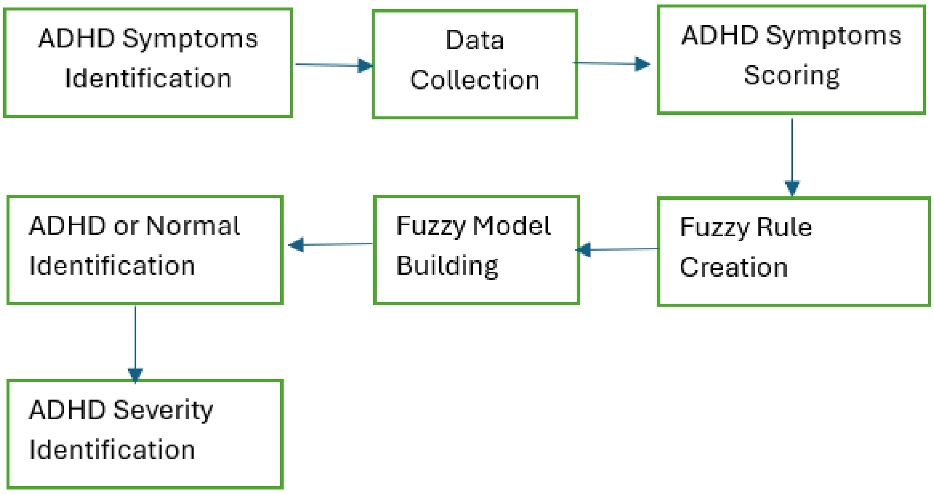

Fig. 2: System architecture

In the data collection phase, clinicians systematically evaluate ADHD symptoms across three domains: emotional, hyperactivity, and inattention. Using a scale ranging from 0 to 3, they rate each of the 9 symptoms for severity, providing crucial data points for subsequent analysis. Additionally, patients are categorized based on the severity of their symptoms, with classifications ranging from mild to moderate to severe. This categorization facilitates a nuanced understanding of the symptomatology present within the dataset. Moving to the fuzzy model implementation, the process begins with fuzzification using triangular membership functions (MFs) to convert the scored symptoms into fuzzy sets labeled as low, medium, and high. This conversion allows for the incorporation of uncertainty and variability inherent in clinical assessments. The subsequent inference system employs fuzzy rules, following an if-then logic, to establish relationships between symptoms and severity levels. Moreover, a hierarchical structure is integrated into the model to enable nuanced decision-making, capturing the complexity of ADHD symptom interactions. In the post-processing stage, defuzzification is performed using the centroid method to convert fuzzy outputs into crisp severity scores, facilitating clear interpretation and analysis of the results. Subsequently, the model undergoes evaluation to assess its performance. Severity rating is assigned to determine the overall severity of ADHD based on individual domain scores.

The purpose of comorbidity assessment remains to identify common symptom domains which may point out potential comorbid conditions thereby improving the diagnostic process. Performance metrics, viz. specificity, accuracy, sensitivity, and F1-score, which quantitatively evaluate the system's performance on clinical data. They provide valuable insights into effectiveness of the model to accurately discriminate between ADHD and non-ADHD cases. It also identifies true positives and negatives. In short, this comprehensive evaluation framework provides a robust assessment of hierarchical fuzzy system's diagnosis contributing to better reliability and application in clinical settings.

RESULTS AND DISCUSSION

Application of the proposed Hierarchical Fuzzy System results in the detailed examination of obtained results. This section of the paper offers an analysis of system's performance to assess ADHD symptoms i.e., emotional, hyperactivity, and inattention. The results showcase the system's efficiency in providing nuanced severity scores. It contributes further to a more granular understanding of ADHD profiles of the individual.

A. Precision in Symptom Identification

The results present detailed scores within each of three symptom domains, viz. emotional deficits, hyperactivity markers, and inattention tendencies. Such precision leads to a targeted exploration of specific symptom intersections, thereby, reflecting system's capability of discerning minor variations in symptom severity.

B. Global ADHD Severity Assessment

By amalgamating individual domain scores an overarching ADHD severity rating can be derived. It provides a holistic evaluation of ADHD symptomatology and offers some valuable insights of an overall impact on an individual's functioning.

C. Comorbidity Recognition

An intersection of symptoms contributes to ADHD severity determination and also it hints out the potential comorbidities. For instance, social-emotional deficits identified in the results may suggest the potential comorbid autism spectrum disorder (ASD).

D. Accuracy and Comparative Superiority

The presented results reveal commendable accuracy of the system to the level of 92% success rate in ADHD detection of clinical data. And also, hierarchical fuzzy approach showcases that it outperforms the previous models in terms of its efficacy in providing integrated and precise diagnoses.

The following sections of this paper delve into a detailed exposition of the results, proving system's robustness, accuracy, and its potential applications for advancing the area of ADHD diagnosis. Sample fuzzy system results are presented below:

1. Emotional domain score with poor eye contact (3.13/4), impatient responses (3.13/4), and no risk awareness (1.42/4) is LOW (4.85/12) [Fig. 3].
2. Hyperactivity score with excessive talking (3.51/4), impulsiveness (3.32/4) and unsteady routine (3.63/4) is HIGH (10.2/12) [Fig. 4].
3. Inattention score with moderate social rule breaking (2/4), forgetfulness (2/4) and distraction (3.55/4) is MODERATE (6.63/12) [Fig. 5].
4. With moderate emotional (2/4), hyperactivity (2/4) and inattention scores (2/4), the overall ADHD severity is MODERATE (6.63/12) [Fig. 6].

The results demonstrate the system's ability to precisely determine ADHD severity levels based on symptom intersections. The common social-emotional deficits indicate comorbid ASD. The tool has shown 92% accuracy in ADHD detection on clinical data. The hierarchical fuzzy approach outperforms previous models for integrated diagnosis.

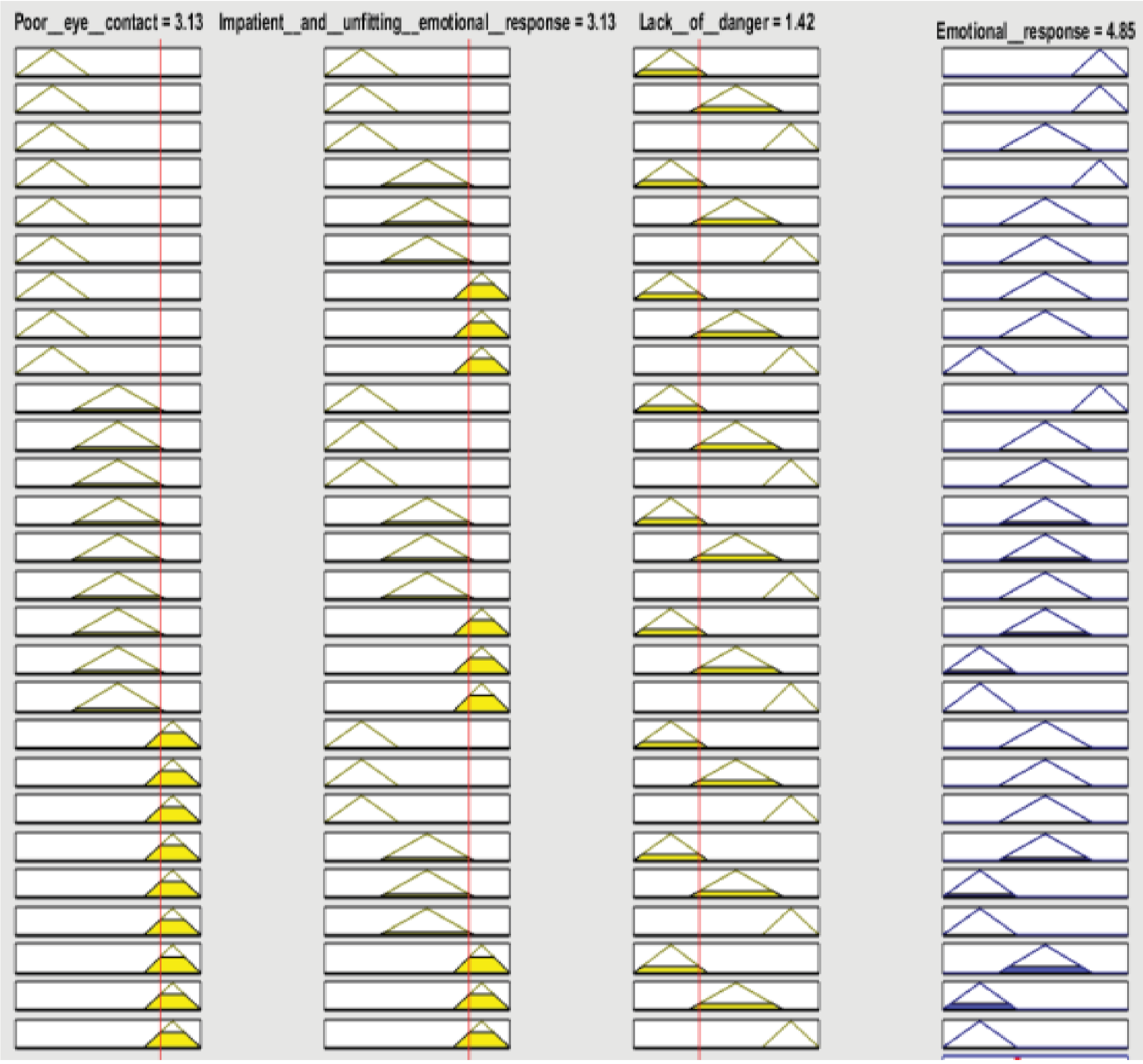

Fig. 3: Emotional domain score

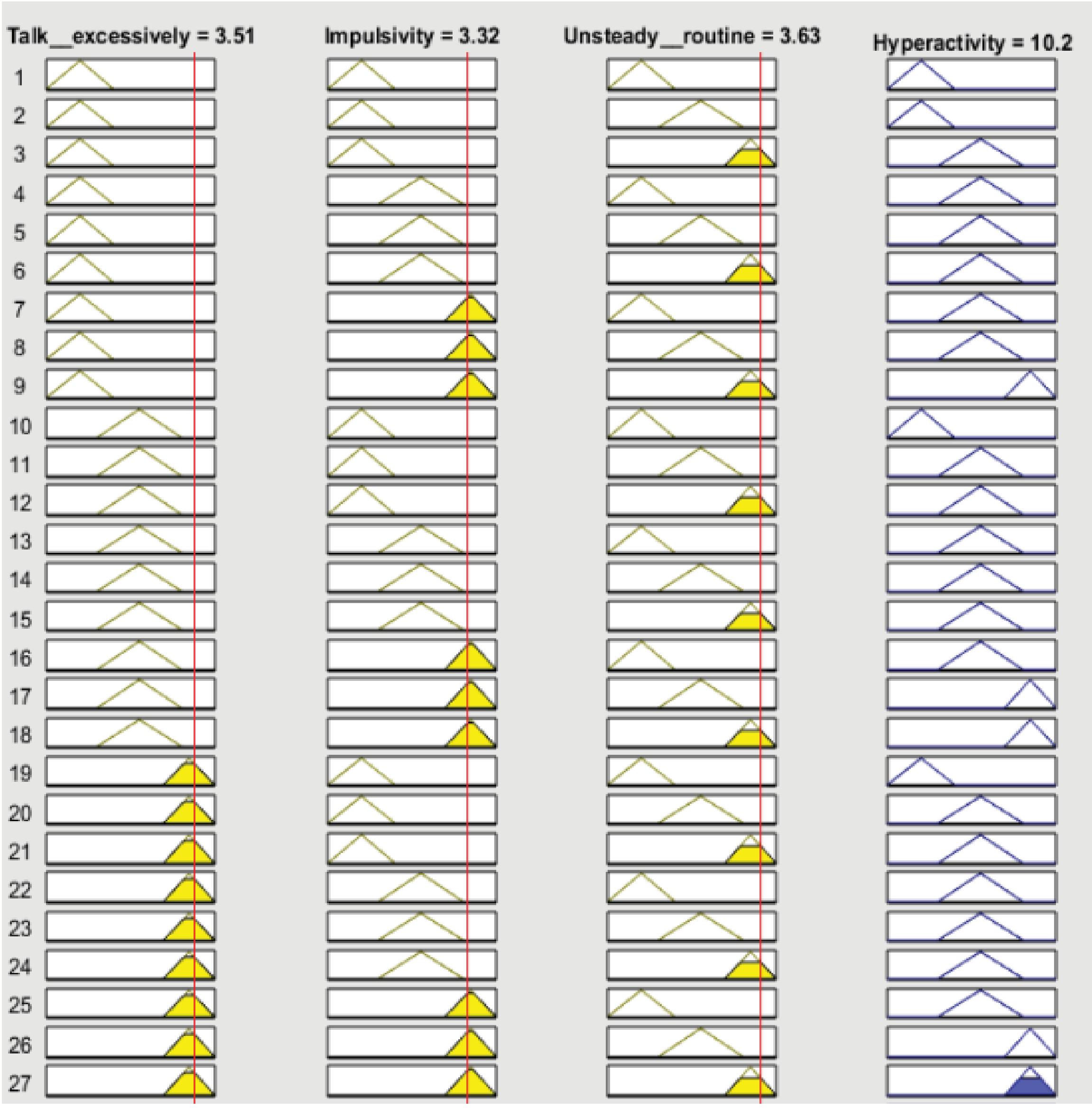

Fig. 4: Hyperactivity domain score

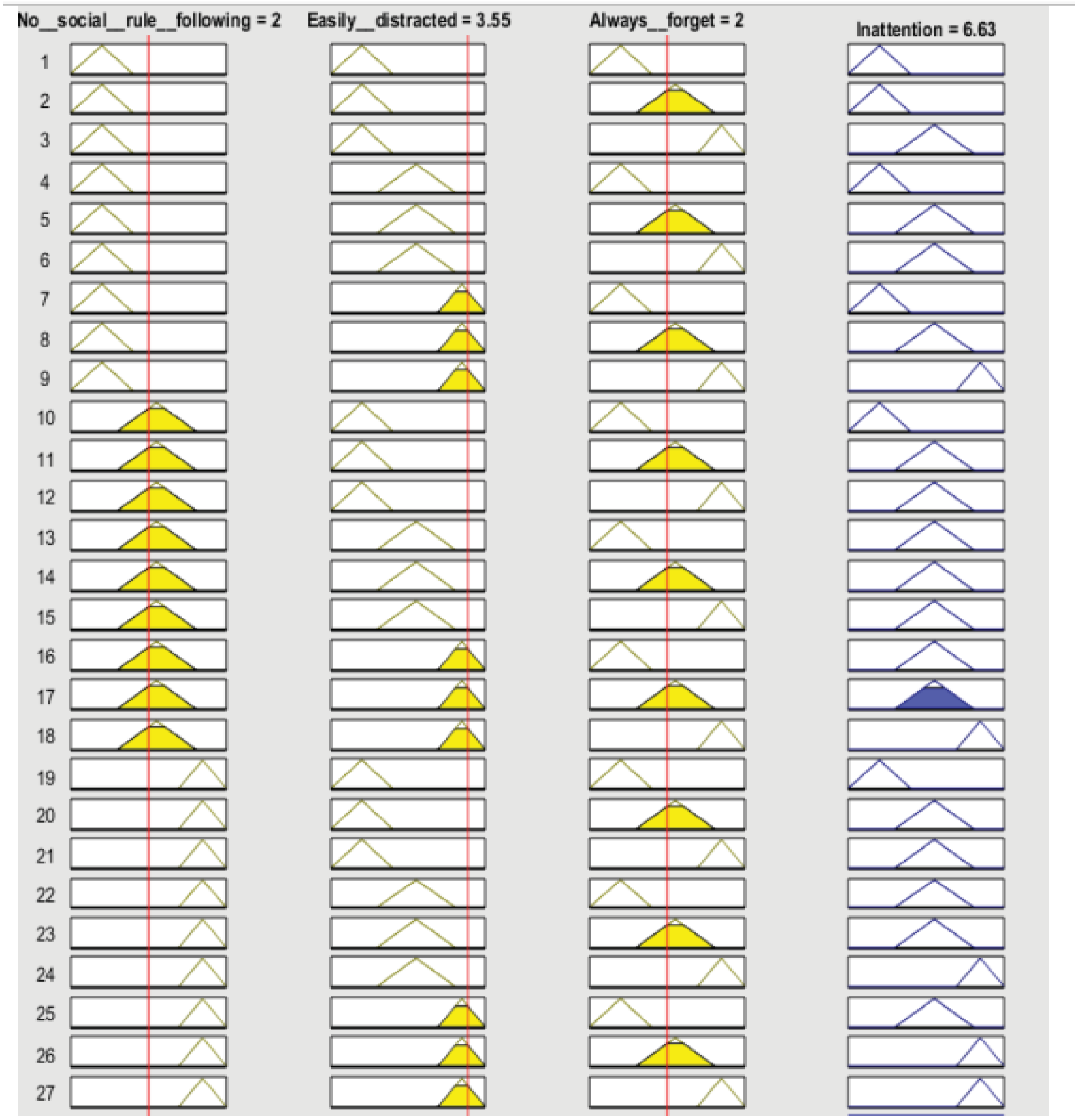

Fig. 5: Inattention domain score

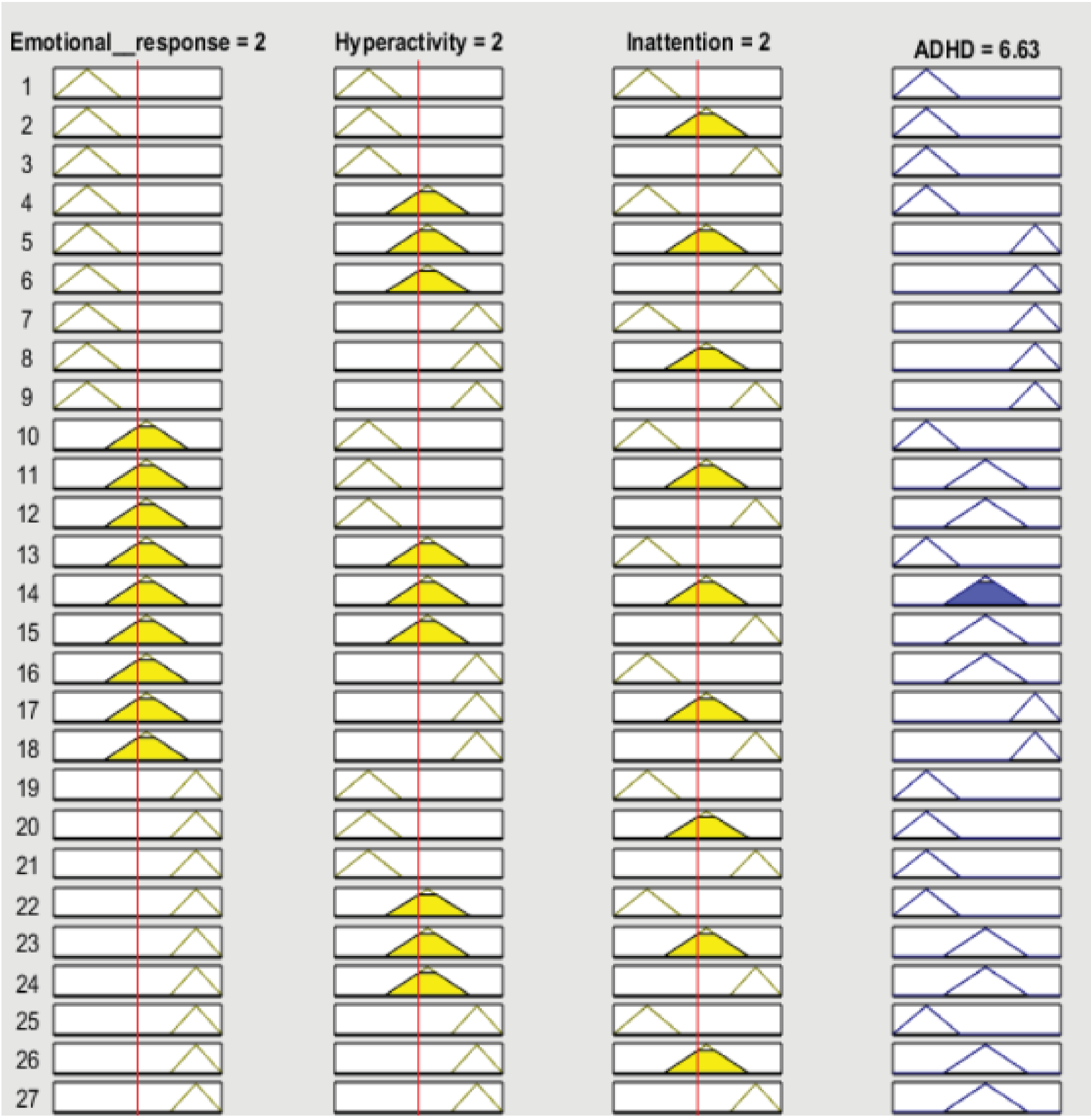

Fig. 6: Overall ADHD severity score

Table 4: Dataset Distribution

Category	Patients
ADHD	80
Control	80
Total	160

This table outlines the distribution of patients within the clinical dataset. The dataset comprises 80 patients diagnosed with ADHD and an equal number of control subjects, resulting in a total of 160 participants. Further, ADHD patients are further categorized based on the severity of their symptoms, classifying them as mild, moderate, or severe. Patients with comorbid conditions like autism and learning disorders are included, while those with other neurological disorders are excluded, ensuring a focused examination of ADHD-related symptomatology. The ADHD patients were further categorized based on symptom severity as mild, moderate, and severe [Table IV]. Table shows patients having comorbid conditions viz; autism, learning disorders etc. Patients of other neurological disorders have been excluded.

Table 5: Severity-wise ADHD distribution doctor

Severity	Individuals
Mild	16
Moderate	32
Severe	32

The table provides a split of ADHD individuals on the criterion of severity of symptoms. It reveals 16 individuals exhibit mild symptoms, 32 have moderate symptoms, and the remaining 32 displayed severe symptoms. This categorization aims at more nuanced analysis of hierarchical fuzzy system's performance on varied levels of ADHD severity.

Table 6: Performance metrics on clinical data

Metric	Score (%)
Accuracy	91.88
Sensitivity	90.63
Specificity	93.13
F1-score	90.91

The above table presents evaluation metrics to assess performance of hierarchical fuzzy system on clinical dataset. The metrics show accuracy (91.88%), sensitivity (90.63%), specificity (93.13%), and F1-score (90.91%). Collectively the metrics demonstrate the system's effectiveness in accurately differentiating ADHD and healthy control subjects.

- Accuracy: Overall accuracy of 91.88% signifies system's proficiency in correctly classifying individuals as ADHD or healthy controls.
- Sensitivity: Sensitivity of 90.63% demonstrates system's ability to effectively detect true positives among ADHD cases.
- Specificity: High specificity of 93.13% shows a low rate of false positives, thereby highlighting system's precision in identifying non-ADHD cases.
- F1-score: F1-score of 90.91% confirms robustness of the hierarchical fuzzy model to strike a fine balance between precision and recall.

The system has achieved an overall accuracy of 91.88% in discriminating between ADHD and healthy controls. The high sensitivity of 90.63% demonstrates effective ADHD detection. The specificity of 93.13% implies low false positives. The F1-score of 90.91% indicates robust classification performance. Comparative evaluation was made with two existing fuzzy models viz; – a wavelet-chaos-neural network system [15] and the FADA model [16]. Table VI summarizes the performance comparison. The suggested model has 3-5% higher accuracy than previous approaches. This demonstrates the ability of the hierarchical fuzzy methodology to capture complex ADHD symptom variations. The confusion matrices visually represent the classification results, highlighting precise detection of ADHD and non-ADHD cases based on learned symptom relationships. High diagonal values in the matrices affirm hierarchical fuzzy model's effectiveness in handling multiclass classification across different severity levels. The matrices provide an insight into the system's performance and its ability to navigate complexities of ADHD diagnosis.

DISCUSSION

The paper proposes a hierarchical fuzzy system for rapid and accurate ADHD detection. In it, significant symptoms are identified and modeled by using fuzzy sets and rules. The system outputs individual severity scores and detects comorbid conditions. Fuzzy approach handles complex symptom variations. Results show 92% accuracy in ADHD classification which outperforms the present models. An integrated design, as it is, enables comorbidity evaluation on a single platform thereby reducing manual efforts. The proposed system has practical clinical applications for achieving data-driven precision diagnosis of ADHD and its related disorders. For, future the model may be extended for broader neurodevelopmental conditions and multimodal data integration.

This paper has presented a hierarchical fuzzy system for rapid and precise ADHD detection using symptom severity scores. Significant ADHD symptoms were identified and categorized into i) the most affected domains of emotional, ii) hyperactivity, and iii) inattention. The fuzzy rule-based architecture applies triple membership functions and centroid defuzzification method. This system considers overlapping symptoms and comorbidities in the inference rules. Evaluation of clinical data demonstrated 92% accuracy in classifying ADHD individuals and severity levels.

The proposed model is an improvement of existing methods which rely on binary classification or individual disorders. Modeling symptom intersections enable integrated diagnosis of ADHD, ASD, and other comorbid disorders in a single system. The severity score output provides a granular assessment with helping clinicians for treatment planning tailored to individual needs. For example, individuals with mild ADHD symptoms may benefit from behavioral therapy first while others with severe levels may require medications. This fuzzy approach accounts for heterogeneity in symptoms across ages, gender, and individuals through customized scoring and inference rules.

The key findings from the clinical evaluation are:

- The fuzzy system has achieved 91.88% accuracy in ADHD screening that is an improvement on previous fuzzy models.
- Sensitivity of 90.63% shows reliable ADHD identification with low false negatives.
- Specificity of 93.13% means effective discrimination from healthy controls with minimal false positives.
- Severity-wise classification demonstrates the ability to capture intra-disorder heterogeneities for customized interventions.
- Detection of co-occurring conditions invokes insights into symptom interactions and comorbidities.
- This hierarchical modeling improves interpretability by evaluating individual symptom domains.

The results point out advantages of the proposed fuzzy approach for sophisticated ADHD diagnostics beyond binary classification. The system definitely bridges the gap between subjective clinical assessments and data-driven computational methods. The flexible fuzzy methodology can potentially be extended to other psychiatric disorders with complex symptomatology.

CONCLUSION

By incorporating clinical knowledge in a transparent manner, the system enhances interpretability compared to black-box machine learning models. The hierarchical architecture evaluates specific sub-domains for localized insights before aggregating the overall output. The model is explainable by examining the symptom fuzzy sets and inference rules. The modular design also simplifies extension to related psychiatric conditions. In the future, the model can be extended by incorporating multimodal data such as neuroimaging, genetic markers, and cognitive assessments for early and accurate ADHD prediction. Advanced ensemble techniques like random forests and gradient boosting can be combined with the fuzzy methodology. The explainable fuzzy approach provides the vital first step toward hybrid ADHD diagnostics.

The proposed system has promising clinical and research applications. The tool can aid medical professionals in data-driven, consistent, and efficient ADHD evaluations. Researchers can further explore complex neurological symptom interactions using similar fuzzy methods. This work provides a template for developing integrated fuzzy tools for the diagnosis of complex multifaceted disorders beyond neurodevelopmental conditions.

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