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Adaptive Neuro Fuzzy Inference System for Diagnosis of Stimulant Use Disorders

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Abstract— The main challenge within the health sector presently is the need for a quick, lower cost and robust disease diagnosis techniques. Adaptive-neuro-fuzzy inference system (ANFIS) models are recognized as efficient models among neuro-fuzzy techniques and additionally amongst different machine learning systems for its learning capability and unambiguous information representation. This study designed an ANFIS model for the detection of stimulant use disorders using hybrid learning techniques to improve the diagnosis based on the conventional model. The system represents stimulant use disorders with 15 symptoms and one output. The study used first-order Sugeno fuzzy system to provide the rule base of the system. The Gaussian membership function was utilized for input and linear membership function was considered for output parameters. The hybrid learning method was employed, comprising of least squares method, and the gradient descent method. The model was trained and validated using clinical data from Specialist Hospital, Yola Nigeria. The performance of model was evaluated in terms of the prediction errors. The results revealed that the system gave an accuracy of 95.6% in detecting severity of stimulant use disorders, indicating that the technique can be very useful in psychological problem detection with minimal errors.

Keywords— Artificial Neural Network, ANFIS, Fuzzy Logic, Medical diagnosis.

1. INTRODUCTION

The need for an efficient medical service has been a great challenge in the medical sector due to the increase in complexity of system, uncertainties, and vagueness in the knowledge and information. Recently, ANFIS seems to be more efficient in terms of high accuracy in diagnosis (Najib *et al*., 2017). ANFIS is one amongst the fashionable categories of integrated computing and machine learning methods, supported mathematical logic and neural network techniques. ANFIS is an applied soft computing model that has wide unfolds application in several sectors due to its ability to provide self-learning intelligent systems, the potential to handle uncertainties, and typical performance. It has been employed in the medical sector to a definite extent, with specific relevancy to the diagnosis process. However, for some areas like diagnosis of stimulant use disorder, a particular field of the medical sector, ANFIS has been lacking within this domain.

Globally, the problem of psychological disorders and early mortality is greatly attributed to stimulant use (Ronsley et al. 2020). UNODC (2019) had estimated that in 2016, 275 million people worldwide, roughly

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5.6% of the global population aged 15 – 64 years, used drugs at least once and 73 million used stimulants. Researches by Ronsley *et al.* (2020); Sara (2014); Gowin, et al. (2019); Serota, et al. (2020); Mathew, et al. (2015); Tran and Kavuluru (2017); Yasin *et al.* (2020) had clearly indicated that stimulant use contributes to a substantial global burden of disease and disorders, and that existing approaches manage these disorders are limited in many ways.

Health disorder if identified early would assist in taking easy preventive measures and aid curing process (Bali, Nathan & Nzadon, 2020). Medical diagnosis of disorders had been considered as a complex task (Ahmad et al. 2017). Introducing ANFIS to the diagnosis of stimulant use disorder may perhaps represent a vital step towards addressing the disorder with efficiency. ANFIS is a machine learning techniques that performs a vital role in prediction of diseases in medical sector. It use fuzzy inference system to combine the unambiguous knowledge representation of fuzzy logic with the learning power of neural networks (Warhade & Hore, 2015).

In this research, ANFIS model have been developed to assist stimulant use patients in assessing the severity level of their disorders. The motivation behind using ANFIS technique is due to its capability to permit fuzzy rules to be extracted from numerical data or professional knowledge and adaptively build a rule base. Moreover, ANFIS has both reasoning and learning abilities. The research consists of four sections: Section I, presents a brief background to the study. Section II, reviewed the previous researches related to the research. Section III, covers the ANFIS design, data preparation, experimental results and discussions of the results, while section IV, the last section concludes the research.

II. LITERATURE REVIEW

A. Fuzzy Logic Techniques

The basic soft computing methods commonly used in the medical sectors are the fuzzy logic and artificial neural network due to their acceptable accuracy within the simulation process. It had been described as an effort to model "human thinking, experience, and perception" in the decision-making method supported imprecise information (Sremac, 2019). Fuzzy logic is viewed as a form of many-valued logic that deals with reasoning that is approximate rather than fixed and exact (Asogbon *et al.*, 2016). However, it lacks systematic procedure for the design of its controller, making it hard to implement an accurate and representative model. Fuzzy logic lacks mechanism to deal with assumptions and fuzzy results (Bali & Garba, 2021).

B. Artificial Neural Network

Kumar & Sharma (2014) regarded neural network as a complex structure of a collection of interrelated neurons that provides substitutes for a complex real life situation. ANNs are applied in the medical diagnosis at present. Biological neuron makes basic decisions by 'firing or not firing,' whereas higher-level decisions require a large number of decisions to be made by the collective input and output of many neurons. Similarly, the number of artificial neurons in a neural network depends strongly on the 'complexity of the system' (Ibrahim *et al*., 2018). Research by (Yasin *et al.* 2020; Bali & Garba, 2021) revealed that, neural networks based methods have ability to learn from the environment, self-organize their structure, and good prediction performance. However, it lacks sufficient model explanation ability.

C. Neuro-Fuzzy-Inference-Systems

Kour *et al*., (2019) described neuro-fuzzy systems as a 'popular soft computing technique' in medical diagnosis used for various disease diagnoses in recent years. Neuro-fuzzy based system is the fusion of neural network and fuzzy logic approaches, to combine the merits of the two approaches to build more intelligent systems. Neural networks and fuzzy logic are the common concepts of artificial intelligent techniques with a human-like reasoning style, to give an improved prediction. One of the most common types of neuro-fuzzy systems is the ANFIS (Dawy & Songya, 2018). The advantage of using ANFIS is its capability to permit fuzzy rules to be extract from numerical data or expert's knowledge and use it to construct a rule base, and also, has reasoning and learning abilities (Bali & Garba, 2021).

ANFIS is efficient prediction model among neuro-fuzzy systems and other machine learning techniques (Najib *et al*., 2017). Dawy and Songya, (2018) clarified that ANFIS model 'embodies' the input data using a membership function with diverse parameters, then concludes results through the output membership function. ANFIS uses either a backpropagation or hybrid algorithm to adjust the membership functions of a Sugeno-type fuzzy inference system (Billah and Islam, 2016). To train a hybrid learning system, ANFIS tune the parameters of the consequent and antecedent parts of the fuzzy rule-based system and merges 'gradient decent method' with the least mean square method to achieve the system purposes. The least square, and gradient descent scale trains the membership function of the fuzzy technique to replicate the training dataset (Omololu & Adeolu, 2018). The root mean square error (RMSE) is a performance measure, to measure between the anticipated output and the actual current output (Devi, Kumar & Kushwaha, 2016). Researches by (Kour et al. 2019; Das et al. 2020) used root mean square error (RMSE), the square root of Mean Squared error to assess how well dataset fit their developed ANFIS models. RMSE presents the typical distance between the target value made by the ANFIS model and the actual value.

III. MEHODOLOGY

To develop and test the proposed model, MATLAB (2021a) was used as the development tool. Since ANFIS is a data driven technique, for training and evaluation of performance, dataset for the research was obtained from Specialist Hospital Yola, the most accessed hospital in Adamawa State, Nigeria. Procedures of this research were approved by the Medical Ethical Committee of the State Ministry of Health, Yola Adamawa State, Nigeria. The data was pre-processed and 226 patients' records with stimulant related disorders were selected as sample size for conducting the research.

The model utilizes five attributes used as input parameters that include behavioural effect, cognitive effect, mood effect, physical effect, and psychological effect. While bipolar depression, manic depression, amnesia,

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and psychosis were used as diagnostic attributes output, represented using linguistic variables mild or moderate or severe. All stimulant-induced cases selected satisfied the clinical criteria for stimulant disorders as defined in DSM-5, which made the data ideal for performing outcome analysis for the study. The data on each patient in addition to age, gender, and address, has various clinical parameters as shown in table I.

Table I: Clinical Parameters in Dataset

Categories of effects	Patient's attribute	Code
1 Behavioral effect (BE)	Superiority or euphoria	SE
	Talkativeness	TA
	Violence	VI
2 Cognitive effect (CE)	Indecisiveness	IN
	Suspicion, worthlessness	SW
	Disorganized speech or thinking	DS
3 Mood effect (ME)	Panic or anxiety	PA
	Confidence	CO
	Insomnia	IA
4 Physical effect (PE)	High temperature or blood pressure	HT
	Kidney, lung, or liver damage	KL
	Heart rate or stroke	HS
5 Psychological effect (SE)	Hallucination or delusion	HD
	Brain or memory problem	BM
	Depression or psychosis	DP

IV. ANFIS MODEL DEVELOPMENT

The dataset used as the input to the ANFIS function after it had been collected and preprocessed was set in a matrix form, where the last column in the matrix is the output. The development of famous neuro-fuzzy model known as ANFIS was achieved with MATLAB Version R2021a (9.10.0.16028886) which served as the core programming tool. Microsoft Excel 2010 Version was used to preprocess the required dataset into a format that could be exported to MATLAB workspace. In this research, hybrid learning algorithm was used for the ANFIS model to identify parameters. The Takagi-Sugeno model was used for its ability to provide more precise solution, which is very important in medical research. Gaussian membership function was used for inputs and the output description. The mf1 command from MATLAB was used to create the membership functions. The two passes for hybrid algorithm, forward pass and backward pass were utilized. After presentation of premise parameters, in the forward pass a node outputs move ahead until layer 4 and the consequent parameters are computed with least square estimate then error measure is computed for each node. In the backward process, the error signs distribute backward to optimize premise parameters using gradient descent. Lastly, to determine how well the developed model works, the

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performance of the model was computed. Three performance measures Mean Square Error (MSE), Mean Absolute Error (MAE), and (RMSE) were used to evaluate the accuracy of the model.

The formula for error criteria are expressed by Equations (1) to (3) as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | x_i - x | \tag{1}$$

Where

n = the number of errors,

Σ = summation symbol,

$|x_i - x|$ = the absolute errors.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (x_i - x)^2 \tag{2}$$

Where

n = the number of errors,

Σ = summation symbol,

$(x_i - x)^2$ = the square of absolute errors.

The Root Mean Squared Error function was used to monitor the training errors, defined as;

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=n}^{n} (yi - \hat{y})^2} \tag{3}$$

Table II: ANFIS Parameters.

Parameter	Value
Type	Sugeno
Input Membership Function	Gaussmf
Output Membership Function	Linear
Learning Rule	Hybrid combines the least-squares estimator and the gradient descent
Epochs	3
De-fuzzification Rule	Wtaver
AND Rule	Prod
Input	[1x5] struct
Output	[1x1] struct
No. of fuzzy rules	243
No. of nodes	524

III. RESULTS AND DISCUSSIONS

As shown in figure 1, this model is composed of 5 inputs and 1 output.

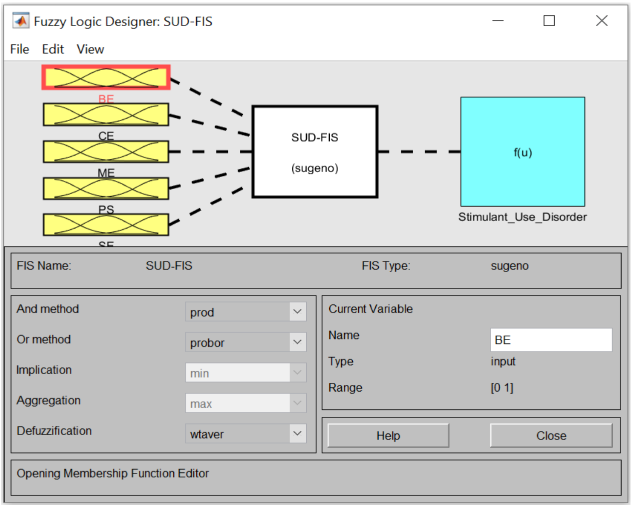

Figure 1: Shows the SUD Fuzzy Inference Engine

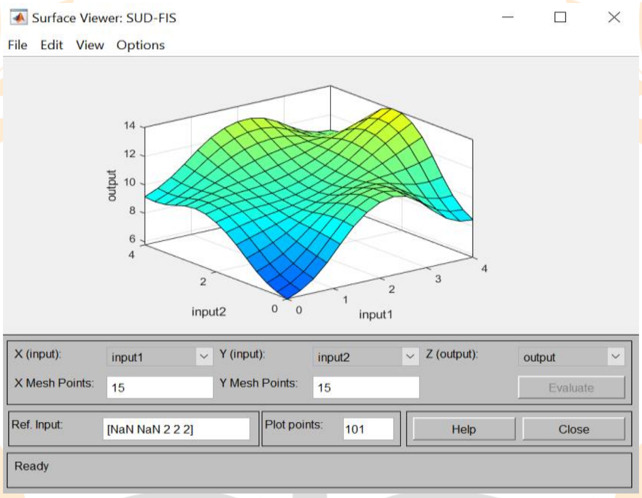

Figure 2: Surface view of the relationships between input and output variables.

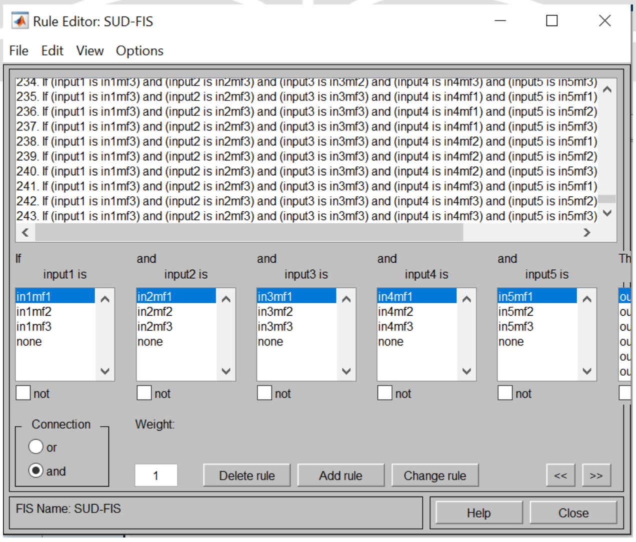

Figure 3: Shows the SUD FIS rules template

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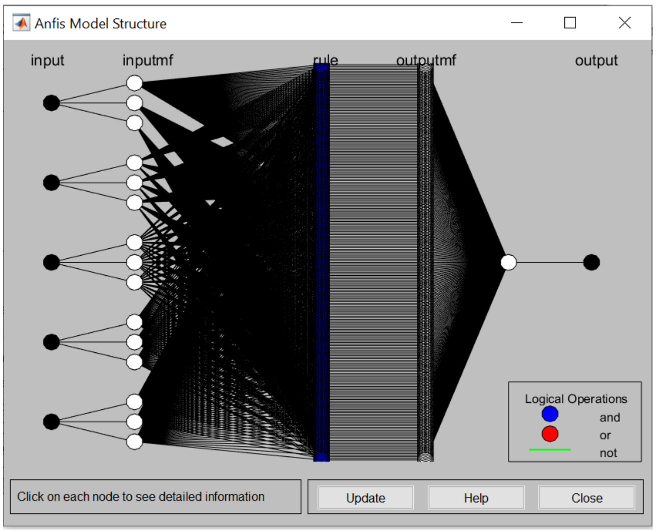

Figure 4: The ANFIS Model Structure

Table III: The performance of the ANFIS model for training, checking, testing and full dataset

Dataset	**MSE**	**RMSE**
Training	0.00000000001	0.00000338946
Checking	0.7531913939	0.867966
Testing	0.23833924	0.4882
Full dataset	0.23833924	0.4882

In this research an adaptive neuro-fuzzy inference system (ANFIS) model for diagnosis of the stimulant use disorders was developed. The ANFIS was trained using the hybrid learning algorithm and was implemented in MATLAB Version R2021a software package with fuzzy logic toolbox. In the developed ANFIS model, the dataset was partitioned into training, testing and checking or validation set. The MinMax normalization technique was used to normalize the medical data and transform into a specific range (0.0 to 3.0). Gaussian membership function (gaussmf) was used for input and linear membership function was utilized for output parameters. Figure 1 shows the developed FIS of the model consisting of five input variables and the one output variable that indicates the outcome of the diagnosis represented by f(u). The ANFIS model includes 243 rules as represented in Figure 3.

Figure 2 illustrates the rule viewer section of the FIS and it displays an interpretation of the entire fuzzy inference process. It represents input text field that allows a user to enter specific input values for all the four diagnosis variables of a particular patient, after the entry, the user then hits the Enter key on the keyboard and the diagnosis outcome for the patient is displayed. 110 training dataset were used to train the model in 3 training epochs with tolerance error of 0.01, and RMSE values of 0.00000338 (error goal). The model was tested with 61 datasets and the rate of testing error was 0.23 and RMSE of 0.4882. Performance of the ANFIS model was evaluated for training checking, and testing based on mean squared error (MSE) root mean square error (RMSE). The result of validation training and testing data was shown in Table III. The lower value of RMSE indicates that the ANFIS model has higher accuracy of 95.6%. The

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results strongly agree with other result reported from literature. It further suggests that ANFIS can aid in the diagnosis of disorder due to stimulant use.

IV. CONCLUSION

The need to get an accurate diagnosis tool has been a matter of concern in medical diagnosis disease. This research introduces the application of ANFIS model with hybrid learning algorithm to detect disorder due to stimulant use. The results obtained showed that the developed ANFIS was a reliable technique with high accuracy. The lower value of RMSE indicates that the ANFIS model has higher accuracy of 95.6%. The outcome strongly agrees with similar results testified in the literature. It further suggests that the developed ANFIS model has the potential to help in the diagnosis of disorder due to stimulant use.

Further Research

The outcome of this research provides information about the need to extend the use of ANFIS in this domain for better diagnosis. In the future research, authors will explore more optimization techniques to improve this approach to increase the accuracy of the model and to apply it to larger datasets on each disorder.

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