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Prediction of Stimulant Related Disorders Using Machine Learning Technique

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ABSTRACT

The advancement in computer technology is of great assistance to medical professionals in diagnosing life-threatening disorders and administering treatment for patients. Quite a lot of researches in literature have applied Machine Learning techniques, to improve the diagnostic process to get the right diagnosis on time, and for accuracy. Adaptive Neuro fuzzy Inference System (ANFIS) is one of the common machine learning and soft computing technique that plays vital role in medical diagnosis of disorders. This study aims to propose an accurate method for diagnosis of disorders related to stimulant use by utilizing the power of ANFIS machine learning techniques. The ANFIS tool in Matlab software environment was used to develop the model. In this research, five parameters were used as input and one parameter as output have been considered for the ANFIS method. The outcomes of this research demonstrated that the ANFIS model using surgeon fuzzy model and Gaussian membership function performed well in analyses on the dataset from Psychiatrics Department Specialist Hospital, Yola. This indicates that the model has potential to be used as intelligent approach for diagnosis of stimulant related disorders.

Keywords: Artificial Neural Network, ANFIS, Fuzzy Logic, Machine Learning, Medical Diagnosis

1. INTRODUCTION

Stimulant related disorders present life-threatening health related problems and also has social and economic effect on wellbeing of affected people. Although certain stimulants have been deemed effective for certain reasons, neuropsychological medical conditions were associated with a number of stimulants. Stimulant disorder is a new diagnostic condition contained in the fifth edition of the Diagnostic and Statistical Manual (DSM-5) mental disorder (American Psychiatric Association [APA], 2013). It covers a variety of risks associated with the use of a broad range of stimulant substances, including amphetamine, caffeine, cocaine, ecstasy, methamphetamine and nicotine (Henry, 2019). Stimulants users have high rates of co-occurring mental illness and innumerable complications (Sara, 2014). Most users do not make effort to identify these disorders at early stage. The users used to recognize the disorder after the usage has caused disorders. The toxic levels of stimulant use cover diverse diseases such as neurological disorders like brain seizures, heart attack, stroke, and psychological disorders such as manic, bipolar depression, anxiety and psychosis (Tran and Kavuluru, 2017; Pure, 2019). Health disorders if identified early would assist in taking easy preventive actions and hasten the curative process (Bali, Nathan & Nzadon, 2020).

In this research, the diagnosis of stimulant related disorder using an ANFIS technique is proposed. ANFIS has been proved to be an indispensable machine learning technique for medical diagnosis of disorders for accurate prediction. ANFIS is a machine learning technique used to explore the learning algorithms of artificial neural network from dataset and interpretation capability of fuzzy logic. ANFIS has both reasoning and learning abilities and it permit fuzzy rules to be extracted from numerical data and adaptively construct a rule base on the rules (Bali & Garba, 2021).

This research is organized into Section 1 to 5. Section 1 presents the background of the research. Section 2 presents brief review on the predictive methods related to the identified medical disorders. Section 3 outlines the ANFIS methodology. Section 4 presents outcomes of the research, and section 5 concludes the work.

2. RELATED WORKS

Prior researches revealed that the use of stimulants such as amphetamine and methamphetamine is common among patients with psychiatric disorders generally (Bramness et al. 2012; Zarrabi, Khalkhali, Hamidi, Ahmadi, & Zavarmousavi, 2016; Henning, Kurtom & Espiridion, 2019). In the medical sector, diagnosis of disorder has been regarded as a complex task (Ahmad, Ahmad, Lu, Khoso, & Huang 2018). The need to detection of disorders or diseases early is very necessary for taking steps towards accurate treatment and securing patient's life (Billah & Islam 2016; Bandyopadhyay & Dutta, 2020). Several machine learning techniques with respect to prediction of medical diagnosis of disorders in the literature have done. They include a hybrid softcomputing neuro-fuzzy model for the diagnosis of depression cases (Ekong & Onibere, 2015); Prediction of mental conditions based on history of present illness in psychiatric notes using deep neural networks (Tran & Kavuluru, 2017); Analysis of medical disease using Neuro-Fuzzy technique (Das, Naik, & Behera, 2020); Selection of learning algorithms for simultaneous identification of depression and comorbid disorders (Ojeme & Mbogho, 2016). These approach and many more showed great promise in accurate identification disorders or diseases among patients. Machine learning approach of ANFIS can equally play a vital role in this aspect.

3. OVERVIEW OF ANFIS TECHNIQUE

ANFIS had been described as a machine learning technique designed to improve a fuzzy logic automatically by utilizing the learning processes from neural network. Implementing ANFIS involves combining the human reasoning ability of fuzzy logic and learning capability of artificial neural network for tuning the fuzzy logic parameters in different architectures, to eliminate the limitation of each model. ANFIS is a well-known data learning method that uses fuzzy logic to convert given inputs into anticipated output through highly connected neural network processing elements, which are weighted to map the numerical inputs into an output. In ANFIS, the number of hidden nodes in neural networks is as well as in a fuzzy system which consists of layer 0 (input), layer-1 (fuzzification), layer 2 and layer 3 (fuzzy inference system), layer 4 (defuzzification) and layer 5 (aggregation). The sample ANFIS architecture is shown in Fig.2 with two inputs and one output.

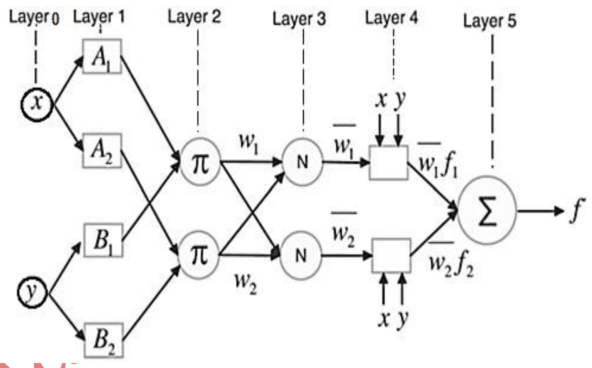

Figure 3: The six layers' general architecture of an ANFIS.

In the ANFIS architecture, a circle indicates a fixed node, whereas a square indicates an adaptive node.

3.1 Mathematical description of the ANFIS architecture

The Sugeno inference model is utilized to generate a nonlinear mapping from input space onto output employing fuzzy IF–THEN rules. An illustration of the fuzzy inference system with two inputs 'x and y' and one output f, based on the first-order Surgeon fuzzy model comprises of two rules explains the structure of ANFIS as:

Rule1: if x is A_1 and y is B_1 then $f_1 = p_1 x + q_1 y + r_1$ (1)

Rule1: if x is A_2 and y is B_2 then $f_2 = p_2 x + q_2 y + r_2$ (2)

Where "x and y are input variables,

Ai and Bi are the fuzzy sets in the antecedents determined for x and y,

fi are the outputs within the fuzzy region specified by the fuzzy rule, and
pi, qi, and ri are the design (consequent) parameters of defuzzification layer that are determined during the training process.

Layer 0: This Layer accepts the inputs represented by the variables x and y.

Layer 1*(*fuzzification): This is the first hidden layer that performs fuzzification operation on linguistic variables. Each node in this layer is a square node that generates a membership function for each input variables. Nodes in this layer represent linguistic variables A1, A2, B1, and B2 of the input variables quantified with fuzzy sets. Let x_1 and x_2 be defined crisp input to the node i, then in the first layer, the output of each node is represented by degree of membership as:

$O_{1,i} = \mu Ai(x)$ *for i = 1, 2,* $O_{1,i} = \mu Bi(y)$ *for i = 1, 2*
(3)

where x and y are the inputs to node i,

Ai and *Bi* are the linguistic variables associated with this node function,

μAi and μBi represents the fuzzy membership function for fuzzy sets Ai and Bi.

O*i* represented output as fuzzy membership grades at the i^{th} node of each layer.

In this research, Gaussian membership function was used to calculate the degree of membership for both the input and output variables. It always has a maximum value of 1 given by:

$$O1,i = \mu Ai(x) = \exp\left[-\left(\frac{x-ci}{ai}\right)^2\right],$$

Such that

$$O1,i = \mu Ai(x) = \frac{1}{1+\left|\frac{x-ci}{ai}\right|^{2bi}},$$

$$O1,i = \mu Bi(y) = \frac{1}{1+\left|\frac{y-ci}{ai}\right|^{2bi}}$$

(4)

where x, y are inputs to node i;

Ai, Bi - Linguistic labels to this node;

ai, bi, and ci are premise parameters that will change the shapes of membership functions.

Layer2 *(Product)*: The nodes are represented by circles and labelled as π, an indication for performing simple multiplier. Each node in this layer calculates the firing strength, w, for a rule, by multiplying the incoming signals from layer1 as input and the weighted output is provided: Given A_1B_1 or A_2B_2 as:

$O_{1,i} = Wi = \mu Ai(x) * \mu Ai(y)$ *for I =1, 2*
(5)

where i= 1, 2 are rules defined generally by either AND or OR operation,
W_i = is the output for each node
Let R represent the rule choice of the layer 2 nodes;
R ={min[AND]} or R ={max[OR]}or R={neutral [NOT]}
Let Wi represent the weights from the rule nodes

The output of each node is the product of all the incoming signals to it and is given by,

$$f(x,y) = \frac{w_1(x,y)f_1(x,y)+w_2(x,y)f_2(x,y)}{w_1(x,y)+w_2(x,y)}$$

(6)

Layer3 *(*Normalization): This is the normalization layer that consists of circled nodes labelled with "*N*". Normalization helps to speed up the training time of the data in ANFIS. There are several statistical normalization techniques. It determines the normalized firing strengths using.

$$O3,i = \bar{w} = \frac{wi}{w_1+w_2},$$

$$= \frac{\mu_{Ai}(x) * \mu_{Bi}(y)}{\mu_{Ai}(x)+\mu_{Bi}(y)}, \text{ for I – 1, 2}$$

(7)

where O is the called output of the normalized firing strengths.

In this research, all the input data were normalized column wise using min–max normalization strategy in order to reduce the range of the feature data to a scale between 0 and 1 using the following formula:

$$y = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (8)$$

Where x = the real value in the column
min(x) = the lowest value in column
max = the highest value in the column
y = the normalized value

Layer 4 (Defuzzification): This layer is composed of adaptive nodes. It calculates the rules outputs for rule consequent layer and each node creates the output, according to the function:

$$O4, i = w_i f_i = w_i (a_i.x_1 + b_i.x_2 + c_i) \quad i = 1, 2$$
(9)

where *Wi* is the normalized firing strength from layer 3.

ai, bi and ci are the consequent parameters of the ith adaptive node, and the output membership functions are first-order polynomials. These are linear functions of the input variables.

Layer 5 (Overall output): The defuzzification layer is a single node that computes the overall output of all incoming signals, as the weighted sum of the outputs from layer 4, defined as:

$$O5, i = \sum_i w_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \quad i=1, 2, . . .$$
(10)

$$\text{Here, } overall \quad output = \frac{w_i . f_i + w_2 . f_2 + ...}{w_1 + w_2 + ...}$$
(11)

3.2 Dataset Description

For this research, the dataset was extracted from the medical records of diagnosed patients with stimulant related disorders at Specialist Hospital, Yola the most accessed hospital in Adamawa State, Nigeria. The diagnostic dependent attributes are the linguistic variables (mild, moderate, and severe). While the output attributes of stimulant related disorders from the population are the bipolar, manic depression, manic episode, amnesia, and psychosis. All stimulant-induced bipolar and stimulant-induced psychosis cases selected satisfied the clinical criteria for stimulant disorders as defined in DSM-5, which made the data ideal for performing result of this work. Further validation of the data was done by a group of seven mental health professionals. The dataset was created by selecting 263 patients' records with disorder as sample size for conducting the study. The five attributes used as input parameters are behavioural effect (BE), cognitive effect (CE), mood effect (ME), physical effect (PE), and psychological effect (SE) while one output, was classified as severity level by mild or moderate or severe.

3.3 ANFIS Model Development

The dataset used as the input to the ANFIS function was set in a matrix form, where the last column in the matrix is the output. After the data had been collected, preprocessed and partitioned into the training, checking, and testing set, the model was developed with Matrix MATLAB Version R2021a (9.10.0.16028886) and Microsoft Excel 2010 Version which was used to preprocess the required dataset into a format that could be exported to MATLAB workspace. The model used Sugeno Fuzzy Inference System (FIS) to relate membership and was tuned using hybrid learning algorithm; least square estimate (LSE) with gradient descent.

4. Results and Discussion

The purpose of this research was to develop an ANFIS model for the diagnosis of disorder in stimulant induced patients. The ANFIS tool in Matlab software was used to develop the model. In this research, five attributes used as input parameters are behavioural effect (BE), cognitive effect (CE), mood effect (ME), physical effect (PE), and psychological effect (SE) while one output, was classified as severity level by mild or moderate or severe. Gaussian membership function (gaussmf) was considered for input and linear membership function was considered for output parameters. The ANFIS model includes 243 rules with the summary of rules represented in Figure 5. The training data was used for constructing the model. The checking data prevents over-fitting and verifies the ANFIS model. The testing dataset was used to verify the accuracy and the effectiveness of the trained ANFIS model for diagnosis of the stimulant use disorder dataset. The structure of the developed ANFIS model shows how each layer in

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the network is connected is presented in figure 1 and it is made up of six layers. The first and sixth layers represent the input and output of entire model. The first layer has four inputs values and the sixth layer has only one output value. The second, third, fourth, and fifth layers signifies the hidden layers of the ANFIS model where several computations are performed on the input values in order to provide a valid output for diagnosis. Figure 5 illustrates the rule viewer section that provides interpretation of the entire fuzzy inference process. It represents input text field that allows a user to enter specific input values for all the diagnostic variables of a particular patient, after the entry, the user then press the Enter key on the and the diagnosis outcome for the patient is displayed. The result of the training and testing sessions of the FIS by the ANFIS module are presented in figure 3, and 4 respectively, with the training dataset appearing in circles, and the testing data looks like pluses superimposed on the training data. An optimal training with average Error of 0.0000039423 ant average testing error of **0.0000**53691 was achieved using 3 the number of epochs.

Table 1: 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

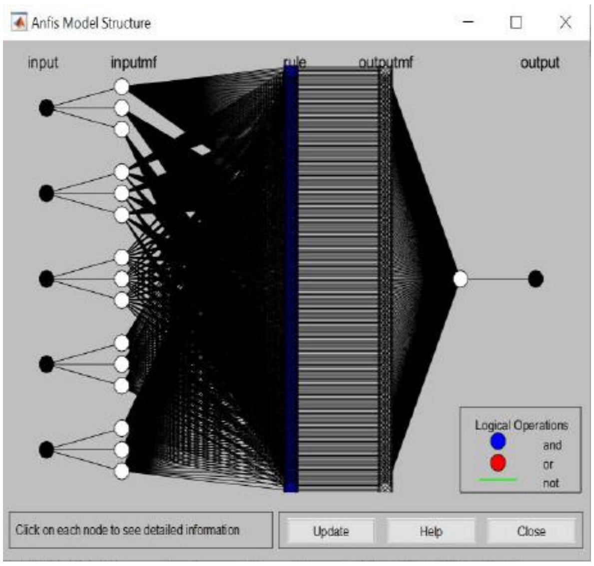

Figure 1: The ANFIS Model Structure

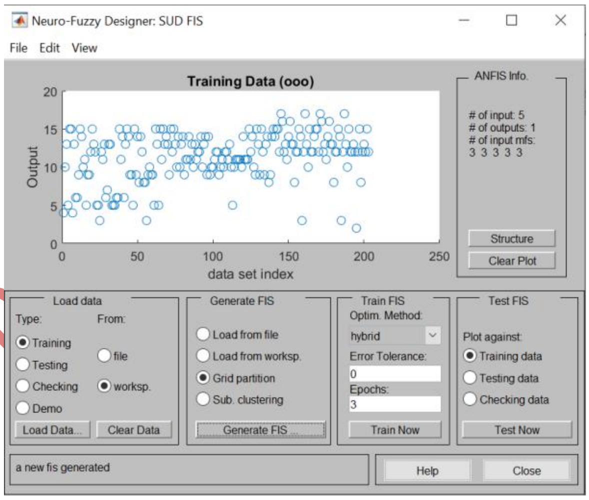

Figure 2: Shows the training dataset before training

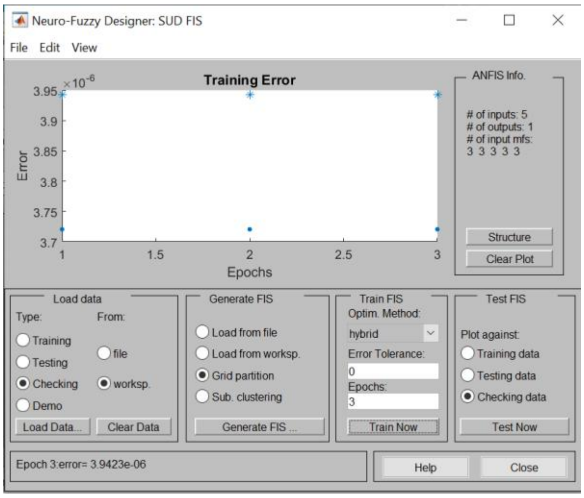

Figure 3: Shows the Training epoch and error

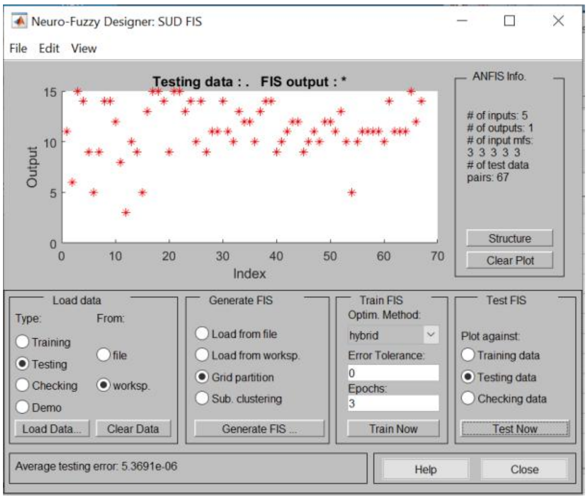

Figure 4: Plot for FIS output, average error value for testing with 3 epochs.

Figure 5: The Chart showing the Rules of ANFIS model illustrating the relationships between input and output variables.

5. CONCLUSION

This work focused on developing an an ANFIS model for predicting stimulants use disorder in stimulant induced patients. The research presents an application of ANFIS model using Gaussian membership functions and hybrid learning techniques in prediction of stimulants use disorders. The model integrate the learning capability of artificial neural network and reasoning ability of fuzzy logic technique. The outcomes of this research demonstrated that the ANFIS model using surgeon fuzzy model and Gaussian membership function performed well in analyses on the dataset from Psychiatrics Department Specialist Hospital, Yola. This indicates that the model has potential to be used as intelligent approach for diagnosis of stimulant related disorders. The research introduced an approach that would assist the physician in medical diagnosis of stimulant use disorders.

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