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ORIGINAL ARTICLE

A neuro fuzzy approach for the diagnosis of postpartum depression disorder

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Abstract
Postpartum depression is a growing public health problem amongst nursing mothers, which is not given much attention in primary health care settings. It is a type of depression experienced after childbirth that affects an estimated 13–19% of nursing mothers. Postpartum depression is very difficult to diagnose and by concentrating on somatic illnesses, most medical practitioners frequently fail to recognize it. In this paper an Adaptive Neuro Fuzzy Inference System was utilized to predict postpartum depression. Thirty-six data instances were used in training the model. The system had a training error of 7.0706e−005 at epoch 1 and an average testing error of 3.0185. This technique will facilitate the prompt and accurate diagnosis of postpartum depression.

Keywords Depression · Postpartum · Neuro fuzzy · Diagnosis

1 Introduction

Medicine is a broad field with mental health being one of its major branches. A major problem in mental health involves the diagnosis of illness which is based on clinical symptoms. Depression is a common mental illness worldwide, with more than 300 million people affected [1]. It can negatively affect a person's feeling, thinking, behavior, ability to function. Symptoms of depressions include feeling sad, lack of interest in games or activities previously enjoyed, weight loss, insomnia, fatigue, feeling worthless, suicidal thought and extreme difficulty in thinking or making decisions [2–4]. Depending on the number and severity of symptoms, a depressive episode can be categorized as mild, moderate or severe. Statistics have shown that depression affects persons across the ages of 15 and 74 with the ages between 25 and 40 having a larger percentage [1].

Nursing mothers are not left out of the category of individuals that can also experience depression. A type of depression experienced after childbirth is called postpartum depression (PPD) and it is a serious mental health condition that affects an estimated 13–19% of nursing mothers [5]. Some investigators have reported a PPD prevalence of 10–15% in developed world and about 22% in developing countries. Cases of up to 35% and above have also been reported in the literature [6, 7]. Postpartum depression is characterized as a persistent low mood in new mothers, which is often accompanied by the symptoms of depression [3, 8]. Postpartum depression differs from the postpartum blue which is a briefer period of emotional disturbance that is experienced among some women within the first few days after childbirth and usually disappear within 10 days [9].

The pathogenesis of PPD is still unclear. However, the role of the hormonal fluctuations in the postpartum period may not be ruled out, with emphasis on the rapid decrease in progesterone, estradiol, and estriol [10]. Also the activity of the hypothalamic–pituitary–thyroid axis and thyroid dysfunction is being canvassed [11]. The risk factors of postpartum depression are usually previous incidence of depression or anxiety during pregnancy, stressful recent life events, poor social support, childcare stress, low self-esteem, and difficult infant temperament. Others may include single marital status, poor relationship with partner, and lower socioeconomic status including income. Incidence of PPD had no relationship with maternal age, parity, gender of child, level of education or ethnicity [6, 7, 12]. Maternal PPD interferes with the affection between mother and child, and therefore, impedes the development of the child [13]. Such impediments include negative effects on cognitive development and social–emo-

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tional development of the child [14]. The family may be froth with vices such as child abuse and neglect, marital violence, divorce, etc. [15]. Diagnosis of PPD is based on clinical symptoms and most psychiatrists often fail to recognize it.

The Adaptive Neuro Fuzzy Inference System (ANFIS) has proven to be a very power tool in medical diagnosis [16, 17]. Literatures have shown that ANFIS-based intelligence systems for diagnosing medical illnesses have yielded excellent results for some mental health-related conditions [17, 18]. ANFIS combines both neural network and fuzzy logic. The technique applied by ANFIS is quite simple. The fuzzy logic component maps each parameter in the dataset to linguistic labels for that parameter using a membership function. This is used to keep track of input data to output data while the neural network component performs computational analysis on the dataset.

2 Review of related works

A lot of research has been conducted using machine learning techniques in diagnosing depression, but to our knowledge, no research has been done on postpartum depression using such techniques. Anish et al. [17] proposed a neuro fuzzy system for modeling depression data. In their work, seventy-six (76) samples of depression data were used to train the fuzzy logic controller using a backward propagation neural network. The model had seven inputs and an output and upon completion of the training the neuro fuzzy model for 30 epochs. The system had a mean square error 0.0116042 which is a result, but probability was used to represent the value of each symptom and this is a slight shortcoming of the system.

In a recent study, neural network was used to forecast depression mood based on self-reported histories [21]. In the work, a supervised learning algorithm was used to train the neural network. The neural network was developed based on a long short-term memory recurrent technique. The result from the system was compared with that of support vector machine using the same dataset. The neural network showed an excellent result compared to the SVM. In a study conducted by Arkaprabha and Ishita [22], the authors used an artificial neural network (ANN) to predict depression among geriatric population at a slum in Kolkata, India. One hundred five patients were used in the study. The ANN was trained and tested and was found to have an error rate of 2.86% and classification accuracy of 97.14%. In a similar study, Subhrangsu et al. [23] modeled depression data using feed forward neural network and radial basis function neural network. Forty-five data instances were used to train both networks. They were trained using the backward propagation learning algorithm. The dataset contained ten inputs and an output. The result of the experiment indicated that the feed forward neural network performed better that the radial basis function neural network. Although neural network is outstanding machine learning tool, but its inability to explain data is a disadvantage.

3 Materials and methods

3.1 Data collection

The dataset was collected from Federal Neuro-Psychiatric Hospital at Uselu, Benin City, Edo State, Nigeria. The Postpartum Depression Screening Scale (PDSS) was the psychometric tool used by the physician to obtain the data. The PDSS is a questionnaire that comprises 35 questions which are used to access the level of postpartum depression in women. The scale of measurement in PDSS ranges from 35 to 175 and scores between 35 to 59, 60 to 79 and 80 to 175 indicate no signs of postpartum depression, significant signs of postpartum depression and occurrence postpartum depression, respectively. The dataset was further preprocessed to the format required for this study. The dataset comprises 59 diagnosed cases and approximately 60% (36 cases) of the entire dataset was used in training of the system while the remaining 40% (23 cases) was used in testing the system.

Tables 1 and 2 show 20 cases of the postpartum depression dataset and summary of the diagnostics result from the 59 cases, respectively. Figure 1 shows the degree of the clinical symptoms in respect to each case shown in Table 1. Figure 2 shows the relationship between the diagnostic value and the diagnostic outcome for each case as represented in Table 2.

Matrix Laboratory (MATLAB) version 7.5.0 (R2007b) was used to implement the ANFIS model. Pearson product–moment correlation feature selection techniques were used to eliminate redundant features in the dataset, allowing prominent features that are capable of predicting postpartum depression to be selected as inputs into the ANFIS model. The Pearson product–moment correlation feature selection techniques extracted six symptoms (feeling sad, lack of interest in activities previously enjoyed, insomnia, extreme difficulty in thinking or making decision, fatigue and suicidal thought or worries about harming baby, or partner) for diagnosing PPD and these symptoms were validated by an experienced neuro psychiatrist. Clinical symptoms [(SA, SB, SC, SD and SE; where SA represents symptom 1 (feeling sad), SB represents symptom 2 (lack of interest in activities previously enjoyed), SC represents symptom 3 (insomnia), SD represents symptom 4 (extreme difficulty in thinking or making decision), SE represents symptom 5 (fatigue) and SF represents symptom 6 (suicidal thought or worries about harming baby, or partner)] were the inputs fed into the model.

Table 1 Twenty cases of the postpartum depression dataset

Sample no.	SA	SB	SC	SD	SE	SF
Case 1	9.34	5.54	5.04	4.47	3.23	9.22
Case 2	2.57	3.69	5.50	3.23	7.42	9.76
Case 3	5.59	1.10	2.94	4.63	4.74	8.67
Case 4	6.93	1.80	7.41	5.35	8.87	7.25
Case 5	2.53	7.98	0.97	4.46	7.88	5.01
Case 6	8.15	3.09	2.44	7.81	9.97	2.21
Case 7	7.52	2.54	4.99	3.76	9.69	1.02
Case 8	6.52	9.19	5.51	1.39	7.30	2.40
Case 9	0.40	9.61	9.17	5.03	1.97	1.24
Case 10	3.33	6.10	0.87	8.49	5.96	6.41
Case 11	0.96	1.75	3.91	9.59	3.87	6.00
Case 12	5.14	6.07	2.40	2.02	9.15	3.02
Case 13	1.28	9.70	3.12	3.30	3.45	5.39
Case 14	0.82	9.30	5.09	8.36	2.29	2.53
Case 15	2.68	1.98	4.33	8.79	1.10	3.60
Case 16	3.59	9.16	2.53	3.53	6.35	1.61
Case 17	2.20	7.34	1.59	4.16	8.34	7.93
Case 18	7.19	0.59	0.80	3.22	1.82	1.62
Case 19	4.57	2.95	8.95	0.02	2.15	3.33
Case 20	3.20	5.76	1.33	1.64	3.30	8.28

Table 2 Summary of diagnostic result

Case no.	Diagnostic value	Diagnostic outcome
Case 1	6.13821259	Severe
Case 2	5.36232275	Moderate
Case 3	4.60847768	Moderate
Case 4	6.27000639	Severe
Case 5	4.80405468	Moderate
Case 6	5.61278131	Moderate
Case 7	4.91943597	Moderate
Case 8	5.38322483	Moderate
Case 9	4.56898532	Moderate
Case 10	5.1944231	Moderate
Case 11	4.34699972	Moderate
Case 12	4.63291062	Moderate
Case 13	4.37412646	Moderate
Case 14	4.73209067	Moderate
Case 15	3.74470717	Mild
Case 16	4.46345434	Moderate
Case 17	5.26032255	Moderate
Case 18	2.54070282	Mild
Case 19	3.65968151	Mild
Case 20	3.91716547	Mild

3.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Inference System is a combination of neural network (NN) and fuzzy logic (FL). The strength of the individual component makes ANFIS a powerful tool. Neural network has its strength in its computational capability and fuzzy logic strength lies in its explanative power. In ANFIS, the fuzzy logic component is in the hidden layer of the neural network and the combination of these techniques makes ANFIS a hybrid system. The ANFIS architecture comprises six layers; they are described below.

Layer 1 This is also known as the input layer. This layer contains six (6) neurons which are the clinical symptoms (feeling sad, lack of interest in activities previously enjoyed, insomnia, extreme difficulty in thinking or making decision, fatigue, suicidal thought or worries about harming baby, or partner). The dataset is fed into the ANFIS and each neuron is analogous to particular clinical symptom. This can be represented mathematically as shown in Eq. (1):

$$O_i^1 = x_i, \tag{1}$$

where

$O_i^1 =$ is the ith neuron output from layer 1, $x =$ symptom value for ith symptom.

Layer 2 This is known as the membership function layer. It is the first hidden layer of the ANFIS architecture.

This layer contains the membership function which maps linguistic variables from layer 1 to linguistic labels in fuzzy a set. Various membership functions exist, but in our model we utilized the bell membership function in mapping these symptoms to a fuzzy set because it has the capability to approach a non-fuzzy set and has a nonzero value at all point. The bell membership function can be represented mathematically as shown in Eq. (2):

$$\mu(x) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}}, \tag{2}$$

where

$a =$ mean of symptom values, $b =$ determines the bell curve of the symptoms, $c =$ center of the curve, $x =$ symptoms value, $\mu(x) =$ membership function of x.

Layer 3 This is also known as the rule layer. It is the second hidden layer of the ANFIS architecture. Each neuron in this layer receives input from the preceding (membership function) layer and computes the truth value for each rule. This layer obeys to the Takagi–Sugeno inference rule which is shown in Eq. (3):

$$O_i^3 = \mu(x) \times \mu(y), \tag{3}$$

where

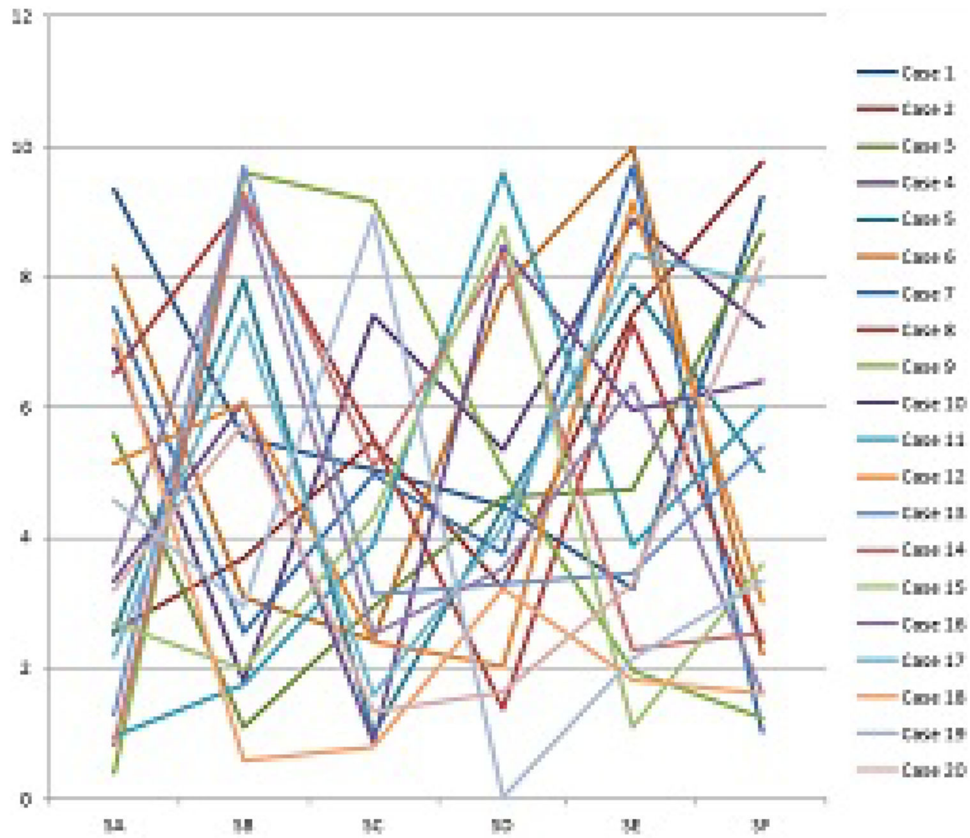


Fig. 1 The degree value of clinical symptoms

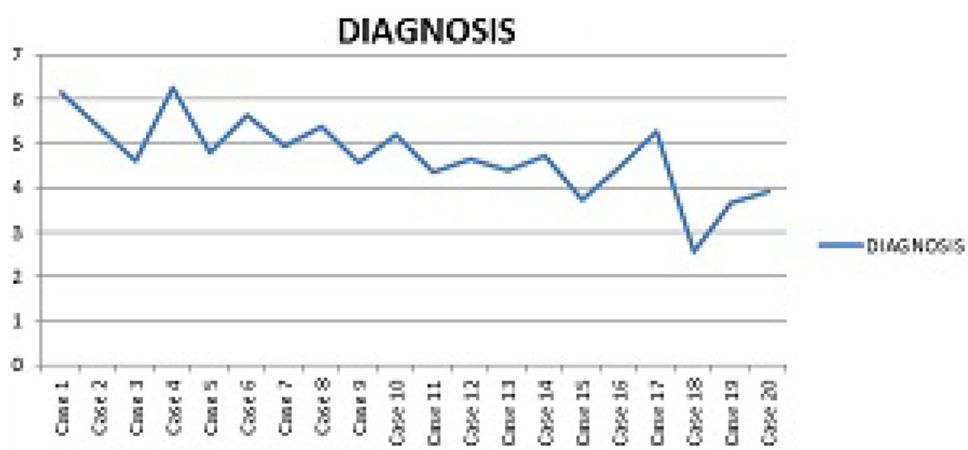


Fig. 2 Relationship between the diagnostic value and the diagnostic outcome

$O_i^3 =$ is the ith neuron output from layer 3, $\mu(x)$ and $\mu(y) =$ membership function of x and y, respectively.

Layer 4 This layer is also known as the normalization layer. It is third hidden layer of the ANFIS architecture. Each neuron in this layer corresponds to exactly one neuron in the rule layer and it calculates the firing strength of each rule. This could be represented mathematically as shown in Eq. (4):

$$O_i^4 = \frac{O_i^3}{O_1^3 + O_2^3 + \cdots + O_n^3}, \tag{4}$$

where

$O_i^4 =$ is the ith neuron output from layer 4, $O_i^3 =$ is the ith neuron output from layer 3, $n =$ total number of neuron in layer 3.

Layer 5 This is also known as the defuzzification layer; it is the fourth hidden layer of the ANFIS architecture. It consists of just a single neuron to which all the neurons from the normalization layer is connected. The output from this layer is derived by multiplying the firing strength of a rule by its consequent parameters. This could be represented mathematically as shown in Eq. (5):

$$O_i^5 = O_i^4(p_i(x) + q_i(y) + r), \tag{5}$$

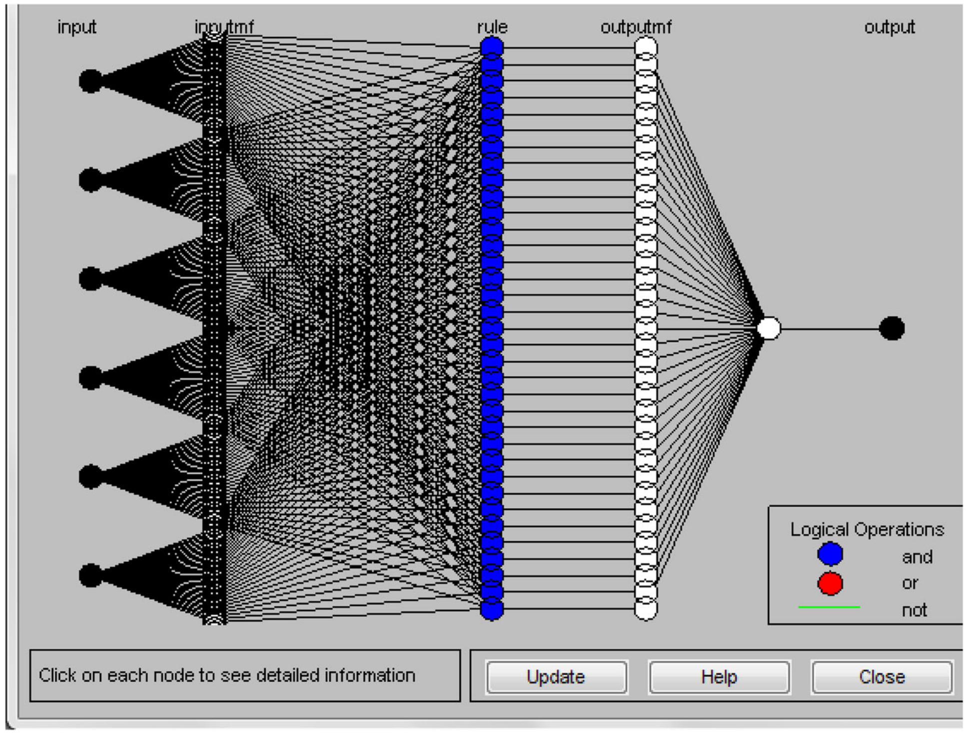


Fig. 3 Adaptive Neuro Fuzzy Inference System (ANFIS) Architecture

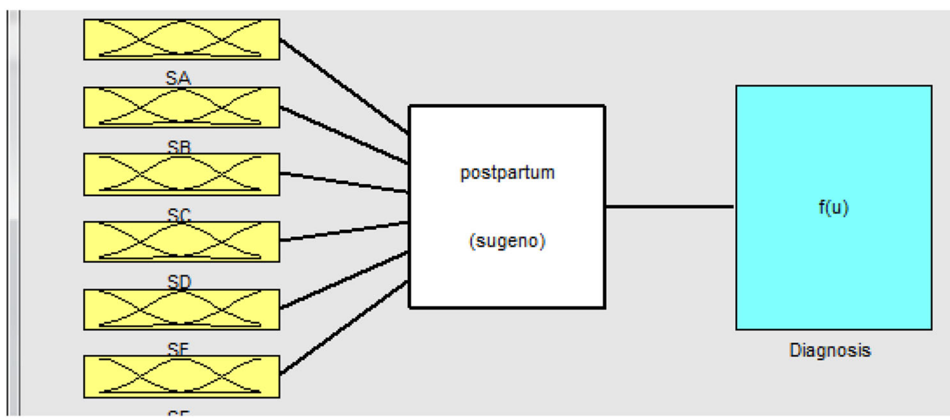


Fig. 4 Fuzzy inference engine

where

O_i^5 = is the ith neuron output from layer 5, p_i, q_i = consequent parameters, r = bias.

Layer 6 This is also known as the output layer; it is the sixth layer of the ANFIS. The neurons in this layer produce the final output of the ANFIS. The input into this layer is gotten from layer 5 and it produces its output by adding its inputs. This can be represented mathematically as shown in Eq. (6):

$$O_i^6 = \sum_i^n O_i^5, \tag{6}$$

where

O_i^6 = is the ith neuron output from layer 6, O_i^5 = is the ith neuron output from layer 5.

4 Results

Tables 1 and 2 show twenty (20) cases of the postpartum depression dataset and summary of the diagnostics result from the 59 cases, respectively. Figure 1 shows the degree of the clinical symptoms in respect to each case shown in Table 1. Figure 2 shows the relationship between diagnostic value and the diagnostic outcome for each case as represented in Table 2.

In our ANFIS model, we utilized a bell membership function and the hybrid optimization learning algorithm which had its error tolerance at 0.05. The dataset used for training was passed through the ANFIS for 30 epochs and upon completion the system had a training error of 7.0706e−005 at epoch 1 and had an average testing error of 3.0185 on the test dataset, which indicates that the system was able to clas-

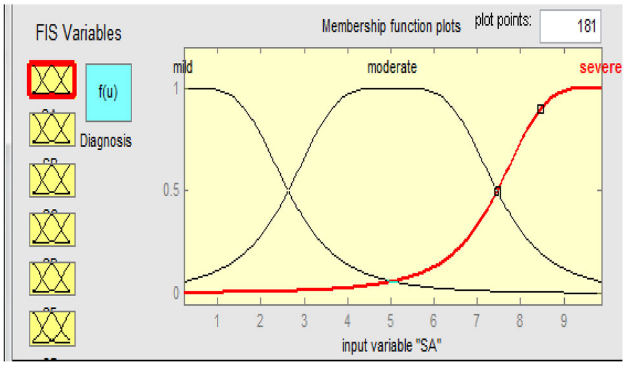


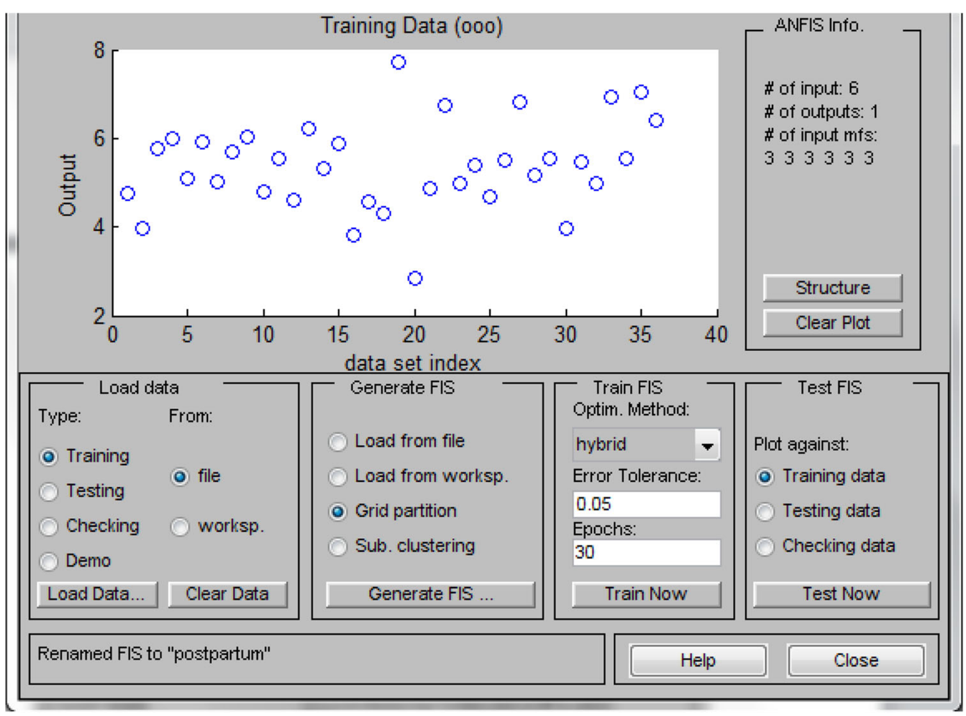
Fig. 5 Membership function for linguistic variable

sify approximately 97% of the test dataset accurately. The dataset used to train and test the ANFIs was passed through an artificial neural network for 20 epochs using a backward propagation learning algorithm and it had a training error of 5.1121 and an average testing error of 7.21311. This indicates that the ANN was able to classify approximately 92% of the test dataset. Figures 3, 4, 5, 6, 7 and 8 show the ANFIS architecture, fuzzy inference engine, membership function for the linguistic variables, training dataset, training process and testing process, respectively. The surface view diagrams where generated at the end of the training process and they are clearly shown in Fig. 9a–f.

5 Discussion

An artificial intelligence (AI) system is a capable tool for fast and accurate diagnosis for mental illness. A significant amount of research has been conducted on mental health with intentions to automate the diagnostic processes using AI [17, 18]. The technique proposed in this paper is the first of its kind used for diagnosing postpartum depression disorder. In this study, an ANFIS model was developed for diagnosing postpartum depression and the result was compared on ANN using the same dataset. The result indicates that the ANFIS performs better than the ANN for predicting postpartum depression disorder. The ANN used a backward propagation learning algorithm while the ANFIS used a hybrid learning algorithm. Using similar neuro fuzzy system Anish et al. [17] formulated a model for diagnosing depression. Our study validates the assertions by Anish et al. [17] in which clinical symptoms were used to develop the ANFIS although the nature of depression in both studies differs. In our model, a bell membership function was used to map linguistic parameters to their labels because it is capable of approaching a non-fuzzy set and has a nonzero value at all points. The type of membership function used in mapping linguistic variables to linguistic labels might affect the performance of the system [19, 20]. Nevertheless, the current study differs from Anish et al. [17] where probability was used to represent the value of each symptom.

Fig. 6 Training dataset set loaded into the ANFIS



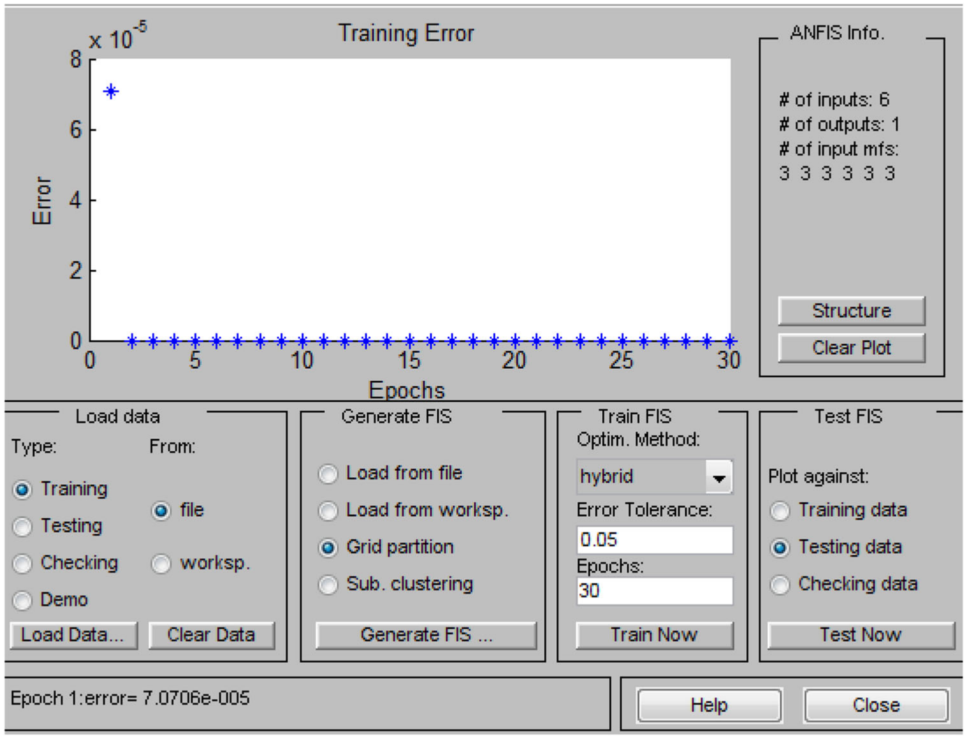


Fig. 7 Training process

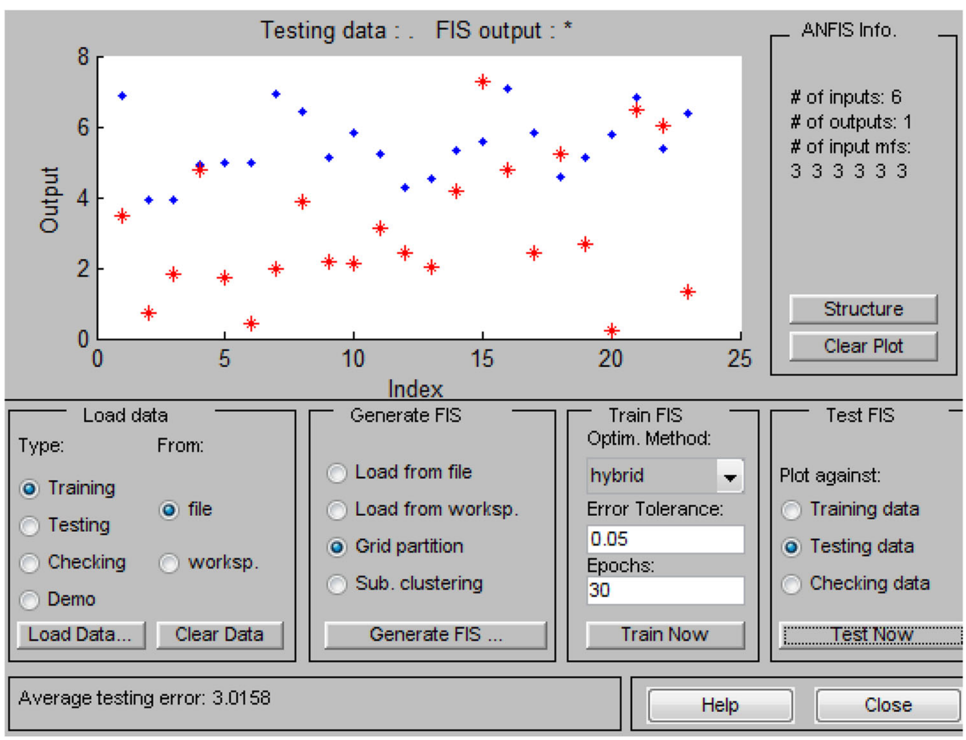


Fig. 8 Testing process

5.1 Conclusion

In this paper, we designed an ANFIS structure for diagnosing postpartum depression and it yielded an excellent result compared to the ANN. Using this model, a system interface can be designed which will utilize the ANFIS architecture. This will assist the medical practitioner in diagnosing postpartum depression.

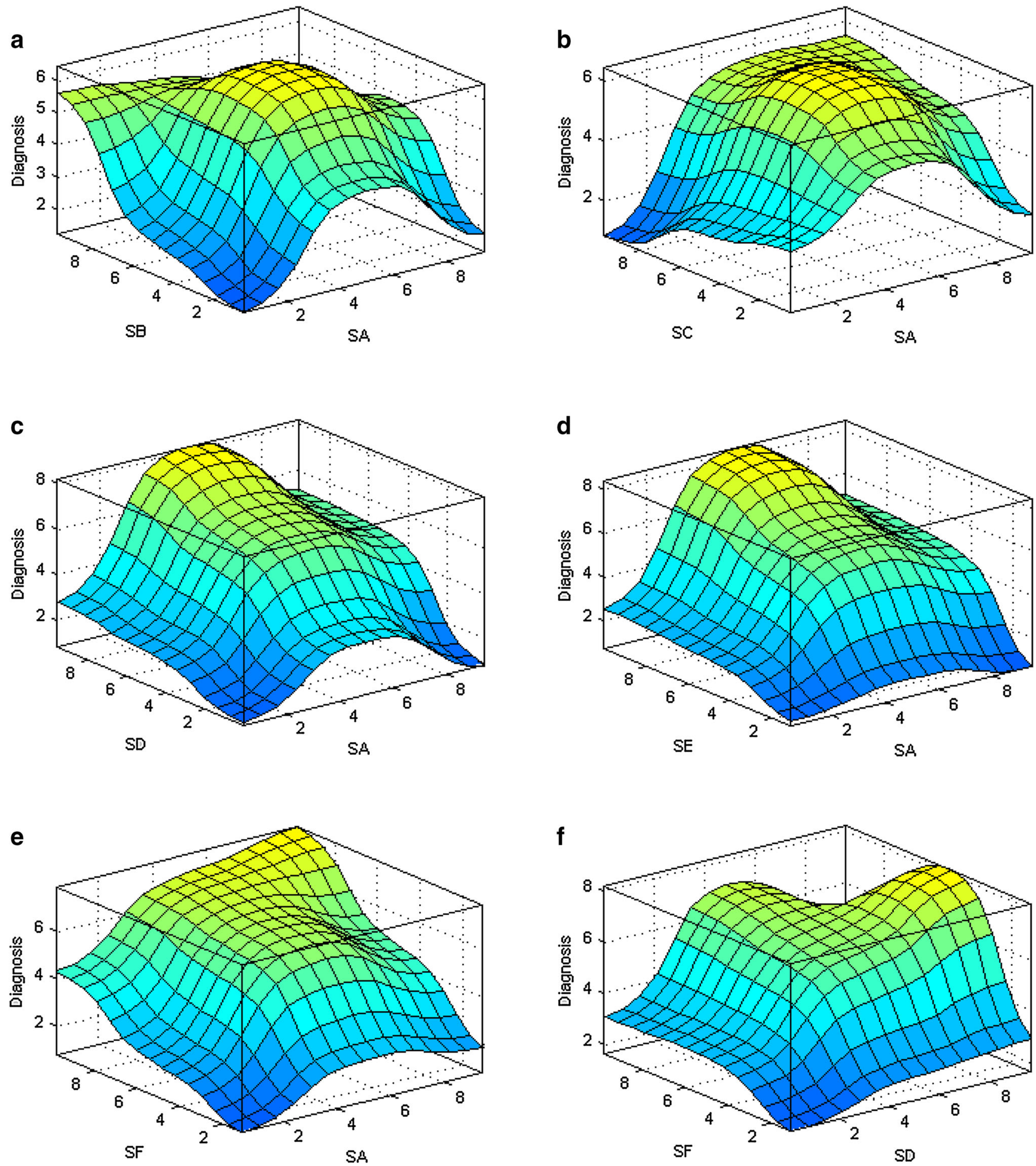


Fig. 9 **a** The relationship between SA (feeling sad) and SB (lack of interest in activities previously enjoyed) to the diagnosis of postpartum depression. **b** The relationship between SA (feeling sad) and SC (insomnia) to the diagnosis of postpartum depression. **c** The relationship between SA (feeling sad) and SD (extreme difficulty in thinking or making decision) to the diagnosis of postpartum depression. **d** The relationship between SA (feeling sad) and SE (fatigue) to the diagnosis of postpartum depression. **e** The relationship between SA (feeling sad) and SF (suicidal thought or worries about harming baby, or partner) to the diagnosis of postpartum depression. **f** The relationship between SD (extreme difficulty in thinking or making decision) and SF (suicidal thought or worries about harming baby, or partner) to the diagnosis of postpartum depression

5.2 Future work

Further research should attempt to design a more sophisticated neuro-fuzzy model that can accommodate larger clinical symptom base for diagnosing postpartum depression as it may help in a more accurate diagnosis of postpartum depression.

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