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Fuzzy Brain Emotional Controller for Heart Disease Diagnosis

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***Abstract*—This article provides a new way for classifying heart disease. A classifier using a controller for brain emotional learning and a fuzzy system is presented. The controller's parameter updating laws are built using the gradient descent method. The method's convergence and stability are ensured by the Lyapunov function. Using the heart disease dataset from the University of California, Irvine (UCI), the performance of the system is examined. In addition, a comparison with different classifiers is provided. The outcomes of our experiments illustrate the efficacy of our strategy.**

***Index Terms*—Heart disease prediction, fuzzy system, Brain emotional learning controller.**

I. Introduction

In today's engineering applications, fuzzy inference systems and neural networks are used widely. There is a significant increase in productivity when fuzzy systems and neural networks are combined [1, 2]. The fuzzy inference system and the cerebellar model articulation controller [1] are two examples of popular methods. Other popular methods include the fuzzy inference system and brain-based learning control systems [3, 4], as well as the fuzzy inference system and the cerebellar model articulation controller [1].

The brain emotional learning controller (BELC) [2] was first presented by C. Lucas and colleagues as one of the most effective methods for the control of nonlinear systems. [2] BELC is also utilized in a wide range of applications, some of which include the prediction of time series [3], image encryption and decryption [1, 4], robot control [5], and chaotic synchronization [4].

In recent years, the role of engineering techniques has grown alongside that of sophisticated algorithms for medical diagnosis. The use of computer-assisted diagnosis, also known as CAD, is extremely important in clinical medicine since it has the potential to significantly increase the percentage of patients who are cured through earlier diagnosis. [6-10] A great number of researchers have presented ways with the goal of enhancing the speed and accuracy with which heart illness can be diagnosed. In 2019, Le et al. proposed a type-2 fuzzy neural network (FNN) for the diagnosis of cardiac illness [6]. This method used FNN for datasets from the University of California, Irvine. In the year 2021, Bakhsh proposed a classification system for heart conditions based on an enhanced deep genetic algorithm (EDGA) [7]. The findings of the study indicated that the EDGA is an appropriate tool for diagnosing heart disease. Convolutional Neural Network (CNN) of ResNet-50 was presented by Charles et al. in 2022 for the purpose of medical diagnosis [11]. This CNN has close to 50 layers, which enables it to attain classification performance.

This research makes a unique contribution to the learning model by describing the emotional signal within the learning rules for classification problems. It is possible to accomplish the desired result by making an informed decision regarding the emotional state of the system. More specifically, the generalization quality and the accuracy of the prediction can be improved by making an informed decision regarding the definition of the reinforcing signal. The results of the simulation and the research that was done on them show how effective the technique that was suggested is.

The rest of this paper can be summed up as follows: Section II describes a fuzzy brain emotional learning controller (FBELC), Section III discusses online learning and convergence analysis, Section IV discusses heart disease diagnosis using the proposed FBELC, and Section V concludes the paper.

II. Fuzzy Brain Emotional Learning Controller

Figure 1 displays the structure of FBELC. The fuzzy inference system and five layers make up an FBELC (input, sensory cortex space, weight space, amygdala and orbitofrontal cortex space, and output space).

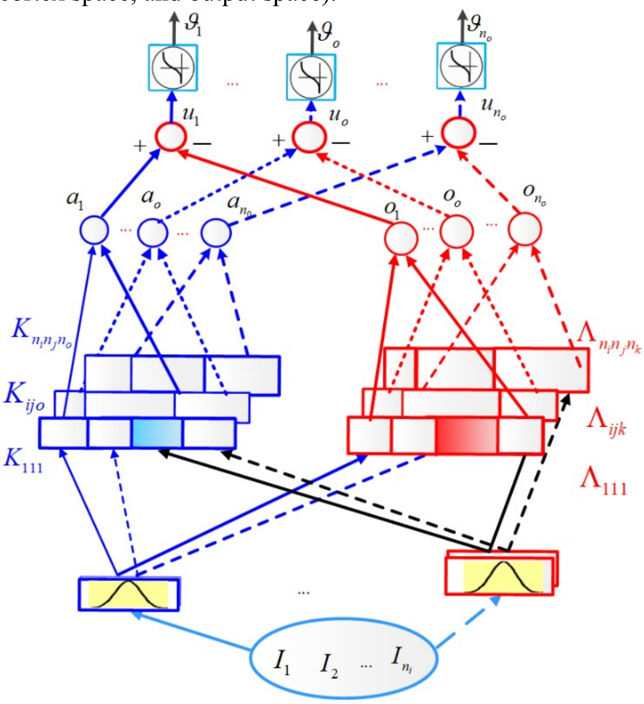

Fig. 1. The structure of FBELC classifier

The fuzzy inference rules are defined as:

If I_1 is G_{1j},…, and I_{n_i} is $G_{n_i j}$, then $a_o = K_{ijo}$ and $o_o = \Lambda_{ijo}$

for $o = 1,2...,n_o$; j=1,2...,n_j; i=1,2...,n_i (1)

where n_i, n_j, n_o are respectively input dimension, layer dimension and output dimension; G_{ij} is the fuzzy set, K_{ijo}, Λ_{ijo} are respectively orbitofrontal cortex weight and amygdala weight, a_o and o_o are amygdala output and orbitofrontal cortex, respectively.

Layer 1: Input space

$I = \left[I_1,\ I_2,...,I_{n_i} \right] \in R^{n_i}$, where n_i is the number of features.

Layer 2: Sensory cortex space:

A Gaussian function is written as

$$G_{ij} = \exp\left(-\frac{(I_i - m_{ij})^2}{2v_{ij}^2} \right) \tag{2}$$

where m_{ij} and v_{ij} are respectively the center and upper dilation.

Layer 3: Weight space K_{ijo} and Λ_{ijo}.

Layer 4: Amygdala and orbitofrontal cortex space

$$a_o = \frac{\sum_{i=1}^{n_i}\sum_{j=1}^{n_j} G_{ij}K_{ijo}}{\sum_{i=1}^{n_i}\sum_{j=1}^{n_j} G_{ij}} \tag{3}$$

$$o_o = \frac{\sum_{i=1}^{n_i}\sum_{j=1}^{n_j} G_{ij}\Lambda_{ijo}}{\sum_{i=1}^{n_i}\sum_{j=1}^{n_j} G_{ij}} \tag{4}$$

Layer 5: Output space

FBELC output is the difference between amygdala and orbitofrontal cortex output. The *o-th* output is then computed as

$$u_o = a_o - o_o \tag{5}$$

Using the sigmoid function for classifying, the output of the FBELC classifier can be written as

$$\vartheta_o = \frac{1}{(1+\exp(-u_o))} \tag{6}$$

for o=1,2,...,n_o

III. Online Learning and Convergence Analysis

A. Online learning

The updating weights Λ_{ijo} and K_{ijo} are calculated as

$$K_{ijo}(k+1) = K_{ijo}(k) + \Delta K_{ijo}(k) \tag{7}$$

$$\Lambda_{ijo}(k+1) = \Lambda_{ijo}(k) + \Delta\Lambda_{ijo}(k) \tag{8}$$

$$\Delta K_{ijo}(k) = l_K (G_{ij} \max(0, Rd_o(k) - a_o(k)) \tag{9}$$

$$\Delta\Lambda_{ijo}(k) = l_\Lambda (G_{ij}(u_o(k) - Rd_o(k)))) \tag{10}$$

where l_K and l_Λ are the learning rates. Rd_o is the reward signal. Select Rd_o as follows

$$Rd_o(k) = \xi_1(t_o(k) - \vartheta_o(k)) + \xi_2 u_o(k) \tag{11}$$

where t_o is the desired output; ξ_1 and ξ_2 are factors corresponding to the desired output error and FBELC output, respectively. A cost function is chosen as

$$\Phi(k) = \frac{1}{2}\sum_{o=1}^{n_o}(t_o(k) - \vartheta_o(k))^2 \tag{12}$$

Using the gradient descent method, obtains

$$\Delta m_{ij} = -l_m \frac{\partial \Phi}{\partial m_{ij}} = -l_m \frac{\partial \Phi}{\partial \vartheta_o}\frac{\partial \vartheta_o}{\partial u_o}\frac{\partial u_o}{\partial G_{ij}}\frac{\partial G_{ij}}{\partial m_{ij}}$$
$$= l_m \sum_{o=1}^{n_o}(t_o - \vartheta_o)\vartheta_o(1-\vartheta_o)(K_{ijo} - \Lambda_{ijo})G_{ij}\frac{2(I_i - m_{ij})}{v_{ij}^2} \tag{13}$$

$$\Delta v_{ij} = -l_v \frac{\partial \Phi}{\partial v_{ij}} = -l_v \frac{\partial \Phi}{\partial \vartheta_o}\frac{\partial \vartheta_o}{\partial u_o}\frac{\partial u_o}{\partial G_{ij}}\frac{\partial G_{ij}}{\partial v_{ij}}$$
$$= l_v \sum_{o=1}^{n_o}(t_o - \vartheta_o)\vartheta_o(1-\vartheta_o)(K_{ijo} - \Lambda_{ijo})G_{ij}\frac{2(I_i - m_{ij})^2}{v_{ij}^3} \tag{14}$$

Then, the updating law is calculated as:

$$m_{ij}(k+1) = m_{ij}(k) + \Delta m_{ij}(k) \tag{15}$$

$$v_{ij}(k+1) = v_{ij}(k) + \Delta v_{ij}(k) \tag{16}$$

B. Convergence Analysis

Define a Lyapunov function as

$$\Psi(k) = \frac{1}{2}\boldsymbol{e}^2(k) \tag{17}$$

where $\boldsymbol{e}(k) = \left[e_1(k),...,e_o(k),...,e_{n_o}(k) \right]$

in which $e_o(k) = t_o - \vartheta_o$

The deviate of Ψ can be written as

$$\Delta\Psi(k) = \Psi(k+1) - \Psi(k)$$
$$= \frac{1}{2}\left(\boldsymbol{e}^2(k+1) - \boldsymbol{e}^2(k)\right)$$
$$= \frac{1}{2}\left(\boldsymbol{e}(k+1) + \boldsymbol{e}(k)\right)\left(\boldsymbol{e}(k+1) - \boldsymbol{e}(k)\right)$$
$$= \frac{1}{2}\left(2\boldsymbol{e}(k) + \Delta\boldsymbol{e}(k)\right)\Delta\boldsymbol{e}(k) \tag{18}$$

Using the Taylor expansion, gets

$$\boldsymbol{e}(k+1) = \boldsymbol{e}(k) + \Delta\boldsymbol{e}(k) \cong \boldsymbol{e}(k) + \left[\frac{\partial \boldsymbol{e}(k)}{\partial \boldsymbol{m}}\right]^T \Delta\boldsymbol{m}$$

Where $\boldsymbol{m} = [m_{11},....,m_{ij},...,m_{n_i n_j}]$

$$\frac{\partial \boldsymbol{e}(k)}{\partial \boldsymbol{m}} = \frac{\partial \boldsymbol{e}(k)}{\partial \boldsymbol{\vartheta}(k)}\frac{\partial \boldsymbol{\vartheta}(k)}{\partial \boldsymbol{m}} = -\frac{\partial \boldsymbol{\vartheta}(k)}{\partial \boldsymbol{m}} \tag{20}$$

$$\Delta\boldsymbol{m} = -l_m \frac{\partial \Psi(k)}{\partial \boldsymbol{m}} = -l_m \frac{\partial \Psi(k)}{\partial \boldsymbol{\vartheta}(k)}\frac{\partial \boldsymbol{\vartheta}(k)}{\partial \boldsymbol{m}} = l_m(\boldsymbol{t} - \boldsymbol{\vartheta})\frac{\partial \boldsymbol{\vartheta}(k)}{\partial \boldsymbol{m}}$$
$$= l_m \boldsymbol{e}(k)\frac{\partial \boldsymbol{\vartheta}(k)}{\partial \boldsymbol{m}} \tag{21}$$

$$\Delta \boldsymbol{e}(k) = -l_m \boldsymbol{e}(k)\left(\frac{\partial \boldsymbol{\vartheta}(k)}{\partial \boldsymbol{m}}\right)^T \frac{\partial \boldsymbol{\vartheta}(k)}{\partial \boldsymbol{m}}$$

Set $Q = \left(\frac{\partial \boldsymbol{\vartheta}(k)}{\partial \boldsymbol{m}}\right)^T \frac{\partial \boldsymbol{\vartheta}(k)}{\partial \boldsymbol{m}}$, then

$$\Delta \boldsymbol{e}(k) = -l_m \boldsymbol{e}(k) Q \qquad (22)$$

From (17) to (22), $\Delta\Psi(k)$ is obtained as:

$$\Delta\Psi(k) = \frac{1}{2}\left(2\boldsymbol{e}(k) - l_m \boldsymbol{e}(k)Q\right)\left(-l_m \boldsymbol{e}(k)Q\right) =$$

$$= \frac{1}{2}\boldsymbol{e}(k)\left(2 - l_m Q\right)\left(-l_m Q\right)\boldsymbol{e}(k) = -l_m Q \boldsymbol{e}^2(k)\left(1 - \frac{l_m Q}{2}\right)$$

$\Delta\Psi(k) \le 0$ if $1 - \frac{l_m Q}{2} \ge 0 \to 0 \le l_m \le \frac{2}{Q}$ then, the system's stability is guaranteed. Choosing l_v can be proved as similarity.

IV. Heart Disease Diagnosis Using FBELC

In order to evaluate the system, some parameters must be calculated; Sensitivity λ_{SEN}, negative predictive value λ_{NPV}, false positive rate $\lambda_{\mathrm{FP\_rate}}$, Specificity λ_{SPE}, Accuracy λ_{ACC}.

$$\lambda_{\mathrm{SEN}} = \frac{\lambda_{\mathrm{TP}}}{\lambda_{\mathrm{TP}} + \lambda_{\mathrm{FN}}} \qquad (24)$$

$$\lambda_{\mathrm{NPV}} = \frac{\lambda_{\mathrm{TN}}}{\lambda_{\mathrm{TN}} + \lambda_{\mathrm{FN}}} \qquad (25)$$

$$\lambda_{\mathrm{FP\_rate}} = \frac{\lambda_{\mathrm{FP}}}{\lambda_{\mathrm{TN}} + \lambda_{\mathrm{FP}}} \qquad (26)$$

$$\lambda_{\mathrm{SPE}} = \frac{\lambda_{\mathrm{TN}}}{\lambda_{\mathrm{TN}} + \lambda_{\mathrm{FP}}} \qquad (27)$$

$$\lambda_{\mathrm{ACC}} = \frac{\lambda_{\mathrm{TP}} + \lambda_{\mathrm{TN}}}{\lambda_{\mathrm{TP}} + \lambda_{\mathrm{TN}} + \lambda_{\mathrm{FP}} + \lambda_{\mathrm{FN}}} \times 100\% \qquad (28)$$

where λ_{TP}, λ_{TN}, λ_{FP}, λ_{FN} are respectively true positives, true negatives, false positives and false negatives.

First, the UCI Starlog heart disease dataset, shown in Table I, contains 270 sets of samples, each with 13 features and 1 output target. Second, Fig. 2 depicts the FBELC method's accuracy value of 94.81% of the test set. Third, Fig. 3 depicts the result of the confusion matrix, which yields the following. The values of λ_{TP}=147, $\lambda_{\mathrm{TN}} = 109$, $\lambda_{\mathrm{FP}} = 11$, and $\lambda_{\mathrm{FN}} = 3$ and λ_{ACC}, λ_{SEN}, λ_{SPEC}, λ_{NPV}, and $\lambda_{\mathrm{FP\_rate}}$ are then obtained using (24)-(28). Finally, table II shows comparisons between our method and other methods, demonstrating our method's superior performance.

TABLE I
THE DATASET OF UCI HEART DISEASE

	Characteristic
1	Slope of the peak exercise ST segment
2	Resting blood pressure
3	Serum cholesterol in mg/dl
4	Exercise-induced angina
5	Maximum heart rate achieved
6	Resting electrocardiographic results
7	Fasting blood sugar > 120 mg/dl
8	Old peak
9	Number of major vessels (0–3)
10	Chest pain type
11	Sex
12	Age
13	Thal

(23)

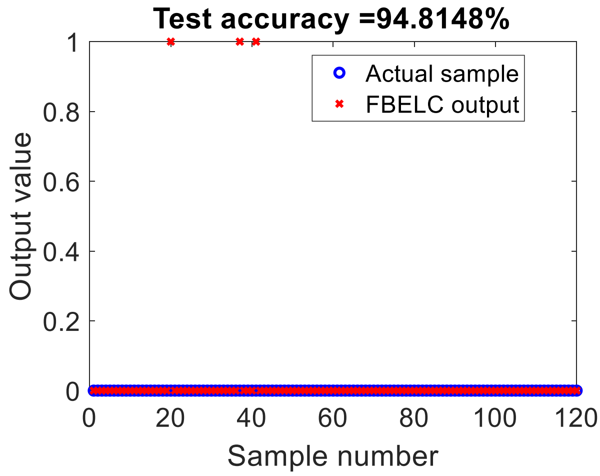

Fig. 2. The accuracy result of heart disease prediction using FBELC

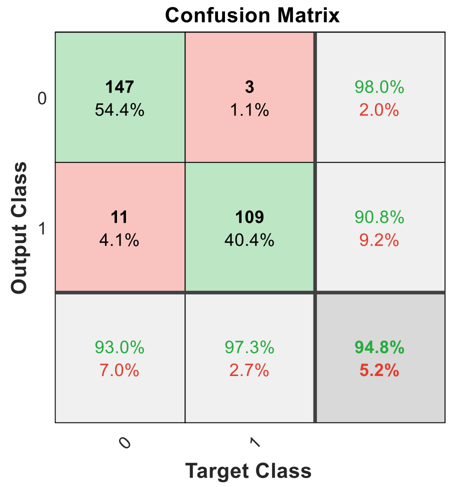

Fig. 3. The confusion matrix of heart disease prediction using FBELC

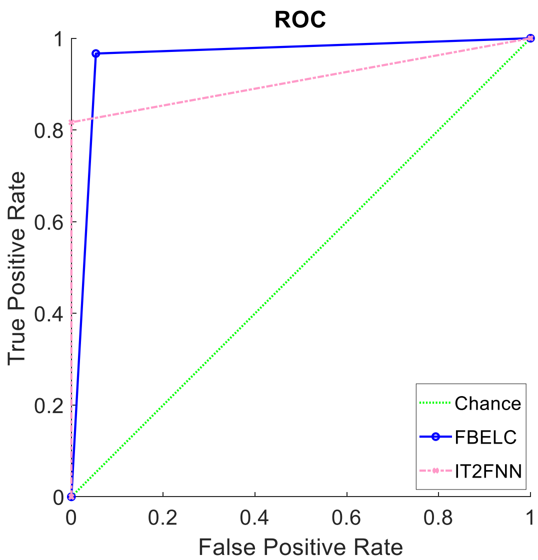

Fig. 4. The ROC of heart disease prediction using FBELC and IT2FNN

TABLE II
CLASSIFICATION PERFORMANCE MEASURE

	ACC	SEN	SPE	NPV	FP_rate
ANN [10]	0.84	0.87	0.79	0.83	0.21
SVM [10]	0.82	0.77	0.89	0.75	0.11
Logistic regression [10]	0.85	0.89	0.81	0.85	0.19
kNN [10]	0.80	0.84	0.76	0.81	0.24
Classification tree [10]	0.77	0.79	0.73	0.79	0.27
Naïve Bayes [10]	0.83	0.85	0.80	0.84	0.20
Kmeans IT2FNN [6]	93.81	--	93.58	--	--
Our method	94.81	0.89	0.9467	0.97	0.09

V. CONCLUSION

For classification, this study successfully proposed an FBELC. This work makes a contribution by combining a BELC with a fuzzy inference system and applying it to heart disease diagnosis. The fuzzy set and the novel setting of the optimization value of the BELC's reward signal, in particular, can improve classification efficiency. The simulation results show that the proposed algorithm has a high degree of generalization and accuracy while remaining simple and easy to implement. As a result of the findings, the proposed classifier appears to be a promising alternative for medical diagnosis. Some optimization algorithm can be applied to find the optimal learning rates such as improved particle swarm, modified grey wolf optimizer. Then, the proposed FBELC can be used in practical experiments in the future.

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