Depression diagnosis using ANFIS model

Ana L. Ojeda-Mares[1], M. Adriana Corona-Nakamura[2], Graciela Lara-López[3] and M. Rocío Aranzazú-Farías-Flores [4]

[1] Universidad Tecnológica de Jalisco, Tecnologías de la Información y Comunicación. Luís J. Jiménez 577. Col. Primero de Mayo, Guadalajara, Jalisco, C.P. 44979. México
[2] Universidad de Guadalajara, División de Electrónica y Computación, Departamento de Ciencias Computacionales. Av. Revolución 1500. Col Olímpica, Guadalajara, Jalisco, S.R. C.P. 44430. México
[1]anliojma@yahoo.com, [2]acoronak@yahoo.com.mx, [3]lara_graciela@hotmail.com, [4]docfari16@yahoo.com.mx

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Abstract. This paper presents the design of a tool that functions in aid of depression diagnosis. The system is based on the ANFIS neuro-fuzzy model and will classify the patients into the depression level in which they are found (sane, low, moderate or severe), based on the symptoms shown by the patient. The evaluations of the patients took place in clinics and one doctor's office in the city of Guadalajara, Jalisco. The proposed system is composed by four stages: the first being the generation of a database by an expert. In the second stage, the most relevant features entered into the database are selected. The third phase is to carry out the fuzzy classification. During the fourth and final stage, the membership functions are optimized with a hybrid model in order to obtain the final diagnosis. The results show that the system works efficiently, with 96% accurately classified examples.

1 Introduction

Just like many other disorders, depression is a sickness with a series of causes, physiopathological mechanisms, and a specific clinical profile, and for which there are strategies to its identification and treatment.

Nowadays, the increase in depression cases has made a great number of researchers join forces in order to better know this problem.

Since 1997, new systems that involve neural network [9] have been developed for the diagnosis of depression. These systems determine whether the person shows depression, schizophrenia, or neurosis (or if he/she is mentally sane), each one of these illnesses being well defined. This is in contrast to the present project in which one of the four degrees of depression is diagnosed, with an overlap existing among the four sets of data. With the expert System for the Diagnosis of Dementia and Depression [12] a similarity occurs. Both depression and dementia contain well-defined sets of data; besides the decision rules used by the system were derived from the published lists of clinical features which distinguish depression from dementia.

Likewise CompTMAP [14] handles patients with some of the most important disorders: schizophrenia, bipolar disorder, and major depressive disorder. It is an automated algorithm designed to be used by psychiatrists and doctors of primary care, although it does not provide a diagnosis.

With other systems, such as EasyDiagnosis Depression, [6] the patient answers a survey via Internet in a subjective manner, making the information obtained unreliable in contrast to this system in which the specialist is present to assess the behavior of the patient and thus the reliability of the answer. Apart from this, EasyDiagnosis makes no diagnosis; it simply follows an order based on probability of the illnesses or the conditions based within its internal logic and the answers given to the questions.

Another system similar to ours is Salomon 2 [4] which determines the relative intensity of depression as measured by the feature symptoms of fixed depressive episodes, based on the scientific criteria of the classification scale ICD-10 [15], the Hamilton Scale [3] and **fuzzy logic**. In this system, the information is given by the patient; thus, just like other systems previously presented, the information is subjective.

Other ANFIS diagnostic systems have been developed; nonetheless they have been made for the diagnosis of different illnesses. [10, 11, 13].

Because of the value of making a precise diagnosis and the advantages that *Soft Computing* technology offers, this project consists of the development of a back-up system for the process of the depressive level diagnosis of a patient, with the end users being psychiatrists, psychologists or primary assistance doctors whose timely diagnosis will be very important for the treatment of this illness.

Diagnosis is the process of determining the stage of an illness, based on its features and the patient's condition. The process of decision-making consists first of creating hypotheses, and then determining which one is the most likely to be true, according to the symptoms and signs shown by the patient. A problem of classification also occurs when assigning each diagnosis hypothesis a type.

The patients were 431 adults of both sexes (ranging in age from 18 to 65 years old) who were interviewed consecutively by the psychiatrist while attending sessions. We also attempted to have the database as balanced as possible, according to the number of patient cases which corresponded to each of the four classes or diagnoses.

The system uses a fuzzy inference model based on adaptive networks from a specific diagnosis of the patient's depressive level (sane, low, moderate, or severe), based on the most representative symptoms of the illness. The system is based on knowledge acquired from real diagnosed cases. The ANFIS model has been used as a solution to the problem given due to the fact that fuzzy logic eases the handling of the imprecise and subjective knowledge used to evaluate the symptoms of a depressive patient where the linguistic labels are qualitative (input variables). This model allowed us to obtain a set of inference rules to determine the diagnosis (output variables). The tool used for the development of the system was *Fuzzy Logic Toolbox* from MATLAB 7.0 of MathWorks Inc. which includes an important cluster of algorithms used in fuzzy logic; amongst others is the ANFIS technique which contains five graphic editors for each phase of the design and analysis of the system.

2 Neuro-fuzzy Models and ANFIS

2.1 Neuro-fuzzy models

Neuro-fuzzy models are characterized because we try to use with them the advantages of neural networks and fuzzy logic models. Neural networks provide learning capacity and ability for generalization; on the other hand, fuzzy logic provides a logical reasoning based on inference rules. So, in applications where information comes from different sources, such as a numerical one and where there are also data that present features like imprecision, uncertainty, subjectivity, etc., a neuro-fuzzy model is recommended in order to obtain the maximum benefit of the available information, and to try to incorporate all the possible knowledge related to the problem.

The most important reason to combine fuzzy systems and neural networks is the learning capacity of the latter ones, because such combinations have the ability to learn linguistic rules or membership functions, or to optimize the available ones. Learn; in this case, means to create a rule base or membership functions based on training with a set of data values presented to these models [7, 8]. In order to build a set of fuzzy rules, at least the initial membership functions must be defined.

2.2 Adaptive Neuro-based Fuzzy Inference System (ANFIS)

The neuro-fuzzy selected architecture for the development of this project is an adaptable neuro-fuzzy network, called ANFIS, which has been developed by Jang in 1993 [5]. This architecture is functionally equivalent to a fuzzy inference system that can be built from the relations between input and output values of a data set. In this inference system, ANFIS tunes the membership functions during the training process of the model. For the initial estimation of these parameters it is possible to use the subtractive clustering method [2]. Fuzzy rules are based on the Takagi-Sugeno inference method, and the conclusions are polynomial functions.

Due to the ease of result interpretation and to its capacity of learning, ANFIS is a good candidate for our classification problem. Besides, we are also interested in using the information and knowledge provided, not necessarily expressed in a numerical way, but through logic rules and values that help to a better understanding of the system behavior.

The data set has the classes of each one of the examples, a reason for doing supervised learning and with disregard of the clustering algorithms for the preliminary estimation of the data set classes.

3 System description

3.1 Generating the database

From the instruments available which aid diagnosis, we chose to apply the hetero-administrated Hamilton scale [3]. This scale evaluates the symptoms and depressive signs of the patients, determining the presence of depression and its severity. It consists of an assessment test based on the items shown in a depressed patient according to the criteria of DSM-IV, and it is applied by capable, trained and specialized personnel.

When planning the fuzzy model, we determined that the most convenient scale would have to handle as few input variables as possible. As a consequence, the system would be optimal and more efficient. There is a six-item version in the Hamilton Scale, and according to research, its efficiency is similar to, and in some cases even superior to, versions of 17 and 21 items. It is a valid, reliable, brief, concise and quickly-applied indicator; ideal for evaluating the symptomatic intensity of depression wherever longer version applications are not possible.

The psychometric equivalence among HDRS-6, HDRS-17 and HDRS-21 enhances the possibility of introducing it in primary assistance [1]. The scoring goes from 0 to 4 points according to the item studied, with the highest value given according to the severity of the symptoms. HDRS-6 consists of a survey of five questions scored from 0 to 4 and one scored from 0 to 2. The nature of the items is qualitative variables. Table 1 shows the six input variables and the sum of the scores. The output diagnosis is shown in Table 2. Therefore, we created the **database** according to the results of the Hamilton scale application that the expert psychiatrist filled in, based on the observations, interviews, and processing of the depressive diagnosis of 431 patients.

Table 1. Number, name and score range of each input variable.

Input variable number	Input variable name	Score range
1	Mood of depression	0-4
2	Feelings of guilt	0-4
3	Work and activities	0-4
4	Mental impairment	0-4
5	Psychic anxiety	0-4
6	General somatic	0-2
7	Sum of scores	0-22

Table 2. Output variable.

Output variable	Levels
Depressive level diagnosis	1 = Sane 2 = Low 3 = Moderate 4 = Severe

3.2 Features selection

In this stage we obtained the most representative features which allowed us to classify the patients into one of the depressive illness levels (sane, low, moderate, severe), that will be the variables to use.

We used the grid method (genfis1) because it works well with the prediction and calculation of the error of training and testing of each possible combination of variables, which, in turn, led us to learn the best combinations of attributes or the most representative of these for the score. At first we trained with odd numbers and tested with evens (Depression $_{\text{ODD-EVEN}}$); then we did the opposite (Depression $_{\text{EVEN-ODD}}$); obtaining better results in the first option (see Table 3).

In order to measure and compare the performance of the ANFIS model we evaluated the errors considering the index measure RMSE (Root Mean Squared Error) defined as:

$$RMSE = \sqrt{\frac{1}{M}\sum_{m=1}^{M}(Y_m - O_m)^2}$$

Where:

M = Total amount of data

O_m = Observed data

Y_m = Predicted data

The input variable that showed less error in individual mode was the 7th, where the training and testing RMS Error were 0.29, as shown in Table 3. In this chart, the best combinations for two and three variables are also shown. The remaining combinations originated major errors.

Table 3. Input variables combinations which showed less error (Depression $_{\text{ODD-EVEN}}$).

Input variables			RMSE Training	RMSE Test
7			0.29	0.29
1	7		0.28	0.29
2	7		0.28	0.29
3	7		0.28	0.29
4	7		0.28	0.29
6	7		0.27	0.28
1	2	7	0.25	0.27
3	6	7	0.26	0.27

For the next stage, the trainings were made considering only the attribute combinations which showed the least training and proving errors (shaded area).

3.3 Fuzzy Classification

This phase was carried out with subtractive clustering (genfis2), determining rules (view Figure 1), centers and sigmas; with the last two parameters we generated the initial gaussian membership functions (shown in Figure 2).

1. If (Sintomatología is Moderado) then (Diagnóstico is Moderado) (1)
2. If (Sintomatología is Sano) then (Diagnóstico is Sano) (1)
3. If (Sintomatología is Leve) then (Diagnóstico is Leve) (1)
4. If (Sintomatología is Severo) then (Diagnóstico is Severo) (1)

Fig. 1. Rules of fuzzy system.

In the subtractive model the parameter that was modified to obtain the four membership functions was the radius of influence.

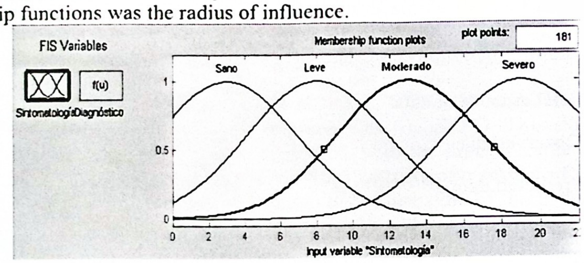

Fig. 2. Initial membership functions.

3.4 Optimization of membership functions

To optimize the Fuzzy Inference System created as the initial structure (previous stage), we used the backpropagation and hybrid learning algorithms; getting the best results with the hybrid ones. We started the neural network learning process and we allowed it to evolve through a certain number of iterations until we found the minimum testing error (view Figure 3).

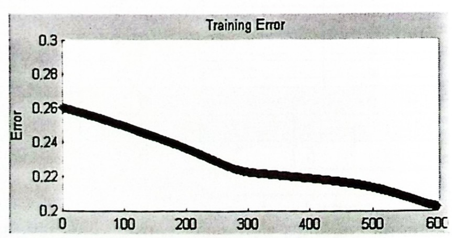

Fig. 3. Error during hybrid learning in 600 epochs or iterations.

The resulting membership functions after learning can be seen in Figure 4.

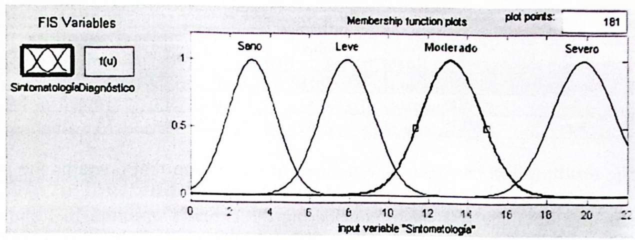

Fig. 4. Optimized membership functions.

Once the final FIS was defined, we verified the functionality of the system. As the threshold we used the central point between two types. Finally, we evaluated the answer of the ANFIS obtained from the testing data cluster (see results in the next section.)

4 Experimental Results

In this section we present the results of the classification of the data base of depression sets. These are based on total of errors and the RMSE. The interest for using both criteria: total of errors and RMSE, is that they show a different point of view about the models, and they allow a better selection of the classifier and, particularly, the selection of a model that generalizes better.

Table 4 shows test results when training took place with odd data and testing with even data. Therefore, the training took place with 50% of the data, and the testing with the other 50%; the latter being new data (unknown by the system). In Tables 4 and 5, in the Model column, HIB represents Hybrid and the corresponding number refers to the epochs or iterations used for the optimization of the membership functions.

Table 5 shows test results when trained with even data and tested with odd data. In Tables 4 and 5 the best results are shaded. In both cases the influence radio was 0.5. The best result is shown in Table 4, where learning happened through the hybrid method and 600 epochs or iterations, obtaining as the best result an RMSE test error of 0.20, corresponding to a total of 9 errors out of 215, indicating 4% error.

Table 4. Errors training with odd data and testing with even data.

Input data	Model	Influence radio	Test		
			RMSE	Total of errors	%
7	$\text{ANFIS}_{\text{HIB 600}}$	0.50	0.20	9	4
6-7	$\text{ANFIS}_{\text{HIB 60}}$	0.80	0.25	13	6
1-2-7	$\text{ANFIS}_{\text{HIB 137}}$	0.80	0.24	12	5

Table 5. Errors training with even data and testing with odd data.

Input data	Model	Influence Radio	Test		
			RMSE	Total Errors	%
7	$ANFIS_{HIB\ 600}$	0.50	0.22	10	5
6-7	$ANFIS_{HIB\ 60}$	0.81	0.25	14	6.5
3-6-7	$ANFIS_{HIB\ 80}$	0.83	0.23	11	5

The resulting FIS has been incorporated to the system that contains the user interface and the one that will be used by the end users.

The user interface was made considering the expert's opinion. In Figure 5 we show the aspect of the system main window, which has a graphic menu containing the main options to work on, these being: *Personal Data, Symptoms Entry, Evaluation, User Manual and Exit.*

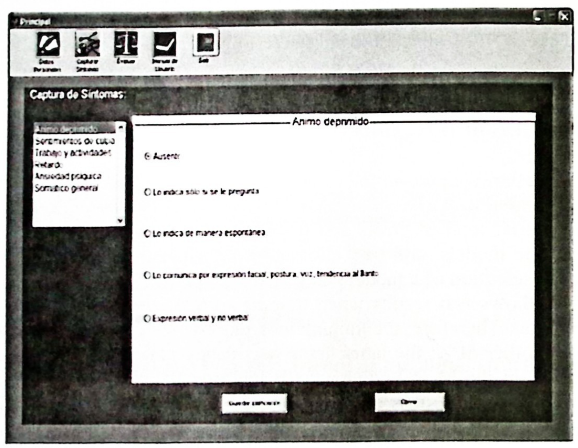

Fig. 5. Symptoms Entry.

The first option, *Personal Data,* allows the specialist to enter basic information that he/she possesses on the patient; such as: name, age, and sex. The data entered are saved in a file called *Diagnosticos* (Diagnoses) to be used in a later external consultation by the doctor.

During the interview with the patient, the doctor will ask several questions and make observations which will allow him/her to answer the survey when he/she presses the option *Symptoms Entry*. There are 5 options for each question, with the exception of the last question which offers only 3 options. When the doctor finishes this process he will have to press the option *Save Score*. By doing this, the doctor will be giving a value to each of the symptoms present in the patient (shown in Figure 5).

After entering the patient's general data and the depression symptoms present, the doctor will be able to enter the option *Evaluate* to see the diagnosis obtained by the system. If the option *Open* is selected, a window will open, as shown in Figure 6, where an image representing the Input data set of the system will be shown, this combined with the file Training.FIS will show the result of the patient diagnosis.

In order to see the result, press the option *View Evaluation*. The results will be shown as in Figure 7: the log viewer graphically shows the rule activation and the exit compositions according to the value of the Input variables.

5 Conclusions and future research

In this paper we have presented the application of an ANFIS Neuro-Fuzzy model, to make a system which will serve as a tool for general doctors and specialists in the diagnosis of depressive illness. As we have seen, the selection and training of the classifier achieves a good percentage of recognition that in the best case was 96% and had nine errors of the 215 variables input; therefore, it can be considered a good solution for this kind of application.

The system has been demonstrated as a useful and simple tool to aid the doctor in his/her job. This system does not replace the expert in making a diagnosis; it is simply a tool to support a decision, because the final diagnosis is in the hands of the specialized doctor.

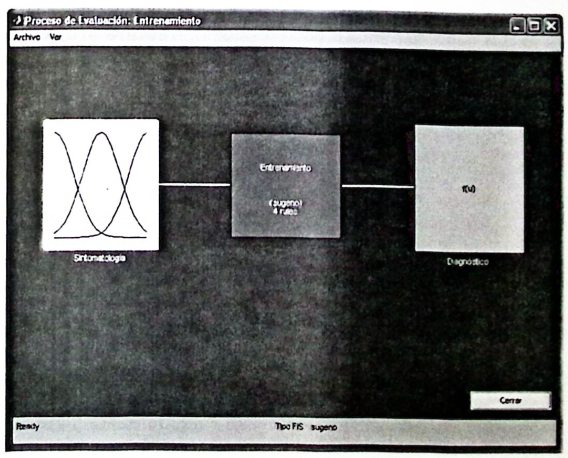

Fig. 6. Opening the training file.

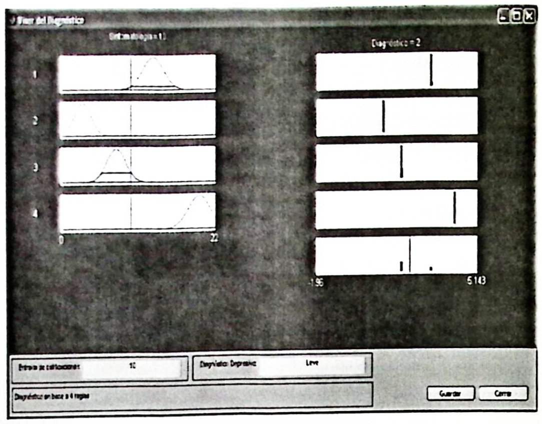

Fig. 7. Patient's Evaluated Diagnosis.

Afterwards, the system will include a mechanism to record patient entries, releases, modifications and consultations, making it an added tool to have a better control of the patient's record, to obtain statistical reports in order to know the tendencies of depressive levels by considering criteria such as age and sex. The ANFIS model used in this paper has shown good results, thus **future projects** could accept this methodology to develop systems for diagnosis of other illnesses related to Psychiatry or Psychology.

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