Chapter 7

From Fuzzy Expert System to Artificial Neural Network: Application to Assisted Speech Therapy

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Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/63332

Abstract

This chapter addresses the following question: What are the advantages of extending a fuzzy expert system (FES) to an artificial neural network (ANN), within a computer-based speech therapy system (CBST)? We briefly describe the key concepts underlying the principles behind the FES and ANN and their applications in assisted speech therapy. We explain the importance of an intelligent system in order to design an appropriate model for real-life situations. We present data from 1-year application of these concepts in the field of assisted speech therapy. Using an artificial intelligent system for improving speech would allow designing a training program for pronunciation, which can be individualized based on specialty needs, previous experiences, and the child's prior therapeutical progress. Neural networks add a great plus value when dealing with data that do not normally match our previous designed pattern. Using an integrated approach that combines FES and ANN allows our system to accomplish three main objectives: (1) develop a personalized therapy program; (2) gradually replace some human expert duties; (3) use "self-learning" capabilities, a component traditionally reserved for humans. The results demonstrate the viability of the hybrid approach in the context of speech therapy that can be extended when designing similar applications.

Keywords: fuzzy expert system, artificial neural network, assisted speech therapy, artificial intelligent system, hybrid expert system

1. Speech therapy: key concepts and facts

Dyslalia is a pronunciation deficiency manifested by an alteration of one or more phonemes due to several causes such as: omissions, substitutions, distortions, and permanent motor impairments. Dyslalia can be simple when it is related with only one sound (eventually in an attenuated form). An extension of pronunciation–articulation disorder related with more sounds and/or groups of syllables is called polymorphic dyslalia [1].

The existence of a dyslalia with defectological significance can be diagnosed after the age of four. Until that, dyslalia is called physiological and it is caused by the insufficient development of the speech-articulator apparatus and the neurological systems implicated in the speech process. This is the age that allows maximization of the therapeutic effects and offers a good prognosis for improvement/correction. The later the therapy begins, the weaker the effect [2].

There are many causes for dyslalia: the imitation of persons with deficient pronunciation, lack of speech stimulation, adults encouraging the preschool child to stabilize wrongful habits, defects in teeth implantation, different anomalies of the speech-articulator apparatus, cerebral deficiencies, hearing loss, weak development of phonetic hearing. Also, in severe dyslalias, heredity is considered an important factor in diagnosing and explaining this deficiency.

Impairment type		**Number of subjects**	**Impairment frequency (%)**	**Overall impairment frequency (%)**
Dyslalia		434	91.2	14.8
Dysarthria		–	–	–
Rhinolalia		7	1.5	0.2
Reading-writing difficulties		–	–	–
Rhythm and fluency difficulties		17	3.7	0.6
Language impairments	Selective mutism	4	0.8	0.1
	General development delays	8	1.6	0.3
Voice impairments		–	–	–
Language impairments in association with:	Autism	4	0.8	0.1
	Down syndrome	2	0.4	0.1
	Intellectual deficiencies	–	–	–
	Deafness	–	–	–
Total		476	100.0	16.2

Table 1. Speech and language impairments distribution (unpublished data from Suceava—Romania Regional Speech Therapy Centre).

In dyslalia, the sounds are not equally affected. Thus, the sounds most affected are the ones that appear later in the child's speech: vibrant—r (very important in Romanian language), affricates—c, g, t, hissing—s, z. In fact, the sounds mostly affected are the ones that require a greater effort to synchronize the elements of the phono-articulator apparatus (elements engaged in the emission of sounds: larynx, vocal cords, tongue, lips, teeth, and cheeks). Their pronunciation involves a certain position of all these elements and a certain intensity of the exhausted air jet [1].

Regarding the frequency of speech impediments and especially the frequency of dyslalia, the statistics from the Suceava Romanian Regional Speech Therapy Centre (**Table 1**; **Figure 1**) reveals the following aspects [2]: (i) Disorders that affect speech are more frequent that the ones affecting the language; (ii) Dyslalia is the most frequent pronunciation disorder, with sounds r and s most affected; (iii) the proportion of children with speech impediments:

- Decreases constantly until first grade;
- Suddenly decreases between first and second grade;
- Decreases slower and slower between second and fourth grade.

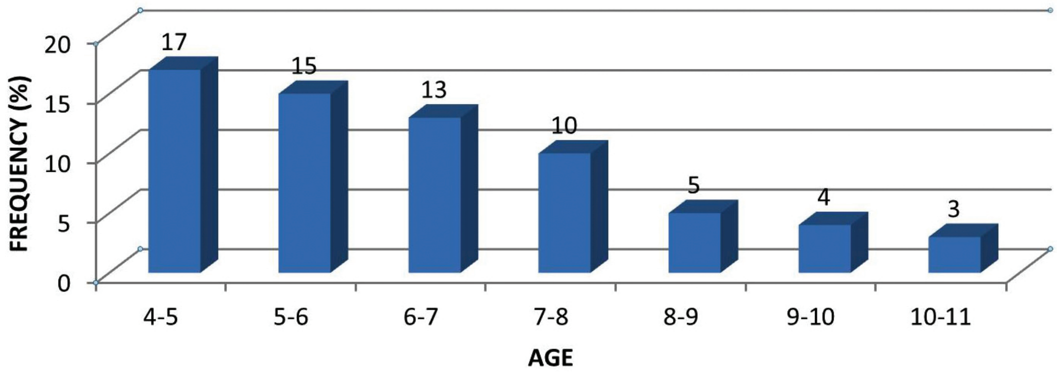

Figure 1. Evolution of speech impairments frequency across subjects' age.

The characterization of the dyslalia dynamics is of great interest also, in regard to the age of the subjects as depicted in **Figure 1**. Before age four no logopedic evaluation was conducted for children since possible speaking problems might be due to insufficient maturation of the phono-articulatory organs and of the involved cortical areas.

After this age, children with speech impairments are integrated in the speech therapy programs. The therapy determines the progressive decrease of the proportion of children with speech problems in relation to their age. At the beginning of the school, the frequency of children with speech disorders decreases suddenly, mainly because of the acquisition of writing and reading skills. Moreover, the corrective effort from the teaching community is highly emphasized. After this age, language disorders are present mainly in children with organ related disorders—structural disorders of the central or peripheral organs of speech.

The main steps of speech therapy together with the place of fuzzy expert system in therapeutic process are presented in **Figure 2**. Each therapy process contains a formative evaluation, which can be followed by the therapy within the family. After 3 months, the speech therapist can finalize the therapy or can reevaluate it [3].

The expert system incorporates information generated from social, cognitive, and affective examination, as well as from the homework reports and results' trends [4]. This allows the expert system to provide critical answers related to the length and frequency of the therapy session as well as the type of exercise to be used and its content.

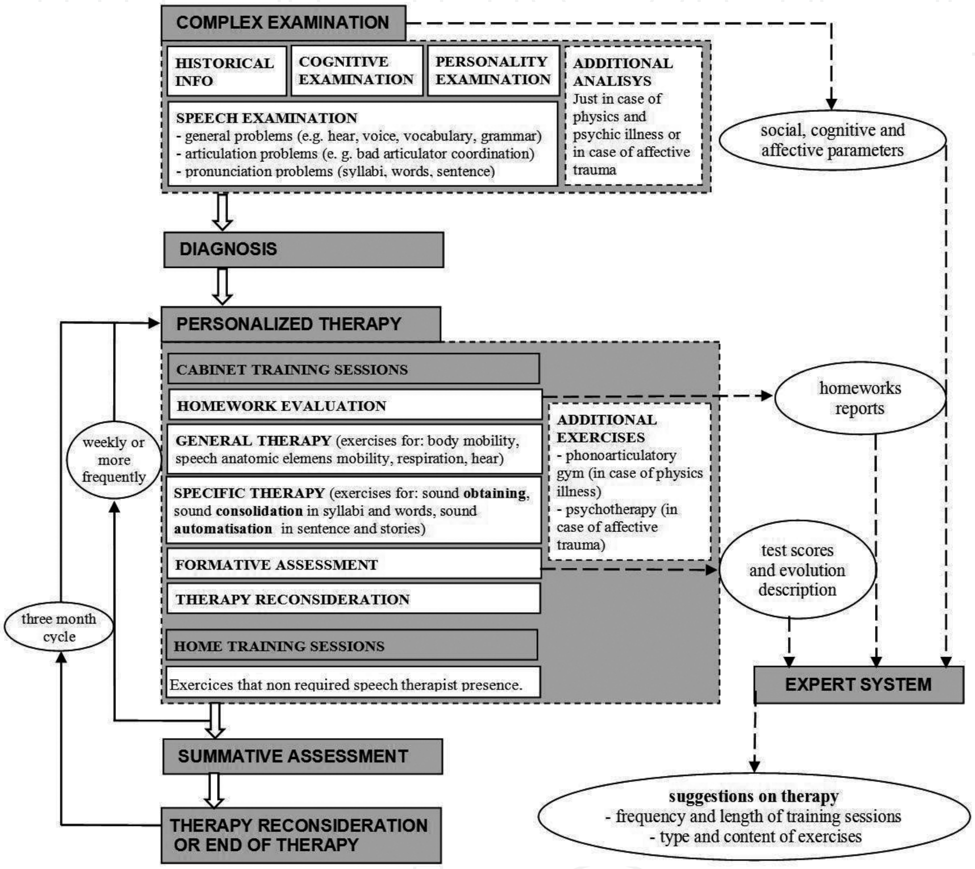

Figure 2. Speech therapy process and fuzzy expert system [3].

The therapy customization assumes a differentiated report related to the therapy stages. Thus, for each subject, there are different weights for each stage within the program structure. The therapy is generally a formative assessment because the speech therapists permanently evaluate the evolution of the patient during the exercises. The therapy is continued in familial environment during home training sessions. Thus, between the weekly sessions, family must provide the child with the adequate environment to consolidate the skills initiated at the specialty clinic.

A summative assessment is conducted every 3 months, and the child's evolution is analyzed over a longer period of time. This is the time for the reconsideration of the therapy and, eventually, for finalizing the therapeutic process.

The expert system is designed to function as a true assistant of the speech therapist. It provides suggestions based on several recordings from the integrated system. Moreover, depending on the assessments performed by the speech therapist at each session and on the homework solving, the human expert receives suggestions regarding the most appropriate exercises to recommend [5].

It is necessary for the speech therapist to have the possibility to intervene in modifying the knowledge database when the suggestion given by the expert system contradicts the speech therapist decision. The system has to self-notify the presence of a contradiction and to ask the human expert to remove the conflict. This principle is useful for the therapeutic system (in general) and for the expert system (in particular), especially in the case of the beginner speech therapist (with less practical training experience). Even if the computer decisions cannot be considered absolutely correct, they can contribute to the overall success of the therapy by raising questions which require further clarifications by consulting a human expert.

2. Expert system validation

Since 2006 we have developed Logomon, the computer-based speech therapy system (CBST) for Romanian language. The modules of the integrated system are briefly presented in **Figure 3** (modules 1,…,9). All administrative tasks are grouped in the Lab Monitor Application. The expert system takes the information it needs from the database of this module. In the first scenario, the child exercises in SLT's Lab using Lab Monitor Application.

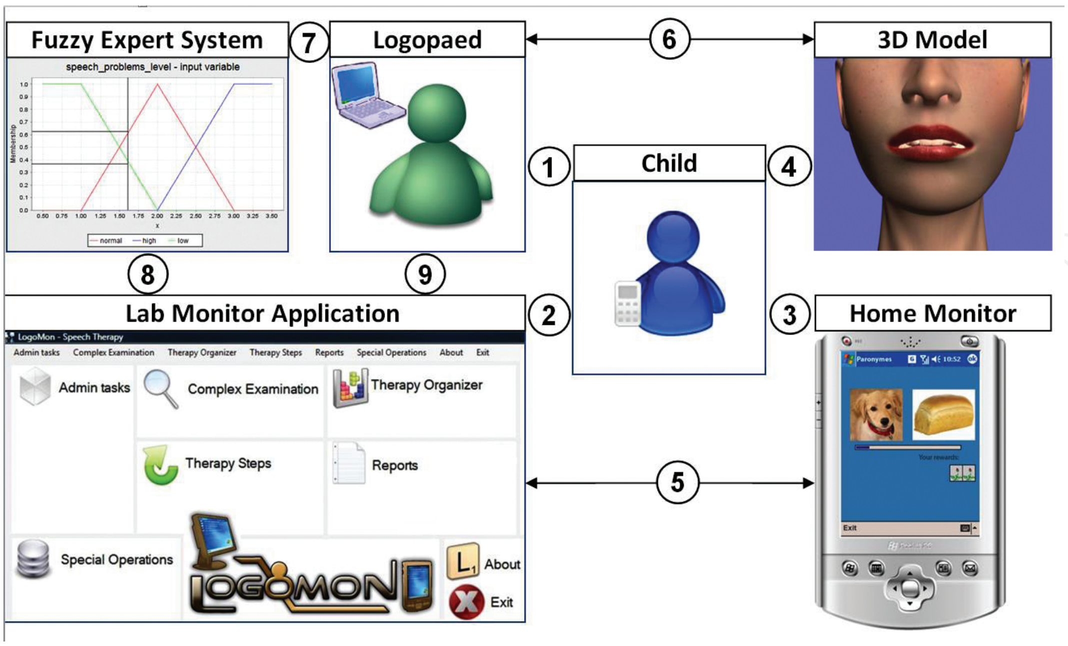

Figure 3. Architecture of Logomon CBST.

Another scenario involves the utilization of a dynamic 3D model, a module that indicates the correct positioning of elements of phono-articulator apparatus for each phoneme in Romanian language (the model can translate and rotate; the transparency of each individual elements—teeth, tongue, cheeks—can also be modified). Homework is mainly generated by the fuzzy expert system that indicates the number, the duration, and the content of home exercises. These exercises are played on a mobile device (Home Monitor), without SLT intervention [6]. The relations between input and output variables are presented in **Figure 4**.

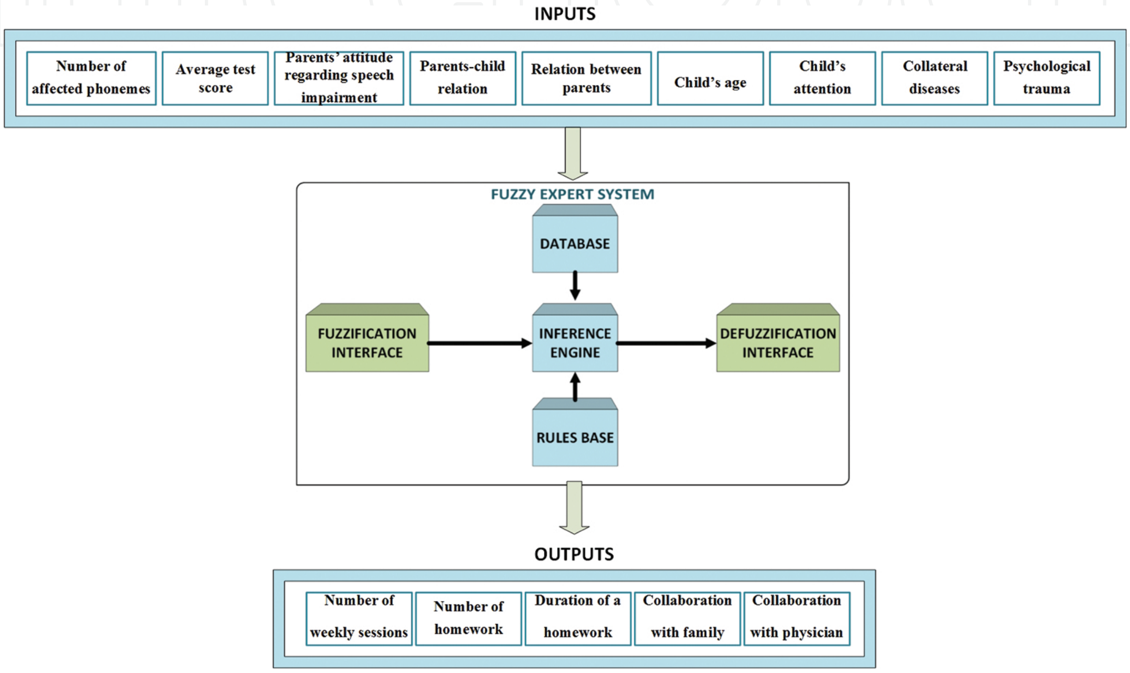

Figure 4. The relation between input and output variables.

The expert system is fed with information taken from three sources: socio-psychological parameters (Lab Monitor Application), tests scores (Lab Exercises), and homework scores (Home Monitor). These numbers are grouped in nine input variables [3].

1. number of affected phonemes (in order to differentiate between simple and polymorphic dyslalia);
2. average test score (indicates the intensity of impairment);
3. parents' attitude regarding speech impairment (the parents' attitude is a key factor in therapy prognosis);
4. parents–child relation (offer important clues regarding the importance of home training sessions);
5. relation between parents (describes the emotional quality of familial environment);
6. child's age (the therapeutical strategy largely vary with subject's age);

7. child's attention (this variable was taken into consideration due to increasing frequency of ADHD—attention deficit disorders—among the children);
8. collateral diseases (AIDS, Down syndrome, intellectual disabilities, nutrition diseases);
9. psychological trauma (shows the child's emotional health).

The expert system outputs five numbers that configure the personalized therapy:

1. number of weekly sessions (how many times in a week the child should encounter SLT?);
2. number of homeworks (how many homework sessions should be?);
3. duration of a homework (how long a homework should last?);
4. collaboration with family (should SLT rely on child's family support?);
5. collaboration with physician (does SLT have to collaborate with a physician?).

One major limitation of such a system is the inability to express and/or mimic emotions such as empathy and to recognize emotional states. To improve this, some studies used the human–computer interaction (HCI) model in which trained individuals reflecting a particular emotional state are used. In our previous work, we explored the possibility of adapting and integrating the classical techniques of emotion recognition in the assisted therapy for children with speech problems [6].

The fuzzy expert system is based on forward chaining of over 200 rules written in fuzzy control language (FCL). The expert system engine is coded in Java language and is integrated in our speech therapy platform. In order to adjust and validate the inferential process, we used our platform for more than 100 children from 2008 to 2015. The extension of our system using an artificial neural network (ANN) is demanding especially because it is relative hard for a SLT to change a fuzzy rule. Thus, in the case of a contradiction between human and artificial expert, an ANN could facilitate the re-training process [7, 8].

3. State of the art in fuzzy expert systems, artificial neural network and medical application

Because of the emergence of interdisciplinary technologies during the past few years, the interaction between doctors and engineers opened unprecedented opportunities, and the medical specialists are employing computerized technologies to assist in diagnosis of, and access to, related medical information.

3.1. Fuzzy expert systems for medical diagnosis

The rapid progress in computer technology plays a key role in the development of medical diagnostic tools that call for the need of more advanced intelligent and knowledge-based systems [9]. This is important since medical diagnosis is characterized by a high degree of uncertainty that can be improved through the application of fuzzy techniques that provide powerful decision support, expert systems knowledge, and enhanced reasoning capabilities in the decision-making process. Also, it provides a powerful framework for the combination of evidence and deduction of consequences based on knowledge stored in the knowledge base [9]. Therefore, fuzzy expert system (FES) can be used in applications for diagnosis, patient monitoring and therapy, image analysis, differential diagnosis, pattern recognition, medical data analysis [10–14].

The areas in which diversified applications are developed using fuzzy logic are fuzzy models for illness, heart and cardiovascular disease diagnosis, neurological diseases, asthma, abdominal pain, tropical diseases, medical analogy of consumption of drugs, diagnosis and treatment of diabetes, syndrome differentiation, diagnosis of lung and liver diseases, monitoring and control in intensive care units and operation rooms, diagnosis of chronic obstructive pulmonary diseases, diagnosis of cortical malformation, etc. The non-disease areas of applications are in X-ray mammography, interpretation of mammographic and ultrasound images, electrographic investigation of human body. Other areas for the applications of fuzzy logic are prediction of aneurysm, fracture healing, etc.

Recent research studies have contributed to the development of diagnostic techniques, quantification of medical expertise, knowledge technology transfer, identification of usage patterns, and applications of FES in practice by the medical practitioners [15]. According to [15], 21% of studies present the development of methodologies and models and 13% studies contributed to the development of neuro-fuzzy-based expert systems [9]. These studies contributed to the development of innovative diagnostic techniques, quantification of medical expertise, and application of fuzzy expert systems and their implementation in practice.

The rationale behind the decision-making process in medical diagnosis is a complex endeavor that involves a certain degree of uncertainty and ambiguity. The computer-assisted expert system that incorporates the fuzzy model has been used to aid the physician in this process [15]. As such, several computer-assisted applications for patient's diagnosis and treatments as well as web-based FES have been recently developed and include ways of handling vagueness

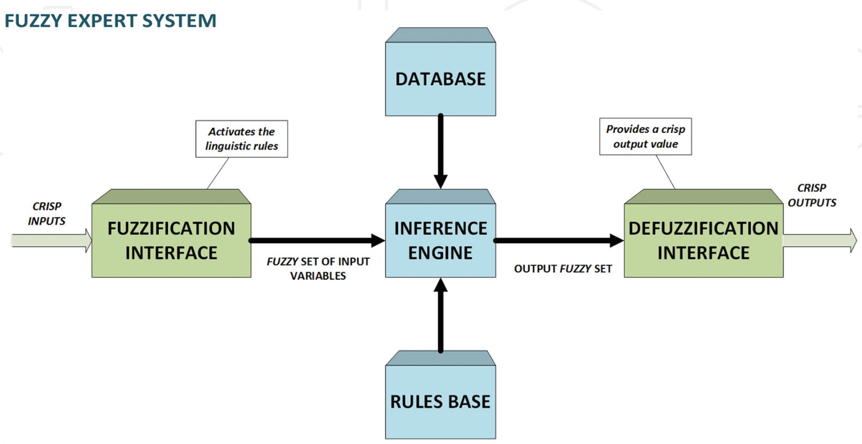

Figure 5. Fuzzy *e***xpert** system architecture.

and complexity (**Figure 5**). Furthermore, disease-focused intelligent medical systems are rapidly emerging and are designed to handle more complex variables such as patient monitoring, predictive values, as well as taking into account assessment and performance parameters.

The architecture of a generic medical fuzzy expert system showing the flow of data through the system is depicted in **Figure 6** [9]. The knowledge base for developed medical FES contains both static and dynamic information. There are qualitative and quantitative variables, which are analyzed to arrive at a diagnostic conclusion. The fuzzy logic methodology involves fuzzification, inference engine, and defuzzification as the significant steps [9].

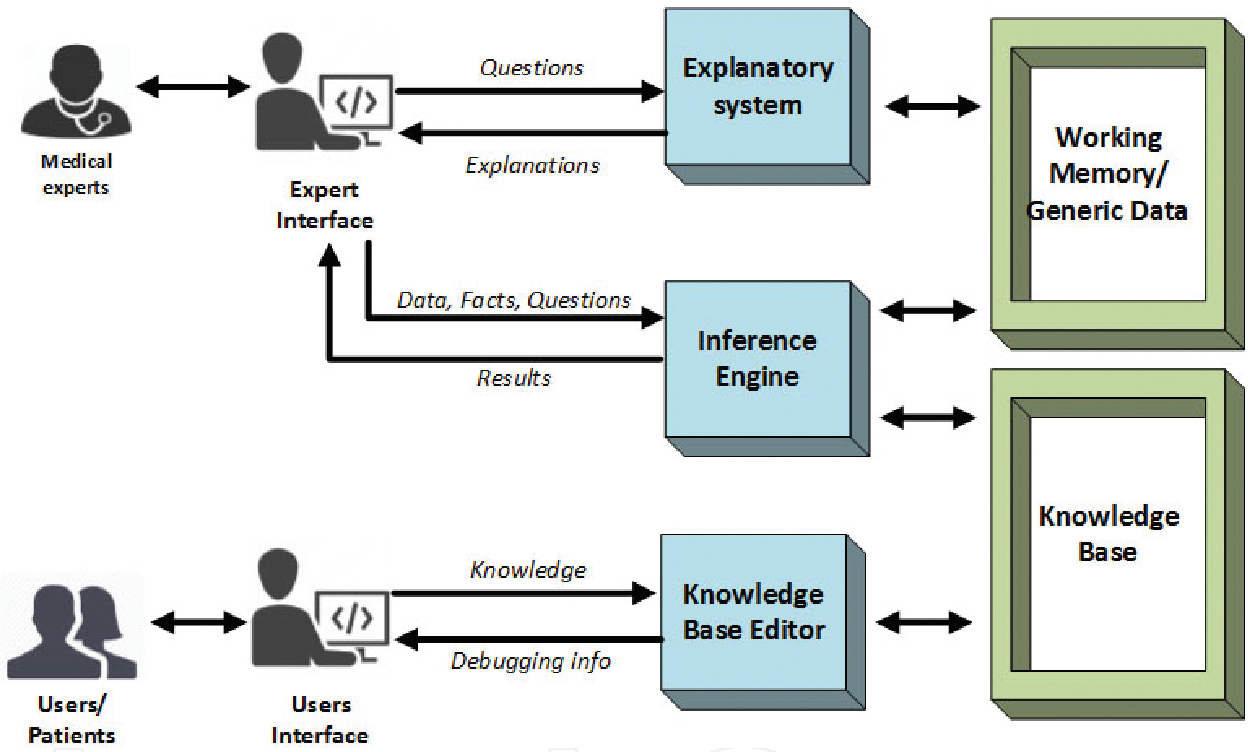

Figure 6. The architecture of a generic medical fuzzy expert system.

The FES uses both quantitative and qualitative analyses of medical data and represents a useful tool in achieving a high success rate in medical diagnosis. These computer-based diagnostic tools together with the knowledge base have proved very useful in early diagnosis of pathologies. On the other hand, the web-based applications and interfaces allow health practitioners to readily share their knowledge and know-how expertise [15].

3.2. Application of artificial neural network in medicine

An artificial neural network (ANN) is a computational model that attempts to account for the parallel nature of the human brain [16]. Analyzing approaches in different scientific procedures, the ability to learn, tolerance to data noises and capability to model incomplete data have made them unique, and once the network has been trained, new data in similar domain may be analyzed and predicted [17].

In the medical field, ANN applications that have been developed use the "classification" principle-based on which patients are assigned to a particular set of classes based on specific biological measures. For example, ANN applications have been used in the diagnosis of diabetes (using blood and urine analyses) [18, 19], tuberculosis [20, 21], leukemia [22], cardiovascular conditions [23] (such as heart murmurs [24]), liver [25], and pulmonary [26] diagnosis, as well as in urological dysfunctions [27], including expert pre-diagnosis system for automatic evaluation of possible symptoms from the uroflow results [28], and ANN applications have also been used in image analyses [29, 30] and in analysis of complicated effusion samples [31]. Finally, a neural networks-based automatic medical diagnosis system has been developed for eight different diseases [32], and in detection and diagnosis of micro-calcifications in digital format mammograms [33].

An ANN is a network of highly interconnecting processing elements (inspired by biological nervous systems—neurons) operating in parallel. The connections between elements largely determine the network function. A subgroup of processing element is a layer in the network. Each neuron in a layer is connected with each neuron in the next layer through a weighted connection [34]. The structure of a neural network is formed by layers. The first layer is the input layer, and the last layer is the output layer, and between them, there may be additional layer(s) of units (hidden layers) [16]. The number of neurons in a layer and the number of layers depend strongly on the complexity of the system studied [34]. Therefore, the optimal network architecture must be determined. The general scheme of a typical three-layered ANN architecture is illustrated in **Figure 7**.

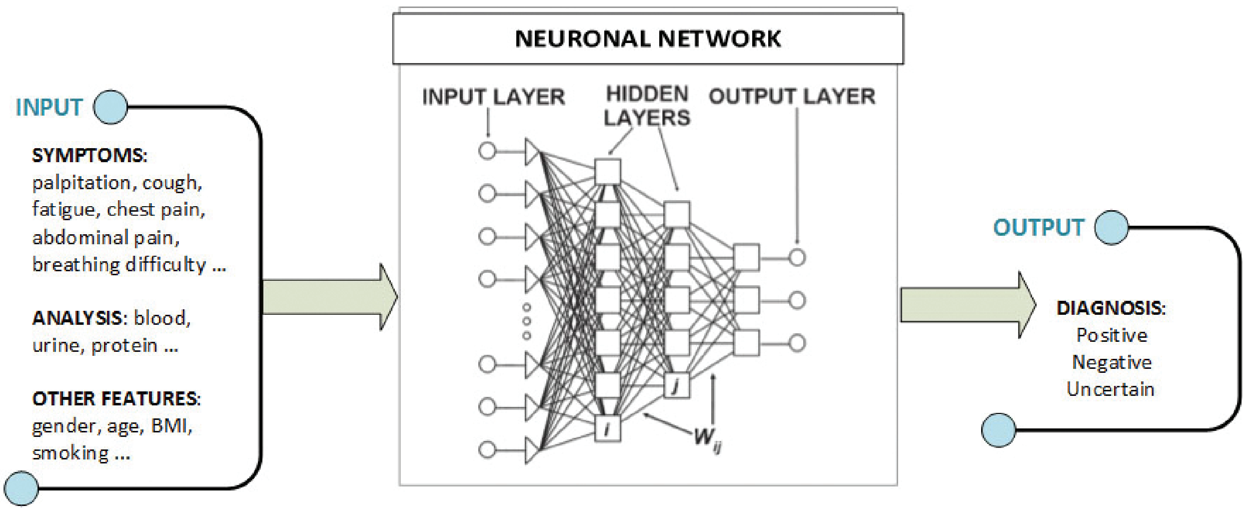

Figure 7. General structure of a neural network (modify after [34]).

Based on the way they learn, all artificial neural networks are divided into two learning categories: supervised and unsupervised. In unsupervised networks, the training procedure uses inputs only, and there are no known answers and the network must develop its own representation of the input stimuli by calculating the acceptable connection weights. On the other hand, training in the supervised learning involves both input and output patterns so that the neural weights can be changed to generate the desired output [16]. In medical applications, supervised networks may be used as alternatives to conventional response surface methodology (RSM) while the unsupervised ones can serve as alternatives to principal component analysis (PCA) in order to map multidimensional data sets onto two-dimensional spaces [17].

Models from ANNs are multifactorial models which can predict, classify, approximate function, or recognize patterns. Theoretically, ANNs are able to estimate any function and if used properly, it can be used effectively in medicine. Outputs from artificial neural networks models are generated from nonlinear combinations of input variables, and such models can be effectively employed to deal with experimental data routinely observed in medicine and to find rules governing a process from raw input data [17].

3.3. Neuro-fuzzy models

The development of intelligent systems in the health field is based on the complementarity between technologies that use the combination between fuzzy logic and neural networks models. This generated the neuro-fuzzy model that takes advantage of both the capability in modeling uncertain data by the artificial neural networks as well as of handling qualitative knowledge. The neuro-fuzzy approaches have been used in several studies to build more intelligent decision-making systems as additional supportive tools for the physicians.

For example, an application of artificial neural networks in typical disease diagnosis using a fuzzy approach was investigated in [35]. The real procedure of medical diagnosis which usually is employed by physicians was analyzed and converted to a machine implementable format. Similarly, in [16], a series of experiments were described and advantages of using a fuzzy approach were discussed.

Neuro-fuzzy (NF) computing becomes a popular framework for solving complex problems based on knowledge expressed in linguistic rules for building a FES, and on data, for learning from a simulation (training) using ANNs. For building a FES, we have to specify the fuzzy sets, fuzzy operators, and the knowledge base. For constructing an ANN for an application, the user needs to specify the architecture and the learning algorithm. Both approaches have their own drawbacks, and they should be combined when building an integrated system [36]. This way we can take advantage of the learning capabilities, which is essential for the fuzzy expert system as well as the linguistic base knowledge that constitutes part of the artificial neural networks.

Therefore, FES and ANNs have attracted the attention of many scientists, and also a huge number of successful applications of them are found in the literature, reporting problems solving in various areas of sciences, such as computing, engineering, medicine, nanotechnology, environmental science, and business.

4. Fuzzy expert system vs. neuro-fuzzy expert system

The fuzzy expert systems (FES) and artificial neuronal network (ANN) have common origin and purposes. They may carry out the logical reasoning, simulating artificial intelligence, by combining the quantitative and qualitative information and meta-knowledge. The advantages and disadvantages of these techniques are complementary. The main disadvantages of FES as regards to the acquisition of knowledge can be easily eliminated using ANN, due to its ability to learn from typical examples. On the other hand, limitations of the ANN related to the man–machine interface and capabilities to explain the reasoning leading to a certain conclusion can be theoretically compensated using the FES [10].

The FES has the following properties: (i) sequential processing; (ii) the acquisition process of knowledge takes place outside the expert system; (iii) the logic is a deducible; (iv) the knowledge is presented in the explicit form; (v) the system is based on the knowledge acquired from human experts; (vi) the rules in the chain of the rules have their origin in the logic of mathematics and fuzzy logic; and (vi) the extraction of the conclusion (implementation of the diagnosis) is done by correlating the exact amount of information and data [10].

The ANN, due to the fact that is designed according to the model of the human brain, has the ability: (i) to learn; (ii) has the advantage of a parallel processing; (iii) the acquisition of knowledge takes place inside the system; (iv) the logic is inductively; (v) the knowledge is the default and gained through examples; (vi), uses parameters and statistical methods for classification and data clustering; and (vii) the extraction of the learned conclusion is made by the approximate correlation of data.

A significant difference between the two instruments lies in the basis of reasoning. As such, the FES is based on the algorithms and deductions, while the ANN is based on the inference from simulating the learning mechanisms of specialized neurons. Based on the techniques used for processing information, the ESF uses sequential methods of processing while ANN has parallel processing, that is, each neuron performs functions in parallel with other neurons in the network.

In the case of learning processes and reasoning in the FES, learning is made outside of the system and the knowledge is obtained from outside and then coded in the knowledge base. For ANN, the knowledge accumulates in the form of weights of the connections between the nodes (neurons), the learning process being internal, permanently adjusting the knowledge deployments as new examples. The FES is based on the method of deductive reasoning, unlike the ANN, in which the methods are inductive. The algorithms of inference of the FES are based on the logic of the sequence "forward or backward" method in the knowledge base, and the ANN uses the approximate correlation of the components of the knowledge base in order to return to items previously learned. The ANN may acquire knowledge through direct learning from examples, which constitutes an advantage, on the basis of algorithms of specific learning with the possibility to learn from the incomplete or partially incorrect or contradictory input data, having the capacity to generalize. On the other hand, the FES has the advantage of a friendly user interface with the possibility of incorporating elements of heuristic reasoning.

One of the basic paradigms of artificial intelligence, with applications in the medical field, is to find a tool which will make it possible to the representation of a large number of meta-knowledge, consistent, and usable for the user. There are two approaches of a computerized system based on knowledge: the first approach is one in which the field of knowledge representation is based on the rules. This involves the necessity that human experts extract rules from its experience and express them in the form of explicit and comprehensible rules. The system has the explanatory and perfect skills and performs well with incomplete information and inaccurate (fuzzy) using the factors of trust, but the construction of such base of knowledge is a difficult task.

The second approach has a connection with the development of the theory of the neuronal networks which is automatically created by a learning algorithm from a variety of inference examples. The knowledge representation is based on the weights of the connections between the neurons. Due to the default representation of knowledge, there is no possibility to identify a problem at the level of the singular neuron. In this case, both working with incomplete information and the provision of evidence of the inference are limited.

From these considerations, combining fuzzy expert system with the neuronal networks will lay the base for the construction of a practical application for strategic decisions, (especially medical decisions), both tactical and operative, and will integrate the advantages of both types of information systems (neuro-fuzzy system expert) [10].

The main challenge in the integration of these two approaches is the creation of the knowledge base when they are only available the rules and examples of data. Additional problems may also occur when incomplete and unreliable information is encoded in neuronal networks. Therefore, it is necessary that the "learning" network is able to work with incomplete information during training in place of using of special heuristic inference.

The inputs and outputs values in a neuro-fuzzy expert system are coded using the analog statuses of neuronal values. An inference is a pair consisting of a vector of the typical inputs and the vector to the corresponding outputs obtained by the expert answers to these questions. Knowledge base of the neuro-fuzzy expert system is a multilayer neuronal network.

To solve the problems raised by the irrelevant values and unknown inputs and outputs of the expert system, the range neuron should be created. The value of the irrelevant or even unknown input and output of the expert system is coded using the full range of status of neurons.

The expert systems become effective and efficient not only to resolve problems of high complexity but also for the decision-making problems, which contain a high degree of uncertainty.

More recently, a hybrid system that includes fuzzy logic, neuronal networks, and genetic algorithms has been developed this required inclusion of additional techniques. The fundamental concept of these hybrid systems consists in complementarity and addresses the weaknesses of each other. The fuzzy expert systems are appropriate especially in the case of systems that have a mathematical model that is difficult to comprehend, for example, when the values of the inputs and of the parameters are vague, imprecise, and/or incomplete. It facilitates the decision-making process in the case of use of the estimated values for the inaccurate information (if the decision is not correct, it may be modified later when more information becomes available). Fuzzy models allow us to represent the descriptive phrases/ qualitative, which are subsequently incorporated in the symbolist instructions (fuzzy rules).

Neuro-fuzzy expert system has the following two functions: (i) the generalization of the information derived from the training data processed by the entries with fuzzy learning and incorporation of knowledge in the form of a neuronal fuzzy network; (ii) the extraction of fuzzy rules "IF THEN" using the importance of linguistic relative diversity of each sentence in a prerequisite ("IF" part), using for this purpose a trained neuro-fuzzy network. The neural network is similar to the standard multilayer network, having in addition, direct connections between the input and output nodes. Activation of nodes is muted, taking the values of +1, 0, or -1.

To work with various fuzzifications in the input and the output layers of the system, it is necessary to interpret the subjective input data. The neuronal network may include groups of fuzzy neurons and groups of non-fuzzy neurons involving shades and accurate data. The output layer will contain only fuzzy neurons.

By incorporating the factor of certainty (groups of non-fuzzy neurons) extends the traditional logic in two ways: (i) sets are labeled from the point of view of quality, and the elements in the same set are assigned different degrees of membership; (ii) any action which results from a valid premise will be executed with a weighting in order to reflect the degree of certainty.

The entrances of the system "suffer" three transformations to become exits: (i) fuzzification of the inputs which consists in the calculation of a value to represent the factor of membership in the qualitative groups; (ii) assessing the rules that consists in the elaboration of a set of rules type "IF THEN"; (iii) outputs defuzzification in order to describe the significance of vague actions through the functions of membership and to resolve the conflicts between competing actions which may trigger [10].

The factor of membership is determined by the function of membership, which is defined on the basis of intuition or experience. To implement a fuzzy system, the following data structure is required: (i) the entries in the system; (ii) the functions of the input membership; (iii) the previous values; (iv) a basis for the rules; (v) the weightings of the rules; (vi) the functions of the output membership; and (vii) exits from the system.

The use of fuzzy logic leads to finding answers and allows drawing conclusions on the basis of vague, ambiguous, and inaccurate information. Fuzzy techniques adopt reasoning similar to human, which allows a quick construction of technical, feasible, and robust systems. The application of the fuzzy methods involves less space of memory and a lot of calculation power in comparison with conventional methods. This fact leads to less expensive systems. The fuzzy expert systems should be constructed in such manner that the overall results are able to change in a way that is smooth and continuous, regardless of the type of inputs. Artificial neural networks have the advantage that it can be included in the fuzzy expert systems, becoming parts of it in the framework of a hybrid neuro-fuzzy expert system. In the majority of the medical applications, the ANN can be used for quick identification of the conditions on the base of FES rules, laying down quickly the rules that should be applied for a given set of conditions.

In conclusion, the specialized literature presents several models of integrating the FES with ANN in the hybrid systems (neuro-fuzzy expert systems), with medical applications. In the strategy of the human expert (programmer), the ANN is driven to solve a problem, and then, the responses are analyzed in order to extract a set of rules. The integrated systems jointly use the data structures and knowledge. Communication between the two components is carried out with both the symbolic and heuristic information, FES characteristics, and with their ANN structures, that is, using weighted coefficients.

5. Results and discussion

To solve issues related to classification, the objects should be grouped in clusters (in our case patients with speech disorders) based on their characteristics (feature vectors) in predefined classes. Classifiers are then built from examples of correct classification by a supervised learning process as opposed to unsupervised learning, where categories are not predefined.

For the classifier design, based on examples of classification, we grouped data into three main sets:

- Training data: data used in the training process to determine the classifier parameters (for example, in the case of the artificial neural networks, it is necessary to determine the weights of connections between neurons) (1).
- Validation data: data used to analyze the behavior during learning algorithm; the performance on the validation set during the learning process is used to decide whether or not learning should be continued (2);
- Test data: used to analyze the performance of a trained classifier (3).

ANN is composed of simple elements operating in parallel. Knowledge of ANN is stored as numerical values that are associated with connections between artificial neurons, named weights. ANN training means changing and/or adjusting the weights values. Most often, ANNs are trained so that for a given input, output returns a value as close to the desired output, a process exemplified in **Figures 8** and **9**.

For this process, a set of training data (pairs input–output) is required. To solve classification problems, we used the tools package offered by Matlab R2014, specifically the neural network Matlab package (nntool—the tool for classification).

We used a feedforward architecture characterized in [37]:

- An entry level that has as many units (attributes) as the input data;

- One or more hidden levels (the higher the number of hidden units, the greater the complexity of the model extracted from the network; however, this can be a disadvantage leading to decreased network capacity to generalization process);
- A level of output with as many units as the number of classes.

There are two main types of artificial neural networks:

- feedforward—with progressive propagation; the main characteristic of these networks is that a neuron receives signals only from neurons located in previous layer(s).
- feedback—with recurrent or regressive propagation; these networks are characterized by the fact that there is a feedback signal from the higher-order neurons, for those on lower layers or even for themselves.

We used a feedforward network for illustration (see **Figure 9**).

To design a simple Matlab neural network for classification ("Pattern Recognition"), we used "*nprtool*" tool that opens a graphical interface that allows specification of a network element characterized by the following:

- a level of hidden units (the number of hidden units can be chosen by the user);
- the logistics activation (logsig) for both hidden units and for the output [(output values ranged between (0.1)];
- the backpropagation training algorithm based on minimization method of conjugate gradient.

The artificial neural networks have the ability to learn, but the concrete way by which the process is accomplished is dictated by the algorithm used for training. A network is considered trained when application of an input vector leads to a desired output, or very close to it. Training consists of sequential application of various input vectors and adjusting the weights of the network in relation to a predetermined procedure. During this time, weights of the connections gradually converge toward certain values so that each input vector produces the desired output vector. Supervised learning involves the use of an input–output vector pair desired [37].

After input setting, the output is calculated by comparing the calculated output with the desired output, and then, the difference is used to change the weights in order to minimize the error to an acceptable level. In a backpropagation neural network, learning algorithm has two stages: the training patterns for the input layer and the updated error propagation. The ANN propagates the training pattern layer by layer, until it generates the output pattern. If this is different from the desired target pattern, it will calculate the error and will be backpropagated from the output to the input. The weights are updated simultaneously with error propagation [37].

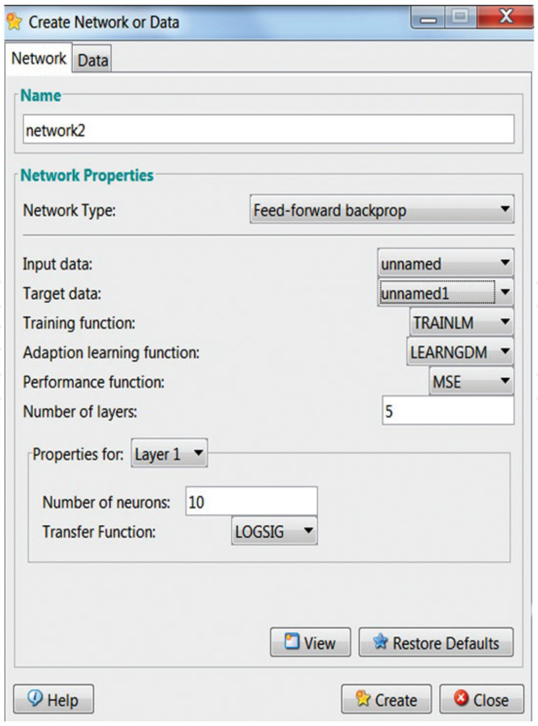

Figure 8. Create network using Matlab.

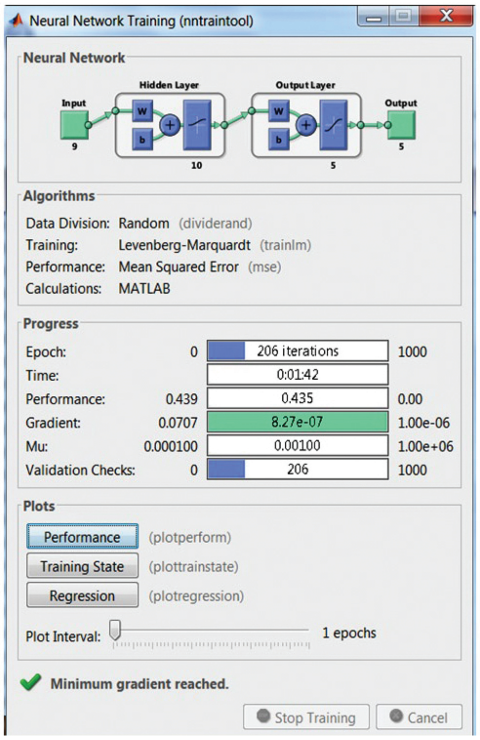

Figure 9. Neural network design and training.

The proposed artificial neural network uses supervised learning with two rules (see **Figures 10** and **11**):

1. extraction of a subset from the training dataset for testing dataset (not used during setting network parameters)

2. maintaining an acceptable level of error in the training set to avoid over learning (learning insignificant details of examples used for training).

The training process is controlled by means of a technique of cross-validation, which consists in splitting the initial random set of data in three subsets: for actual training (training); for controlling learning (validation); and for classifier's quality assurance (testing).

We used backpropagation as the correction algorithm (regressive propagation of errors) with propagation of the error signal in the opposite direction compared to how the signal travels during the working phase.

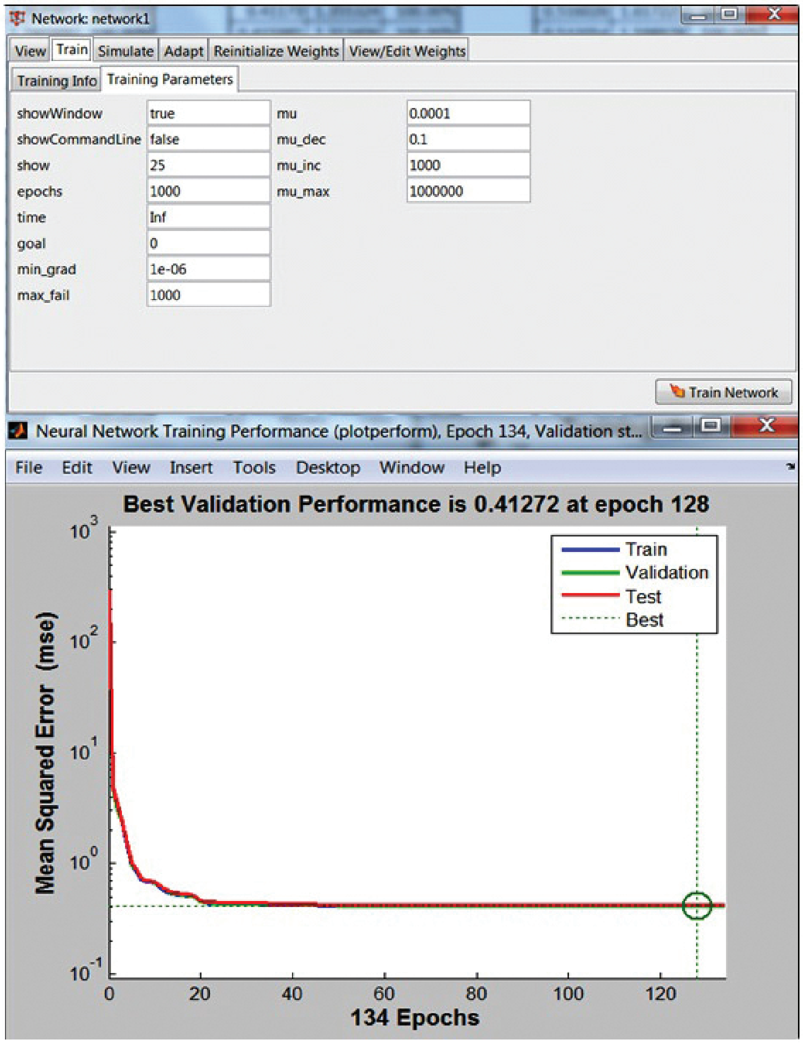

Figure 10. Network training parameters and best validation performance.

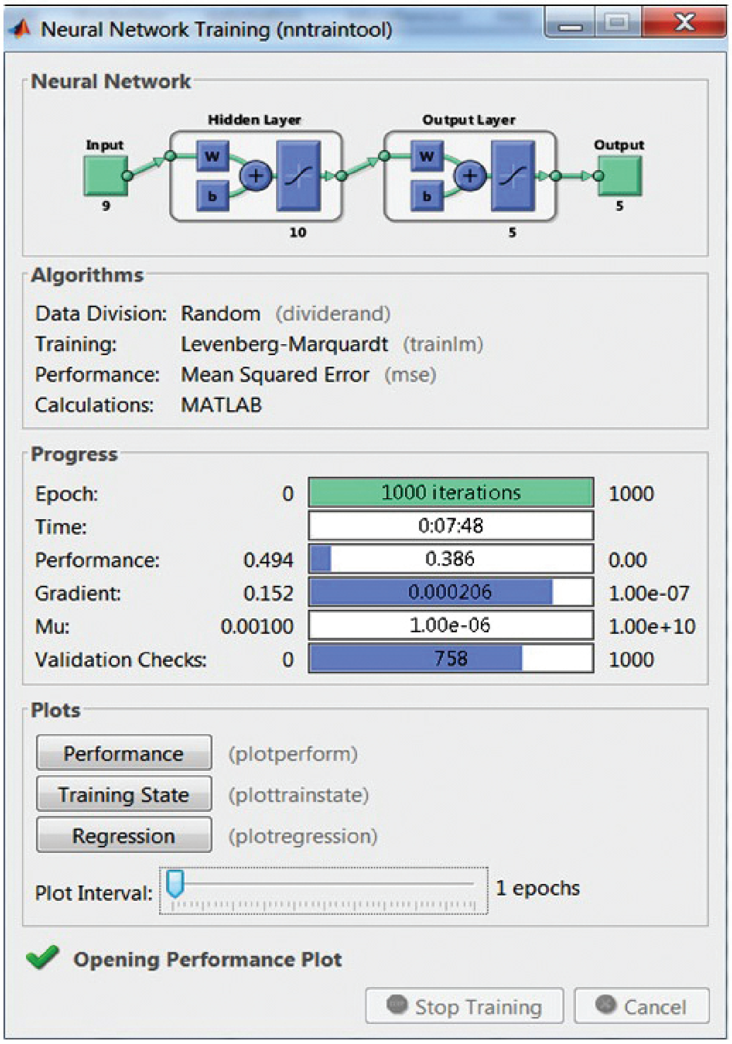

Figure 11. Neural network after 1000 iterations.

The training of the neural network lasted 1000 epochs. Matlab interface allows us to display graphs of the statistical parameters, for example, the mean square error, regression (the correlation between desired values and targets, and the values ??obtained; The R correlation close to 1 means a value very close?? to the desired one). Mean values ??for MSE and R are available after training in the main window, under Results section. Identification of classes of subjects from the dataset tested with ANN was achieved with high specificity and accuracy (see **Figures 12** and **13**).

One of the trivial artificial neural network is SOM—self-organizing map, which is mainly used for data clustering and feature mapping (see **Figures 14** and **15**).

The quality of a classifier in terms of correct identification of a class is measured using information from confusion matrix that contains the following:

- The number of data correctly classified as belonging to the class interests: true positive cases (TP);

- The number of data correctly classified as not belonging to the class of interest: true negative cases (TN);
- The number of data misclassified as belonging to the class of interest: false positive cases (FP);
- The number of data misclassified as not belonging to the class of interest: false negative cases (FN).

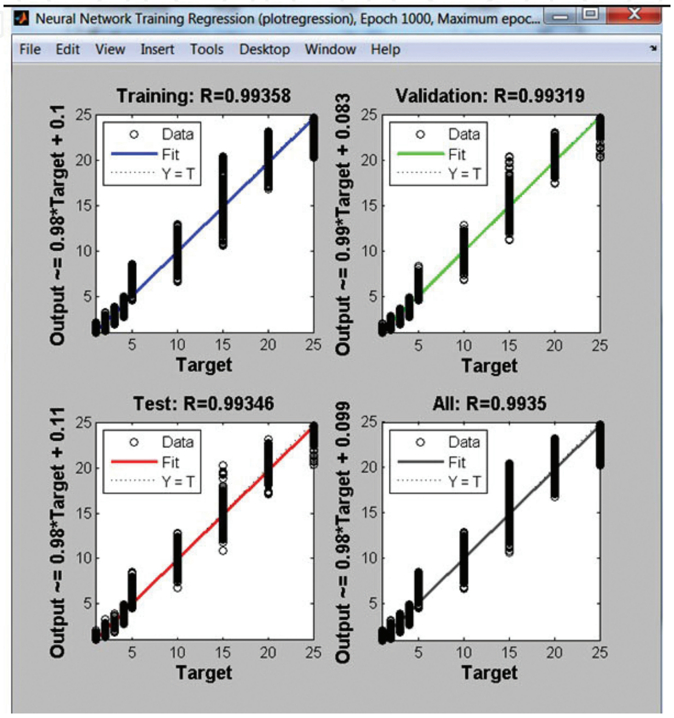

Figure 12. Neural network training regression.

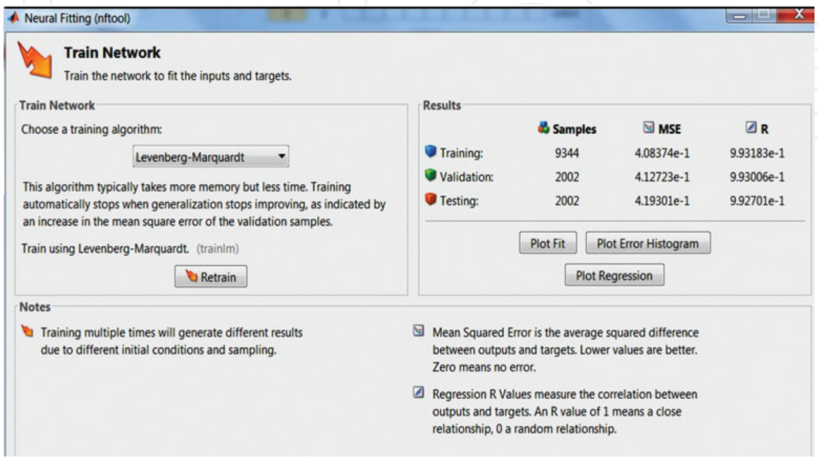

Figure 13. Train the network to fit the input and targets.

http://dx.doi.org/10.5772/63332

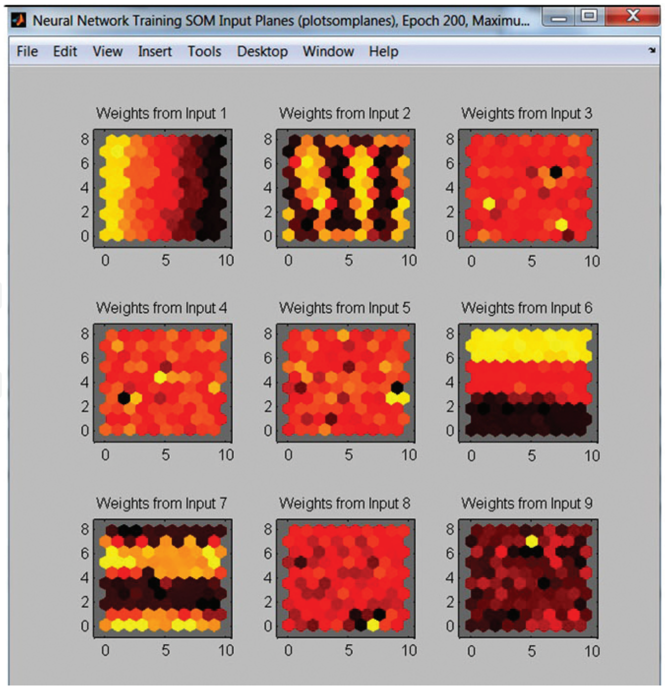

Figure 14. Neural network training self-organizing map (SOM) Input Planes, epoch 200.

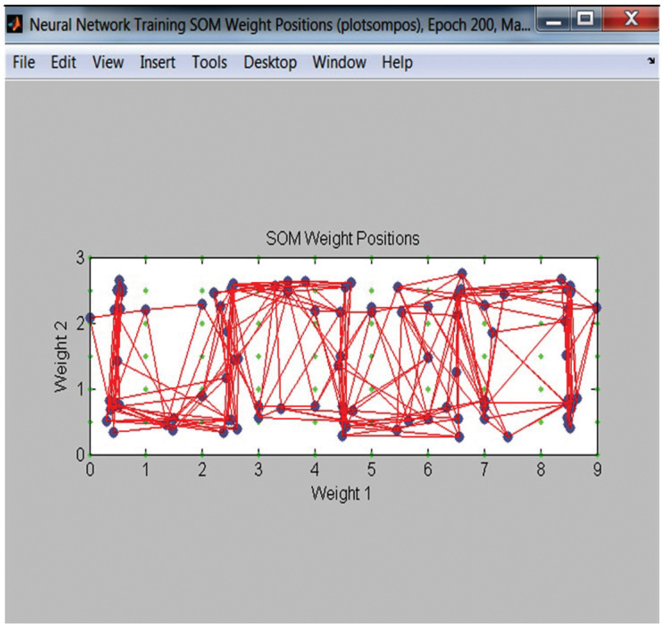

Figure 15. Neural network training Self-Organizing Map (SOM) Weight Positions, epoch 200.

Based on these values, we calculated the following measures:

$$\text{Sensitivity} = \text{TP}/(\text{TP} + \text{FN})$$

$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FP})$$

Precision = TP/(TP + FP)

Recall = TP/(TP + FN)

F = 2 × precision × recall/(precision + recall)

	Training			Cross Validation			Testing		
Model Name	**RMSE**	**r**	**MAE**	**RMSE**	**r**	**MAE**	**RMSE**	**r**	**MAE**
MLPR-1-O-M (Regression MLP)	0.508933	1.402201	0.409704	0.322604	0.922972	0.255361	0.358704	0.96404	0.290742
MLPC-1-O-M (Classification MLP)	0.327037	1.220537	0.244729	0.321762	1.156201	0.219466	0.40723	1.18764	0.282503
LinR-0-B-R (Linear Regression)	0.392882	1.147459	0.321291	0.436575	1.334644	0.352292	0.55806	1.462276	0.455368
LinR-0-B-L (Linear Regression)	0.392851	1.145372	0.321291	0.436507	1.329756	0.352205	0.557872	1.453303	0.455158
LogR-0-B-R (Logistic Regression)	0.392077	1.238948	0.325784	0.428968	1.46138	0.322088	0.527981	1.59547	0.390729
LogR-0-B-L (Logistic Regression)	0.39111	1.230656	0.327396	0.423441	1.447031	0.322429	0.519991	1.579243	0.3882
MLPR-1-B-L (Regression MLP)	0.387056	1.198567	0.317948	0.421741	1.419294	0.335343	0.519126	1.529009	0.411309
MLPC-1-B-L (Classification MLP)	0.38846	1.141375	0.319109	0.394126	1.255082	0.311733	0.487495	1.489909	0.383896
PNN-0-N-N (Probabilistic Neural Network)	0.085338	0.456856	0.04353	0.271987	1.451648	0.11348	0.280823	1.952781	0.10972
RBF-1-B-L (Radial Basis Function)	0.662088	1.442092	0.534637	0.650547	1.28424	0.540903	0.616498	1.289826	0.504839
GFFR-1-B-L (Reg Gen Feedforward)	0.271436	1.084635	0.219762	0.303184	1.088514	0.240272	0.415099	1.284186	0.334125
GFFC-1-B-L (Class Gen Feedforward)	2.311805	11.90048	1.371521	4.419387	11.95021	2.995643	5.125515	13.28726	3.688224
MLPRPC-1-B-L (Reg MLP with PCA)	0.881967	2.045036	0.720389	0.813134	2.04216	0.673859	0.836139	2.042751	0.688616
MLPCPC-1-B-L (Class MLP with PCA)	0.542446	1.381137	0.477375	0.545818	1.408567	0.499732	0.593192	1.471763	0.531133
SVM-0-N-N (Classification SVM)	0.978216	3.46208	0.775134	0.57077	1.854557	0.461521	0.37726	1.215167	0.319964
TDNN-1-B-L (Time-Delay Network)	0.379655	2.001422	0.316254	0.407738	1.357801	0.318339	0.492179	1.460222	0.374016
TLRN-1-B-L (Time-Lag Recurrent Network)	0.471094	1.868466	0.393253	0.495184	1.631292	0.411436	0.547943	1.703328	0.44724
RN-1-B-L (Recurrent Network)	0.425129	1.325358	0.351005	0.398425	1.612961	0.298228	0.478658	1.58024	0.350892
MLPR-2-B-L (Regression MLP)	0.320861	1.233744	0.265915	0.331135	1.207313	0.26449	0.357926	1.260343	0.284382
MLPC-2-B-L (Classification MLP)	0.315982	1.167649	0.247558	0.357427	1.398602	0.242102	0.458333	1.542289	0.307155
MLPR-1-B-R (Regression MLP)	0.301484	1.14782	0.229342	0.33914	1.300022	0.233399	0.436376	1.420916	0.29758
MLPC-1-B-R (Classification MLP)	0.329803	1.479794	0.266462	0.33202	1.113177	0.250788	0.399761	1.220224	0.297668
MLPR-2-O-M (Regression MLP)	0.221099	1.074964	0.120141	0.113037	0.961053	0.054785	0.151261	0.932933	0.064494
MLPC-2-O-M (Classification MLP)	0.348334	1.121105	0.268159	0.318955	0.867087	0.223579	0.369996	0.924195	0.258641
MLPR-2-B-R (Regression MLP)	0.203215	0.933993	0.137048	0.231383	0.966788	0.141672	0.246501	1.069248	0.143614
MLPC-2-B-R (Classification MLP)	0.384336	1.4615	0.321085	0.432656	1.692839	0.343492	0.523127	1.739074	0.407794
MLPRPC-1-O-M (Reg MLP with PCA)	0.945582	1.954717	0.778937	0.666084	1.83967	0.536057	0.712878	1.839316	0.576275
MLPCPC-1-O-M (Class MLP with PCA)	0.545546	1.582078	0.484669	0.521149	1.344116	0.495434	0.553071	1.412793	0.514216
MLPRPC-1-B-R (Reg MLP with PCA)	0.54491	1.34828	0.467731	0.557591	1.428227	0.475297	0.613538	1.527512	0.504508
MLPCPC-1-B-R (Class MLP with PCA)	0.540359	1.434408	0.479016	0.546114	1.337124	0.501908	0.571789	1.370814	0.517757
GFFR-1-O-M (Reg Gen Feedforward)	0.454291	1.575135	0.374846	0.375064	1.214175	0.291732	0.420285	1.159984	0.329084
GFFC-1-O-M (Class Gen Feedforward)	0.324176	1.029036	0.253448	0.313517	0.903713	0.226223	0.396962	1.007077	0.281022
GFFR-1-B-R (Reg Gen Feedforward)	0.338294	1.11053	0.282375	0.391334	1.27208	0.313176	0.519232	1.459908	0.4269
GFFC-1-B-R (Class Gen Feedforward)	0.380846	1.311824	0.315869	0.418067	1.516297	0.310688	0.517929	1.633733	0.37983
RBF-1-O-M (Radial Basis Function)	0.894092	1.921294	0.741068	0.621811	1.60236	0.516025	0.665073	1.605045	0.552353
RBF-1-B-R (Radial Basis Function)	0.653407	1.435348	0.532607	0.636503	1.28697	0.533418	0.603007	1.287842	0.500127
TDNN-1-O-M (Time-Delay Network)	0.533729	1.451931	0.396164	0.340023	1.162859	0.209211	0.402151	1.168537	0.254628
TDNN-1-B-R (Time-Delay Network)	0.295563	1.069168	0.253161	0.283278	0.960019	0.233299	0.297115	0.964466	0.249916
RN-1-O-M (Recurrent Network)	0.394225	1.378934	0.319767	0.323742	1.351473	0.241807	0.385874	1.635519	0.275718
RN-1-B-R (Recurrent Network)	0.397754	1.582702	0.322333	0.428865	1.776686	0.313778	0.521978	1.855299	0.380998
TLRN-1-O-M (Time-Lag Recurrent Network)	0.294567	1.088781	0.23422	0.25323	0.93366	0.174036	0.304505	0.991213	0.210027
TLRN-1-B-R (Time-Lag Recurrent Network)	0.346775	1.28851	0.276559	0.407926	1.355195	0.291143	0.506161	1.658579	0.360642

Figure 16. A multilayer perceptron network (MLP) best performance.

The results show that the best performance was obtained using a multilayer perceptron network (MLP). MLP is a feedforward neural network comprising one or more hidden layers. Like any neural network, a network with backpropagation is characterized by the connections between neurons (forming the network architecture), activation of functions used by neurons and learning algorithm that specifies the procedure used to adjust the weights. Usually, a backpropagation neural network is a multilayer network comprising three or four layers fully connected [37].

Each neuron computes its output similar to perceptron. Then, input value is sent to the activation function. Unlike perceptron, in a backpropagation neural networks, the neurons have sigmoid-type activation functions. Derivative function is very easy to calculate and ensure the output range [0, 1]. Each layer of a MLP neural network performs a specific function. The input layer accepts input signals and computational rarely contains neurons that do not process input patterns. Output layer supports output signals (stimuli coming from the hidden layer) and lays it out on the network. Detects hidden layer neurons traits and their weight is hidden patterns of input traits. These characteristics are then used to determine the output layer to the output pattern.

The backpropagation algorithm is a supervised learning algorithm named generalized delta algorithm. This algorithm is based on minimizing the difference between the desired output and actual output by descending gradient method. The gradient tells us how the function varies in different directions. The idea of the algorithm is finding the minimum error function in relation to relative weights of connections. The error is given by the difference between the desired output and the actual output of the network. The most common error function is the mean square error (**Figures 16** and **17**).

RMSE is the mean square error and is used to characterize the scattering of the data in relation to the average. In our case, in all three stages of ANN testing, we obtained RMSE values below 0.5, with 100% identification of classes as shown in **Figure 18**.

Performance Metrics

	Training			Cross Validation			Testing		
Model Name	RMSE	r	Correct	RMSE	r	Correct	RMSE	r	Correct
MLPR-1-O-M (Regression MLP)	0.193136	0.504298	100.00%	0.40441	1.276899	100.00%	0.411551	0.828285	94.44%
MLPC-1-O-M (Classification MLP)	0.292957	0.659528	100.00%	0.423566	0.766415	100.00%	0.360862	0.77623	100.00%
LinR-0-B-R (Linear Regression)	0.334444	0.771683	100.00%	0.36981	0.774197	100.00%	0.378221	0.679267	94.44%
LinR-0-B-L (Linear Regression)	0.320609	0.723112	100.00%	0.382431	0.899123	100.00%	0.373497	0.713072	94.44%
LogR-0-B-R (Logistic Regression)	0.323498	0.802886	100.00%	0.411873	0.883485	100.00%	0.429729	0.777518	100.00%
LogR-0-B-L (Logistic Regression)	0.320243	0.756819	100.00%	0.399313	0.862804	100.00%	0.406476	0.735547	100.00%
MLPR-1-B-L (Regression MLP)	0.321919	0.701325	100.00%	0.448925	1.193378	100.00%	0.338979	0.690299	94.44%
MLPC-1-B-L (Classification MLP)	0.29544	0.929712	100.00%	0.504155	1.517705	100.00%	0.524958	1.351233	100.00%
PNN-0-N-N (Probabilistic Neural Network)	4.27E-06	2.41E-05	100.00%	0.578235	1	100.00%	0.522295	1	100.00%
RBF-1-B-L (Radial Basis Function)	0.391416	0.896709	100.00%	0.370999	0.691104	100.00%	0.468485	0.883554	100.00%
GFFR-1-B-L (Reg Gen Feedforward)	0.230875	0.608818	100.00%	0.513599	1.403539	100.00%	0.492597	1.227754	94.44%
GFFC-1-B-L (Class Gen Feedforward)	2.631665	11.12665	29.85%	2.33251	5.953767	42.11%	3.168973	10.87653	16.67%
MLPRPC-1-B-L (Reg MLP with PCA)	0.539245	1.436432	100.00%	0.505726	1.220976	100.00%	0.450536	0.946967	100.00%
MLPCPC-1-B-L (Class MLP with PCA)	0.604741	1.112989	100.00%	0.631973	1.093975	100.00%	0.440293	0.863168	100.00%
SVM-0-N-N (Classification SVM)	0.278716	0.667789	95.52%	0.324384	0.573036	94.74%	0.326516	0.558213	100.00%
TDNN-1-B-L (Time-Delay Network)	0.341169	0.862838	100.00%	0.721197	1.834166	100.00%	0.531575	0.985912	100.00%
TLRN-1-B-L (Time-Lag Recurrent Network)	1.009541	1.902801	100.00%	0.707728	1.619331	100.00%	0.906855	1.618652	100.00%
RN-1-B-L (Recurrent Network)	0.378266	0.882711	100.00%	0.465783	1.180841	100.00%	0.390453	0.773721	100.00%
MLPR-2-B-L (Regression MLP)	0.310913	0.896222	100.00%	0.476074	1.445478	100.00%	0.536759	1.04037	100.00%
MLPC-2-B-L (Classification MLP)	0.276627	0.854803	100.00%	0.497293	1.247617	100.00%	0.475513	1.028863	100.00%
MLPR-1-B-R (Regression MLP)	0.287202	0.768005	100.00%	0.406402	1.018289	100.00%	0.364087	0.870826	100.00%
MLPC-1-B-R (Classification MLP)	0.258878	0.717773	100.00%	0.414439	1.198915	100.00%	0.32167	0.687884	100.00%
MLPR-2-O-M (Regression MLP)	0.320195	0.69593	100.00%	0.445851	1.09194	100.00%	0.325504	0.728061	100.00%
MLPC-2-O-M (Classification MLP)	0.665406	1.262284	100.00%	0.586722	1.249546	100.00%	0.505312	1.243577	100.00%
MLPR-2-B-R (Regression MLP)	0.232608	0.747501	100.00%	0.410747	0.847326	100.00%	0.329586	0.68689	94.44%
MLPC-2-B-R (Classification MLP)	0.266694	0.745959	100.00%	0.344822	0.973972	100.00%	0.322039	0.714744	100.00%
MLPRPC-1-O-M (Reg MLP with PCA)	0.507237	1.213724	100.00%	0.477877	1.059424	100.00%	0.578924	1.194079	100.00%
MLPCPC-1-O-M (Class MLP with PCA)	0.57946	1.458307	100.00%	0.506006	1.161451	100.00%	0.445815	1.024323	100.00%
MLPRPC-1-B-R (Reg MLP with PCA)	0.49895	1.472947	100.00%	0.481242	0.966154	100.00%	0.555227	1.320027	100.00%
MLPCPC-1-B-R (Class MLP with PCA)	0.532171	1.479628	100.00%	0.440814	0.816954	100.00%	0.453173	0.812813	100.00%
GFFR-1-O-M (Reg Gen Feedforward)	0.270117	0.819621	98.51%	0.477297	0.929855	100.00%	0.458854	1.079618	94.44%
GFFC-1-O-M (Class Gen Feedforward)	0.3695	1.101388	100.00%	0.391954	0.822629	100.00%	0.319803	0.552367	100.00%
GFFR-1-B-R (Reg Gen Feedforward)	0.26564	0.766449	100.00%	0.486714	1.097254	100.00%	0.483942	1.302634	94.44%
GFFC-1-B-R (Class Gen Feedforward)	0.319684	0.808798	100.00%	0.37662	0.763517	100.00%	0.401291	0.794602	100.00%
RBF-1-O-M (Radial Basis Function)	0.551233	1.150324	100.00%	0.542021	0.974906	100.00%	0.393073	0.868909	100.00%
RBF-1-B-R (Radial Basis Function)	0.382085	0.841063	100.00%	0.37343	0.862982	100.00%	0.420303	0.819838	100.00%
TDNN-1-O-M (Time-Delay Network)	0.193776	0.849372	100.00%	0.541533	0.976413	100.00%	0.478553	0.881798	100.00%
TDNN-1-B-R (Time-Delay Network)	0.343269	1.009517	100.00%	0.489615	1.053666	100.00%	0.542653	0.973057	100.00%
RN-1-O-M (Recurrent Network)	0.566416	1.428649	100.00%	0.602502	1.37504	100.00%	0.653149	1.362624	100.00%
RN-1-B-R (Recurrent Network)	1.002518	2.107082	80.60%	1.266936	2.103606	73.68%	0.96296	1.911124	61.11%
TLRN-1-O-M (Time-Lag Recurrent Network)	0.403019	1.071385	100.00%	0.539168	1.007768	100.00%	0.40355	0.952376	100.00%
TLRN-1-B-R (Time-Lag Recurrent Network)	0.416302	0.921486	100.00%	0.589876	1.371814	100.00%	0.400352	0.779646	100.00%

Figure 17. Performance metrics. A multilayer perceptron network (MLP) best classification results (100% for training data vs. 100% for validation data vs. 100% for testing data).

Performance Metrics

	Training	Cross Val.	Testing
# of Rows	9344	2002	2002
RMSE	0.47151	0.281644	0.321151
Correlation (r)	1.538889	0.826787	0.84907
# Correct	9344	2002	2002
# Incorrect	0	0	0
% Correct	100.00%	100.00%	100.00%

Figure 18. Performance metrics.

In medical applications, it is required to use a neuro-fuzzy hybrid system that can be fitted with a neural network that presents many advantages such as: flexibility, speed, adaptability. The structure of a hybrid system is represented in **Figure 19**:

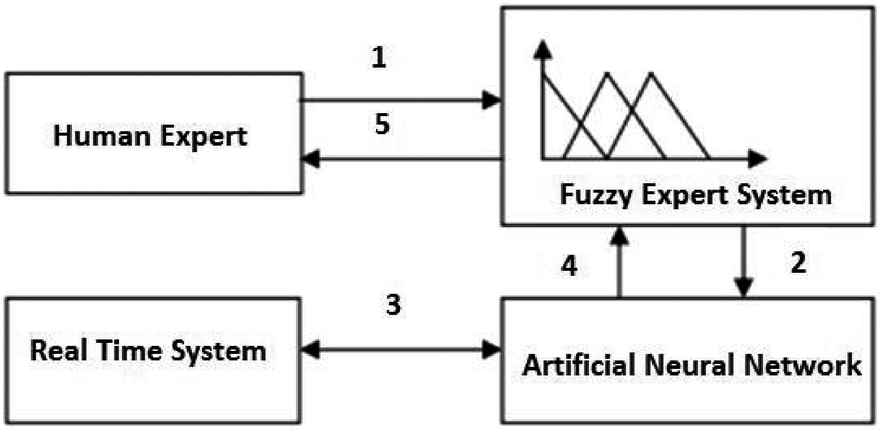

Figure 19. Hybrid neuro-fuzzy expert system [37].

The human expert knowledge is translated as symbolic (1) and is used for ANN initialization (2). The network is trained on a real inputs and outputs system (3). The knowledge obtained using ANN (4) is processed in a fuzzy manner for the determination of fuzzy rule, which are finally communicated to the human expert (5) [37]. These hybrid systems are suitable for the acquisition of knowledge and learning, and they can achieve inclusive process using weighting of the fuzzy neural network connections. Using a simple learning algorithm, such as backpropagation, neuro-fuzzy hybrid systems can identify fuzzy rules and then learn the associated functions of inferences. In summary, the hybrid system can also learn linguistic rules (fuzzy) as well as optimizing existing rules.

During generation and validation of expert system rules, we observed a positive correlation between speech disorders and eating disorders (obesity), so that a higher Body Max Index (BMI) exacerbated learning and speech difficulties in children. This is consistent with previous work demonstrating that risk of being obese in young adulthood was increased if the child had learning difficulties, scholastic proficiency below the class average, received special education, or had scholarly difficulties in childhood [38]. Therefore, our future studies will address the causal relationship between overweight, obesity, and various functions related to speech disorders and learning abilities during a longer period of time.

6. Conclusions

Each decision technique has specific advantages and drawbacks when it is used in medical field. Thus, a FES is able to make inferences with approximate data and, more importantly, it can track the decision-making process (i.e., the chain of activated rules). However, the rules must be written and, eventually, modified by human expert only. On the other hand, the artificial neural networks are the best choice when dealing with a large quantity of data and wish to obtain the related pattern but unable to provide useful information on how a specific conclusion is reached.

Due to the complementarity of expert system and artificial neural networks, several attempts to integrate these techniques have emerged. For example, combining qualitative modeling (based on fuzzy if-then rules) with quantitative modelling (used when all we have is chunks of already classified data) represents a major step forward. The hybrid neuro-fuzzy expert system is able to both learn by examples and organize knowledge and meta-knowledge in the form of fuzzy rules. For this type of system, we first fuel neural network with symbolic information and then adapt the raw model using individual examples. At the end of the process, we are able to extract symbolic information from trained neural network.

To the best of our knowledge, there are few, if any, studies based on the utilization of above-mentioned hybrid techniques in speech and language therapy of children. In this chapter, we have proposed and validated this original approach using Logomon, the first CBST for Romanian language. We have demonstrated that it is possible to use the equivalent relation between a fuzzy expert system and an artificial neural network in order to capitalize on the advantages of both techniques. The results are very encouraging and provide strong impetus to continue these studies by extending rules database and by optimizing integration between the two parts of inferential system.

Acknowledgements

These authors contributed equally to this book chapter, and the work was supported by the Romanian National Program PN-II-ID-PCE-2012–4-0608 no. 48/02.09.2013, “Analysis of novel risk factors influencing control of food intake and regulation of body weight”.

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