Prediction of school dropout risk group using Neural Network

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A New Method for Prediction of School Dropout Risk Group Using Neural Network Fuzzy ARTMAP

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Abstract - *Dropping out of school is one of the most complex and crucial problems in education, causing social, economic, political, academic and financial losses. In order to contribute to solve the situation, this paper presents the potentials of an intelligent, robust and innovative system, developed for the prediction of risk groups of student dropout, using a Fuzzy-ARTMAP Neural Network, one of the techniques of artificial intelligence, with possibility of continued learning. This study was conducted under the Federal Institute of Education, Science and Technology of Mato Grosso, with students of the Colleges of Technology in Automation and Industrial Control, Control Works, Internet Systems, Computer Networks and Executive Secretary. The results showed that the proposed system is satisfactory, with global accuracy superior to 76% and significant degree of reliability, making possible the early identification, even in the first term of the course, the group of students likely to drop out.*

Keywords: higher education, school dropout, prediction dropout, artificial neural networks (ANN), Fuzzy ARTMAP neural network.

1 Introduction

Historically, school dropout is one of the most complex and crucial problems in education, causing social, economic, political, academic and financial damage to all the people involved in the educational process, from the students to the governmental and promotional agences that long for efficient strategies to reduce the indexes of school dropout, since the measures adopted up to now did not have the desired effect.

In relation to higher education, school dropout is an international problem. Although its indexes show considerable variations among different nations, they show that in fact school dropout is present and strikes more and more a higher number of higher educational institutes (HEI) worldwide.

It is worth mentioning the United States - USA, with a dropout rate in colleges and universities of around 40%, representing a decline in the index of students graduated in higher education [1]. Conversely, China and India empower higher education, increasing the conclusion index [2]. Between these extremes lies Brazil, presenting a mean dropout index of about 20% [3].

Even taking into account all the differences and specificities of the (HEI) of different nations, the difficult task of solving the evasion problem is still common ground between them [4].

From this perspective, prevention and intervention programs are developed and structured taking into account the results of researches that identify the possible causes that generate the phenomenon of evasion. However, such measures could be more fruitful if there was prior knowledge of the students prone to evasion. And, for this, the development of methods, instruments or systems capable of previously making this identification is necessary.

To meet this need an intelligent, ambitious and innovative system was developed, for the prediction of risk groups of student dropout in presential higher education courses [5], using artificial intelligence techniques, the Fuzzy ARTMAP Neural Network [6-8]. This network has a structure in which the training is carried out in a supervised and self-organized way, with the possibility of continued learning [6].

This paper aims at presenting and making the developed intelligent system available as a possibility of identifying, in a proactive, continued and accurately the students of the traditional presential education, prone to evasion in higher education. And also to disseminate their fruitful results that contributed to the development of prevention and intervention programs, in order to improve retention of those students identified in the institution [5].

Further, this paper is structured as follows: Section 2 – the publications considered more relevant to this proposal. Section 3 - the ART and Fuzzy ARTMAP networks and their training algorithms. Section 4 - the study area, the construction of database and the development of the intelligent system in question. Section 5 - the implementation of the system. Section 6 - the results and analyses of the tests performed. Section 7 - the most relevant conclusions of the experiment.

2 Brief review

Most of the works analyzed, considering the causes of evasion in higher education, are critical and theoretical productions and present as results the factors that most influenced school evasion in the Brazilian higher education, its consequences and possible ways to overcome them [9]. The educational situation in Brazil is perceived through statistical data of private and governmental schools and research by governmental organs [10]. In a more global view, besides theoretical models with explanatory schemes about the causes of evasion [11], there is a comparative study among countries with poor education and with an insignificant evasion index [12] as well as a study with students that constantly shift from one school to another, showing similar causes for the evasion to occur [13].

In relation to the analysis and prediction of school evasion using intelligent system, productions where Data Mining techniques were used [14-16] and Artificial Neural Networks [17-20], e.g., Multi-layers Perceptron Network (MLP). In all of them, the results obtained were: the identification of causal descriptive patterns that lead the students to leave school and the verification of the efficiency and performance of the techniques used. The variables that can influence the students' evasion were also investigated in distance-learning courses.

This study [21] investigates group risk of students prone to evasion in e-learning courses, uses the combination of three machine learning techniques, including, Fuzzy ARTMAP neural network. This one is the most significant for the elaboration and development presented here.

3 ART and Fuzzy ARTMAP neural networks

The Artificial Neural Networks (ANN) [19] are computational tools that emulate the human brain and learn with the experience, trying to model and simulate its learning process, organizing its neurons in such a way that they will be capable of processing the information.

A typical neural network consists of several neurons, arranged in adjoining layers, connected by synapses (communication channels) associated to certain weights attributed to connections among the neurons, where all the knowledge of a ANN is stored. They always have an input and an output layer, with the possibility of having between them a varied number of layers, called hidden or intermediate layers.

The use of neural networks offers some benefits and capabilities that in synthesis are: non-linearity, input-output mapping, adaptability ("stability-plasticity" dilemma) [6], response to evidence, contextual information, fault tolerance, uniformity of analysis, neurobiological analogy.

The ART network systems are able to solve the "stability-plasticity" dilemma. They are plastic because they are able to learn to adapt to a changing environment and, at the same time, preserve their previously learned knowledge while maintaining their ability to learn new patterns, therefore they are stable.

In the Fuzzy ARTMAP model, two ART modules are interlinked through an inter-ART module, called Field Map. This module has a self-regulatory mechanism called match tracking that seeks for "marriages" or combinations among the categories of ART_a and ART_b modules, aiming to increase the generalization level and reduce the network error [6].

The Fuzzy ART neural network uses the theory of the fuzzy sets [22], employing the minimum operator ($\wedge$) AND Fuzzy, enabling the treatment of patterns of binary and analogical input, in an interval [0, 1], and increasing the generalization ability of the network.

3.1 Algorithm of an Fuzzy ART neural network

The algorithm of an Fuzzy ART neural network consists, essentially in the sequence described below [22]:

3.1.1 Normalizing of input data

The input data are represented by the vector $\boldsymbol{a} = [a_1 \; a_2 \; a_3 \; . \; . \; . \; a_M]$. Normalizing of this vector should be according to the (1) [22]:

$$\bar{\boldsymbol{a}} = \frac{\boldsymbol{a}}{|\boldsymbol{a}|} \quad , \text{ where: } \quad |\boldsymbol{a}| = \sum_i^M a_i \tag{1}$$

where:

$\bar{\boldsymbol{a}}$: normalized input vector;

$|\boldsymbol{a}|$: norm of the input vector $\boldsymbol{a}$;

a_i : element of he input vector $\boldsymbol{a}$ with index i.

3.1.2 Coding of the input vector

The complement coding is performed according to (2), to preserve the scope of information [22]:

$$\bar{a}_i^{\,c} = 1 - \bar{a}_i \tag{2}$$

where:

$\bar{a}_i^{\,c}$: complementary element of the element of the normalized input vector;

$\bar{\boldsymbol{a}}^{c}$: complementary vector of the normalized input.

Thus, the network input vector will be vector $\boldsymbol{I}$, presented in (3) [22] .

$$\boldsymbol{I} = \left[\bar{\boldsymbol{a}} \quad \bar{\boldsymbol{a}}^{c} \right] \tag{3}$$

$$\boldsymbol{I} = \left[\bar{a}_1 \;\; \bar{a}_2 \ldots \bar{a}_M \;\; \bar{a}_1^{c} \;\; \bar{a}_2^{c} \;\; \bar{a}_M^{c} \right]$$

3.1.3 Activity vector

The activity vector of the recognition layer F_2 is indicated by $\boldsymbol{y} = [\; y_1 \;\; y_2 \;\; y_3 \; . \; . \; . \; y_N \;]$, being N the number of categories created in F_2. Thus, one has [22]:

$$y_j = \begin{cases} 1, \text{ if the neuron } j \text{ of } F_2 \text{ is active, if } \quad j = J \\ \\ 0, \text{ otherwise, if } \quad j \neq J \end{cases}$$

3.1.4 Parameters of the Fuzzy ART neural network

Three parameters are essential in the processing of the Fuzzy ART network, they are [22]:

- Choice parameters (α) : $\alpha > 0$;
- Training parameters (β) : $\beta \in [\,0,\, 1\,]$;
- Vigilance parameters (ρ) : $\rho \in [\,0,\, 1\,]$.

3.1.5 Initialization of the weights

Initially, all the weights have values equal to 1, as in (4) [22]:

$$w_{j1}(0) \; = \; w_{j2}(0) \; = \; \dots \; = \; w_{NM}(0) \; = \; 1 \qquad (4)$$

3.1.6 Choice of a category

Considering an input vector $\boldsymbol{I}$ in F_1, the choice of the category j in F_2 attends to the choice function T_j defined in (5) [22]:

$$T_j(\boldsymbol{I}) = \frac{\left| \boldsymbol{I} \wedge \boldsymbol{w}_j \right|}{\alpha + \left| \boldsymbol{w}_j \right|} \qquad (5)$$

where:

$\wedge$: operator AND-Fuzzy, defined by (6):

$$\left(\boldsymbol{I} \wedge \boldsymbol{w} \right)_i \; = \; \min(I_i \, , \, w_i) \qquad (6)$$

The system chooses the category that corresponds to the active J neuron, according to (7) [22]:

$$J = \arg \max_{j=1,\dots,N} T_j \qquad (7)$$

If more than one neuron with maximum activation exists, the chosen category will be the one which has the smallest index j.

3.1.7 Resonance or Reset

The resonance occurs if the vigilance criterion, (8), is met.

$$\frac{\left| \boldsymbol{I} \wedge \boldsymbol{w}_j \right|}{\left| \boldsymbol{I} \right|} \; \geq \; \rho \qquad (8)$$

If the vigilance criterion, (8), is not met, the reset occurs. In the reset, the J neuron of the F_2 is excluded of the searching process. So, a new category is chosen through the application of the (7) so that the resonance process will be performed. This procedure is performed until the network finds a category that fulfills (8).

3.1.8 Learning (Updating the weights)

After the input vector $\boldsymbol{I}$ has completed the resonance state, the training and learning process occurs and, consequently modifying the weight vector, given by (9) [22].

$$\boldsymbol{w}_J^{\text{new}} = \beta \, (\boldsymbol{I} \wedge \boldsymbol{w}_J^{\text{old}}) + (1 - \beta) \, \boldsymbol{w}_J^{\text{old}} \qquad (9)$$

where:
J : active category;
$\boldsymbol{w}_J^{\text{new}}$: updated weight vector;
$\boldsymbol{w}_J^{\text{old}}$: weight vector regarding the previous updating.

If the training parameter β = 1, there is the fast training.

3.2 Algorithm of an Fuzzy ARTMAP neural network

The algorithm for the processing of the Fuzzy ARTMAP Neural Network [7], occurs in the following way:

3.2.1 Input data

The input vectors of the Fuzzy ARTMAP network are represented by:

- $\boldsymbol{a} = \left[\boldsymbol{a}_1 \;\; \boldsymbol{a}_2 \; \dots \; \boldsymbol{a}_P \right]$: ART_a input, data sampling;
- $\boldsymbol{b} = \left[\boldsymbol{b}_1 \;\; \boldsymbol{b}_2 \; \dots \; \boldsymbol{b}_P \right]$: ART_b input, desired output;

where:
P : the number of subvectors of the $\boldsymbol{a}$ and $\boldsymbol{b}$ vectors.

3.2.2 Weight matrices

The weight matrices associated to the ART_a (matrix $\boldsymbol{w}^a$) and ART_b (matrix $\boldsymbol{w}^b$) modules, as well as to the Inter-ART (matrix $\boldsymbol{w}^{ab}$) module, are initiated with values equal to 1, since all the activities are inactive.

3.2.3 Parameters of the Network

The parameters used in the processing of the Fuzzy ARTMAP network are the same used in the Fuzzy ART network. However, each module ART_a and ART_b receives a specific pattern. Besides these, there is the vigilance parameter of the Inter-ART module, being: $\rho_{ab} \in [0\,,\,1]$.

3.2.4 Match Tracking

In the Fuzzy ARTMAP neural network the modules ART_a and ART_b, are processed and, after resonance is confirmed in each one of them, one has:

- active category for the module ART_a : J
- active category for the module ART_b : K

After the confirmation of the resonance in each module, the test match tracking is performed, given by (10) [7]:

$$\left| \boldsymbol{x}^{\mathrm{ab}} \right|_i = \frac{\left| \boldsymbol{y}_i \wedge \boldsymbol{w}^{\mathrm{ab}}{}_J \right|}{\left| \boldsymbol{y}_i \right|} \tag{10}$$

By the vigilance criterion, we have that [7]:

- If, $\left| \boldsymbol{x}^{\mathrm{ab}} \right|_i \geq \rho_{\mathrm{ab}}$ - the training pair should be confirmed;
- If, $\left| \boldsymbol{x}^{\mathrm{ab}} \right|_i < \rho_{\mathrm{ab}}$ - another index *J*, that satisfies the vigilance parameter should be found.

Otherwise, small increases are successively made to the vigilance parameter of the module $\mathrm{ART_a}$, until the vigilance criterion is satisfied.

3.2.5 Learning (Updating Weights)

Only after the state of resonance occurs, the process of training and learning is performed, modifying the weight vector given by (11) and (12), respectively, modules $\mathrm{ART_a}$ and $\mathrm{ART_b}$ and, (13) and (14) module Inter-ART [7].

$$\boldsymbol{w}^{\mathrm{a}}\, J^{\mathrm{new}} = \beta(\boldsymbol{I} \wedge \boldsymbol{w}^{\mathrm{a}}\, J^{\mathrm{old}}) + (1-\beta)\boldsymbol{w}^{\mathrm{a}}\, J^{\mathrm{old}} \tag{11}$$

$$\boldsymbol{w}^{\mathrm{b}}\, K^{\mathrm{new}} = \beta(\boldsymbol{I} \wedge \boldsymbol{w}^{\mathrm{b}}\, K^{\mathrm{old}}) + (1-\beta)\boldsymbol{w}^{\mathrm{b}}\, K^{\mathrm{old}} \tag{12}$$

$$w^{\mathrm{ab}}\, JK^{\mathrm{new}} = 0, \text{ para } k = 1,2,\ldots,N, \quad k \neq K \tag{13}$$

$$w^{\mathrm{ab}}\, JK^{\mathrm{new}} = 1 \tag{14}$$

4 Methodology

This study was conducted under the Federal Institute of Education, Science and Technology of Mato Grosso - IFMT. The universe of interest are the students enrolled in the Colleges of Technology (CT) in Automation and Industrial Control, Control Works, Internet Systems, Computer Networks and Executive Secretary at IFMT, attending presential courses in the morning, afternoon and evening. The choice is justified in view of the high dropout rates, verified by previous statistical studies, noting that CT Automation and Industrial Control, reached a dropout rate of 62.46% from 2004 to 2010 [5].

In the implementation and pilot test of the intelligent system proposed, the neural network was fed with data belonging to all the students enrolled in the CT, from 2004 to 2009, making a total of 1650 samples for the training phase, constituting the basis historical data. For diagnosis 499 samples, of data from the students enrolled in 2010 and 2011 were used [5].

The database for prediction of the risk group prone to evasion consists of the students' characteristics such as demographic factors, and factors internal and external to the school. These characteristics were lifted from data from the selection processes at IFMT, the Q-Selection, which stores the answers of the socioeconomic questionnaire filled by the students on the day they enroll for the selection examination and the Q-Academic, system of integrated academic management, where all the academic history of the IFMT students is concentrated [5]. It is that the database does not contain the names of the students, which are identified, only by numbers.

The input vector of the Fuzzy ARTMAP neural network is composed by 16 parameters considered as significant for the school dropout prediction and the output of the network constituted by two classes, evasion and non-evasion. The input-output vector pairs are represented in the binary coding, being the input vector composed by 41bits and, the expected response represented by 1 bit. A summary of the input and output variables of the neural network can be visualized in Table I.

TABLE I. Composition of input and output vectors.

	Characteristics of the Subvectors of *a* and *y*			
	Position	**Name**	**Abbreviation**	**Size**
Variable of the Input Vector (*a*) of the Network	$\boldsymbol{a}_1$	Gender	Gen	1 bit
	$\boldsymbol{a}_2$	Age Group	Ag	3 bits
	$\boldsymbol{a}_3$	Ethnicity	Etn	3 bits
	$\boldsymbol{a}_4$	Marital Status	MSt	3 bits
	$\boldsymbol{a}_5$	People/House	P/H	3 bits
	$\boldsymbol{a}_6$	Family Income	FI	3 bits
	$\boldsymbol{a}_7$	Has a Computer	Comp	1 bit
	$\boldsymbol{a}_8$	Parents' Education	PE	3 bits
	$\boldsymbol{a}_9$	School of Origin	SO	3 bits
	$\boldsymbol{a}_{10}$	Self-Evaluation	SEv	3 bits
	$\boldsymbol{a}_{11}$	Where From	WF	1 bit
	$\boldsymbol{a}_{12}$	Distance School-Residence	DistSR	3 bits
	$\boldsymbol{a}_{13}$	Means of Transport	MT	3 bits
	$\boldsymbol{a}_{14}$	Work	Wk	3 bits
	$\boldsymbol{a}_{15}$	Study Shift	SS	2 bits
	$\boldsymbol{a}_{16}$	Students/Classroom	S/C	3 bits
Output Vector (*y*)	$\boldsymbol{y}$	Non-Evasion	NEv	1 bit
		Evasion	Ev	

5 Fuzzy ARTMAP neural system proposed for the evasion prediction

The data that involve the study about evasion, are sometimes, complex, subjective, non-linear, inter-related and keep in themselves the specificities inherent to the different levels of teaching, courses and institutions that one can analyze, thus choosing ANN, as among its potentialities there is the possibility of processing problems where complex and unknown relations are involved among different sets of data

and, also adjust the relations of non-linearity between the input and outup variables [5]. More specifically, the Fuzzy ARTMAP network, where the training is carried out in a supervised and self-organized way, with possibility of continued learning, as implemented in [23]. Its application potential aims at solving several problems of classification and of approach of non-linear functions and showing prompt reply.

The input of the Fuzzy ARTMAP network proposed is represented by vector $\boldsymbol{a}$ (input of the module $\mathrm{ART_a}$) and its desired output, in the training phase, represented by vector ***b*** (input of the module ART_b), being these ones described in the following way:

$$\boldsymbol{a} = [\boldsymbol{a}_1 \ \boldsymbol{a}_2 \ \boldsymbol{a}_3 \ . \ . \ . \ \boldsymbol{a}_{16}]$$

$$\boldsymbol{b} = [\ b\ ] \quad , \quad \text{where: } b = \text{“0” ou “1”}$$

The subvectors $\boldsymbol{a}_1$, $\boldsymbol{a}_2$, $\boldsymbol{a}_3$, . . . $\boldsymbol{a}_{16}$ of the vector ***a*** (Table I) are row vectors which contain the binary representation of the students' characteristics. Each bit corresponds to one component of the corresponding vector.

The network output is represented by the activity layer vector F_2 (***y***) and provides answers in the binary coding with 1 bit, being that code "1" corresponds to students' evasion and code "0" to non-evasion, defined as follows:

$$\boldsymbol{y} = [\ y\ ] \ \text{(\textit{Fuzzy} ARTMAP network output)}$$

The model proposed in this study consists of an intelligent system (flowchart shown in Fig. 1) for the study of students' evasion in the IFMT, using an Fuzzy ARTMAP Neural network [6-8], Logic Fuzzy [24] and/or Dempster-Shafer's Theory of Evidence - TDS [25].

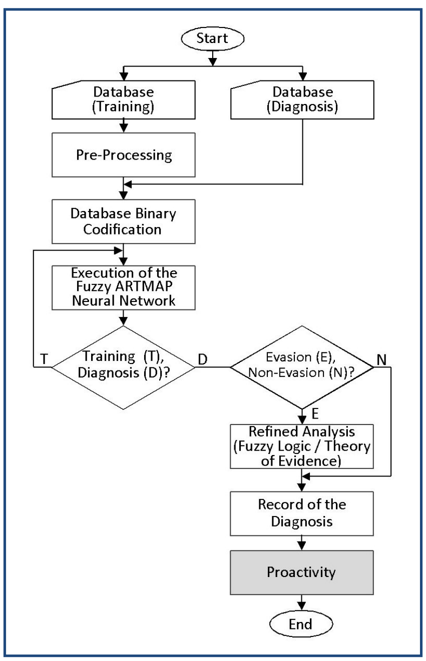

Fig. 1. Flowchart of the neural system proposed to perform the prediction of the evasion group risk.

The information of the database is pre-processed and converted into a binary database. The essentially binary conception is considerably worthwhile, because the neural network presents a more efficient behavior (prompt and better quality of answers) and allows the extraction of knowledge in a continuous way (continued training), seeking for a better adaptation to the conditions of the institution and improvement with time.

In the phase of the neural analysis, if the answer is negative in relation to evasion, no action is adopted; just the register of the mentioned information is performed. If the answer of evasion is positive, the following step corresponds to a better discrimination about the quality of information (fine analysis) based on the use of Fuzzy module [24] and/or of the Dempster-Shafer's Theory of Evidence [25]. Later, solutions that aim to revert students' evasion will be proposed (proactive action).

6 Application and analysis of the results

The intelligent system, using a Fuzzy ARTMAP, Neural Network proposed to make the prediction of the risk group of students prone to evasion, was simplemented and tested with a database composed by 1.650 rows e 42 columns in the training phsase of the network. A sample with 499 lines and 41 columns in the phase of validation and diagnosis, about 30% of the training samples. Each line represents the inputs standard vector and its corresponding desired output, in the training. The data of the columns from 1 to 41 represent the attributes correspondent to vector ***a***, input of the module ART_a. In column 42 are represent the desired outputs, vetcor ***b*** (input of the module ART_b) of the Fuzzy ARTMAP neural network.

The parameters used in the database processing are specified in Table II.

TABLE II. Specification of the parameters: Fuzzy ARTMAP neural network.

Parameters and References Values	
Parameters	***Values***
Choice parameter ($\alpha > 0$)	0.001
Training rate ($\beta \in [0,1]$)	1.0
Vigilance parameter module ART_a ($\rho_a \in [0,1]$)	0.2
Increasing in the vigilance parameter ρ_a (ε)	0.05
Vigilance prameter module ART_b ($\rho_b \in [0,1]$)	0.999
Vigilance parameter module inter-ART_{ab} ($\rho_{ab} \in [0,1]$)	0.7
Vigilance parameter in the match tracking ($\rho_{amat} \in [0,1]$)	0.75

After the network training five simulations were performed, based on data for the diagnosis, for the validation of the model proposed, being that, in one of them the samples were processed in a naturally random way and the others in a randomized way.

The results of the processing were compared and analyzed, using a criterion, called "voting criterion" [7], "0" or "1" of higher incidence for each of the inputs. The result of higher incidence constitutes the output of the neural network.

Later, comparing the output from the network with the real situation of each sample of the group of students analyzed, it was possible to investigate the coincidence of the evasion ("1") and non-evasion ("0") among the samples processed and the reality.

After concluding the phases of the processing of database through an Fuzzy ARTMAPNeural Network and respective analyses necessary to the understanding of the behavior in relation to students' evasion and non-evasion, the results were compiled and, briefly, shown in Table III.

TABLE III. Quantitative and perceptual results of the diagnosis of school evasion prediction .

Diagnosis of School Evasion	Quantitative and Percentages Values: Output of Network					
	Evasion		*Non-Evasion*		*Total of Samples*	
	Number	*%*	*Number*	*%*	*Number*	*%*
Samples	90	100	409	100	499	100
Corrects	88	97.8	295	72.1	383	76.7
Errs	2	2.2	114	27.9	116	23.3

The reading, interpretation and data analysis in Table III show that:

- of 499 samples, 90 of them corresponded to the evaded students and, 409 students who had concluded or attending a course, that is, not-evading.
- of 90 samples of evasion, the proposed system identified 88 evasion possibilities and ignored 2, with a margin of success of 97.8%.
- among the 409 samples of non-evasion, the Fuzzy ARTMAP network proposed recognized 295 samples in this situation and did not hit the target in 114, getting it right in 72.1% of the cases.
- it reached the global accuracy of 76.7%, finding correctly 383 samples of a total of 499.

The quantitative and percentage results of the previous diagnosis of the students with possibility of evasion can be perceived, more clearly in the graphs of Fig. 2 and Fig. 3, respectively.

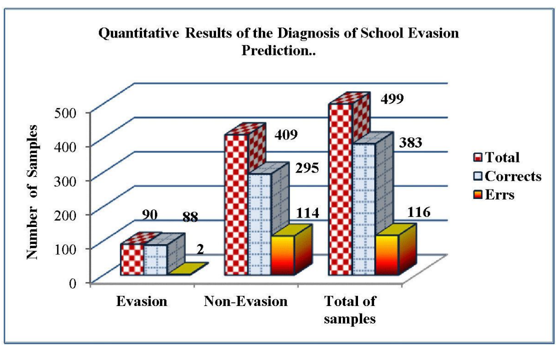

Fig. 2. Qualitative result of prediction of school evasion.

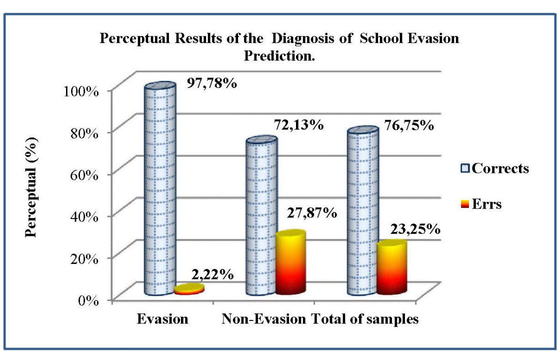

Fig. 3. Percentage result of school evasion.

Considering the experiment done and consistency of the results obtained, it can be inferred that the intelligent system, using Fuzzy ARTMAP, neural network proposed to identify the students prone to evasion, is a model with a significant degree of reliability and expresses accurately the situation in which the students analyzed are.

Conclusion

This study presented an innovative method to identify, in a proactive, continued and accurate way, the students considered to belong to the risk group of school dropout, using Fuzzy ARTMAP neural network.

The analysis of the results showed that the proposed system is satisfactory, with global accuracy superior to 76%, and with a significant degree of reliability, making possible the early identification, even in the first term of the course, the group of students likely to drop out. The anticipated identification of this group of students enables the institutional education, alongside the multidisciplinary team to adopt strategic, proactive and individualized measures with the aim of reducing or even mitigating the students' evasion.

It has been noted the consistency of the results, the accuracy and the efficiency of the system. However, one is dealing with the prediction of actions that come from the deliberations and decisions of human beings. Therefore, one recognizes the limitations of the methodology and its possible flaws, since the predictions fall beyond the complete determinism being evasion the result of a stochastic process.

After the conclusion of this draft experiment, it has been verified that the method can be extended and recommended for implementation to other groups where considerable levels of evasion were observed, adjusting it to the specificities of each group to be investigated.

The system proposed, using the Fuzzy ARTMAP Neural Network has the advantage of the possibility of working with a set of complex data, as well as the insertion of new training patterns without the necessity of restarting the process, in view of its plasticity, therefore allowing for continuous learning.

Hence, based on the results of the experiment, it is evident that the method proposed is a powerful, robust and innovative tool for the prediction of risk groups of student dropout, in higher education presential courses. It fills the gap existent in the worldwide scientific community productions, regarding the issue in question, and contributes with something that it is useful to society. Thus, with proactive action, to get a student with the potential to become a dropout to be successful is a noble mission, because they are dreams that become reality.

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