2013 IEEE 25th International Conference on Tools with Artificial Intelligence

An Intelligent System for Prediction of School Dropout Risk Group in Higher Education Classroom based on Artificial Neural Networks

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***Abstract*— School dropout is one of the most complex and crucial problems in the field of education. It permeates the several levels and teaching modalities and has generated social, economic, political, academic and financial damage to all involved in the educational process. Therefore, it becomes essential to develop efficient methods for prediction of the students at risk of dropping out, enabling the adoption of proactive actions to minimize the situation. Thus, this work aims to present the potentialities of an intelligent system developed for the prediction of the group of students at risk of dropping out in higher education classroom courses. The system was developed using a Fuzzy-ARTMAP Neural Network, one of the artificial intelligence techniques, which makes the continued learning of the system possible. This research was developed in the technology courses of the Federal Institute of Mato Grosso, based on the academic and socioeconomic records of the students. The results, showing a success rate of the dropout group around 92% and overall accuracy over 85%, highlights the reliability and accuracy of the system. It is highlighted that the strength and boldness of this research lies in the possibility of identifying early the eminent school dropout using only the enrollment data.**

Keywords-dropout prediction; intelligent system; Fuzzy-ARTMAP neural network; higher education; proactivity.

I. INTRODUCTION

Throughout the history of Education, the phenomenon of school dropout permeates the various levels and modalities of teaching and generated social, economic, political, academic and financial damage to all people involved in the educational process. It is a complex and crucial problem [1], arising from the overlapping of social, economic, cultural and academic factors, as well as demographic variables and individual attributes that influence the decision of the university students to stay or leave the course.

Given this situation, over the last years, monitoring, empirical studies, scientific research and statistical surveys on school dropout were carried out in Brazil, aiming to adopt measures to solve or reduce the exiting high levels and, thus, avoid both the social and financial losses. However, the measures that have been adopted so far have not had the desired effect.

The studies on school dropout in Brazil are incipient and scarce, if compared to developed countries where systematic studies and research are numerous. In the United States, more than 14 thousand sites cover the issue [2].

Academic studies and scientific research on school dropout and retention of students in higher education began in the thirties in the United States, in an unassuming and limited way. In the sixties, the concern with the situation, the complexity of the phenomenon and the need to find solutions, intensified research and development of measures in order to minimize school dropout [3]. The term retention, considered more objective and proactive, is largely used in the international literature to denote the set of measures aimed to maintain the student in the institution. Countries like Australia and the United States have addressed the issue in a scientific manner and, considering it of high relevance, created managements or directorates for the management of retention [4].

In this work, the term school dropout will be used, to define a student who has abandoned a course of study, according to the report of the Special Study Committee on Dropping out in Brazilian Public Universities [5].

In Brazil, higher education undergoes an evaluation through the Higher Education Census, conducted annually by the National Institute for Educational Studies and Research Anísio Teixeira (INEP). The analysis of the report of the Higher Education Census in 2011 [6] shows a dropout rate around 20.5% in Brazilian higher education.

Under the Federal Institute of Mato Grosso (IFMT) - Cuiabá Campus, locus of the research development, a statistical study was carried out for the identification and analysis of the prevalent and determinant factors of school dropout in the Higher Education Course of Technology (CST) in Industrial Automation, in the period from 2004-2010. It was noted that of the 389 students enrolled in the course, 243 are dropouts, representing a rate of 62.46% of school dropout [7]. This high rate of school dropout is a real threat to the higher education and constitutes a challenging task for the institution, since the goal is to reduce this rate to 10%.

Therefore, the current analysis of the indices of school dropout within Brazil [6] and the survey of the school dropout in the CST of the IFMT [7], highlights the worrying state of fatigue and fragility in which the higher education is. This confirms the need to obtain satisfactory results, in mitigating this phenomenon and enabling an education of

1082-3409/13 $31.00 © 2013 IEEE
DOI 10.1109/ICTAI.2013.33

quality, boosting the Nation for the sustainable socioeconomic development, and perhaps, guarantee every citizen the right, which they are entitled to work, health, leisure, dignity, citizenship and, the long awaited happiness and peace [1].

In this context, it becomes indispensable to carry out systematic studies, observing the signs of impending dropping out, develop and implement strategies to favor the early identification of the students vulnerable to dropping out. Thus enable the application of proactive actions to reverse the intentions of quitting. The methods to predict dropping out are feasible of being used in collective manner; however, the action on behalf of the permanence of the students must be individualized, meeting their specific needs. This conviction meets what is emphasized by [8], that dropping out can constitute itself as a collective phenomenon, but it is always an individual process.

The variables involved in the dropping out process keep in themselves a host of specificities inherent to the different levels of teaching, courses and institutions that can be analyzed, are complex, subjective, non-linear and inter-related. A feasible possibility to represent situations of complexity, subjectivity, non-linearity, and unknown relationships among different sets of data, such as the case of school dropout, is the use of Artificial Neural Networks (ANNs) [9], one of the paradigms of the Artificial Intelligence (AI) [10].

The Artificial Neural Networks (ANNs) are computational systems that emulate the human brain in the interpretation and processing of information, and also learning through experience, enabling them to make more reliable generalizations. This generalization capability allows the development of systems with ability to process intractable problems, dealing with non-linear, imperfect and missing variables, interact with noisy data and yet, present fast response and expected outcome.

Among the scientific publications there are few references pertaining to the analysis and prediction of student dropout in higher education classroom courses, using artificial neural networks. The works considered more relevant for this research are the one by Lykourentzou [11], which investigates the risk group of students likely to evade in e-learning courses and uses the combination of three techniques of machine learning, among them the Fuzzy-ARTMAP neural network. The other work is by Mustafa [12] which uses the regression and classification tree to identify school dropout, based on the date the student enrolled in the course. He concluded that the data chosen produce results with a low level of accuracy.

This work aims to present the potentialities of an intelligent system, able to perform the prediction of group of students at risk of dropping out in higher education classroom courses, accurately and continuously, reliably inferring about the condition of the students analyzed in relation to school dropout. The system was developed using a Fuzzy-ARTMAP Neural Network, one of the artificial intelligence techniques, associated with the Fuzzy Logic [13] module and a module of Dempster-Shafer Theory of Evidence [14]. The Fuzzy-ARTMAP neural network [15-17], is one of the networks of the ART family (Adaptive Resonance Theory) [15, 18], has an architecture whose training is carried out in a supervised and self-organized way, with the possibility of continued learning [17, 19].

Thus, the proposed intelligent system is bold and innovative, able to identify in a proactive, continued and accurate way the students, from the conventional classroom education, prone to higher education dropout. The results contribute to the elaboration of individualized prevention and intervention programs, seeking the permanence of these students identified in the teaching institution.

It is noteworthy that, in addition to the already described singularities of this system, compared to scientific works on the issue, the strength and the boldness of this research lies in the possibility of the early identification of the imminent school dropout using only the data contained in the registration questionnaire.

Subsequently, after this introduction, Session 2 presents the delimitation of the research and construction of the database. The Fuzzy-ARTMAP and ART neural networks are addressed in Session 3. In Session 4 we describe the development of the Fuzzy-ARTMAP neural network proposed for the prediction of school dropout. The implementation of the system, the results and analyses of the simulations are presented in Session 5. The most relevant considerations of this study are in Session 6.

II. Delimitation of the Research and Construction of Database

A. *Scope and Universe of the Research*

The courses are analyzed within the scope of the Federal Institute of Education, Science and Technology of Mato Grosso - IFMT, Cuiabá Campus.

Primarily, the universe of interest for this research are the students enrolled in Colleges of Technology (CST), classroom-based, since the focus of the investigation is the phenomenon of school dropout in higher education courses. The CST analyzed are: Industrial Automation and control, Control of works, Systems for the Internet and Computer networks.

B. *Survey Data Collection*

The original data, actual or historical used in this research, concerning the answers of the socioeconomic questionnaires, provided by the students at registration for the selection exam, are stored in the system data manager Selection-Q that are in the database of the selective processes of the IFMT.

The socioeconomic questionnaire consists of 23 questions, and 13 answers are selected as predictor characteristics of dropout for analysis in this research proposal.

In addition to the data of the questionnaire, other characteristics were considered such as the distance between home and school, obtained by analyzing the neighborhood where the student lives, period of study and percentage of frequency, collected in the Academic-Q (managing system of academic data of the students).

For this investigation, the characteristics selected as predictors for the analysis and identification of school dropout are: gender, age, ethnicity, marital status, number of people living in the house with the student, family income, may not have a computer at home, parents' education level, school of origin, self-assessment as a student, origin, distance from school-residence, transport, work status, period of study and percentage of frequency.

The data collected for the analysis consists of a seven-year period, from 2004/2 to 2011/2.

The database for the input and output of the neural network is a set of pairs "input-output", resulting from the comparison and compilation of the spreadsheets extracted from the Selection-Q and Academic-Q.

The input vector of the neural network consists of 16 parameters considered to be significant for the prediction of school dropout and the network output consists of two classes, dropout and non-dropout. The pairs of vectors input-output desired are represented in binary encoding, being the input vector composed of 41bits and, the predicted answers represented by 1 bit.

The names of the students have been omitted to protect their identity, being identified with numbers in the final spreadsheet [1].

III. Fuzzy-ARTMAP and ART Neural Networks

A. *Adaptive Resonance Theory (ART)*

The Adaptive Resonance Theory (Adaptive Resonance Theory - ART) was developed by Stephen Grossberg in 1976, as a theory of human cognitive information processing, based on the physiology of the nervous system.

In neural networks, the term "resonance" refers to the state of the network, where a set of data, previously stored in a category (prototype vector), has a very close relationship or match with the set of data of actual input (input vector) of the network. This relationship or mach take the networks of the ART family to the state of resonance, which allows learning, that is, the ART networks only learn in their state of resonance.

The degree of similarity between the data of the prototype vector and the input vector determines a similarity rule which defines the collection of data in the output categories.

The ART networks systems are able to solve the dilemma "stability-plasticity". They are able to self-organize, in real time, producing stable recognition categories, as it gets input patterns beyond those originally stored, that is, they are able to learn and adapt in a changing environment. Thus, they are plastic, and, at the same time, can retain the knowledge learned previously, maintaining their ability to learn new patterns, therefore they are stable.

B. *Basic ART Neural Network*

The basic structure of an ART neural network, shown in Fig 1, consists of two subsystems of attention and orientation [20], where some elements such as: two layers of neurons (F1 and F2) and their synaptic weights (Wij amd Vji), the module parameter vigilance (ρ) and the module reset are arranged and inter-linked.

The subsystems of attention and orientation are complementary and interact to perform the processing of the input patterns.

The attention subsystem through the layers of comparison (F_1) and recognition (F_2), fully connected with the bottom-up (W_{ij}) and top-down (V_{ji}) weights, performs the processing of known input patterns, in a short term memory (STM), generating responses and more accurate inner representations of these patterns. The pattern vector is the input to F_1.

The orientation subsystem inhibits the attention subsystem when an unknown pattern is presented to the network. The reset module controls the dynamics of the attention subsystem based on the vigilance parameter (ρ). Whilst the vigilance parameter determines the degree of similarity between the input pattern vectors and the synaptic weights of F_1 and F_2.

The neurons of the recognition layer (F_2) represent the categories or groups (clusters) formed. When the network stabilizes, the top-down (V_{ji}) weights corresponding to each neuron in F_2, represent a prototype vector for that neuron.

There are two sets of synapses, each with its own weight, and the bottom-up (W_{ij}) weights interconnect each unity of the F_1 layer to all the units of the F_2 layer, and, the top-down (V_{ji}) weights interconnect each unit of the F_2 layer to all the units of the F_1 layer.

The layer of comparison or layer F_1 receives the input vector and transfers it to the recognition layer or layer F_2, seeking its best "match" or combination. The best "match" occurs when it finds the single neuron, whose set of weights corresponds closest to the input vector.

The attention subsystem indicates the winner category, while the orientation subsystem accepts the indicated category or triggers the search for a new category.

Briefly, the process of classification of an ART network consists of four phases [21]:

- Recognition: recognizes the stimuli produced in layer F_2 and selects the category of higher value after calculating the function choice.

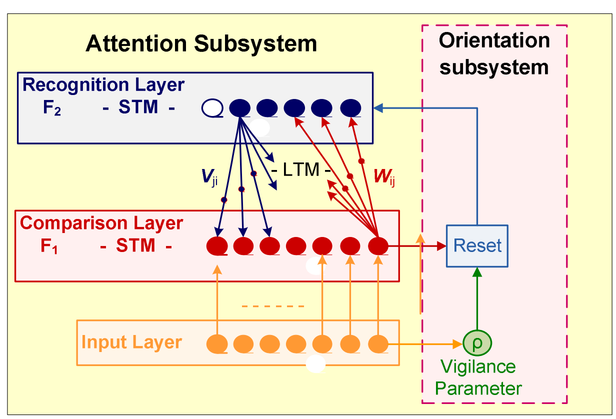

Figure 1. Basic architecture of an ART neural network.

- Comparison: through the vigilance parameter, tests the similarity between the input vector and the prototype vector, whether allowing or not the inclusion of the pattern input in the category. If the vigilance parameter is not met, the input vector is stored in another neuron.

- Search: for every new input vector, searches for a neuron in layer F_2 to represent it.

- Training: the training only starts after the conclusion of the search process, it can occur quickly or slowly.

C. *Fuzzy-ART Neural Network and Fuzzy-ARTMAP*

The neural network or the Fuzzy-ART is similar to the ART network, and, more specifically, in the case of binary input patterns, such as those used in this research, they are computationally identical. The Fuzzy-ART network [22] uses the theory of the fuzzy sets, using the minimum operator (   ) and, performs the standardization and encoding of their components during the pre-processing of the input vectors.

The Fuzzy-ARTMAP model is based on Fuzzy logics operations incorporated in the ARTMAP model. In this model, also known as predictive ART, two ART modules are interconnected, through the inter-ART module, called Field Map. This inter-ART module has a self-regulating mechanism called match tracking, which seek for matches or combinations between the categories, aiming to increase the degree of generalization and decrease the network. It forms predictive associations between the categories of the ART_a e ART_b modules and performs a self-organized tracking and recognition of categories, searching a match or combination, in relation to random sequences of input patterns. If the ART_a and ART_b modules are not connected, each of them gets self-organized, grouping their respective input sets.

The architecture of the Fuzzy-ARTMAP neural network, has been designed to conduct supervised learning in an environment or set of multidimensional data. When the Fuzzy-ARTMAP network is used in a learning problem situation, it is trained until it can classify correctly all the training data.

The mathematical development and the algorithms for the processing of a Fuzzy-ART and Fuzz-ARTMAP neural network are found, respectively in [22] and [16], and applied in [23]. The flowchart shown in Fig. 3 provides, in a simplified, all procedures of the algorithm for training of the neural network fuzzy ARTMAP.

IV. Fuzzy-ARTMAP Neural System Proposed for the Prediction of Dropout

In this research, the intelligent system model proposed was developed using a Fuzzy-ARTMAP neural network associated with a Fuzzy Logic module[13] and, in a second simulation, a model that uses the Dempster-Shafer Theory of Evidence - TDS [14]. They make it possible to accurately and reliably identify at an early, higher education students at the dropout risk group, attending classroom courses at IFMT, as a database of information extracted at registration for student selection exam.

The implementation of the proposed prediction system follows a standard procedure with four phases of action, as follows: preliminary phase, pre-processing, data processing and the phase of interpretation, assessment and analysis of the result. The structure and sequence of development of this work are shown in the flowchart of Fig. 2.

The preliminary phase defines the situation to be investigated, the scope of the research; the selection of original or raw databases and the characteristics that compose them; the delimitation of the sample and the choice of the RNA to be used.

Then, in the pre-processing phase, one performs the "cleansing" and filtering of the raw data selected is carried out, alongside the categorization of student characteristics and the treatment of information. The analog, pre-processed databases are encoded to binary code and converted into binary databases, one for the training and the other for the diagnosis of the ANN. The design of a neural system primarily binary is considerably advantageous in relation to the formulation of the hybrid Fuzzy-ARTMAP neural network (binary and analogue data). Thus, it presents a more efficient behavior (faster and better quality and accurate answers) and allows the extraction of knowledge continuously (continuous training [19]), seeking a better adaptation to the conditions of the institution and the improvement over the years.

After the binarization the data are arranged in rows. Each row of the set of data gives the student characteristics of the students, which make up the input vector (41 bits) of the neural network and represent a sample. The desired output of the network, also binary (1 bit), is formed by the student status (non-dropout (0) or dropout (1)) provided by the database. The desired input and output vectors are presented to the inputs of the ART_a and ART_b modules, respectively, for the processing of information.

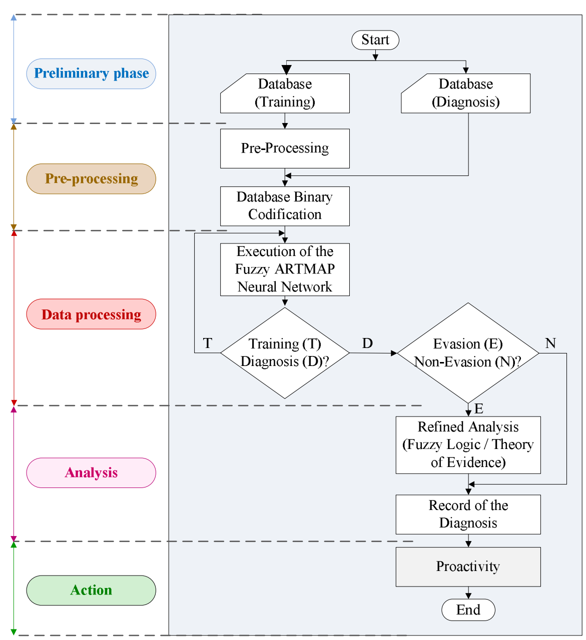

Figure 2. Flowchart of the structure and sequence of development of the neural system proposed to perform the prediction of the evasion group risk.

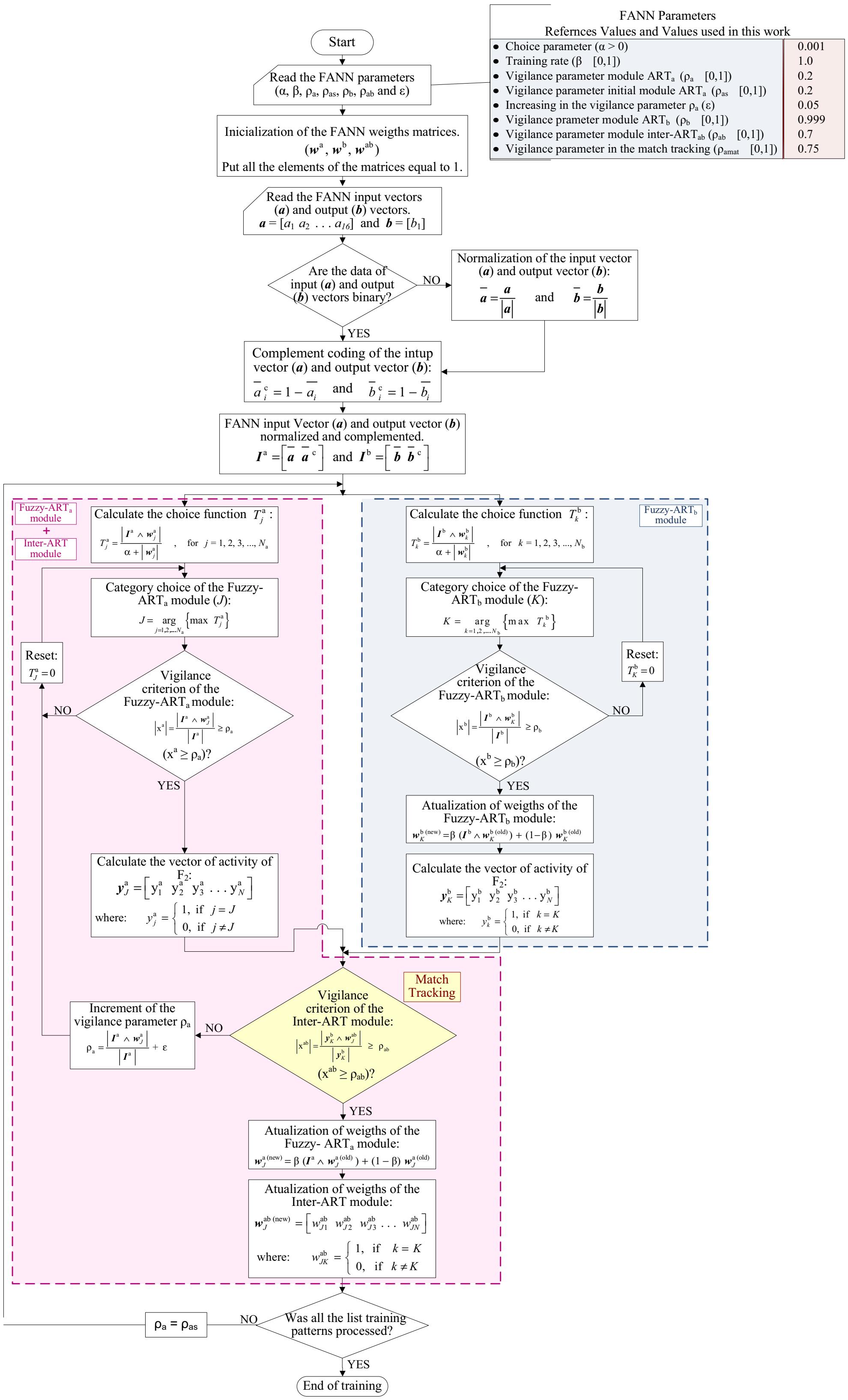

Figure 3. Flowchart of the structure and sequence of development of the neural system proposed to perform the prediction of the evasion group risk.

After processing the data, one reaches the phase of interpretation, analysis and assessment of results. At this stage, if the output of the neural network response in relation to drop out is negative, with class "0" (bit equal to 0) no action is adopted, only the recording of the information. If the answer to dropout is positive, with class 1 (bit equal to 1), this information passes through the Fuzzy module, specifically for this study, to a better discrimination about the quality of information (refined analysis).

The refined analysis consists of identifying, among the predictive characteristics, which ones would have greater influence and weight in the decision of the student to drop out.

The end of the process is the phase of Action. Based on the results of analysis, planning of individualized actions is performed (proactive action), to attend the needs of each student identified in the risk group, providing conditions for their stay in the institution. It is highlighted that the proactivity is an activity which depends heavily on the actions of the institution.

V. Application and Analysis of the Results

In this study, in particular, the input of the Fuzzy-ARTMAP network proposed is represented by vector a (input of the ART_a module) and its respective desired output, in the training phase, represented by vector b (input of the ART_b module), described as follows:

$$\boldsymbol{a} = [\boldsymbol{a}_1\ \boldsymbol{a}_2\ \boldsymbol{a}_3\ \ldots\ a_{16}] \quad \text{and}$$
$$\boldsymbol{b} = [\ b\ ] \quad \text{where: } b = \text{“0” or “1”}$$

The subvectors $\boldsymbol{a}_1$, $\boldsymbol{a}_2$, ... $\boldsymbol{a}_{16}$ of the vector $\boldsymbol{a}$ (Table I) are lines vectors containing the binary representation of the students' characteristics. Each bit corresponds to a component of the associated vector.

The output of the network is represented by the activity vector of F_2 layer ($\boldsymbol{y}$) and provides answers in binary encoding with 1 bit (Table I), whether the code "1" corresponds to student's dropout and code "0" to absence of dropout students, defined as:

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

In the phase of validation and diagnosis of the Fuzzy-ARTMAP neural system, in this study, two samples were used, one of them with 389 lines and the other with 499 lines, both with 41 columns, about 30% of the total of the training samples. Each line has the characteristics of a student and represents the input pattern vectors and their respective desired output, in the training. Data from columns 1 to 41 represent the attributes corresponding to vector $\boldsymbol{a}$, input of the ART_a module. In column 42 the data represent the desired outputs, vector $\boldsymbol{b}$ (ART_b input) of the Fuzzy-ARTMAP neural network.

The Fig. 4 shows the relationship between the number of students enrolled and dropouts in higher education courses in industrial automation, from 2004 to 2011. This data were analyzed in the samples used in the phase of validation and diagnosis of the Fuzzy-ARTMAP neural system.

TABLE I. Composition of the 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	

The parameters used in the database processing are specified in Table Notes - FANN Parameters, in the flowchart of Fig. 3.

After training of the network five simulations were carried out with the database for the diagnosis, to validate the proposed model, and in one of them the samples were processed in a naturally aleatory way and in the others randomly.

The results of the processing were compared and analyzed, using the "voting criterion" [16], the output "0" or "1" has been checked for higher incidence of each of the entries. The result of highest incidence constituted the output of the neural network.

Subsequently, comparing the resulting output of the network with the real situation of each sample of the group of students analyzed it was possible to determine the match of dropout ("1") and non-dropout ("0") between samples processed and reality.

After the processing phase through the Fuzzy-ARTMAP neural system and the analyses pertinent and necessary to the understanding of the network behavior in relation to the students' dropout and non-dropout, the results were compiled and, concisely shown in Table II - A and II - B.

The data from Table II - B show the results of simulation B, which considered only the students who abandoned their courses in the first year, from 2004 to 2011, obtaining success rates of 94.4% in relation to dropout students and overall of 85.6%. In other study, which considered only the students who abandoned their courses in the first semester, from 2004 to 2011, obtaining success rates of 97.8% in relation to dropout students and overall of 76.7% [23].

The interpretation and analysis of the data resulting from simulation A (Table II - A), in which all the students who abandoned their courses, between 2004 and 2010, have been considered, confirms the level of accuracy obtained in simulation B and in [23]. The system proposed identified 231 possibilities of dropout and ignored 12, out of a total of 243 dropout students, obtaining a rate of accuracy of 95.1%. Of the 146 samples of non-dropout students, 135 were recognized, signifying an accuracy level of 92.5%. In this simulation, the Fuzzy-ARTMAP neural system reached the overall level of accuracy of 94.1%.

The quantitative and perceptual results of the diagnosis of dropping out obtained in simulation A, can be noticed, more clearly, in the graphs of Fig. 5.

Based on the tests performed and the consistency of the results obtained, it can be inferred that the intelligent system, using the Fuzzy- ARTMAP neural network, proposed to identify the students likely to drop out, is a model with a significant degree of reliability and accurately expresses the situation of the students analyzed.

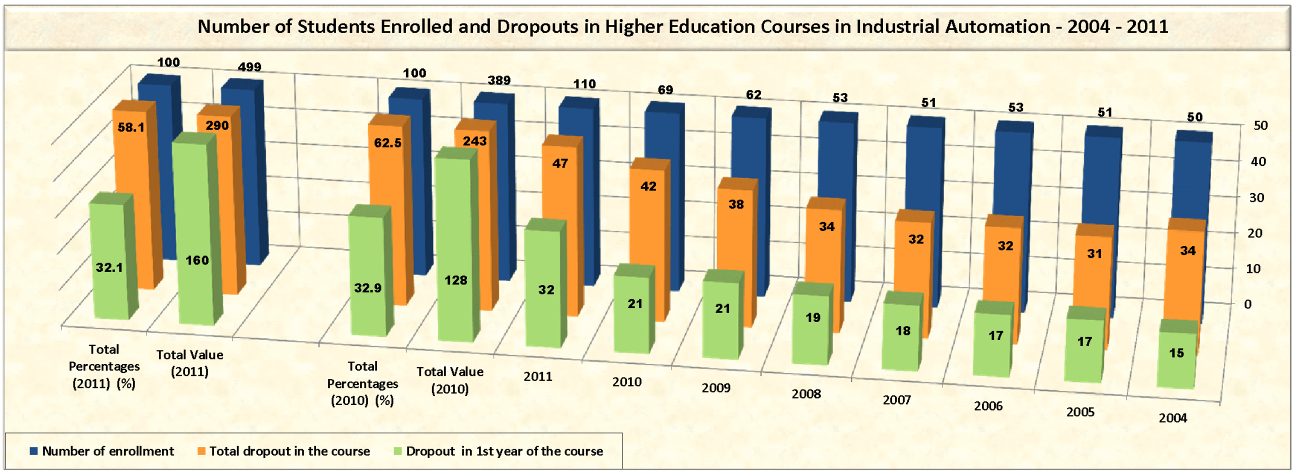

Figure 4. Number of students enrolled and dropouts in higher education courses in industrial automation from 2004 to 2010.

TABLE II. RESULT OF THE DIAGNOSIS OF STUDENT DROPOUT

A - TOTAL DROPOUT: PERIOD FROM 2004 TO 2010.

Diagnosis of Student Total Evasion 2004/2010	Quantitative and Percentages Values: Output of Network					
	Evasion		*Non-Evasion*		*Total of Samples*	
	Number	*%*	*Number*	*%*	*Number*	*%*
Samples	243	100	146	100	389	100
Corrects	231	95.1	135	92.5	366	94.1
Errs	12	4.9	11	7.5	23	5.9

B - DROPOUT 1ST YEAR: PERIOD FROM 2004 TO 2011.

Diagnosis of School Evasion 1th year 2004-2011	Quantitative and Percentages Values: Output of Network					
	Evasion		*Non-Evasion*		*Total of Samples*	
	Number	*%*	*Number*	*%*	*Number*	*%*
Samples	160	100	339	100	499	100
Corrects	151	94.4	276	81.4	427	85.6
Errs	9	5.6	63	18.6	72	14.4

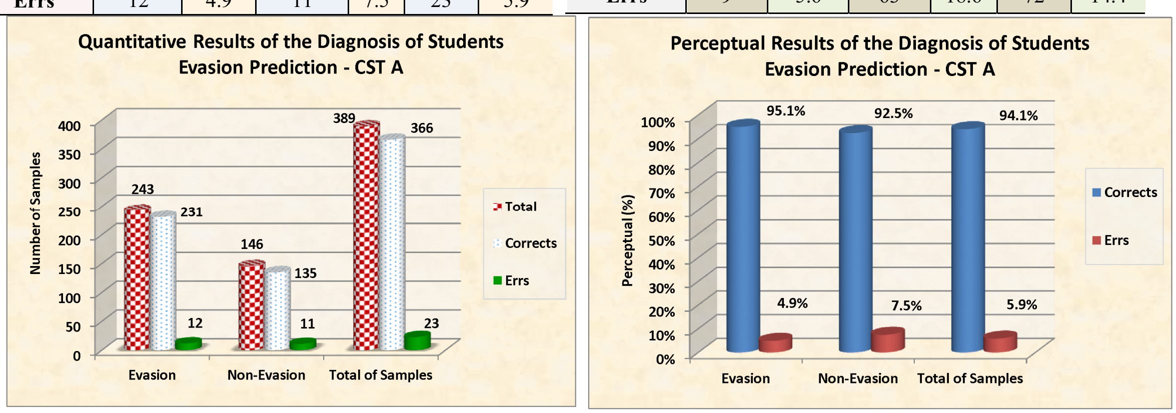

Figure 5. Quantitative and perceptual results of the diagnosis of students total evasion from 2004 to 2010.

VI. FINAL CONSIDERATIONS

This work is supported by a research which aims to propose an innovative method, to identify, proactively, continuously and accurately the students considered to be in the dropout risk group, in higher education classrooms, with a database using information collected from students' registration. For this purpose, we have implemented a Fuzzy-ARTMAP neural network system associated with the Fuzzy module and a module of Dempster-Shafer Theory of Evidence.

From the analysis of the results it can be inferred that the system proposed is appropriate, effective and with a significant degree of reliability and achieved an overall success rate between 85% and 94% in the early identification of the dropout risk group.

The comparison of the results obtained with the Fuzzy-ARTMAP neural system, adopted in this study, with those described by Mustafa [12] with the application of decision trees classification (between 28% and 38% of success rate) to identify dropout likelihood based on the data from the enrollment of students, show the quality and relevance of the neural system.

This study deals with the prediction of actions resulting from resolutions and decisions of human beings. Thus, it recognizes the limitations of the methodology and the possible flaws, given that the predictions outside the complete determinism being the dropout the result of a stochastic process.

Therefore, considering the results, it is evident that the Fuzzy-ARTMAP neural system is a powerful, bold and innovative tool for predicting risk groups of student dropout in higher education classrooms, filling in the existent gap in the productions of the international scientific community, regarding the matter discussed in this study, thus contributing with something useful to society. Being able to proactively lead a student who might otherwise drop out to be successful is a noble mission, a dream that can come true.

ACKNOWLEDGMENT

To the Federal Institute of Mato Grosso for the availability of the database of the Academic-Q and selection-Q systems that fostered this research, as well as, CAPES for the financial support.

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