Predicting Early Students with High Risk to Drop Out of University using a Neural Network-Based Approach

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***Abstract*—This research is focused on the use of an Artificial Neural Network-based prototype in order to measure and predict the probability that students drop out of university. This probability is calculated in an early stage when the students get enrolled in some of the university study programs. Once we obtain the results they are analyzed and compared in order to know how the factors affect to the model behavior and the predicted result. Finally, we describe how this research can assist student advisors by using a support tool that helps them to identify in a fast way those students with a high risk of dropping out of university, and help them before they quit school.**

Keywords-artificial neural networks; students drop out; early prediction; university drop out

I. INTRODUCTION

Dropping out of university is a common problem with students in México [1]. For governments, this is a worrisome situation since the state must provide all support to students in order to allow them to graduate with a professional college degree and advanced technical skills.

Providing higher education to all sectors of a nation's population means confronting social inequalities deeply rooted in history, culture and economic structure that influence an individual's ability to compete. Quality assurance in higher education has raised to the top of the policy agenda in many nations [2][3].

Some studies show that students' previous behavior is a good predictor of future behavior [4][5][6]. This way, the Universidad Tecnológica de León (UTL) applies a survey to know some aspects about the students' life. This survey involves questions about students' family and their relationship which each member, vices, health and frequent diseases, skills and assignments that are relevant to them finishing the program successfully. However, this survey many times is not used correctly, since it collects too much information and it is hard to understand for most of the teachers and advisors, since they are not trained as psychologists and by consequence they do not have this profile.

In the scholar model of the UTL, students are grouped and each group has a teacher that acts as an advisor for the group. Advisors are responsible to follow the academic performance of their groups. They do some activities related to the students' behavior in order to detect those students with a high risk to drop out of university. The most valuable instrument that advisors have in order to detect those students with a high risk is the information provided by a personal interview with each student of the group. This is a highly time-consuming task, and it requires a lot of days even weeks since some groups have up to 30 students. Many times, students drop out of university before attending an interview with the advisor and the advisor is unable to detect students' problems. Detection of student's problems is a hard task since most of the teachers have not been trained as a psychologist. This way, the proposed solution is very important, since it can be used as an advice tool in order to help advisors to detect those students with a high risk to drop out of university, since the very first course.

In this research, a Back Propagation Artificial Neural Network-based system is proposed in order to measure the university students dropping out probability once they are enrolled in some university academic study program. This research was developed at the UTL and it was applied to students enrolled in the Information and Communication Technologies academic programs. In the second section, an introduction to educational data mining is described since this research is related with educational purposes but also, it involves data analysis and pattern discovery to estimate a future behavior. In the third section, the dataset used for prediction is described. In the fourth section, the neural network architecture is analyzed but also, the reason why that technique was used is described. In the fifth section, the prototype development is described. In the sixth section, the obtained results are discussed. Finally, in the seventh section, conclusions and future research are described.

II. EDUCATIONAL DATA MINING

Into the educational field, there is a wide variety of problems concerning students' behavior and some kind of development using intelligent computational techniques and algorithms are well documented. For example, some researches are focused to discover if a student is cheating on an online assessment when he/she is taking it [7][8]. Others are focused on studying how students learn [9].

In all cases mentioned above, data mining plays a very important role in order to provide with solutions in each described scenario and it is called "educational data mining".

Educational data mining is an emerging discipline, concerned with developing methods for exploring the unique types of data that come from the educational context [10].

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Close works with this paper are the research works related with the students' successful academic performance. Nearly all works try to identify the main factors that could be used as the best predictors for successful students more than measure or build a computational predictive model [7][8][9][11][12]. However, that approach is complex to be applied for most of teachers in their advisory sessions, and they must follow the educational model including procedures, formats and surveys and its implementation may require a lot of effort and spent time since in the UTL, the number of factors to be considered to predict are too many. The closest work to this research that was found was [3]. In that research, a Bayesian classification model is proposed in order to classify students in one of two groups: performance or underperformance. This classification is made using a dataset that includes some students' features. However, in this research, since the number of features is considerably large and the features relationship is unknown, a Bayesian based-model was not used. Instead, an Artificial Neural Network-based (ANN) [13] approach was used since it is a more soft-classification technique and they are widely applied in pattern recognition and prediction problems when data nature, mean or relationships between them are unknown [13].

III. THE TRAINING DATASET

The dataset used in this research includes many features from students. Those features are collected from a survey to all new students when they get enrolled in the UTL. The survey features include information about high school name and type (government or private), high school final grade, vices and addictions (alcohol, smoke, drugs, etc.), common diseases, relationship with parents, brothers and family, different kinds of problems: economics, transport, delinquency, etc. The dataset had 302 total historic records with 34 features. The dataset was split in two parts: 219 records were used to train the neural network and the remaining 83 records were used in prediction. The used records correspond to historical data in order to allow measuring the neural network accuracy. Fig. 1 shows the factors taken from the initial survey, which students previously answered when they get enrolled into the university.

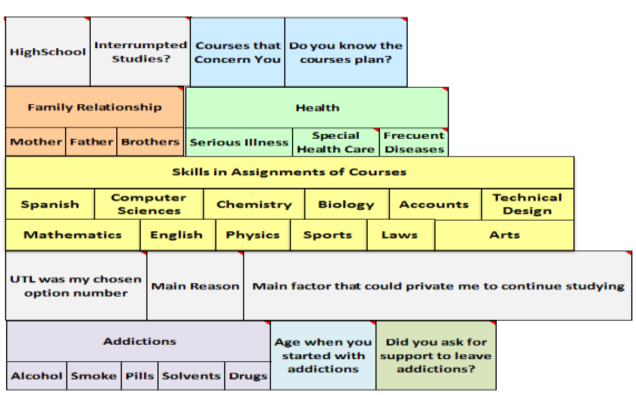

Figure 1. Survey factors that are used in order to predict graduate students' probability.

The survey is answered by new students when they get enrolled in the UTL. It has been applied since year 2000 and it was applied on paper. Only until year 2010, the survey began to be applied on a web-based system. This means that a large number of surveys remained on paper. However, many of them no longer exist because teachers and advisors got rid of them every three years. For this reason, only 302 surveys could be found for the Information Technologies area. This scenario is similar for the other areas in the UTL.

IV. NEURAL NETWORKS

A. *Neural Network Architecture*

The main ANNs' advantage is learning capability. ANN's are very important in many technological fields; for example, biometric recognition sensors (fingerprints, retinal scanners, etc.), pattern recognition (handwriting recognition, face recognition, etc.) [14][15][16][17][18]. Neural networks have demonstrated they are functional because they have achieved good results. For example, in diagnosis of breast cancer, neural networks performance was in 89% to detect positive cases and the average for the same task performed by specialists was 84% [14]. Artificial neural networks are often compared with logistic regression, and it can be seen that both models perform on about the same level more often than not, with the more flexible neural networks generally outperforming logistic regression in the remaining cases [23].

A wide range of types of neural networks has been developed to date; for example, Radial Base [27][28][29], Hopfield [30][31][32][33] and Back Propagation (with many variants) [13][34]. Many of them are based on the basic Perceptron ARN [19][20][21][22]. In this research, a multilayer neural network with error back propagation and momentum was used [22][34].

B. *Neural Network Design*

The neural network input layer was designed using all dataset features and one additional threshold neuron (33 + 1 neurons). The final number of nodes for the hidden layer was 69. One layer of hidden neurons is generally sufficient for classifying most data sets. The number of neurons in the hidden layer needs to be set empirically, e.g., by cross-validation or bootstrapping [23]. The output layer has only one neuron with two limit values: 0 and 1, since only two possibilities are considered to measure the final status for the students when they leave the university. The two possible scenarios for any student that leaves the university are: 1: if the student successfully finished his studies and gets graduated; 0: if the student drops out the university. However, an interesting approach with ANN's is that their output values may have intermediate values between 0 and 1, considering that output value as the probability that any student have to finish his studies. A higher value in the output neuron means that the student has major probability to successfully finish his studies. For this research, if the neuron is activated (with a value major or equals to 0.50) is considered that the student will have a good probability to

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finish his studies successfully and advisors could be focused firstly on those students for whom its output value was less than 0.5. Fig. 2 shows the neural network design architecture.

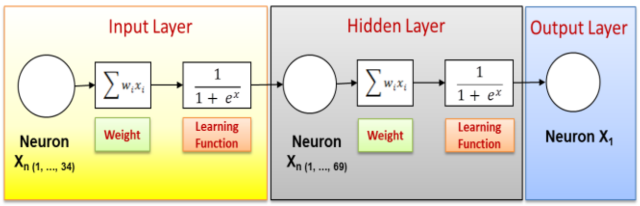


Figure 2. Neural network design architecture.

Fig. 2 shows the architecture design for the used neural network. In the model of an ANN, the most important part is the neuron. The neuron receives a set of input signals from the environment (each survey factor) or from another neuron.

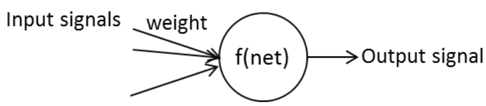


Figure 3. Illustration of an artificial neuron.

As shown in Fig. 3, an artificial neuron receives input signals, and each input signal has a weight. Also, each neuron computes a net input signal using the input signals and the weight of each input signal. Net input signal was calculated using Equation (1):

$$net = \omega_1\chi_1 + \omega_2\chi_2 + \ldots + \omega_i\chi_i \qquad (1)$$

where *net* is the net input signal, W_i is the current weight for each neuron and X_i is each input value. Once the net input signal was calculated, the output (also called activation signal) must be calculated. The output signal was calculated using a sigmoid function:

$$1 \,/\, (1 + e^{-\lambda(net - \theta)}) \qquad (2)$$

where λ is a parameter to control the steepness of the function and usually equals to 1, q is a bias or threshold value. When simple neurons implement, for example, Boolean functions, it is easy to calculate them. But, when prior knowledge about the function is missing - except for data -, the θ and ω_i values are adjusted through training [13].

The neural network training was performed using the Neuroph Studio software [25]. The optimal neural network parameters were: *learning rate = 0.1428*; *momentum = 0.8192*; *training error = 0.01*. Fig. 4 shows the training performance.

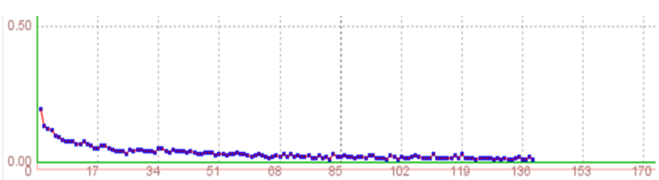


Figure 4. Neural network raining performance.

As it is shown in Fig. 4, approximately 135 iterations were needed in order to achieve the training error. After the neural network was trained, it was used with the test records in order to calculate and evaluate the results.

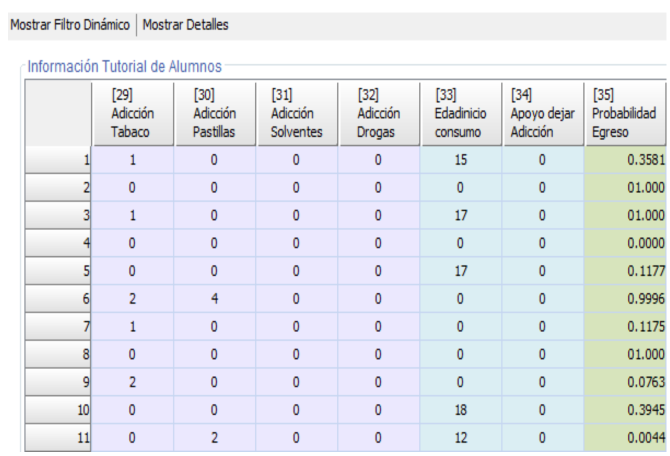
V. PROTOTYPE BUILDING

In order to use the neural network designed and trained previously, a software prototype was developed. It was developed in the Java programming language [24]. Fig. 5 shows the main user interface.

Figure 5. Prototype main user interface.

Into the main interface, the user must select and load the neural network file (created with Neuroph Studio in the neural network design stage). The prototype uses the Encog framework in order to manipulate and use the neural network [26].

Once the neural network is loaded, the next step is load a file containing the students' enrollment key field. Then, the system queries for those students' data into a database, in order to compute their success probability, and finally it will display a table containing all students' data including their success probability. Fig. 6 shows an example of a table results displayed by the program.



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Información Tutorial de Alumnos

	[29] Adicción Tabaco	[30] Adicción Pastillas	[31] Adicción Solventes	[32] Adicción Drogas	[33] Edadinicio consumo	[34] Apoyo dejar Adicción	[35] Probabilidad Egreso
1	1	0	0	0	15	0	0.3581
2	0	0	0	0	0	0	01.000
3	1	0	0	0	17	0	01.000
4	0	0	0	0	0	0	0.0000
5	0	0	0	0	17	0	0.1177
6	2	4	0	0	0	0	0.9996
7	1	0	0	0	0	0	0.1175
8	0	0	0	0	0	0	01.000
9	2	0	0	0	0	0	0.0763
10	0	0	0	0	18	0	0.3945
11	0	2	0	0	12	0	0.0044

Figure 6. Results table example.

Fig. 6 shows how the system calculates and presents the results. Each part of the survey is marked with a distinct color and the last column represents the probability that students successfully finish their studies.

VI. RESULTS

To measure the results, sample records were taken from the original dataset. Table 1 shows how the sample is distributed.

TABLE I. SAMPLE DATASET SUMMARY

Gender	Finished Successfully	Dropout
Female	12	29
Male	18	24
Total	30	53

As it is shown in Table 1, the sample contains 41 records for women (12 finished successfully, 29 dropped out) and 42 records for men (18 finished successfully, 24 dropped out).

In a first-view, major drop outs are for women (29) and a woman is ranking less on successfully finishing her studies. In the sample, only 29% of women finished successfully their studies and the other 71% dropped out. For male data, 43% finished successfully their studies and the other 57% dropped out.

Unfortunately, the university does not know the factors that cause those students' drop out. The only evidence, in most cases is that the student fails to assist to his courses, but underlying causes remain unknown for nearly all cases. Teachers including the advisor know the causes why students that dropped out but, this only happens when students tell them why they are leaving the school. However, even in these cases, the cause or factor is not recorded. This is important to be mentioned because the students' data that we have in order to predict their probability to finish their studies successfully is the survey that they must answer once they are enrolled into the university programs.

Fig. 7 shows the results produced by the system using the dataset mentioned in Table 1. It is divided in two sections. On the left section, the results for students that drop out of university are shown. In the right section, the results of the students that finished their studies successfully are shown. That records was subtracted randomly from the original dataset and it was not used on the training stage. Record Id column is a unique id assigned to each record. Desired output column means the student real result: 0 if the student drops out, 1 if the student finished successfully. The output column shows the result produced by the system. System error column is calculated as:

$$\textit{Desired output - System output} \tag{3}$$

Based on the obtained results by the program, reliability was in a 76%. That means that program failed to predict 20 cases and asserts to predict the remaining 63 cases.

Record Id	Desired Output	System Output	System Error	Gender
1876	0	0.1085	-0.1085	M
1826	0	1	-1	F
1884	0	0.9994	-0.9994	F
1855	0	0.9989	-0.9989	F
1832	0	0.1175	-0.1175	F
1825	0	0.1175	-0.1175	M
1834	0	0	0	F
1851	0	0	0	F
1864	0	0.1174	-0.1174	F
1867	0	0.1275	-0.1275	F
1830	0	0.7853	-0.7853	F
1846	0	0.9994	-0.9994	M
1866	0	1	-1	M
1838	0	0.3756	-0.3756	F
1845	0	0.9996	-0.9996	M
1842	0	0.1153	-0.1153	F
1848	0	0.8919	-0.8919	F
1833	0	0	0	M
1880	0	0.1219	-0.1219	M
1871	0	1	-1	M
1859	0	1	-1	F
1862	0	1	-1	M
1849	0	0	0	M
1852	0	0.1182	-0.1182	F
1850	0	0.1247	-0.1247	M
1853	0	0.1176	-0.1176	M
1835	0	0.1182	-0.1182	F
1869	0	0.9991	-0.9991	F
1872	0	0.114	-0.114	F
1839	0	0.9988	-0.9988	F
1825	0	0.1175	-0.1175	M
1828	0	0.3945	-0.3945	M
1865	0	0.1179	-0.1179	F
1879	0	0	0	F
1863	0	0.117	-0.117	F
1888	0	1	-1	M
1824	0	0.9996	-0.9996	F
1870	0	0.9276	-0.9276	M
1841	0	0.1174	-0.1174	M
1840	0	0	0	F
1900	0	1	-1	M
1836	0	0.9973	-0.9973	F
1860	0	0.1178	-0.1178	M
1856	0	1	-1	M
1849	0	0	0	M
1847	0	0.069	-0.069	F
1854	0	0.0661	-0.0661	M
1844	0	0.9902	-0.9902	F
1877	0	0.0006	-0.0006	M
1831	0	0.1475	-0.1475	F
1872	0	0.114	-0.114	F
1837	0	0.1175	-0.1175	F
1827	0	0.0763	-0.0763	F
1843	0	0.0005	-0.0005	M
1873	0	0.1162	-0.1162	M
1875	0	0.3821	-0.3821	M
1849	0	0	0	M

Record Id	Desired Output	System Output	System Error	Gender
1890	1	0.9994	0.0006	F
1857	1	0.1552	0.8448	F
1821	1	1	0	M
1901	1	0.9916	0.0084	M
1868	1	1	0	F
1899	1	1	0	M
1858	1	0.9995	0.0005	M
1894	1	0.1668	0.8332	F
1887	1	1	0	F
1829	1	0.0044	0.9956	M
1896	1	1	0	M
1822	1	0	1	M
1892	1	0.1199	0.8801	M
1895	1	0.9996	0.0004	M
1882	1	0.0882	0.9118	F
1878	1	0.0169	0.9831	M
1885	1	0.1183	0.8817	M
1820	1	1	0	F
1893	1	1	0	M
1890	1	0.9994	0.0006	F
1823	1	0.1177	0.8823	F
1892	1	0.1199	0.8801	M
1883	1	0.9898	0.0102	M
1897	1	1	0	F
1898	1	0.0002	0.9998	F
1858	1	0.9995	0.0005	M
1819	1	0.3581	0.6419	F
1874	1	0.9996	0.0004	M
1887	1	1	0	F
1857	1	0.1552	0.8448	F
1821	1	1	0	M
1886	1	0.9967	0.0033	M
1889	1	1	0	M
1868	1	1	0	F
1861	1	0.211	0.789	F
1878	1	0.0169	0.9831	M
1894	1	0.1668	0.8332	F
1885	1	0.1183	0.8817	M
1881	1	0.9994	0.0006	M
1891	1	0.5898	0.4102	M
1822	1	0	1	M
1892	1	0.1199	0.8801	M
1882	1	0.0882	0.9118	F
1883	1	0.9898	0.0102	M
1897	1	1	0	F
1898	1	0.0002	0.9998	F
1820	1	1	0	F
1893	1	1	0	M

Figure 7. Results obtained by the system.

A failed prediction means that desired output was 0, and program output value was major or equals to 0.5. The 0.5 value is the output neuron's threshold activator and, while the output value is greater, the probability for students finish their studies successfully increased.

An interesting aspect in the survey is the "main factor" column. In this part, the students must select their main issue that could impede them to finish the school program. Fig. 8 shows the frequency of answers for this column.

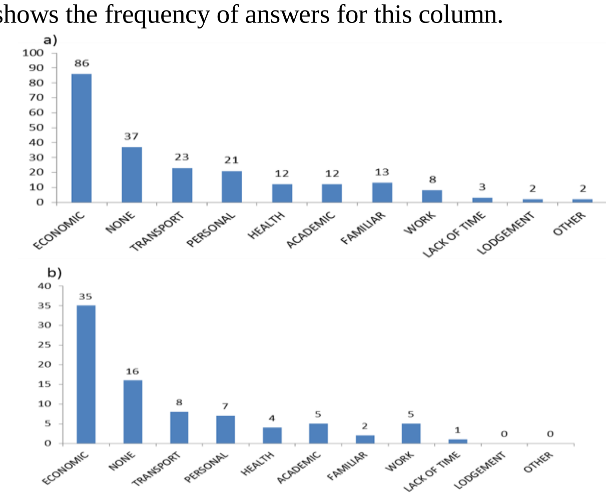

Figure 8. Frequency of responses for column "main factor".

Fig. 9a shows the frequency of answers in the training dataset, and Fig. 9b corresponds to the test dataset. In both cases, the major frequency is the economic factor. However, the second factor varies from males and females.

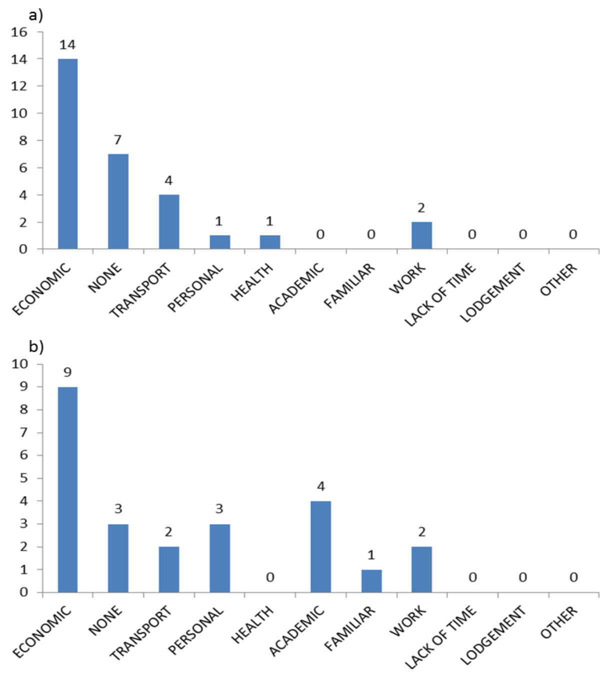

Figure 9. Drop out frequency of responses for column "main factor".

As it is shown in Fig. 9, the second most frequent factor for drop out in female students was "none" (9a), while for males was "academic" (9b). On the skills part, frequencies are shown in Table 2.

TABLE II. SKILLS FREQUENCY FOR MEN AND WOMEN

Assignment skills frequency	Gender	
	Female	*Male*
Spanish Skill	97.56%	85.71%
Spanish Dificult	2.44%	4.76%
Spanish No Answer	0.00%	4.76%
Computer Skill	73.17%	80.95%
Computer Diificult	21.95%	9.52%
Computer No Answer	4.88%	4.76%
Mathematics Skill	41.46%	33.33%
Mathematics Diificult	53.66%	59.52%
Mathematics No Answer	4.88%	2.38%
English Skill	34.15%	42.86%
English Diificult	65.85%	50.00%
English No Answer	0.00%	2.38%
Technology Skill	56.10%	85.71%
Technology Diificult	36.59%	4.76%
Technology No Answer	7.32%	4.76%

In Table 2, major frequency skills are in Spanish course, but more difficult courses are mathematics and English for both, men and women. The difficult issue for computers and technology are more frequent on women than on men. An important aspect here is that neural network cannot be trained if we skip the survey's skills section. A deeper study is needed in order to understand how these factors alter the final result, but it requires some data mining techniques to achieve that goal since we are dealing with a considerably amount of data and fields.

VII. CONCLUSIONS AND FUTURE RESEARCH

This information is relevant in a first-stage, because it allows advisors to identify those students with a high risk to drop out of university from the beginning. For the cases where the program fails to predict the correct result, some inconsistences in the survey answers were found. For example, some students indicated to have high ability in math, but in another survey section, they wrote comments indicating that they felt concern by math. Additionally, as seen on Fig. 8, in the results section, those women that dropped out the school and where the system predicted a high probability to finish successfully, the second major cause was "none". This can be explained in an empirical way because teachers are noticed frequently by female students that they have unplanned pregnancies. This type of information cannot be inferred by the survey. Maybe a new question about the student's sexual life could be useful to predict this type of drop outs. The UTL continues to support this research in order to implement this prototype as an active module on its scholar control system to be used by teachers and advisors as a complementary advice tool.

Future research will include modifications to the survey to add more information features. Is planned to add more neurons to the neural network output layer in order to have multiple outputs and, later calculate their average and use it as the result. Also, is necessary a deeper study in how the survey's factors affect to the students behavior and their decision to leave the school.

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