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Machine Learning: Vocational Guidance and the Profile of the Student Entering a Study Program

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Abstract

Admission to a higher education institution is oriented to principles and methods established by them, for admission or not, the applicant tries to demonstrate his or her competencies to choose an ideal professional career, the university accreditation model in its standard 18 reference on admission to the study program and that must be in accordance with the admission profile; Machine learning through the decision tree technique becomes indispensable for the solution of human behavior problems since through binary regions it identifies groupings with homogeneous data, the objective of this research was to develop a decision tree based on a neural network that allows classifying the vocation of the applicant to a certain study program based on the profile of the entrant; To ensure that the applicant knows his/her competencies, the knowledge, aptitudes and attitudes raised have been considered, the neural network considered 3 incoming axon's and one outgoing axon; Finally, the decision tree contains 4 levels of information, the result of the tree model gives a value of 0.939, a value that guarantees the application of the global model for the prediction of the entry or not of applicants to certain careers, also this model is supported by the sensitivity results with values of 0.818 and 0.983 for the classes "yes" or "no" enters respectively, A cross-sectional analytical study has been carried out.

Keywords: *admission to the study program, admission conditions, decision tree, neural network, career guidance, pillars of knowledge.*

1. Introduction

Vocational guidance teaches students to identify their cognitive abilities and competencies and thus have a first approach to the areas of knowledge that a professional profile requires and this can be developed through vocational tests, which, for their construction, need different types of tests that can guarantee through their results the choice of professional careers. Refers Pulido et al. (2009) that, the earlier "this process is initiated, the more adequate the results will be" (p. 49). It must even be integrated into the educational dynamics of universities (Calle & González, 2013) as it could be, the tutoring area. Gonzalez (1999) cited by Guerra Rubio and Quevedo Guerra (2007) manifest as a "... Fear of failure, of one's own and others' disappointment, are often habitual feelings of the pre-university youth that become a source of anxiety and stress" (p. 2), highlighting the question: what could they study? and the answer is definitely a

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professional career according to the student's abilities and competencies; Maura (2001) On the other hand, he says that the problem of choosing a profession occurs worldwide and that "there are many factors that influence the professional choice (...) The analysis and interpretation of how and why to choose a profession is dependent on the theoretical position (...) of vocation and vocational orientation" (p. 49).

Vocational guidance makes it possible to bring the student closer to the competencies of the professional career through a specialist called a counselor, who, apart from placing him in a specific area, must train him to handle with the appropriate knowledge a changing and complex world in his professional life (León Mendoza & Rodríguez Martínez, 2008); On the other hand, Vidal Ledo and Fernández Oliva (2009) They emphasize that vocational guidance is not given in a single moment but must accompany the student throughout his or her formation of "... so that they know and make decisions to build their own knowledge according to their vocation" (p. 1). Including León Mendoza and Rodríguez Martínez (2008) They claim the same thing. On the other hand Orrantia and Silva (2014) They affirm that guidance should be given, on the one hand, for new entrants and, on the other, for those who are close to entering the labour market.

The importance of vocational guidance is to provide support to the decision with self-knowledge of their interests, skills, aptitudes, clear objectives and with a future perspective, in this way a wrong choice or fortuitous abandonment would be avoided (Erazo Guerra & Rosero Morales, 2021). Similarly, Mendoza (1994) cited by Ramos Monsivais and González (2020) They refer to the student to reflect before choosing a professional career because it will determine the actions that he or she will have to endure in the future.

Student dropout is largely determined by academic performance in most cases, but there are exogenous and endogenous factors that will determine its success, according to some authors Martínez-Pérez et al. (2020) They point out that dropout or failure can occur when the student repeats one or more subjects on more than one occasion. In addition, according to Martínez-Pérez et al. (2020) Hold:

... that among the determinants of university student dropout are vocational problems, the economic situation of their families, academic performance, and some of the causes of the latter involve: low motivation due to vocational problems; previous academic weaknesses; weaknesses in teaching and learning methodologies and dissatisfaction with the career, among others (p. 2).

On the other hand Albarran-Peña (2019) It states that this phenomenon is a product of the behavior of human beings, who learn and their behavior varies according to personal or institutional difficulties. For this reason, the vocational orientation tests must be developed by psychologists, they are the ones who must provide support against the decision made by the applicants, the lack of vocational guidance would be causing professional instability and development of society (Salas Moya et al., 2020).

These statements mean that vocational guidance is analyzed from different profiles, starting from the entry, student, graduate and professional profiles; This research work connotes the issue of the admission profile due to its vital contribution to training and academic development, becoming a possible negative factor for student dropout. A good contribution given by Dillon-Pérez et al. (2023) is that "there are many professionals in the psychological field, and mainly psychopedagogy, who offer their professional services in order to contribute in a technical way to making this choice of professional career the right one" (p. 80).

The approach of the entry profile is currently gaining importance for study programs since the definition of their requirements are the product of the analysis of the graduation profile and the needs of the stakeholders, thus seeking to ensure their continuous improvement (Sineace, 2018). Some universities do not take this issue and avoid

establishing strategies to know the skills and abilities of incoming students (Torres-Zapata et al., 2019). Likewise, having the appropriate characteristics (knowledge, competencies and skills) according to the profile will enable the student to adapt to the university system (Álvarez Pérez & López Aguilar, 2019). Adds Morphofunction (2020) that the factors consistent with the profile mostly determine academic performance.

One of the ways to address the above problems is to resort to Artificial Intelligence (AI) which, according to Badaró, Ibañez, Agüero (2013) cited by Ocaña-Fernández et al. (2019b) simulates the capabilities and behaviors that the human brain develops; also Ponce Cruz and Herrera (2010) talks about the simulation of the acting functionalities of the human being through artificial models; Russell et al. (2011) It classifies them through different definitions:

Those at the top refer to mental processes and reasoning, while those at the bottom refer to behavior. The definitions on the left measure success in terms of fidelity in the way humans act, while those on the right refer to an ideal concept of intelligence, which we will call rationality. A system is rational if it does "the right thing," based on its knowledge (p. 2).

Most of the algorithms of neural networks are oriented to the education sector due to the wide usefulness that is given to them, such as in the processes of admission, dropout, conduct, methodological strategies and other applications of decisive use, in addition, the subcommittee ISO/IEC JTC/1 SC/42 of the International Organization for Standardization (ISO) is developing the standards for the use of AI (Peña et al., 2020). On the other hand, Sánchez Sordo (2019) argues that "connectivism integrates principles of networks, complexity, self-organization, and aspects of extended mind" (p. 23), the human brain has a network of connections that when performing an action these networks interconnect; Redecker (2009) cited by Sánchez Sordo (2019) that networks are divided into two parts: external "structures that we create to keep up-to-date, create and connect with new knowledge; and its nodes the entities (people, websites, applications, etc.), with which individuals connect to form a network" and internally:

"Personal learning networks can be perceived as existing structures in our minds in the connection and creation of patterns of understanding, since, as Siemens (2006a) states, we adapt the connections of our brain to process the environment in which we move, given that probably the brain thanks to its plasticity (Bartra, 2007) restructures its connections with the use of technology, because the digital learning networks that we generate, we could say that they are also generated at the neural level (Downes, 2012), which implies a solid relationship between the organization and functioning of the brain, the tools and what we learn". (p. 23)

From the above, we can say that connectivism represents the human brain and AI simulates it through the Machine Learning algorithms represented in the computer. Acosta et al. (2020) that Machine Learning extracts information from the data it processes to then learn and generate behaviors, if there are variations, the algorithm has the ability to adapt them based on the objective set, the most used and reliable technique are decision trees that for Landa et al. (2021) They mention that they are supervised learning algorithms applying the divide-and-conquer technique; for Mitchell (2000) cited by Landa et al. (2021) the decision tree is based on the rule of type If... Then, in addition, they mention that the "decision tree develops a test as it travels towards the leaves achieves a decision, contains internal nodes, probability nodes, leaf nodes, and arcs" (p. 623).

Neuroscience studies the brain's nervous system, which determines cognitive functions and human behavior. Barrios Tao and Gutiérrez de Piñeres Botero (2020), that "neuroscience alone does not have the explanations for all phenomena, but it is able to provide information about the brain's abilities and limitations in the face of learning" (p. 378). Likewise, many studies are giving importance to cognitive neuroscience that studies

the human mind, as a result of which educational neuroscience is gaining strength in academic studies. Argue Fuentes Canosa and Collado Ruano (2019) that "educational neuroscience is constituted as an ontologically and epistemologically interdiscipline situated at the center of the convergence between the sciences of the mind and the brain" (p. 99). They also mention that it is the "intersection between neuroscience, cognitive science, and education" (p. 97).

From the above and justified, this research aimed to develop a decision tree based on a neural network that allows classifying the vocation of the applicant to a certain study program based on the profile of the incoming student who requires a study program.

2. Materials and Methods

According to the methodological strategy, and given the importance of carrying out a vocational orientation test to the applicants, an observational research was considered, this test was developed according to the characteristics of the admission profile, which the study programs propose and which are published in the admission prospectus; To identify whether the applicant's capabilities are in line with the chosen channel, the Machine Learning algorithm is applied; developing a cross-sectional analytical study at all times (Zacarias & Supo, 2020). The population is focused on the applicants who participate in a certain selection process, the application of the test must be carried out before the applicant registers or when requesting information, it lasts from 10 to 15 minutes without the need to have a facilitator to resolve any doubts. Given that the algorithm to be developed must work at any time and space of selection, neither the year of application nor the University were considered.

Article 98 of University Law No. 30220, published in the official gazette El Peruano, mentions that "The competition consists of a competitive examination. knowledge as the main mandatory process and an assessment of Skills and attitudes in an optional complementary way. The Statute of each university establishes the modalities and rules that govern the ordinary admission process" (p. 19). In addition the Accreditation Model published by the National System of Evaluation, Accreditation and Certification of Educational Quality (SINEACE), on the admission process, in standard 18 mentions "... it is considered one of the aspects that influences student dropout" (p. 73); Likewise, it can be mentioned that it is the study program that determines the criteria of the admission profile, which will be evaluated in the admission process after evaluation of the graduate profile in order that the incoming student has good chances of success in his or her university life (Sineace, 2018).

Express Rodriguez et al. (2007) on competencies and synthesizes them through knowledge, skills and values, taking into account that their contents determine the knowledge, know-how and know-how of the human being. Also Gámez et al. (2012) He mentions that the admission profile is an input that allows strengthening strategies for the evaluation of competencies, capacities and skills of students for university success. Says Pérez Borges (2019) that at the university level there is a need for a comprehensive education "that allows the acquisition of practical knowledge, competencies and aptitudes for communication, critical and creative analysis, combining traditional theoretical and practical knowledge with science and technology and promoting an education for life" (p. 197), on the contrary Alarcón Ortiz et al. (2019) He relates it to a comprehensive action:

... Mastery of processes in higher education, their functioning and their relationships (knowing), as well as understanding the context and clear identification of the activities and problems to be solved (knowing how to know); to execute a planned set of actions mediated by procedures, techniques, strategies with self-evaluation and constant correction (know-how) (...) Knowing how to be and knowing how to live together are articulated in attitudes and values (...) (p. 9)

Even Belykh (2019) emphasizes the "ability to be successful and live a full life in harmony with oneself and with one's natural and social environment (hence the expansion of Delors' educational goals towards knowing how to be and knowing how to live together, or living well)" (p. 167).

Finally, Delors (1996) cited by Ramírez-Díaz (2020), mentions that the pillars of knowledge for the profile of the entrant are:

Knowing how to be: Critical and autonomous thinking of construction of one's own judgment, manifests the knowledge acquired throughout life.

Knowing how to know: The acquisition of knowledge through attention, memory, and thought: a means and an end in human life

Know-how: Related to professional practice and competencies

Knowing how to live together: Linked to interpersonal relationships and emotional intelligence, as well as to the behaviors acquired from experience. (p. 6)

From the above, we can affirm that universities can establish the evaluation criteria respecting the main mandatory, but it also mentions that "they can establish other forms of access in accordance with the law", therefore, the aptitude and attitude exams could be considered as part of the admission process, see table.

Table 1 Characteristics considered by channel.

Pillars of Knowledge	Percentage	Profile of the entrant	Competences	Questions
Knowing how to learn	Percentage by pillars of knowledge established by professional careers	Characteristics required for the profile of the entrant	Knowledge Test	Number of questions by pillars
Know-how			Aptitude Test	
Knowing how to live together			Attitude Testing	
Knowing how to be				

Note. Own elaboration

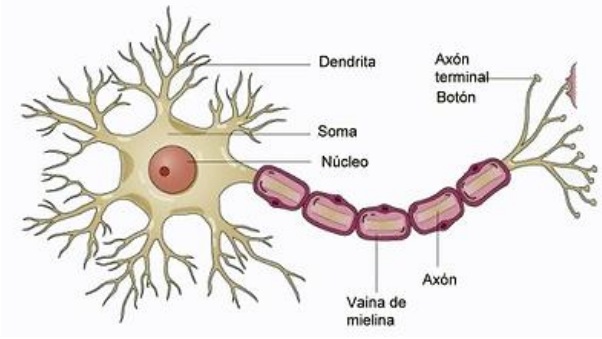
The orientation survey must be anonymous and must only contain criteria established in the know-how to learn, do, live together and be, the number of questions must be related to the proposed subjects according to the entry profile and the specific competencies; to evaluate the answers of the subjects, the Likert scale (0. Doesn't dominate, 1. Dominate regularly, 2. Dominates and 3. It totally dominates.)

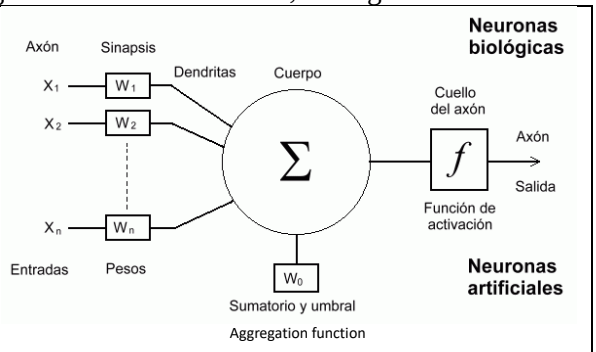
2.1 Artificial intelligence

Quoting Porcelli (2020) and Rouhiainen (2018), consider that artificial intelligence (AI) is defined as the ability to create highly intelligent programs, compiled by computers and simulating human thinking for accurate decision-making and predictions; Similarly, Ocaña-Fernández et al. (2019a) consider it to be part of computer science based on the intelligent study of human behavior; On the subject of education, AI is considered as an "administrative, academic and research management tool that allows us to address issues related to student dropout, academic performance, the teaching and learning process, intelligent tutoring, social inclusion, intercultural education, among others" (p. 355).

2.1.1. Artificial Neural Network (ANN). Mentioned Nacelle and Mizraji (2009) that its use represents "the brain, in an attempt to solve problems by employing knowledge gained from similar cases solved in the past. That does not mean that their behavior is the same as that of the brain, but if we seek to emulate certain remarkable qualities of the brain, which are not achieved with standard computers" (p. 2), they also refer to the Sanchez et al. (2016) that an RNA is a pattern of related artificial neurons, in turn, Flores et al. (2021) They argue that it is a tool that allows solving multiple problems related to education as a result of research related to education, in their study Jurado and Fellman

(2020) develop an ANN whose purpose is to allow "to positively identify the personal qualities and the marked passion that the students may present at the time of developing their evaluative activities within the teaching and learning process, such preferences and motivations are necessary for the implementation of scientific specialization activities under modern conditions", for what has been analyzed we can mention that an ANN represent artificial neurons in the human brain through Mathematical Patterns, see figure.





Note: https://images.app.goo.gl/F2bgTG2Vjh76ena59 | *Note*: http://www.cs.us.es/~fsancho/?e=72

Figure 1 Biological Neural and Artificial Neural Network

2.1.2. Decision Trees (DA). Mentioned Origel-Rivas et al. (2020) which are techniques for classifying data or objects in the form of trees and branches, capable of simulating their behavior based on training and test samples, to then predict the class to which the following new data belong, on the other hand, Ramírez and Grandón (2018) He compares it as a hierarchical model of decisions and consequences, complying with the division of data into segments, for this tree construction it is considered where to divide the data. And when to stop the division? mentioned by (Kotu & Deshpande, 2014) cited by (Ramírez & Grandón, 2018), the elements that an AD considers, is the decision node, such as the characteristic of the object, and the other, leaf node considered as a final node. Its relationship with ANN is that both belong to continuous learning that are used as classifiers for the understanding of the information that is presented in a categorical way (Origel-Rivas et al., 2020).

2.1.2.1 Research Development

As part of the application, the pillars of knowledge were considered, article 98 of the University Law No. 30220 and standard 18 of the accreditation model of university higher education study programs, the following table can be structured:

Table 2 Structure set per channel (example channel I)

Pillars of Knowledge	Percentage	Profile of the entrant	Competences	Questions
Knowing how to learn	%	...	Knowledge	...
Know-how	%	...	Skills	...
Knowing how to live together/be	%	...	Attitudes	...

Note. Own elaboration

The structure of table 2 classifies the pillars of knowledge in relation to their competencies and profile of the entrant, it is observed that the pillars of knowledge are classified based on percentages considering article 98 of the University Law, these percentages can define the number of questions and score, the profile of the entrant must meet certain purposes for each pillar, This is due to the conceptual connotation of themselves.

2.1.2.2. Artificial Model of the Neural Network. According to Cazarez (2020), the neural network model must consist of layers, for this research work the following were considered:

Data from entries xij classified into tests of knowledge, aptitude and attitude.

The input layer that considers the sum of the data.

The hidden layer that considers the input layers and their respective synaptic weights wij

Hi Propagation Rule Defined by Synaptic Weights and Input Data $h_i(x_1, x_2, x_3, \dots, x_n, w_{i1}, w_{i2}, w_{i3}, \dots, w_{in}) = \sum_{i=1}^{n} w_{ij} x_j$

For proper functioning, a threshold can be considered determined through the parameter , θ_iwhich consists of subtracting from the postsynaptic potential: $.\sum_{i=1}^{n} w_{ij} x_j - \theta_i$

Finally, for the output layer, activation functions are considered as long as the data is within the parameters determined in the thresholds. In addition, for this study the output is considered as a stepwise function with digital notation represented by all-nothing neurons or threshold devices: . In Opinion $y_i = f_i(h_i) = f_i\left(\sum_{j=0}^{n} w_{ij} x_j\right) f_i\left(\sum_{j=1}^{n} w_{ij} x_j - \theta_i\right)$(Larrañaga et al., 1997) Consider 2 states:

$$y_i = \begin{cases} 1 \rightarrow \sum_{j=1}^{n} w_{ij} x_j \geq \theta_i \\ 0 \rightarrow \sum_{j=1}^{n} w_{ij} x_j < \theta_i \end{cases}$$

As it is considered a sigmoidal activation function, the nonlinear function is applied to determine its final values between 0 and 1, having as its inflection point the x=0 raised by (Peirotén López de Arbina, 2018), and determining the following equation:

$y_i = \frac{1}{1+e^{-\left(\sum_{j=1}^{n} w_{ij} x_j - \theta_i\right)}}$, siendo $y_i \in [0,1]$, and applied to multi-layered perceptrons.

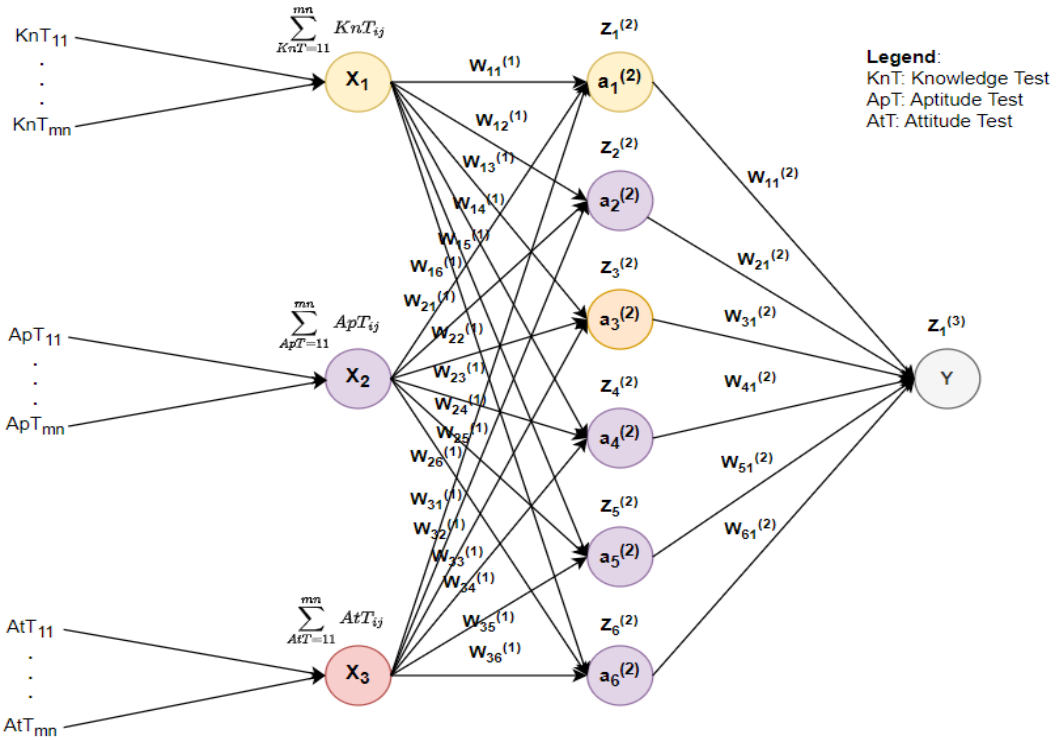


Figure 2 Neural network model for vocational guidance based on the profile of the entrant.

Note: Authors' own elaboration

Figure 2 represents the model of the ANN where different questions were considered for each channel, these have been classified into three axons, (x_1, x_2, x_3) the first axon represents 50% for the knowledge test (knowing how to learn), the second axon 25% for the aptitudinal (knowing how to do) and the third axon 25% for the attitudinal (knowing how to live together and know how to be). Each axon generates 6 weights, so it would be 18 weights times 3 axon's$(w_{11}{}^{(1)}, w_{12}{}^{(1)}, \dots, w_{16}{}^{(1)}, w_{21}{}^{(1)}, w_{22}{}^{(1)} \dots, w_{26}{}^{(1)}, w_{31}{}^{(1)}, w_{32}{}^{(1)}, \dots, w_{36}{}^{(1)})$, and when calculated by the aggregation function: , we would have as a result: , and consequently the generation of the activation function , which represents the sigmoidal function for the hidden layer.$Z^{(2)} = x * w_{ij}{}^{(1)}(Z_1{}^{(2)}, Z_2{}^{(2)}, \dots, Z_6{}^{(2)})a^{(2)} = f(Z^{(2)})$

The resulting layer "y" is a product of the activation functions of the hidden layer with the weights "w" constructing an aggregation function and a sigmoidal activation.$(a_1{}^{(2)}, a_2{}^{(2)}, \dots, a_6{}^{(2)})Z^{(3)} = a^{(2)} * w^{(2)} y = f(Z^{(3)})$

If the results are unreliable, the mean square error cost function can be used: $j = {}^{1}/_{2} * e^2$ and the application of the descending gradient of the second derivative of the function (LeCun et al., 2012).

3. Application

The application of the ANN was applied to 200 students of the different study programs, considering that it is a vocational orientation questionnaire related to the competencies and profile of the entrant, the consolidated information was entered in a spreadsheet with answers according to the Likert scale (0. Doesn't dominate, 1. Dominate regularly, 2. Dominates and 3. It totally dominates), see table.

Table 3 Answers on vocational guidance considering the profile of the entrant.

NumPostulante	Knowledge Test	Aptitude Test	Attitude Test	Resultado
1	1.74	1.50	0.40	NO
2	1.16	2.00	1.20	SI
3	1.68	1.50	1.40	SI
4	1.84	2.00	2.00	SI
5	1.74	2.00	2.20	SI
6	1.26	1.50	1.60	SI
7	0.89	3.00	1.60	SI
8	1.21	1.50	1.60	SI
9	1.58	2.50	1.20	SI
10	1.26	2.50	2.00	SI
11	2.05	2.50	1.80	SI
12	2.00	1.50	1.00	SI
13	1.47	2.00	1.80	SI
14	1.53	2.00	1.80	SI
15	1.37	1.50	0.80	NO
16	1.79	1.00	2.20	SI
17	1.32	3.00	1.80	SI
18	1.84	1.50	1.40	SI
19	1.63	2.00	2.20	SI
20	1.26	1.50	0.80	NO
21	2.42	1.00	1.80	SI
22	1.37	1.00	1.40	NO
23	1.16	1.50	1.00	NO
24	1.79	3.00	1.60	SI
25	0.95	2.00	1.00	NO
26	1.37	1.50	1.20	NO
27	1.32	1.00	1.00	NO
28	1.79	2.00	2.20	SI
29	1.16	1.50	1.40	NO
30	1.21	2.00	2.40	SI
31	1.84	2.00	1.60	SI
32	1.32	1.50	1.60	SI
33	1.53	2.00	2.00	SI

Note: Authors' own elaboration.

The data in Table 3 represent the degree of knowledge, attitudes and aptitudes that applicants respond to based on the profile of the entrant of a certain channel to which they apply (Table 2), of the total number of questions asked, 11.5% of applicants do not meet the required competencies so their admission is negative, 88.5% of applicants meet the pillars of knowledge in different ways and achieve their admission to the University; Values less than 0.946 determine the non-mastery of the subjects established within the Knowing Knowing pillar, on the contrary, the remaining values determine possibilities of mastery, also, values less than 0.607 for the Know-how pillar determine the failure of Aptitude Mastery, the remaining values determine mastery approximations, finally, values less than 0.438 also determine the failure of attitude for the Knowing to Be and Knowing How to Live Together pillars, In other words, the student does not meet the skills or abilities for the study program.

The results of the surveys have been classified based on the competencies of the applicants (knowledge, attitudes and aptitudes), for this the decision trees were used in order to calculate regions that allow to classify new characteristics among the regions found, that is, iteratively create binary partitions on each region of interest, the idea is to identify groupings with homogeneous data, To do this, we first establish a probabilistic condition and depending on it, we will classify the data into two regions (Yes and No), from there we will be interpreting the conditions according to whether it is data represented by the decision nodes or by leaf nodes as the final part, see figure.

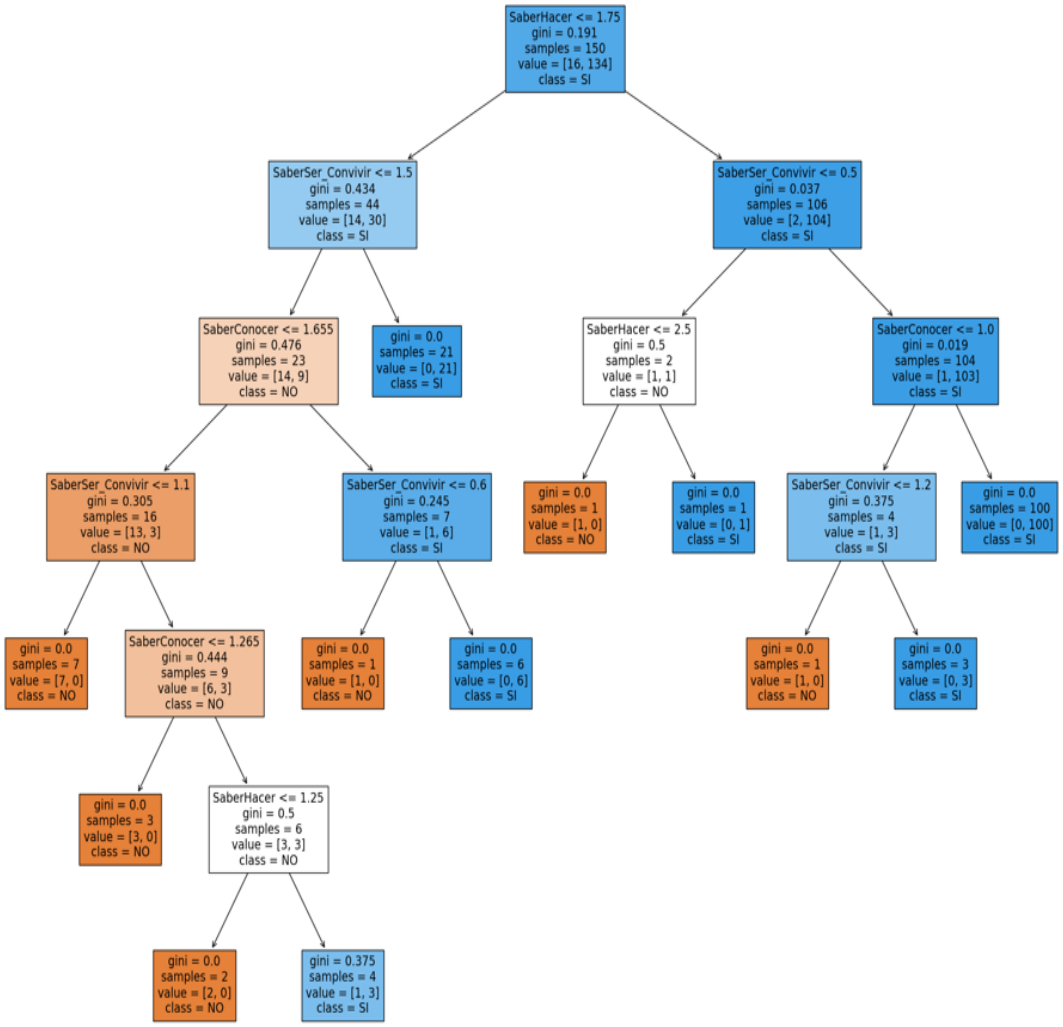


Figure 3 Sorting the results through the decision tree.

From the figure, a decision node is shown that will have 2 leaf nodes, for example, the Know>=1.25 node, determines two thresholds or classes: left (no) and right (yes), the Gini indices determine the purity of the data, that is, if a node $Gini = 1 - \left({}^{2}/_{(2+0)}\right)^2 - \left({}^{0}/_{(2+0)}\right)^2 = 0$ is not allowed to enter the data in the region. and 0 enter, on the other hand (1,3) we mention that 1 does not enter and 3 enters, with respect to the values on the right side the $Gini = 1 - \left({}^{1}/_{(1+3)}\right)^2 - \left({}^{3}/_{(1+3)}\right)^2 = 0.375$, by the result we mention that there is impurity in its data so an additional node is created. To determine the impurity of the decision nodes, you will need to calculate the weighting of the nodes and select the lowest value for the cost function or lowest impurity level (best classification).

The confusion matrix, also called the error matrix, shows the degree of performance of a prediction model constructed through current values and predictors and, classified in the assertion of true and false, López et al. (2018) They state that "It is a contingency table that serves as a statistical tool for the analysis of paired observations" (p. 216), for our case, the results are given as follows:

```
array([[178,   3],
       [ 12,  54]]
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Figure 4 Confusion Matrix

Note: Authors' own elaboration.

From the figure, the rows of the matrix contain the amounts of the real values both for the "no" admission class (first row), i.e. 6 applicants and for the "yes" admission class (second row) 42 applicants, at the time of establishing the predictions 5 applicants were obtained as "no" and 45 with "yes" admission, finally, The main diagonal is represented by 45 applicants who enter and 5 who do not. The accuracy value of the global model is 0.939, in terms of accuracy or positive predictive (correct identifications) it was 0.93684211 and 0.94736842 for the corresponding classes, also, the sensitivity results for the "yes" and "no" classes have been 0.818 and 0.983 respectively, finally, the F1 score that measures the robustness of the model was 0.95956873 and 0.87804878 respectively for each class.

4. Discussion

Article 98 of University Law No. 30220 mentions that the important exam is that of knowledge and the evaluations of aptitudes and attitudes are considered complementary and optional, in view of this, it must be specified that the failure of the continuity of studies of a university student depends on different factors, one of them is the poor choice of career. This is due to the fact that the student discovers his or her abilities and competencies during the formative years, which, for some, is detached from his or her initial choice; The questions of the admission exam are classified based on the pillars of knowledge, but for this article, some may give more emphasis to knowing how to know and less interest to the other two, the results of the neural network and the decision tree allow applicants to be directed towards a career according to their competencies and abilities and that may have been previously established within the parameters allowed for each segment or channel by binary selection. On the other hand, there are vocational orientation tests that guide applicants in the choice of their career; Considering Standard 18 of the University Accreditation Model, it is necessary to involve the profile of the incoming student in the orientation because this is the product of the evaluation of the graduation profile and the permanence of the student.

5. Conclusions

The neural network has been created based on the pillars of knowledge and characteristics of the incoming profile described in Table 1 and can admit different questions according to the channel of study, considering three axon's and a resulting layer; For the activation function, the sigmoidal function has been proposed.

In order to obtain high reliability of the neural network, a second derivative had to be applied to the activation functions and 6 hidden layers had to be chosen.

The decision tree has been built based on the neural network with 4 levels of branching, this has allowed the result of the global model to be 0.939, a value that guarantees its application, in addition, when analyzing the precision of the classes, high values were obtained that strengthen the global model, these values are 0.818 and 0.983 for the classes "yes" and "no" enters respectively.

The robustness of the decision tree model considered as F1 score was 0.9595 and 0.8780 for the "yes" and "no" classes, respectively.

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