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Professor Strengths that Transform Learning: Analysis from the Perspective of Artificial Intelligence

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***Abstract*– In the learning process, a series of variables related to both students and professors come into play. This study investigates the main strengths of a professor that aid in the student's learning process. The research is based on a proprietary database consisting of 17 independent variables and one dependent variable, referred to as Professor Strengths. Using artificial intelligence techniques and a 50%-50% cross-validation process, the behavior of the dependent variable is predicted with an accuracy exceeding 80%. Furthermore, this process allows for the identification of the main independent variables leading to optimal prediction of the dependent variable. These variables are: encouragement of the topics covered, made an effort to ensure everyone learns, adapted teaching methods, in-depth learning, and would enroll in another activity with this professor. When trained and validated with 100% of the data, an effectiveness of 85% is achieved.**

***Keywords*: professor strengths; data mining; cross-validation; J48; Weka.**

I. INTRODUCTION

In recent years, artificial intelligence has made significant advancements across all fields. However, its application in educational processes has not progressed at the same pace [1]. Therefore, it is crucial to accelerate its study in this field to achieve greater benefits for the entire academic community [2], while also seeking to integrate these techniques with all pedagogical processes. In this context, this research is based on a self-developed database, with its structure modified from the following link: https://edificando.unal.edu.co/portal/docentes. In the restructured database, the behavior of a dependent variable called Professor Strengths (P18) is analyzed, along with 17 independent variables: Hours of contact with the professor (P1), reason for course enrollment (P2), adequate preparation of classes (P3), adequate guidance (P4), promoted connections with other subjects and/or contexts (P5), pleasant work style (P6), encouraged argumentation and critical reflection (P7), promoted autonomous learning (P8), encouragement of the topics covered (P9), was respectful (P10), made an effort to ensure everyone learns (P11), adapted teaching methods (P12), respected the rules (P13), was fair (P14), learned from evaluations (P15), in-depth learning (P16), and would enroll in another activity with this professor(P17). Through artificial intelligence techniques, the study seeks to identify the main independent variables that have the greatest influence on the different states of the dependent variable.

Education is a process that goes beyond the knowledge acquired by students. In this regard, artificial intelligence greatly enhances personalized processes [3] and can correct many of the deficiencies that lead to a professor not being considered good by their students, such as accessibility issues, the ability to convey knowledge at the students' level, low emotional intelligence, and poor communication skills [4]. However, to achieve this correction, greater integration of scientific research (Artificial Intelligence), education [5], and improved governance of each educational institution [6] is necessary. Likewise, it is important to consider aspects related to professor's knowledge, infrastructure, and information technology [7, 8], as well as the relationship between artificial intelligence and creativity [9]. Other studies related to the application of artificial intelligence in the field of education can be found in the various literary references cited in this research article [10,11,12,13].

Recently, some artificial intelligence fields, such as data mining, have led to the creation of educational data mining [14], which allows for the development and analysis of educational techniques and data. This field involves both education and computer science [15]. Additionally, artificial intelligence has been applied in other areas of education, such as language teaching through content generators [16], professional-level text translation [17], and studies based on GPT [18], which show that students prefer practices based on clarity and interactions. Other similar studies have also used data mining to analyze student projects [19] and to develop learning systems that complement teachers' instructions [20]. These processes can include many characteristics of learning methodologies, such as self-regulation processes in young people [21], analysis of professor's organizational climate [22], and the study of strengths, values, and habits that play an important role in pedagogy [16].

Various literature reviews indicate that there is no analysis of characteristics (independent variables) based on artificial intelligence techniques that can identify whether a professor possesses strengths (dependent variable) that students consider crucial to their learning process. This gap provides additional justification for this research. Highlighting that this work will allow for the establishment of targeted policies and actions aimed at improving teaching quality and, consequently, the quality of educational institutions, which will ultimately benefit the entire community. Additionally, other complementary studies in this area are referenced [24, 25, 26].

Finally, for better development, this article has been structured as follows: a) Materials and Methods. This section presents each step of the methodology used to solve this problem, utilizing previous methodological works by the same author based on the Weka platform [27,28]. b) Results. The logical consequence of applying each step of the proposed methodology. c) Discussions. Comparison of this study with other similar works. d) Conclusions, Acknowledgements, and References used.

II. METHODOLOGY

The definition of the methodology begins with the restructuring of the results obtained in a survey (belonging to a university in the central region of Colombia) provided in the following internet link: https://edificando.unal.edu.co/portal/docentes. This survey is chosen because it is designed to help identify and refine the strengths and areas of improvement of the teachers. The implementation of this survey allows for the structuring of a proprietary database, which serves as the source for this methodology and consists of the following phases: I) Definition of the survey. II) Sample size. III) Creation of the Database. IV) Structuring of the Weka file: Header and Detail. V) Reduction of the independent variables. VI) Prediction of the dependent variable.

Phase I: Definition of the Survey.

Based on the surveys conducted in the previous phase, a database is established following the structure shown in Table 1. In Table 2, variables P1 through P17 are the independent variables, while variable P18 serves as the dependent variable.

Phase II: Sample Size

The original survey was administered to 100% of the students. However, only those surveys that were completed in their entirety were selected. Additionally, it is important to note that, for confidentiality reasons, only group responses are generated for each question. Therefore, it is necessary to interpret the results based on the weight assigned to each possible response (Table 1), keeping in mind that cells in black represent invalid responses, so their weighting is zero. For example, if question P1 was answered by a group of 45 students, of whom 10 selected option 1 (weight 1), 15 selected option 4 (weight 4), and 20 selected option 5 (weight 5), the weighted response would be calculated as follows: (10*1+15*4+20*5) /45 = 3.7, which is equivalent to 75.5%.

Table 1: New survey 1: Lowest score. 5: Highest score

#	QUESTION	**Weight**				
		1	2	3	4	5
P1	Hours of contact with the professor					
P2	Reason for course enrollment. 1: There was no other option, 2: Another reason, 3: It was mandatory, 4: It was optional, 5: It was elective.					
P3	Adequate preparation of classes					
P4	Adequate guidance					
P5	Promoted connections with other subjects and/or contexts					
P6	Pleasant work style					
P7	Encouraged argumentation and critical reflection					
P8	Promoted autonomous learning					
P9	Encouragement of the topics covered					
P10	Was respectful					
P11	Made an effort to ensure everyone learns					
P12	Adapted teaching methods					
P13	Respected the rules					
P14	Was fair					
P15	Learned from evaluations					
P16	In-depth learning					
P17	Would enroll in another activity with this professor					
P18	Professor Strenghts					

Phase III: Creation of the Database.

Once the survey has been administered and interpreted, the results are used to define a data structure as illustrated in Tables 2a and 2b This database allows for the definition of all prediction processes for the dependent variable and the existing relationships between this variable and the independent variables. The variable P18 can have values A, B, or C depending on the case: If P18 < 60, the value is C; if 60>=P18 < 80, the value is B; if 80<= P18 <= 100, the value is A. These references A, B, and C are based on the possible evaluations a teacher can receive at the university under study.

Phase IV: Structuring the Weka File. Header and Detail.

The results from Phase III allow for the definition of the files that will feed into the open-source machine learning and data mining platform called Weka [29]. A file is defined, which consists of two parts: a header and a detail. This file will serve as the basis for the subsequent phases of this analysis using artificial intelligence techniques.

Table 2a: Structure of the New Database

P1	P2	P3	P4	P5	P6	P7	P8	P9
80,0	100,0	80,0	60,0	20,0	80,0	20,0	100,0	20,0

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DO NOT REMOVE

P1	P2	P3	P4	P5	P6	P7	P8	P9
20,0	60,0	20,0	20,0	20,0	40,0	20,0	20,0	20,0
50,0	60,0	90,0	60,0	60,0	60,0	60,0	60,0	60,0
73,6	66,8	96,6	91,5	94,9	88,5	88,1	91,5	84,7

Table 2b: Structure of the New Database

P10	P11	P12	P13	P14	P15	P16	P17	P18
20,0	40,0	100,0	100,0	100,0	80,0	20,0	20,0	C
20,0	20,0	20,0	40,0	40,0	40,0	20,0	20,0	C
60,0	90,0	60,0	60,0	90,0	60,0	60,0	100,0	B
86,4	91,5	85,5	99,6	97,9	93,6	91,5	81,3	A

Phase V: Reduction of the Independent Variables.

The ARFF file defined in Phase IV is loaded and interpreted using the Weka platform. In this platform, through the 'Attribute Selection' option and the 'Chi-Square' sub-option, the independent variables that provide the most information for predicting the dependent variable are selected.

Phase VI: Prediction of the Dependent Variable.

With the variables selected in the previous phase, the ARFF file (Phase IV) is restructured. Then, using intelligent techniques such as decision trees, the prediction of the dependent variable is performed. Additionally, classification matrices, accuracy, and confusion matrices are obtained, along with the pruned decision tree. This tree illustrates the different interrelationships between the independent variables and the various states of the dependent variable (leaves). Finally, these results are compared with other artificial intelligence techniques

III RESULTS

As a result of applying the methodology described in each of its phases to the data, the following results are obtained:

Phase I: Definition of the Survey.

The restructured survey, as shown in Table 1, consists of 18 questions. The first 17 questions represent the independent variables, denoted as P1 – P17. Question 18, denoted as P18, represents the dependent variable. The survey is administered to 100% of the statistically valid population (see Phase II) at a university in the central region of Colombia.

Phase II: Sample Size.

As stated in the previous phase, this survey was administered to 100% of the students enrolled in the first and second semesters of 2023, totaling 57,058 and 55,663 students respectively, for a total of 112,721 students (https://estadisticas.unal.edu.co/Matriculados/). However, only 69,300 students, representing 61.4% and equivalent to 4,754 groups, responded to the survey. It is noteworthy that the survey was fully completed by 68,617 students (equivalent to 3,483 groups), which represents 60.8% of the student population. This is a statistically valid sample for conducting this analysis.

Phase III: Creation of the Database.

The interpretation and weighting of the survey results, according to Phase II of the methodology, allows for the creation of a data structure as illustrated in Table 2. This table contains the results by groups of students, totaling 3,843 groups (rows) and 18 columns (variables).

Phase IV: Structuring the Weka File. Header and Detail.

The database illustrated in Table 2 allows for the definition of the file that will be loaded into the Weka platform. This file consists of two parts: a Header (Table 3), which defines the data structure, and a Detail (Tables 4a and 4b), which stores all the data from Table 3. A snippet of Table 4 is illustrated.

Table 3: Header of the Weka File

@relation	professor satisfaction
@Attribute P1	numeric
@attribute P2	numeric
@attribute P3	numeric
@attribute P4	numeric
@attribute P5	numeric
@attribute P6	numeric
@attribute P7	numeric
@attribute P8	numeric
@attribute P9	numeric
@attribute P10	numeric
@attribute P11	numeric
@attribute P12	numeric
@attribute P13	numeric
@attribute P14	numeric
@attribute P15	numeric
@attribute P16	numeric
@attribute P17	numeric
@attribute P18	{A,B,C}

Table 4a: Detail of the Weka File

P1	P2	P3	P4	P5	P6	P7	P8	P9
20	40	80	20	20	40	20	20	20
80	40	20	20	20	20	20	20	20
80	60	80	40	20	20	20	20	20

Table 4b: Detail of the Weka File

P10	P11	P12	P13	P14	P15	P16	P17	P18
40	40	20	40	20	20	20	20	C
20	20	20	20	20	20	20	20	C
80	20	20	20	80	20	20	20	C

Phase V: Reduction of the Independent Variables.

Using the Chi-Square option from the Attribute Selection tab in the Weka platform, the variables are ranked to establish the weight of each one. Table 5.

Table 5: Ranking of Variables

Var	Weight	%	%Accum	Sel
P9	2287,70	7,76%	7,76%	**
P16	2554,86	8,67%	16,42%	**
P17	2402,86	8,15%	24,57%	**
P11	2382,36	8,08%	32,65%	**
P12	2377,60	8,06%	40,72%	**
P7	2282,35	7,74%	48,46%	
P15	2260,25	7,67%	56,13%	
P6	2131,78	7,23%	63,36%	
P5	1773,44	6,01%	69,37%	
P8	1759,63	5,97%	75,34%	
P4	1741,41	5,91%	81,25%	
P3	1451,75	4,92%	86,17%	
P10	1278,14	4,34%	90,50%	
P14	1109,77	3,76%	94,27%	
P13	1024,48	3,47%	97,74%	
P2	378,52	1,28%	99,03%	
P1	286,76	0,97%	100,00%	
Total	29483,63			

Due to the large amount of data analyzed, the variables marked with ** in Table 5 are sufficient to achieve an adequate prediction of the variable P18. Consequently, the ARFF file from Step IV is restructured to include only these variables. This restructuring is done directly within the Weka platform.

Phase VI: Prediction of the Dependent Variable.

Once the ARFF files defined in Phase IV are restructured, a process for predicting the dependent variable is carried out using the J48 algorithm in the Weka platform. This algorithm is used because, after grouping the records into clusters, only 3,483 remain. This makes the algorithm highly efficient when working with small datasets (see phase II of this section). Through this process, a prediction accuracy of over 80.8% for the dependent variable is achieved when using a 50%-50% cross-validation process. When the data is trained and validated with 100% of the dataset, an effectiveness of 85% is achieved. Additionally, the respective classification matrices (Table 6), accuracy (Table 7), and confusion matrices (Table 8) are calculated. The results of this technique are also compared with other artificial intelligence techniques (Table 9). Furthermore, Figure 1 illustrates the pruned decision tree, which shows the relationships between the independent variables and the different states of the dependent variable.

IV DISCUSSIONS

The results found in this section show that only four variables are sufficient to determine whether a teacher possesses strengths that transform learning. These variables are: encouragement of the topics covered (P9), made an effort to ensure everyone learns (P11), adapted teaching methods (P12), in-depth learning (P16), and would enroll in another activity with this professor (P17). Additionally, a more detailed analysis of Figure 1 shows that a P9 value greater than 84% is sufficient for the professor to be considered as having strengths that aid learning. On the other hand, when P9 <= 84%, identifying these strengths in the professor depends on the interrelationship of the other variables as illustrated in Table 10.

Table 6: Classification Matrix

Variable	#	%
Correctly Classified Instances	2816	80.8498 %
Incorrectly Classified Instances	667	19.1502 %
Kappa statistic	0.5688	
Mean absolute error	0.1767	
Root mean squared error	0.3102	
Relative absolute error	56.0863 %	
Root relative squared error	78.1522 %	
Total Number of Instances	3483	

Table 7: Precision Matrix

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
0.934	0.322	0.862	0.934	0.897	0.853	A
0.534	0.092	0.641	0.534	0.582	0.788	B
0.552	0.021	0.707	0.552	0.62	0.869	C
0.808	0.243	0.797	0.808	0.8	0.839	← prom

Table 8: Confusion Matrix

a	b	c	Classified as
2220	147	9	a = A
325	437	57	b = B
31	98	159	c = C

Table 9: Comparison with other Artificial Intelligence Techniques

Artificial Intelligence Technique	%Success (50% - 50%)
Bayes Net	79.75%
NaiveBayes	80.64%
SMO	81.62%
RBFNetwork	79.90%
MultilayerPerceptron	81.76
BFTree	81.53%
DecisionStump	77.26%
FT	81.30%
J48Graf	80.93%
LADTree	81.71%
LMT	81.96%
NBTree	79.70%
RandomForest	80.39%
RandomTree	76.34%
RepTree	81.71%

The relationships illustrated in Table 10 show that it is not necessary to achieve high performance in all four selected variables (P9, P11, P12, P16, and P17) to achieve optimal performance in the P18 variable (professor strengths). In some cases, achieving high performance in just one of the selected variables can result in a rating of A (Lines 7, 8, 9, and 10 – Table 10). On the other hand, the first 6 lines of Table 10 show that low values in the P18 variable are highly related to low values in the variables P9, P11, P12, P16, and P17.

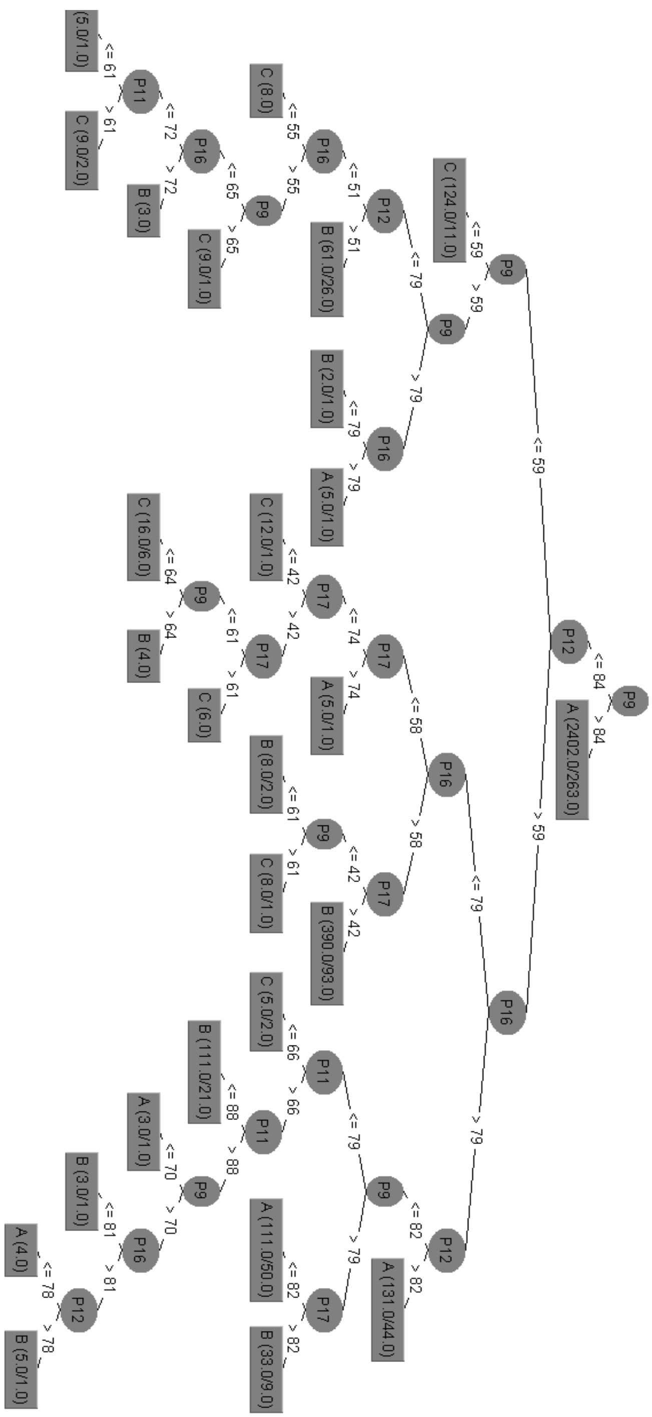

Figure 1: Pruned Decision Tree

Table 10: Relationship Between Independent Variables and Dependent Variable. P9<= 84%

Line	Relationships Between Independent Variables	P18
1	P12 <=59% y P9 <= 59%	C
2	P12 <= 59% y 59% <= P9 <= 79% y P12 <= 51% y P16 <= 55%	C
3	P12 <= 59% y 59% <= P9 <= 65% y P12 <= 51% y 55% < P16 <= 72%	C
4	P12 > 59% y P16 <= 58% y 42% <= P17 <= 61%	C
5	P12 > 59% y P16 > 58% y P17 < 42%	C
6	59 < P12 <= 82% y P9 > 79% y P11 < 66%	C
7	79% < P9 <= 84% y P16 > 79%	A
8	P12 > 59% y P17 > 74%	A
9	79% < P9 <= 84%	A
10	P12 > 50% y P16 > 79%	A
11	Other cases	B

On the other hand, although various literature reviews indicate that artificial intelligence and data mining have been widely used in education [20,14,16 1], it is highlighted that there are no studies related to establishing a set of independent variables that determine teaching strengths that truly aid learning. Only a few works by the same authors are related to these topics [30]. Therefore, this research enables the establishment of targeted educational policies, benefiting students, professors, educational institutions, and society at large. Additionally, an analysis of Table 9 shows that while there are other artificial intelligence techniques that may produce slightly better results, these techniques encapsulate the results, making it very difficult to extract them and, consequently, to identify the independent variables with the greatest influence on the dependent variable. This aspect would significantly hinder their practical applicability. Additionally, it is important to highlight that, although the research can be applied across a wide variety of contexts and fields, its main limitation lies in the need to repeat the methodology each time the database or application context changes. However, the step-by-step design of the methodology facilitates its replication whenever necessary. Finally, it is emphasized that educational institutions could benefit from this study by developing a continuous improvement plan that allows them to address deficiencies and optimize the strengths of their educational processes and teaching staff.

V. CONCLUSIONS

This research starts from a set of 17 independent variables and the methodology described successfully reduces this set to 5 variables, which predict the behaviour of the dependent variable with an effectiveness of over 80% when trained and validated with a 50%-50% of the data (cross-validation). However, when trained and validated with 100% of the data, this prediction reaches 85% effectiveness. These variables are: encouragement of the topics covered (P9), made an effort to ensure everyone learns (P11), adapted teaching methods (P12), in-depth learning (P16), and would enroll in another activity with this professor (P17). The other independent variables do not have significant relevance. Although the independent variables found may vary in a different context, applying the step-by-step methodology developed in this research to a new data context allows for the redefinition of the selected set of independent variables. This process is feasible as the methodology was developed using an open-source platform.

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