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Modeling Job Satisfaction of Peruvian Basic Education Teachers Using Machine Learning Techniques

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Abstract: Teacher job satisfaction is an important aspect of academic performance, student retention, and teacher retention. We propose to determine the predictive model of job satisfaction of basic education teachers using machine learning techniques. The original data set consisted of 15,087 instances and 942 attributes from the national survey of teachers from public and private educational institutions of regular basic education (ENDO-2018) carried out by the Ministry of Education of Peru. We used the ANOVA F-test filter and the Chi-Square filter as feature selection techniques. In the modeling phase, the logistic regression algorithms, Gradient Boosting, Random Forest, XGBoost and Decision Trees-CART were used. Among the algorithms evaluated, XGBoost and Random Forest stand out, obtaining similar results in 4 of the 8 metrics evaluated, these are: balanced accuracy of 74%, sensitivity of 74%, F1-Score of 0.48 and negative predictive value of 0.94. However, in terms of the area under the ROC curve, XGBoost scores 0.83, while Random Forest scores 0.82. These algorithms also obtain the highest true-positive values (479 instances) and lowest false-negative values (168 instances) in the confusion matrix. Economic income, satisfaction with life, self-esteem, teaching activity, relationship with the director, perception of living conditions, family relationships; health problems related to depression and satisfaction with the relationship with colleagues turned out to be the most important predictors of job satisfaction in basic education teachers.

Keywords: feature selection; predictive model; random forest; supervised learning; XGBoost

1. Introduction

Studying the different aspects related to the teacher continues to be important. One of these is job satisfaction, which is found within the emotional dimension [1]. It is important to mention that in the educational field the highest rates of stress, anxiety and irritability have been found to affect the level of teachers' job satisfaction [2]. Teacher job satisfaction is considered a key factor in the effectiveness not only of themselves, but also of the

students, the school environment and the educational system in general [3,4]. It is currently known that satisfaction or dissatisfaction of the teachers with their work life could have a determining impact on the quality of teaching and student achievement [5–8].

In Peru, according to the Ref. [9], 42.1% of teachers have a regular level of satisfaction, that is, they have a low positive attitude about their work. In this scenario, it is of utmost importance to conduct studies to better understand the job satisfaction of teaching professionals, using current methods and tools. In line with this idea, the Ref. [10] recommends conducting studies that allow the analysis of how to avoid the lack of satisfaction in order to favor the non-appearance of burnout and demotivating symptoms in teachers. Studies close to this problem have been employing machine learning techniques, such as logistic regression, random forests, decision trees, AdaBoost algorithm, K-Nearest Neighbors, support machines, Naive Bayes with great success in the prediction of employee desertion in several organizations [11–13].

These techniques are also being employed to explore and discover reliable predictors in large volumes of data, with a large number of dimensions [14]. It is also possible to find factors affecting employee job satisfaction using Gradient boosting and Random Forests algorithms [15]. Another study developed by the Ref. [16] demonstrates the use of artificial neural networks to find the association between demographic variables, coaching leadership and job satisfaction of elementary school teachers in Korea with better results than multiple regression. Prediction of employee job satisfaction was also addressed using deep neural networks [17], decision tree algorithm (CART) and neural networks [18].

Although there are important advances in this area, most of them address job satisfaction in a more general way, on the other hand, there are studies that attempt to explain teacher job satisfaction using techniques such as linear hierarchical models [19], structural equation modeling [20], and analysis of variance (ANOVA) [21].

The contributions of this research are:

- We determined that the XGBoost and Random Forest algorithms allow us to obtain predictive models of job satisfaction of Peruvian basic education teachers with a balanced accuracy of 74%, sensitivity of 74%, F1-Score of 0.48, negative predictive value of 0.94, higher values of true-positives (479 instances) and lower values of false-negatives (168 instances). These values are unprecedented in the prediction of job satisfaction of basic education teachers in Peru.
- We were able to identify that the economic income, the satisfaction with: life, self-esteem, pedagogical activity and relationship with the director, in addition to perception of living conditions, satisfaction with their family relationships, problem of depression-related health and relationship satisfaction with colleagues turned out to be the most important variables in predicting teachers' job satisfaction.
- Finally, we made available to the scientific community a set of pre-processed data with 13,302 records, 11 predictive columns and 1 to predict, to perform replicate experiments with other machine learning algorithms. We obtained these columns after the feature selection process applied to the original data set, which initially had 15,087 records and 942 columns.

We organized the remaining of the paper as follows: Section 2 describes the state-of-the-art, including studies addressing job satisfaction. Section 3 presents the methodology adopted for the experiments. Section 4 shows the results and discussions. Finally, in Section 5 we present our conclusions.

2. State-of-the-Art

Below, we present recent related studies:

In the Ref. [22] the effect of principal support on teacher turnover intention in Kuwait was studied. The researchers used the technique of structural equations. Their results suggest that the principal's support is desirable and positively affects teachers' job satisfaction.

In the study by the Ref. [23], they analyzed the role of emotional regulation traits and satisfaction with life in teachers from southern Spain. The data set consisted of

423 records from a survey prepared by the researchers. They used a technique called structural equations. They conclude that job satisfaction is the main determinant of teachers' life satisfaction.

The study in the Ref. [24] explored the job satisfaction of physical education teachers in Galicia-Spain. The data set consisted of 300 records obtained from a survey of physical education teachers. The authors used the Chi-square technique for the analysis of ordinal variables and ANOVA for the numerical variables. They conclude that job satisfaction improves when there is full support from educational administrators, high unemployment standards, appreciation for teaching work, and camaraderie among peers.

Next, we present the application of machine learning algorithms in the prediction of job satisfaction.

The authors of the Ref. [25] seek to identify if a teacher will be satisfied with a new placement before being transferred, they collect information through a survey on teacher job satisfaction and other factors that affect teacher satisfaction. After that, they carried out data analysis using classifiers such as Logistic Regression, Decision Tree, Random Forest and Gradient Boosting. The results suggest that the Decision Tree classifier provides better accuracy in identifying teacher job satisfaction with a new workplace.

In the study by the Ref. [17], they evaluated five machine learning algorithms such as: Random Forest, Logistic Regression, Support Vector Machine, Gradient boosting (GB) and extreme GB (EGB) in predicting job satisfaction. The researchers used a data set containing text reviews of Google, Facebook, Amazon, Microsoft and Apple employees. The authors employed feature selection techniques such as: inverse term frequency (TF-IDF), bag of words (BoW), global vectors (GloVe). Their results indicated that TF-IDF feature selection technique allowed the logistic regression, random forest and extreme GB (EGB) algorithms to obtain an accuracy of 78%, as well as the gradient boosting and Support Vector Machine algorithms to obtain an accuracy of 77%. Finally, the authors implemented a multi-layer perceptron with 83% accuracy.

The study by the Ref. [18] established a predictive model for job satisfaction of construction workers. They employed CART (Classification and Regression Tree) decision tree algorithms and Neural Networks. The data set consisted of 280 cases of empirical data. They showed that the CART model obtained an accuracy of 76.15%, compared to 71.70% for the neural network.

Another study by the Ref. [26], states that measuring job satisfaction of workers is a problem in prestigious organizations, since the sudden resignation of a worker could cause losses in the organization. Therefore, they presented two techniques for predicting job satisfaction in Jordan, the Artificial Neural Networks and the J48 decision tree implemented in the Weka program. The data set for the experiments was obtained from an online questionnaire.

The study by the Ref. [27] states that one of the existing problems in all organizations, especially in schools, is proliferation of data and how this data will be helpful for intervention programs and decision making. According to this, the Ref. [27] proposed to show the effectiveness of data mining analysis in predicting job satisfaction of school administrators. They obtained the data set for the experiments through a survey developed by the Department of Education of Surigao del Norte in the Philippines. They employed Naive Bayes, C4.5 decision tree and K-Nearest Neighbors (KNN) algorithms. Their results regarding accuracy are 80.89%, 74.52% and 71.97% using the C4.5, Naive Bayes and K-Nearest Neighbors algorithms, respectively.

The study by the Ref. [28], the authors studied the available approaches to predict job satisfaction, looking for identify the main factors influencing the job satisfaction of IT professionals and explore the possibilities of generalizing job satisfaction prediction models to other areas of the IT industry. They employed Random Forest, Logistic Regression, Support Vector Machines and Neural Networks algorithms. They obtained the data set from Stack Overflow's developer survey and IBM's HR analytic data set. The results

show that the Random Forest algorithm obtained the best-value scores for accuracy of 0.80, precision of 0.74, specificity of 0.80 and an F1 of 0.75.

From what the Ref. [17] has done, we could observe that in the prediction of job satisfaction the algorithms of Logistic Regression, Random Forest and Extreme GB (EGB) obtained accuracy values of 78%, in the study by the Ref. [28] we observed that the Random Forest algorithm obtained an accuracy value of 80% thus surpassing algorithms such as Logistic Regression, Support Vector Machines and Neural Networks. This evidence shows that the Random Forest algorithm is a candidate for a good predictor of teacher job satisfaction, without losing sight of algorithms such as Logistic Regression, Extreme Gradient boosting and Gradient boosting whose accuracy values are very similar to those of the aforementioned algorithm [17].

The use of algorithms from the category of decision trees for the prediction of job satisfaction, such as CART (Classification and Regression Tree) used in the study of the Ref. [18,25] and C4.5 used in the study of the Ref. [27] obtained an accuracy of 76.15% and 80.89% respectively, thus surpassing even neural network algorithms as in the case of the Ref. [18], Naive Bayes and k-nearest neighbors in the Ref. [27]. This evidence shows that decision trees perform well in predicting job satisfaction.

The studies by the Ref. [26,28] employed studies of neural network algorithms as part of the experiments to predict job satisfaction, where in the case of the Ref. [28] the Random Forest algorithm obtained an accuracy of 0.80, thus outperforming the neural network algorithm by a small margin of 0.01. In the case of the Ref. [26], the neural network algorithm and the J48 decision tree algorithm are validated as good algorithms for predicting job satisfaction.

Our review of the state-of-the-art shows studies that address the relationships between different variables and teacher job satisfaction. One of the most used techniques is structural equations [22,23,29–33]. Other studies use techniques such as Chi-square and ANOVA [24], MANOVA [34], Pearson correlation [35], hierarchical linear models [36], independent samples t-test, coefficient Pearson Product Moment Correlation and Stepwise Regression [37], to name a few.

In the review of the scientific literature, we found a few studies that address this issue from a machine learning approach, where these are: identification of the job satisfaction of a teacher in a new workplace [25], prediction of job satisfaction of teachers Google, Facebook, Amazon, Microsoft, and Apple employees [17], construction employee job satisfaction prediction [18], worker job satisfaction prediction [26], satisfaction prediction of school administrators [27], prediction of job satisfaction in information technology workers [28] or modeling teacher job satisfaction using artificial neural networks [16].

However, all the studies that we have identified analyze the relationship between the variables studied by applying traditional techniques such as structural equations, Pearson or Spearman correlation coefficients, Chi-square, ANOVA and its variants. On the other hand, the studies that use automatic learning carry out their experiments on data sets with information other than basic education teachers, which means that our results are closer to the reality studied.

3. Materials and Methods

In Figure 1 we show the phases of data cleaning and pre-processing, feature selection and predictive modeling. Next, we describe each of these phases. In addition, in Appendix A.4, we attach the data dictionary of the columns that we used for Figures 2 and 3.

3.1. Data Cleaning and Preprocessing

We obtained the data set used for this study from the Encuesta Nacional a Docentes (ENDO) developed by the Peruvian Ministry of Education during 2018 [38]. The dimension of this data set is 15,087 instances and 942 attributes. The information contained in this survey is divided into the following categories: demographics, housing and home; initial training; professional career and current job; health; economy; in-service training and

education; media and information technologies; opinion and perception; and teaching practices. Table 1 shows a global summary of the data set generated by the *create_report* function of the Data-Explorer package of the R language.

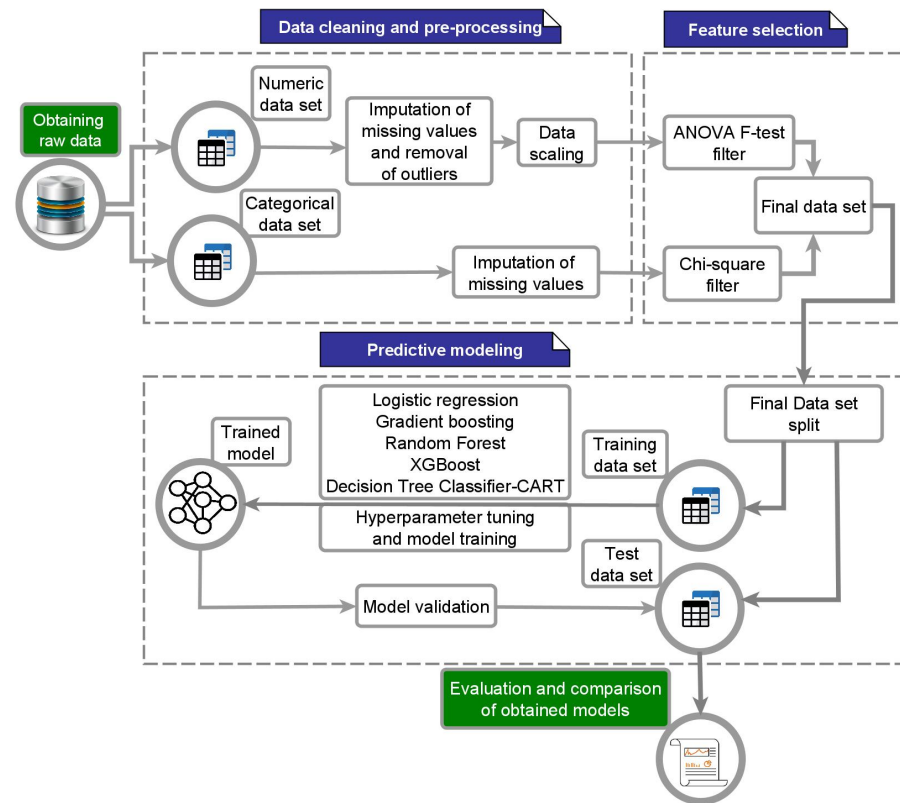


Figure 1. Proposed methodology for modeling teacher job satisfaction.

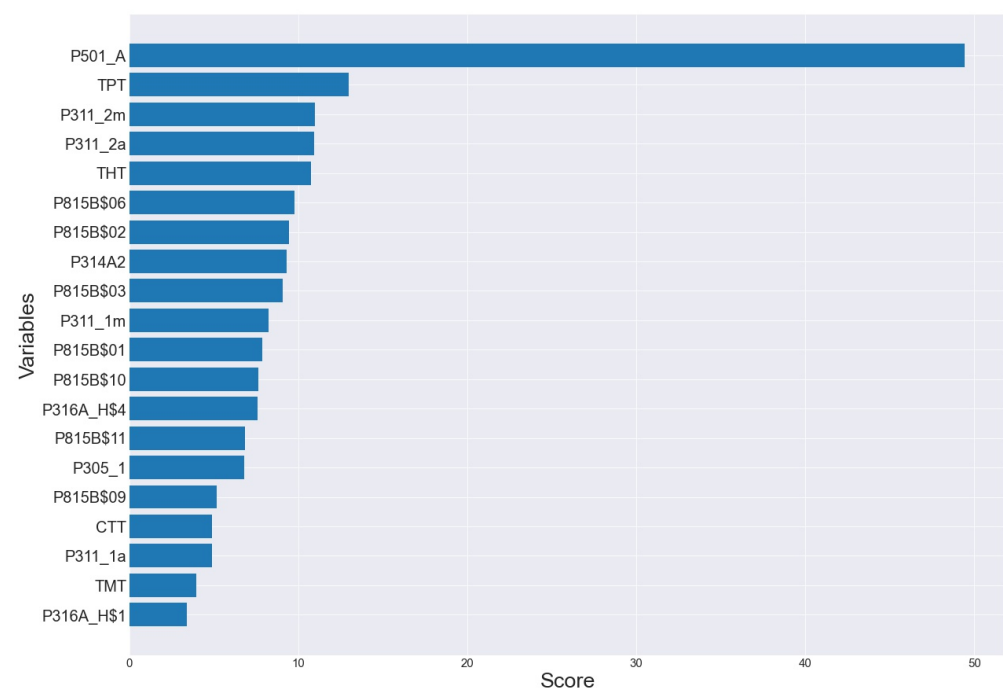
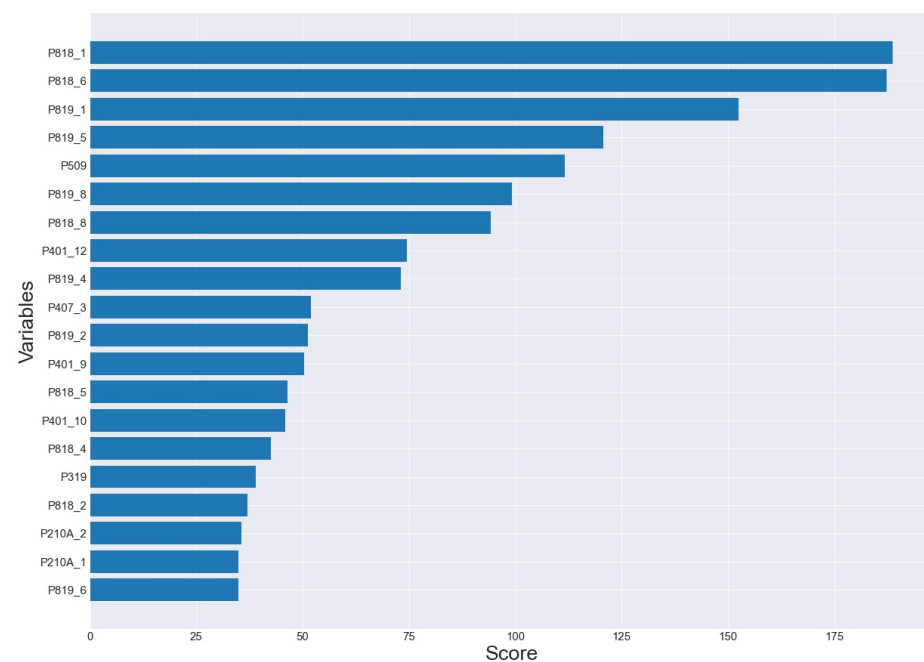


Figure 2. ANOVA scores in predicting teacher job satisfaction.

Table 1. Overall summary of ENDO-2018 data set.

Name	Value
Rows	15,087
Columns	942
Discrete columns	66
Continuous columns	873
All missing columns	3
Missing observations	4,717,895
Complete rows	0
Total observations	14,211,954

**Figure 3.** Chi-Square scores in the prediction of teacher job satisfaction.

Of the 942 columns, we made a first manual selection of 407 variables belonging to the 9 categories mentioned above. The exclusion criteria were those columns with only one value for all the rows, as well as those with more than 40% of missing values, because these can cause errors or unexpected results, as suggested by the Ref. [39]. At this point it is important to clarify that some variables were empty due to the nature of the questions. For example, column P323 corresponding to the question: “If you could go back, would you choose to be a teacher again?” with alternatives of yes and no; answering yes to this question implied leaving column P324 empty corresponding to the question: Why would you not choose to be a teacher again, in order to move on to question 325. After this analysis, columns with at least 20% of missing data were filtered out, leaving 370 columns. It should be clarified that in this survey there were values with NEP code corresponding to the cells where the respondent did not specify the answer, so it was also necessary to input them.

In relation to the target variable, we constructed it from the answers to the question: All things considered, how satisfied are you with your job at this educational institution, which is found in the Opinion and Perception category of the survey in question.

3.1.1. Inputting Missing Values and Eliminating Outliers

In this task we proceeded to separate the data set into numerical with 40 columns and categorical 330 columns, then imputed by mode for the categorical variables. According to the Ref. [40,41] this procedure consists of filling in the missing data for each variable by mode when it is a categorical variable and by median for numerical variables. In relation to

the numerical variables, it is important to clarify that this data set presented extreme values, so it was decided to impute the missing values by the median, because this measure is more representative and is not affected by the presence of these. These types of imputations in the statistical field are called simple imputation methods [42,43].

The Local Outlier Factor (LOF) algorithm identified 1785 instances as outliers in the numerical data set, and after identification these instances were removed in parallel in both data sets. For this algorithm the degree to which an object is extreme depends on the density of its local neighborhood, and it is possible to assign a LOF value to each object that would represent the probability that it is an extreme value [44]. For this technique we identified outliers as points with considerably lower density than their neighbors.

3.1.2. Robust Scaling Data

We applied this standardization method because it works with the median instead of the mean, as it is known that the median is more representative when there are some outliers. We calculated the median (50th percentile) and the 25th and 75th percentiles. Then, we subtracted the median from the values of each variable and divided it by the value of the interquartile range ($IQR = p_{75} - p_{25}$). The new values have a mean and median of zero and a standard deviation of 1 [39]. We show the equation we used in Appendix A.1.

3.2. Feature Selection

In this phase, we used the *SelectKBest* class of the Scikit-learn machine learning library. This implementation allowed the selection of the best features based on univariate statistical tests. According to the Ref. [45] this class allows the selection of the k features with the highest scores. To determine these scores, when input variables are numerical and the target variable is categorical it is possible to use the ANOVA F-statistic implemented in the *f_classif()* function and when both are categorical we can use the Chi-square statistic implemented in the *chi2()* function of the library in the Ref. [39].

3.2.1. ANOVA F-Test Filter

For the selection of characteristics by this filter, we set up parameters *score_func* = *f_classif* and *k* = 'all' in class *SelectKBest*, giving as input the numerical data set and the teacher job satisfaction as the target variable. This configuration made it possible to obtain the scores shown in Figure 2. In addition, we shown the equations we used in Appendix A.2.

3.2.2. Chi-Square Filter

To use this filter we used the *SelectKBest* class of the aforementioned library, with the parameters *score_func* = *chi²* and *k* = 'all'. To use this filter, first the ordinal coding of the categorical attributes was performed [46]. We detail this coding below. We calculated the score, returned by the mentioned function, using Equation (1) which corresponds to Pearson's Chi-square statistic [47]. Pearson's Chi-square statistic is a test of independence between two categorical variables [39].

$$\chi^2 = \sum_{i=1}^n \frac{(O_i - E_i)^2}{E_i}. \quad (1)$$

O_i are the observed values. E_i are the expected values.

The scores obtained by this statistic are shown in Figure 3.

3.2.3. Construction of the Final Data Set

We constructed the final data by analyzing the relationship between the number of features and the accuracy gain in a logistic regression model, with a stratified cross-validation with 10 folds and 3 replicates. First, we applied this procedure to the categorical data set with the *Chi - square* filter; then, on the numerical data set with the *ANOVA F - test* filter. In Figure 4, we showed that the gain margin in accuracy for the model is

not significant as the number of features increases, so we chose nine features from the categorical data set and one from the numerical data set.

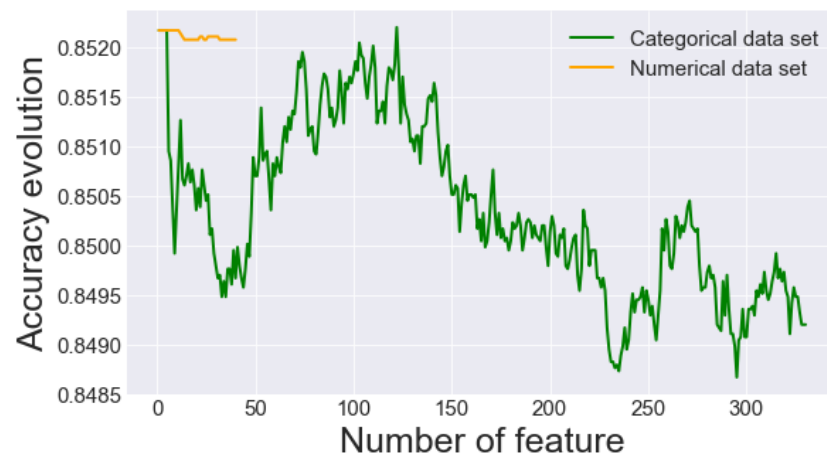


Figure 4. Evolution of accuracy and number of features.

In Table 2, we show the description of the selected features and the respective naming in the ENDO-2018 data set.

Table 2. Description of selected characteristics.

Description	Designation
Life satisfaction.	P818_1
Satisfaction with their self-esteem.	P818_6
Satisfaction with their pedagogical activity.	P819_1
Satisfaction with the relationship with the principal.	P819_5
Perception of living conditions.	P509
Satisfaction with their salary.	P819_8
Satisfaction with family relationships.	P818_8
Depression in the previous year.	P401_12
Satisfaction with their relationship with colleagues.	P819_4
Total income in the previous month.	P501_A

Of this final data set, variable *P401_12* is of nominal type, *P501_A* is of continuous numeric type, and the rest are of ordinal type.

Finally, we encoded the nominal variables with the *sklearn.preprocessing.OneHotEncoder* module and the ordinal variables with the *sklearn.preprocessing.OrdinalEncoder* module, as described in the official *Sklearn* manual [45] and the study presented by the Ref. [48]. The *OneHotEncoder* coding transforms a variable with n observations and k categories into k binary variables with n observations each [49,50]. *OrdinalEncoder* coding, on the other hand, assigns an integer to each category, provided that the number of existing categories is known. In this case, no new column is added to the data, however it implies an order for the variable [49]. Table 3 shows the structure of the final data set. The variable Job Satisfaction constitutes our target variable, where one represents dissatisfied and zero represents satisfied.

3.3. Predictive Modeling

3.3.1. Training and Test Data Set

We performed this task partitioning the data set into 70% for training and 30% for model validation, as [51,52] performed. We obtained 9911 instances to train and 3991 instances to validate as result of this partition.

After partitioning the data set, we verified the distribution of the classes in the target variable of the training data set, we show this distribution in Figure 5a, where we can see that this variable is partially unbalanced. According to the Refs. [53,54] unbalanced data can affect the result of the classification models, as they tend to bias the results towards the majority class. We solved this problem performing data balancing to the training data set, using the oversampling technique that consists of adding data to the minority class until we achieved a balance in both classes. Figure 5b shows the distribution of the classes after balancing the data.

Table 3. Statistical summary of metrics in the training data set.

	P40112No	P40112Si	P501A	P509	P8181	P8186	P8188	P8191	P8194	P8195	P8198	JobSat
0	1	0	−0.06520	2	2	3	2	2	3	2	2	0
1	1	0	0.59641	2	2	3	3	2	2	2	3	0
2	1	0	−0.24108	2	3	3	3	3	3	3	3	0
...
13,299	1	0	0.59641	2	2	2	2	2	2	2	2	0
13,300	1	0	1.01516	2	3	2	2	2	3	2	3	0
13,301	1	0	1.01516	2	3	2	2	2	2	2	3	0

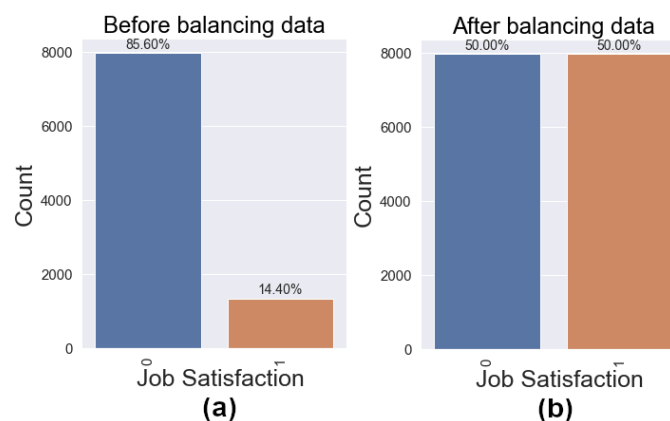


Figure 5. Class distribution in the target variable. (a) Before data balancing. (b) After data balancing.

3.3.2. Hyper-Parameter Tuning and Model Training

To model training we used the Logistic Regression, Gradient Boosting, Random Forest, XG-Boost, Decision Trees-CART algorithms. To train the model, we considered optimal *hyper-parameter* values that we calculated from a hyper-parameter tuning.

We tuned the hyper-parameters using the technique called Grid Search (GS), which is a widely used method to explore the configuration space of hyper-parameters in the field of machine learning [55,56]. GS performs an exhaustive search for the optimal configuration for a fixed domain of hyper-parameters, i.e. it trains a machine learning model with each combination of possible hyper-parameter values and then performs performance evaluation on the cross validation test data set of according to a previously defined metric [57]. In this study we used the sklearn GridSearchCV class, the area under the ROC curve score for classifier evaluation, and a cross-validation with $k = 10$. The main hyper-parameters for each model were taken from the list recommended by the Ref. [56,58]. The names, range of values, description, default values and optimal values of each one of the hyperparameters that we use for each model are in Table 4.

3.3.3. Model Validation

We performed model validation on the test data set. We obtained the results of the present study from this task.

3.3.4. Evaluation and Comparison of Models Obtained

At this point we had to calculate the metrics of accuracy, sensitivity, specificity, area under the ROC curve (AUC), positive predictive value, negative predictive value. However, because the distribution of classes in the target variable is not balanced, we selected the best model based on sensitivity, area under the ROC curve (AUC), lower number of false-negatives and higher number of true-positives that we obtained from the confusion matrix. We show the structure of the confusion matrix for two classes in Figure 6.

Table 4. Hyper-parameter settings.

Model	Hyper-Parameter	Value Range	Description	Default Values	Optimal Values
LR	penalty	["l1", "l2", "elastic-net"]	"Penalty type"	l2	l2
	C solver	[0.001, 0.01, 0.1, 1, 10] ["lbfgs", "liblinear", "newton-cg", "newton-cholesky", "sag", "saga"]	Inverse of regularization strength Algorithm to use in the optimization problem.	1.0 lbfgs	1 liblinear
RF	n_estimators	[10, 17, 25, 33, 41, 48, 56, 64, 72, 80]	Number of decision trees in the random forest.	100	64
	max_depth	[3,5,7]	Maximum depth of trees.	none	7
	Criterion	["gini", "entropy"]	Function that measures the quality of the division.	gini	entropy
	min_samples_split	[2,5]	Minimum number of samples required to split an internal node.	2	5
	min_samples_leaf	[1,2]	Minimum number of samples required for a leaf node.	1	2
	max_features	["auto", "sqrt"]	Number of randomly selected features without replacement in the division.	auto	auto
XGB	n_estimators	[10, 17, 25, 33, 41, 48, 56, 64, 72, 80]	Number of decision trees in XGB.	100	72
	max_depth	[3,5,7]	Maximum depth of trees.	6	3
	learning_rate	[0.1]	learning rate	0.3	0.1
	subsample	[0.6: 0.9] step 0.1	Fraction of observations that will be random samples for each tree.	1	0.9
	colsample_bytree	[0.6: 0.9] step 0.1	Fraction of columns that will be random samples for each tree.	1	0.6
GB	n_estimators	[10, 17, 25, 33, 41, 48, 56, 64, 72, 80]	The number of sequential trees to model.	100	48
	max_depth	[3,5,7]	Maximum depth of trees.	3	3
	min_samples_split	[500: 1000] step 5.05	Minimum number of samples required at a node for splitting.	2	949
	min_samples_leaf	[20, 28, 37, 46, 55, 64, 73, 82, 91, 100]	Minimum number of samples required in a leaf node.	1	55
	max_features	["auto", "sqrt", "log2"]	Number of features to consider when looking for the best split.	None	log2
	subsample	[0: 1] step 0.1	Fraction of observations to select for each tree.	1.0	0.3
DT-Cart	learning_rate	[0.01: 0.1] step 0.03	Learning rate.	0.1	0.09
	Criterion	["gini", "entropy", "log_loss"]	Function to measure the quality of a division.	gini	entropy
	max_depth	[2:10] step 1	Max Tree Depth	None	6
	min_samples_split	[1: 10] step 1	Minimum number of samples required for splitting on an internal node.	2	2
	min_samples_leaf	[2: 10] step 1	Minimum number of samples required in a leaf node.	1	3
	max_features	["auto", "sqrt", "log2", "none"]	Number of features to consider when looking for the best split of the tree.	None	None

		Predicted class	
		Negative	Positive
Real class	Negative	True negatives (TN)	False positives (FP)
	Positive	False negatives (FN)	True positives (TP)

Figure 6. Structure of a confusion matrix for two classes.

In Appendix A.3, we detailed the metrics for the confusion matrix.

4. Results

We made our experiments with the free Python machine learning library scikit-learn [45]. We trained and validated our models in a computer with these characteristics: AMD A12-9700P RADEON R7, 10 COMPUTE CORES 4C+6G at 2.50 GHz, 12 GB RAM, Windows 10 Home 64-bit operating system and x64 processor.

We evaluated the performance of five machine learning algorithms in the prediction of job satisfaction of basic education teachers in Peru. These algorithms are: Decision Trees-CART, Gradient Boosting, Logistic Regression, Random Forest and XGBoost.

In the Table 5 we show the main metrics that we obtained in the training stage with the hyper-parameter values presented in the previous section in combination with the K-Fold Cross-Validation technique with $k = 100$. Here it can be seen that the Random Forest model obtained the best results in 6 of the 8 metrics evaluated. These values are: mean accuracy of 0.77, mean sensitivity of 0.81, mean negative predictive value of 0.79, mean F1 score of 0.78, mean area under the ROC curve of 0.85, and a mean Cohen's Kappa Coefficient of 0.53.

Table 5. Statistical summary of metrics in the training data set.

Model	DT-CART	GB	LR	RF	XGB
Accuracy	0.75 ± 0.03	0.76 ± 0.04	0.74 ± 0.03	0.77 ± 0.04	0.76 ± 0.04
Sensitivity	0.70 ± 0.05	0.78 ± 0.05	0.75 ± 0.05	0.81 ± 0.05	0.79 ± 0.05
Specificity	0.80 ± 0.04	0.73 ± 0.05	0.73 ± 0.05	0.73 ± 0.05	0.73 ± 0.05
PPV	0.78 ± 0.04	0.75 ± 0.04	0.73 ± 0.03	0.75 ± 0.04	0.75 ± 0.04
NPV	0.73 ± 0.04	0.77 ± 0.04	0.74 ± 0.04	0.79 ± 0.04	0.78 ± 0.05
F1-Score	0.73 ± 0.04	0.76 ± 0.04	0.74 ± 0.04	0.78 ± 0.03	0.77 ± 0.04
AUC	0.83 ± 0.03	0.84 ± 0.03	0.82 ± 0.03	0.85 ± 0.03	0.85 ± 0.03
Kappa	0.50 ± 0.07	0.51 ± 0.07	0.47 ± 0.07	0.53 ± 0.07	0.52 ± 0.08

In Table 6, we observe the results of applying the ANOVA test to the Cohen's Kappa metric that we obtained after applying the K-Fold Cross-Validation technique with $k = 100$ in the training stage. The calculated F value=11.489; p -value < 0.05, shows us that there are significant differences between the models analyzed.

Table 6. ANOVA test in Cohen's Kappa metric.

Kappa					
	Sum of squares	gl	Quadratic Mean	F	Sig.
Between groups	0.231	4	0.058	11.489	0.000
Within groups	2.490	495	0.005		
Total	2.721	499			

In Table 7, we show the results of Duncan's test for comparison of means with Cohen's Kappa metric. Here we find that group 4 is made up of the XGBoost and Random Forest models, this shows that in the training stage these algorithms have better performance in

predicting job satisfaction of basic education teachers. We also show that the lowest value of the Logistic Regression algorithm with a mean value of Cohen's Kappa of 0.4727280 is in group 1.

Table 7. Duncan's test on Cohe's Kappa metric.

Duncan		Kappa			
		Subset for Alpha = 0.05			
Model	N	1	2	3	4
LR	100	0.4727280			
DT-CART	100		0.4952041		
GB	100		0.5118734	0.5118734	
XGBoost	100			0.5229337	0.5229337
RF	100	1.000			0.5338400
Sig.		1.000	0.0970000	0.2710000	0.2770000

Figure 7 shows the confusion matrix of the models studied for the test data set. The confusion matrix of the Random Forest (c) and XGBoost (e) models show the lowest values of false-negatives 168 (dissatisfied teachers that the model classified as satisfied teachers), the highest values of true-positives 479 (dissatisfied teachers that the model classified as dissatisfied).

Regarding the value of true negatives (Class 0: satisfied teachers) the Decision Trees-CART algorithm obtained the best result with 2710 (satisfied teachers that were correctly classified as satisfied). The lowest value of false-positives 634 (satisfied teachers who were classified as dissatisfied) was also obtained with the same algorithm.

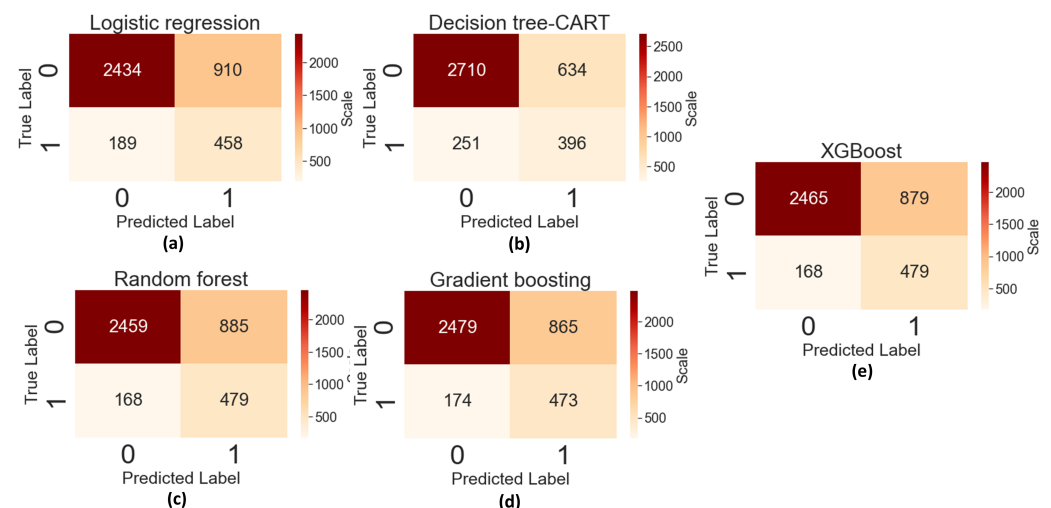


Figure 7. Confusion matrix of the studied models. (a) Logistic regression. (b) Decision tree-CART. (c) Random forest. (d) Gradient boosting. (e) XGBoost.

Figure 8 shows the metrics we obtained after predicting the test data set. We will consider these metrics for the selection of the best model in predicting the job satisfaction of basic education teachers. Note that we obtained very similar values of Cohen's Kappa metric between the XGBoost, Gradient Boosting and Random Forest models close to 0.33. The lowest value in this metric of 0.30 was obtained by the Logistic Regression model. Although models such as XGBoost, Gradient Boosting and Random Forest are formed by an ensemble of trees or estimators, the experiments show that in this metric the Decision Trees-CART algorithm slightly outperforms the ensemble models with a value of 0.34. Values

obtained in the kappa coefficient of 0.33 and 0.34 by the models indicate an acceptable agreement between the actual classification and the predicted classification [59,60].

With respect to the sensitivity metric, we obtained the best value with the Random Forest and XGBoost models of 0.74. In our problem domain, this value indicates the probability that the model correctly classifies a teacher belonging to the dissatisfied class [61]. The value obtained from this metric is very similar to that reported by the Ref. [17] in their “Review prognosis system to predict employees job satisfaction using deep neural network” they obtain a value of 0.75 for satisfied employees and 0.77 for dissatisfied employees. In the study entitled “A data mining based model for the prediction of satisfaction in the Surigao del Norte Division of the Department of Education” presented by the Ref. [27], they obtained a value of 0.72 for the k-nearest neighbors algorithm, in the case of the Naive Bayes algorithm a value of 0.74 and for the C4.5 algorithm a value of 0.80. It is important to clarify that these results were obtained for administrative employees and not for basic education teachers. To date, there are no studies that address the prediction of basic education teacher job satisfaction with the machine learning approach.

Since the test data set was not balanced, we decided to use the balanced accuracy metric, which is ideal for evaluating the performance of machine learning models on data sets with these characteristics [62–64]. In Figure 8, we can observe that the XGBoost, Random Forest and Gradient Boosting models obtain values close to 0.74, being the highest in the analyzed models. The value of this metric is similar to the results reported by the Ref. [18] where the authors compare job satisfaction prediction models for construction workers, with the CART and Neural Network algorithms, obtaining a value of 0.76 with the algorithm. of Decision Tress-CART. In the study in reference, the researchers used a data set of 280 instances with 20 independent variables. The feature selection technique for categorical variables used by the aforementioned authors is the same as that used in our study.

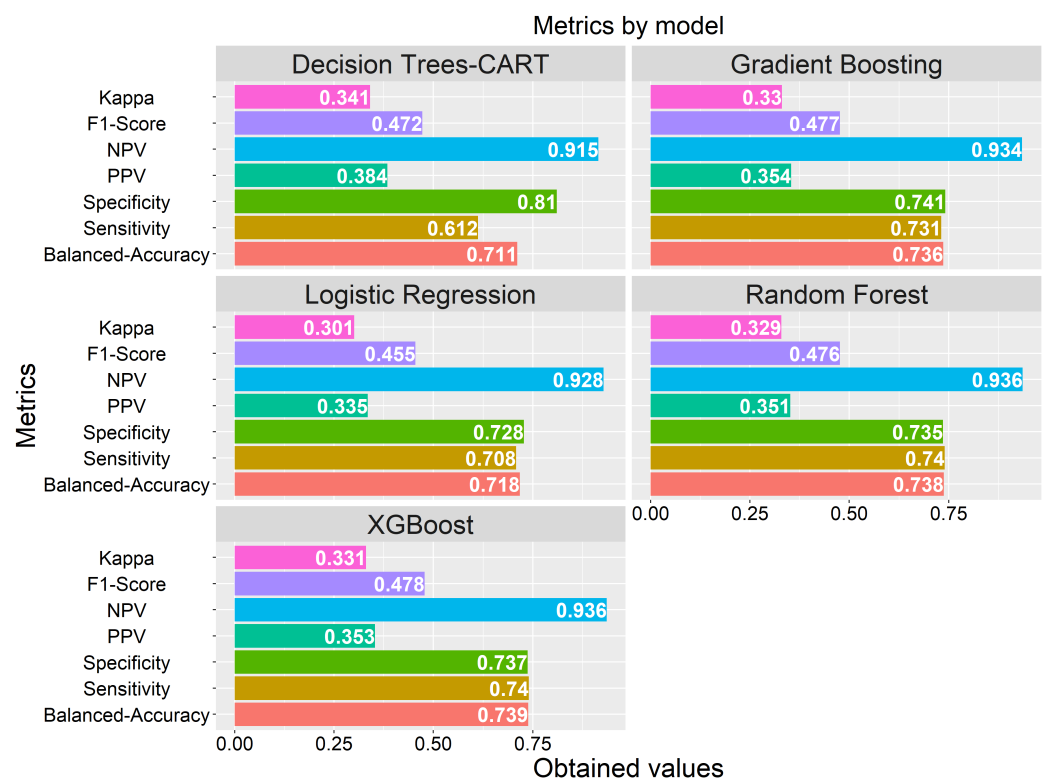


Figure 8. Metrics obtained on the test data set.

We obtained similar values of F1-Score = 0.48 with XGBoost, Gradient Boosting, and Random Forest. Decision Trees-CART obtained a very close value of 0.47.

Also note in Figure 8 that the highest value of the metric called negative predictive value (NPV) was 0.94 and we obtained it with the Random Forest and XGBoost algorithms.

Finally, Figure 8 also shows that Decision Trees-CART obtained a specificity value of 0.81, this suggests that this algorithm is adequate to predict class 0; that is, the satisfied teachers. Another metric, in the context of our study, that allows us to know the probability that the teacher is dissatisfied given that he was classified as such, is the positive predictive value. This value was also higher in the model built by the Decision Trees-CART algorithm. The positive predictive value was 0.38 in the model built by the Decision Trees-CART algorithm.

Figure 9 shows the area under the ROC curve that we have obtained after the prediction on the test data set. The models built with the Gradient Boosting and XGBoost algorithms obtain a value of $AUC = 0.83$, very close to this value is the Random Forest model with $AUC = 0.82$. With this, we demonstrate that the discriminant capacity of these models for the dissatisfied and satisfied class is good, as stated by the Ref. [65].

It is important to note that in the feature selection process, as shown in Figures 2 and 3 and Table 2, we found three variables which are: satisfaction of their relationship with the director, satisfaction with their life and satisfaction of their relationship with their colleagues that were reported by the Ref. [22–24] as variables that are significantly related to teacher job satisfaction. Our study confirms these findings.

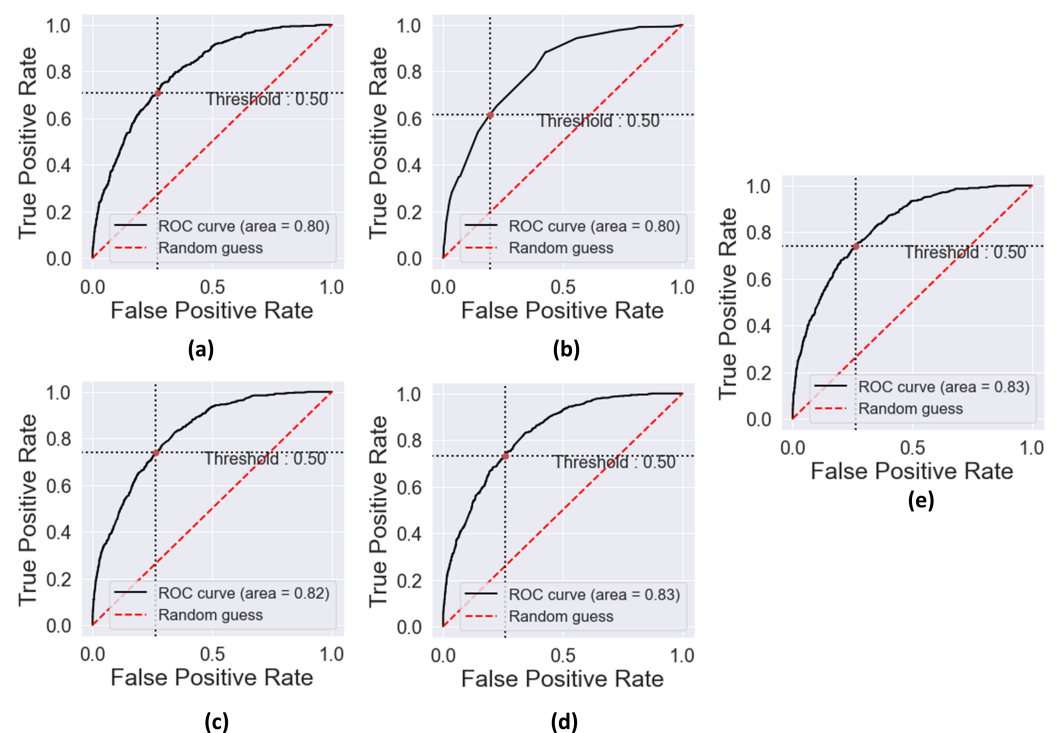


Figure 9. Area under the ROC curve. (a) Logistic Regression model. (b) Decision Tree-CART model. (c) Random Forest model. (d) Gradient Boosting model. (e) XGBoost model.

Finally, in the educational sphere, our results provide new variables that could serve to better understand teacher job satisfaction. They also suggest that such variables should be considered when formulating teacher reassessment policies and reforms.

5. Conclusions

Our study identified and analyzed the most important and reliable predictors of job satisfaction of Peruvian basic education teachers based on data from the national survey of teachers ENDO-2018 prepared by the Ministry of Education of Peru. Since the original data set had numerical and categorical variables, it was necessary to carry out differentiated treatments, so we performed the selection of characteristics using the *ANOVA F – test* filter

for the numerical variables and the *Chi – Square* filter for the categorical variables. The results show that the most important variables in the prediction are economic income, satisfaction with life, self-esteem, pedagogical activity, the relationship with the director, the perception of living conditions, with family relationships; health problems related to depression, and satisfaction with the relationship with peers. After evaluating and comparing the models built by the Logistic Regression, Decision Trees-CART, Random Forest, Gradient Boosting and XGBoost algorithms, our results show that in the test data set the XGBoost and Random Forest algorithms obtain similar results in 4 of the 8 metrics evaluated, where these are: balanced accuracy of 74%, sensitivity of 74%, F1-Score of 0.48, negative predictive value of 0.94. However, in terms of the area under the ROC curve, the XGBoost algorithm obtained 0.83, while Random Forest obtained 0.82. These algorithms also obtained the highest true-positive values (479 instances) and lowest false-negative values (168 instances) in the confusion matrix.

We hope the results of our study will serve as a starting point for the development of increasingly optimal predictive models of teacher job satisfaction classification, using other more sophisticated algorithms such as artificial neural networks.

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Appendix A

Appendix A.1

The Equation (A1) formally shows this type of data scaling.

$$scaled_value = \frac{value - median}{p_{75} - p_{25}}. \quad (A1)$$

where, p_{75} and p_{25} are the 75th and 25th percentiles respectively.

The implementation of this scaling method is found in the *RobustScaler* class of the sklearn pre-processing module.

Appendix A.2

The *F* statistic allows to obtain these scores, which we can see in Equation (A2).

$$F = \frac{\frac{SSBG}{df_1}}{\frac{SSWG}{df_2}}. \quad (A2)$$

SSBG = Sum of squares between groups:

$$SSBG = \sum_{j=1}^m \sum_{i=1}^{n_j} (y_{ij} - \tilde{y}_j)^2. \quad (A3)$$

SSWG = Sum of squares within groups:

$$SSWG = \sum_{j=1}^m n_j(\bar{y}_j - \bar{y})^2. \quad (A4)$$

In addition, $df_1 = m - 1$, $df_2 = n - m$, m is the number of levels of our target variable and n is the number of observations, \bar{y}_j is the mean in group j , \bar{y} is the total mean [66].

Appendix A.3

Balanced accuracy For binary classification this value is equal to the arithmetic mean of the sensitivity and specificity.

$$balanced_accuracy = \frac{1}{2} \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right). \quad (A5)$$

TP are the true-positives. TN are the true negatives.

FN are the false-negatives. FP are the false-positives.

Sensitivity Represents the proportion of true-positives that the model predicted correctly (Positive Class 1: Dissatisfied).

$$Sensitivity = \frac{TP}{(TP + FN)}. \quad (A6)$$

Specificity Represents the proportion of true negatives that the model predicted correctly (Negative Class 0: Satisfactory).

$$Specificity = \frac{TN}{(TN + FP)}. \quad (A7)$$

Positive predictive value (PPV) Also called precision, represents the probability of an instance being of the positive class having been predicted as positive by the model.

$$PPV = Precision = \frac{TP}{(TP + FP)}. \quad (A8)$$

Negative predictive value (NPV) Represents the probability of an instance being of the negative class having been predicted as negative by the model.

$$NPV = \frac{TN}{(TN + FN)}. \quad (A9)$$

Cohen's kappa coefficient Measures the agreement between classifiers.

$$kappa = \frac{(Pr(a) - Pr(e))}{(1 - Pr(e))}. \quad (A10)$$

where, $Pr(a)$: the percentage of agreement observed.

$Pr(e)$: is the probability that the inter-rater agreement is due to chance.

Area under the ROC curve (AUC). Indicates how good the model is at discriminating instances of the positive class and the negative class. This value fluctuates between 0 and 1. According to the Ref. [67], the closer this value is to 1, the greater the discriminating capacity of the model.

Appendix A.4

Table A1. Data dictionary of the features selected with the ANOVA F-test filter.

Description	Variable
Total income in the previous month	P311_2m
Time since first job as a teacher	TPT
Number of months you have been working at this school as a contract	P311_2m
Number of years you have been working consecutively at this school as a contract	P311_2a
Travel time in hours to work	THT
Number of times you attended services or performances of film features in the past 12 months	P815B\$06
Number of times you visited monuments in the last 12 months	P815B\$02
Average number of students per classroom	P314A2
Number of times you visited archaeological sites in the last 12 months	P815B\$03
Number of months you have been working at this school as appointed	P311_1m
Number of times you visited museums in the last 12 months	P815B\$01
Number of times you visited book fairs in the last 12 months	P815B\$10
Amount of time spent working as a team or conversing with colleagues from your school	P316A_H\$4
Number of times you visited craft fairs in the last 12 months	P815B\$11
Number of public schools in which you currently teach	P305_1
Number of times you visited libraries or reading rooms in the last 12 months	P815B\$09
Total cost of commuting to work	CTT
Number of years you have worked consecutively at this school as appointed	P311_1a
Commute time in minutes to work	TMT
Time spent teaching classes in a typical week	P316A_H\$1

Table A2. Data dictionary of the features selected with the Chi-Square filter.

Description	Variable
Satisfaction with your life	P818_1
Satisfaction with your self-esteem	P818_6
Satisfaction with your pedagogical activity	P819_1
Satisfaction with the relationship with the director	P819_5
Perception of living conditions	P509
Satisfaction with your salary	P819_8
Satisfaction with their family relationships	P818_8
The year before she suffered from depression	P401_12
Satisfaction with the relationship with their colleagues	P819_4
Frequency with which you work with poor lighting in class	P407_3
Satisfaction with the achievements of their students	P819_2
The previous year he suffered stress	P401_9
Satisfaction with the conditions of your future retirement	P818_5
The previous year he suffered anxiety	P401_10
Satisfaction with education that you can give your children	P818_4
If you could choose any teaching position in the country, would it be in the same district?	P319
Satisfaction with your health	P818_2
Qualification of the teaching methodology used by teachers in their teacher training	P210A_2
Qualification of the thematic contents of the courses/learning areas received in their teacher training	P210A_1
Satisfaction with their relationship with parents	P819_6

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