Algorithms for Classifying the Results at the Baccalaureate Exam - Comparative Analysis of Performances

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Summary
In the current context of digitalization of education, the use of modern methods and techniques of data analysis and processing in order to improve students' school results has a very important role. In our paper, we aimed to perform a comparative study of the classification performances of AdaBoost, SVM, Naive Bayes, Neural Network and kNN algorithms to classify the results obtained at the Baccalaureate by students from a college in Suceava, during 2012-2019. To evaluate the results we used the metrics: AUC, CA, F_1, Precision and Recall. The AdaBoost algorithm achieves incredible performance for classifying the results into two categories: promoted / rejected. Next in terms of performance is Naive Bayes with a score of 0.999 for the AUC metric. The Neural Network and kNN algorithms obtain scores of 0.998 and 0.996 for AUC, respectively. SVM shows poorer performance with the score 0.987 for AUC. With the help of the HeatMap and DataTable visualization tools we identified possible correlations between classification results and some characteristics of data.

Key words:
Classification algorithms, data visualization.

1. Introduction

In order to improve students' school performance, it is necessary to identify possible correlations between the final results obtained at exams and various factors such as previous acquisitions in certain subjects. Simply studying the results of 20-30 subjects can lead to realistic conclusions. However, if we refer to the thousands of results recorded over several years, we need special techniques and working methods.

In our study, we aimed to use classification algorithms specific to machine learning in order to analyze the classification performance of students' results at the Baccalaureate exam. At the same time, we will try to identify possible correlations between the results obtained and the presence in the data set used of certain characteristics by using visualization techniques such as HeatMap and DataTable.

The classification algorithms used are: AdaBoost, SVM (Support Vector Machine), kNN (k Nearest Neighbors), Neural Network and Naive Bayes. As evaluation metrics of algorithms' performance we use: AUC (Area Under the ROC Curve), CA (Classification Accuracy), F_1 (F-score), Precision and Recall.

The dataset used comprises 2245 records organized in an Excel file. These represent the results obtained by students from a college in Suceava at the Baccalaureate exam, between 2012 and 2019.

We will train several models using subsets obtained from the initial data by removing certain characteristics, in a data preprocessing stage, in order to identify certain possible correlations between results and this characteristics of data.

As a work environment, we will use a special open source instrument, created for machine learning and data visualization, named Orange.

We will make comparisons between the classification performances of the algorithms using data from 2019, from 2018-2019 and from 2012-2019. We will also study the results obtained by models using data without some characteristics, removed in preprocessing stage.

The rest of the paper is organized as follow. Section 2 makes an overview of classification algorithms, Section 3 describe the working methodology, Section 4 discuss the achieved results and finally some conclusions are presented.

2. Classification algorithms - overview

Building models that learn from data belongs to the field of machine learning. It is based on learning algorithms that can be classified into: supervised, unsupervised, semi-supervised learning and reinforcement learning algorithms [1].

Supervised learning algorithms use labeled data to solve classification and regression problems [2].

2.1 kNN (K-Nearest Neighbors)

kNN is a non-parametric classification method that is based on classifying an instance according to the closest k examples. To measure how similar two instances are, a

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series of distances are used such as: Mincowski, Euclidean, Manhattan, cosine function, and others [3].

Considering two points in the n-dimensional space of the characteristics, P_1 ($x_1,\ldots,x_n$) and P_2 ($y_1,\ldots,y_n$), these distances can be defined as follows [4]:

The Mincovski distance (see Eq. 1):

$$d(P_1, P_2) = \left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{\frac{1}{p}} \quad (1)$$

For p=2 the Euclidean distance is obtained (see Eq. 2):

$$d(P_1, P_2) = \sqrt{(x_1 - y_1)^2 + \cdots + (x_n - y_n)^2} \quad (2)$$

The Manhattan distance (see Eq. 3):

$$d(P_1, P_2) = \sum_{i=1}^{n} |x_i - y_i| \quad (3)$$

The cosine function defines the similarity, s, of two instances as the ratio between the scalar product of the vectors $\overrightarrow{P_1}, \overrightarrow{P_2}$ and the product of their Euclidean lengths [5] (see Eq. 4):

$$s(P_1, P_2) = \frac{\sqrt{\sum_{i=1}^{n} x_i y_i}}{\sqrt{\sum_{i=1}^{n} x_i^2}\ \sqrt{\sum_{i=1}^{n} y_i^2}} \quad (4)$$

2.2 SVM (Support Vector Machine)

The classification algorithm is based on the division of the data set by means of hyperplanes in order to delimit distinct categories of characteristics. To maximize the distance between these hyperplanes, the space of the initial characteristics is transformed with the help of functions called kernels. These can be: linear, polynomial, sigmoid and radial. In our study we will use a radial kernel, RBF (Radial Basis Function) [6].

2.3 AdaBoost (Adaptive Boosting)

AdaBoost is an iterative quick-adaptive algorithm that consists of combining several weak classifiers in order to obtain a classifier with improved performance. After each iteration, the weak classifiers will be selected to be trained in the next step based on the weights assigned to the erroneous classifications. The algorithm is continued until the maximum number of iterations, set as a parameter, is reached, or until the classification is made without errors. The algorithm proves to be very efficient in the case of classification problems with two distinct values for the target variable, for example promoted / rejected [7].

2.4 Naive Bayes

Naive Bayes is a classification algorithm that is based on Bayes' theorem that determines the probability of objects or events to belonging to a certain class. This method achieves very good results for real data, being one of the most efficient algorithms for machine learning [8].

Considering a set of values for the vector of independent characteristics ($x_1, \ldots, x_n$) and c_k a value of a class of the k possible classes (in our paper, k = 2: promoted / rejected). The probability of assigning a class label in relation to the recorded data is given by the relation (see Eq. 5):

$$P(c_k | x_1, \ldots, x_n) = \frac{P(x_1, \ldots, x_n | c_k) * P(c_k)}{P(x_1, \ldots, x_n)} \quad (5)$$

Given the naive assumption of the independence of attribute values, we can write the relationship (see Eq. 6):

$$P(x_i | c_k, x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n) = P(x_i | c_k), pentru\ i = 1, 2, \ldots, n. \quad (6)$$

Given relation (6), the relation (5) can be rewritten as follows (see Eq. 7) [9]:

$$P(c_k | x_1, \ldots, x_n) = \frac{P(c_k) * \prod_{i=1}^{n} P(x_i | c_k)}{P(x_1, \ldots, x_n)} \quad (7)$$

2.5 Neural Network

Neural network-based algorithms are used in various classification problems such as: natural language processing, image and speech recognition. Like biological neural networks, an artificial network is made up of entities called neurons. The simplest neural model is the perceptron with a single layer of neurons [10]. The input layer contains values of the characteristics vector ($x_1, \ldots, x_n$). Each of these values will be found in a certain weight, w_i, in the result obtained by summing and applying an activation function (Fig. 1) [11].

Deep neural networks are used to solve more difficult classification problems. They contain one or more hidden layers, completely connected to the previous layers by means of ponders. Networks can be fee-forward or multilayer with distributed parallel processing using the backpropagation method [13].

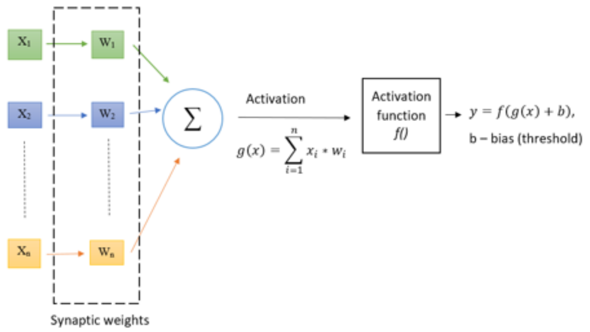

Fig. 1 Artificial neuron [12].

3. Methodology

The aim of this paper is the comparative analysis of the classification performances offered by the kNN, SVM, Naive Bayes, Neural Network and AdaBoost algorithms and the identification of possible correlations between the obtained results and certain data characteristics.

3.1 Data set

The data used represent the results obtained at the Baccalaureate exam by the students from the "Dimitrie Cantemir" Economic College from Suceava, in the period 2012-2019.

Table 1: Data structure

Name	*Type*	*Role*
Proba 1	numeric	feature
Proba 2	numeric	feature
Proba 3	numeric	feature
Media	numeric	feature
Statut	**categorical**	**Target Variable**
An	numeric	feature
Sex	categorical	feature
Specializarea	categorical	feature
Profil	categorical	feature
Competențe digitale	categorical	feature
Competențe lingvistice	categorical	feature
Proba D	categorical	feature
Promoția curentă	categorical	feature

For each year, the results were obtained by exporting from the computer application used in this exam, in the form of an Excel file. The data in these files were merged into a single Excel file with 2245 valid records. Following the exclusion of some characteristics regarding students' personal data, exam rooms and other organizational details, we used the data structure presented in Table 1.

The description of the data used is given in the Table 2:

Table 2: Data description

Name	*Description*	*Values*
Proba 1	Romanian Language and Literature	numerical values in the range [-2,10], -2 is for an absent student
Proba 2	Math results	numerical values in the range [-2,10], -2 is for an absent student
Proba 3	Profile-specific results	numerical values in the range [-2,10], -2 is for an absent student
Media	Final results	numerical value in the range [0.10], 0 for absent students
Statut	Final results	Promovat/ Respins
An	the year of the exam	2012-2019
Sex		Masculin/ feminin
Specializarea	specialization of the student's class	7 different specializations
Profil	student class profile	Real/ Servicii
Competențe digitale	the ability to use the computer	qualifying
Competențe lingvistice	communication skills	qualifying
Proba D	name of the Proba 3	7 different values
Promoția curentă	student promotion	Da/Nu

3.2 Working procedure

In order to achieve the objectives of this paper, we used the Orange tool as a working environment, which is free and dedicated to machine learning and data visualization. The working procedure consists in building an operational flow. The classification algorithms receive data from this flow, following the preprocessing and validation of the data from the Excel file that constitutes the input in the operational flow. Preprocessing consists of selecting valid instances, establishing the target variable and the role for each data characteristic. The evaluation of the results of the classifications performed by the algorithms used is done through a cross-validation technique that involves the use of evaluation metrics such as: F_1, Precision, Recall, CA and AUC. Next, the HeatMap and DataTable tools for data visualization are connected to the operational flow (Fig. 2).

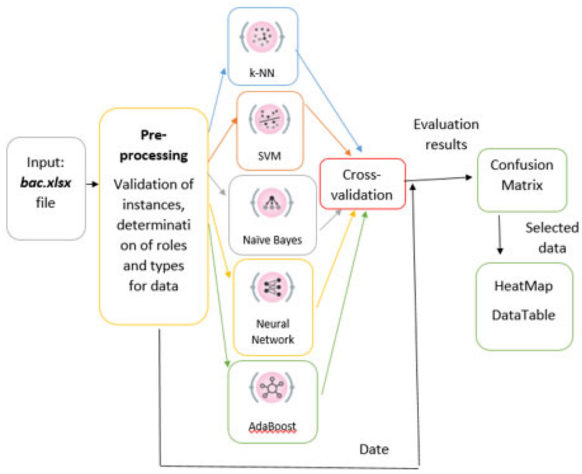

Fig. 2 Description of the operational flow.

4. Results

As can be seen from Fig. 3, the AdaBoost algorithm obtains very good results in classifying students in two categories: promoted and rejected. It is followed by the Naive Bayes algorithm with a score for AUC of 0.999 and 0.986 for CA. Neural Network gets 0.998 for AUC and 0.982 for CA. The weakest results are obtained by the SVM algorithm with a score of 0.987 for AUC and 0.957 for CA.

Model	AUC	CA	F1	Precision	Recall
kNN	0.996	0.984	0.984	0.985	0.984
SVM	0.987	0.957	0.956	0.958	0.957
Neural Network	0.998	0.982	0.982	0.982	0.982
Naive Bayes	0.999	0.986	0.986	0.987	0.986
AdaBoost	1.000	1.000	1.000	1.000	1.000

Fig. 3 Results.

Analyzing the confusion matrices that describes the results of the classifications with the algorithms used, we can draw the following conclusions:

- 99,7% of the promoted (PROMOVAT) students are classified correctly by the kNN algorithm and 94.7% of the rejected (RESPINS) ones are classified as rejected. 5.3% of rejected students are classified as promoted, and 0.3% of promoted students are erroneously classified as rejected (Fig. 4);

Predicted

Actual	PROMOVAT	RESPINS	Σ
PROMOVAT	99.7 %	0.3 %	1680
RESPINS	5.3 %	94.7 %	565
Σ	1705	540	2245

Fig. 4 Confusion Matrix for kNN.

- The Neural Network algorithm correctly classifies 98.9% of the promoted and 95.9% of the rejected students. Also, this algorithm erroneously classifies 4.1% of rejected and 1.1% of promoted students (Fig. 5);

Predicted

Actual	PROMOVAT	RESPINS	Σ
PROMOVAT	98.9 %	1.1 %	1680
RESPINS	4.1 %	95.9 %	565
Σ	1685	560	2245

Fig. 5 Confusion Matrix for Neural Network.

- The Naive Bayes algorithm correctly classifies 98.4% of the promoted and 99.3% of the rejected students. This algorithm erroneously ranks 0.7% of rejected students and 1.6% of promoted students (Fig. 6);

Actual \ Predicted	PROMOVAT	RESPINS	Σ
PROMOVAT	98.4 %	1.6 %	1680
RESPINS	0.7 %	99.3 %	565
Σ	1657	588	2245

Fig. 6 Confusion Matrix for Naïve Bayes.

- The SVM algorithm correctly classifies a percentage of 99.5% of those promoted and only 84.4% of those rejected. This algorithm also classifies 15.6% of rejected students as promoted and only 0.5% of promoted students are misclassified (Fig. 7).

Actual \ Predicted	PROMOVAT	RESPINS	Σ
PROMOVAT	99.5 %	0.5 %	1680
RESPINS	15.6 %	84.4 %	565
Σ	1760	485	2245

Fig. 7 Confusion Matrix for SVM.

Detailed information about each area in the confusion matrices can be obtained by connecting the HeatMap and DataTable visualization tools to the data flow.

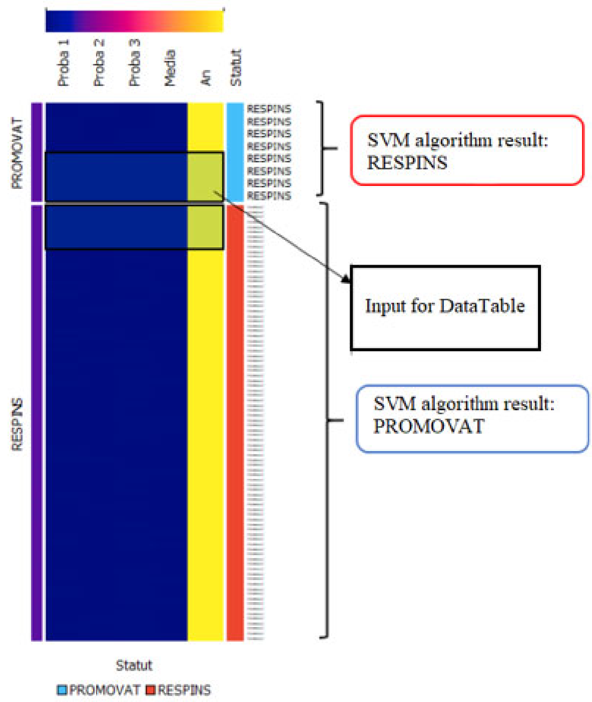

Fig. 8 HeatMap.

We selected the data subset corresponding to the erroneous classifications made with the SVM algorithm and connect it to the HeatMap (Fig. 8).

By making a partial selection and connecting it to the DataTable we get details about the highlighted instances (Fig. 9).

	Statut	Statut(SVM)	Proba 1	Proba 2	Proba 3	Media	Profil	Proba D	Promotia curenta	Specializarea	Sex	Competente lingvistice	Competente digitale	An
1	PROMOVAT	RESPINS	5.40	7.40	5.45	6.08	Servicii	Logică, argumentare și comunicare	DA	Tehnician în activități economice	feminin	Utilizator Mediu	Utilizator Mediu	2017
2	PROMOVAT	RESPINS	5.60	5.55	7.80	6.31	Servicii	Logică, argumentare și comunicare	DA	Tehnician în gastronomie	masculin	Utilizator Avansat	Utilizator Mediu	2016
3	PROMOVAT	RESPINS	6.70	5.10	7.45	6.41	Servicii	Geografie	DA	Tehnician în activități de comerț	feminin	Utilizator Mediu	Utilizator Mediu	2014
4	PROMOVAT	RESPINS	6.40	5.10	6.85	6.11	Servicii	Geografie	NU	Tehnician în gastronomie	feminin	Utilizator Experimentat	Utilizator Experimentat	2014
5	RESPINS	PROMOVAT	5.40	5.00	7.10	5.83	Servicii	Geografie	DA	Tehnician în activități economice	masculin	Utilizator Experimentat	Utilizator Mediu	2019
6	RESPINS	PROMOVAT	5.00	6.55	6.40	5.98	Servicii	Logică, argumentare și comunicare	DA	Tehnician în activități economice	feminin	Utilizator Avansat	Utilizator Mediu	2019
7	RESPINS	PROMOVAT	5.00	5.00	5.75	5.25	Servicii	Logică, argumentare și comunicare	DA	Tehnician în activități de comerț	masculin	Utilizator Mediu	Utilizator Mediu	2019

Fig. 9 Visualization with DataTable

We identify possible correlations between the classification results and the details about the data selected for viewing:

- the average of incorrectly classified students is close to;
- the result of one of Proba 1, Proba 2 and Proba 3 tests is below;
- most of students took the Proba D test in Logic *(Logică, argumentare și comunicare*), argumentation and communication or Geography (*Geografie*).

The performance of classification algorithms depends on the size of the data set (Table 3). To perform this comparative analysis, we ran algorithms for a data set that includes records from 2019 (326) and another that contains 627 instances corresponding to the results from 2018 and 2019.

Table 3: Classification results on data sets of different sizes

Classifi-cation algorithm	***AUC***	***CA***	***F1***	***P***	***R***
Years	2018-2019				
kNN	0.995	0.979	0.979	0.979	0.979
SVM	0.993	0.954	0.953	0.954	0.954
Neural Network	0.995	0.978	0.978	0.978	0.978
Naive Bayes	0.997	0.982	0.983	0.983	0.982
AdaBoost	1.000	1.000	1.000	1.000	1.000
Year	2019				
kNN	0.999	0.972	0.972	0.973	0.972
SVM	0.993	0.966	0.966	0.966	0.966
Neural Network	0.996	0.969	0.969	0.969	0.969
Naive Bayes	0.982	0.954	0.955	0.958	0.954
AdaBoost	1.000	1.000	1.000	1.000	1.000

The hierarchy of classification results is also maintained for the data set covering the years 2018 and 2019, but there are differences for the 2019 data set. Considering the CA metric, we observe the following order: kNN (0.972), Neural Network (0.969), SVM (0.966), Naïve Bayes (0.954). The performance of the AdaBoost algorithm remains unchanged regardless of the size of the dataset. Surprising results are provided by the SVM algorithm, which seems to better classify the 2019 dataset.

If the Digital Competences (*Competențe digitale*) feature and then the Digital Competences and Language Competences (*Competențe lingvistice*) features are removed from the initial dataset, we notice that the performance of the kNN and AdaBoost classification algorithms remains approximately the same. The Neural Network algorithm obtains better results in the absence of the characteristics specified above, for both runs.

The performance of the Naive Bayes algorithm is better in the absence of the Digital Competences and Language Competences features. SVM classifies students' results, in the absence of Digital Competences, with low performance, but classification performances are not as much influenced if Language Competences are eliminated (Table 4).

Table 4: Classification results in the absence of some features in the data set

Classifi-cation algorithm	**AUC**	**CA**	**F1**	**P**	**R**
Without „Competențe digitale”					
kNN	0.996	0.983	0.983	0.983	0.983
SVM	0.991	0.943	0.941	0.945	0.943
Neural Network	0.998	0.988	0.988	0.988	0.988
Naive Bayes	0.999	0.985	0.985	0.986	0.985
AdaBoost	1.000	1.000	1.000	1.000	1.000
Without „Competențe digitale” and „Competențe lingvistice”					
kNN	0.997	0.984	0.983	0.984	0.984
SVM	0.992	0.954	0.953	0.954	0.954
Neural Network	0.999	0.989	0.989	0.989	0.989
Naive Bayes	0.999	0.990	0.990	0.990	0.990
AdaBoost	1.000	1.000	1.000	1.000	1.000

5. Conclusions

In our study we analyzed the performance of AdaBoost, Neural Network, SVM, kNN and Naive Bayes algorithms in classifying the results obtained at the Baccalaureate and the correlations between results and certain data characteristics and as well the size of the data set. For this we used a cross-validation technique that involves the calculation of evaluation metrics: AUC, CA, F_1, Precision and Recall. The algorithms ran for different data sets, processed in the preprocessing stage that was included in the operational flow after the Excel file *bac.xlsx* (input). This data constituting an input for the algorithms used. The values of the metrics used in the evaluation are in the range [0.956 - 1]. A hierarchy by performance of the algorithms used, given by the AUC metric is: AdaBoost, Naive Bayes, Neural Network, kNN and SVM.

The size of the data set influences the classification performances of the algorithms, which are generally lower once the number of instances used is lower.

In the case of the SVM algorithm, the Digital Competences characteristic is better correlated with the results obtained compared to the use of the data set from which the Digital Competences and Linguistic Competences characteristics were extracted. On the other hand, the Naive Bayes algorithm achieves better results without the two features mentioned.

With the exception of the Naive Bayes and AdaBoost algorithms, the results of the classifications viewed with the confusion matrices reveal that rejected students are classified as promoted in a higher percentage than the erroneous classification of promoted students. A possible explanation would be the imbalance between the number of instances with Promoted status (1680) and the number of instances with Rejected status (565).

By connecting the HeatMap and DataTable visualization tools to the confusing matrices in the operational flow, details can be obtained about certain subsets of data that can provide additional explanations on the results obtained by the classification algorithms..

The use of specific tools and techniques for the analysis of educational data may reveal correlations that would be impossible or very difficult to find in other conditions and would lead to an improvement in the conditions that generate performance.

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