Data analytics model to predict possible disciplinary sanctions against officials who hold popularly elected positions in Colombia

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KEYWORDS

ABSTRACT

This article describes the design of a data analytics model to predict possible disciplinary sanctions against officials who hold popularly elected positions in Colombia, a data exploration process was carried out and different Machine Learning models were applied in order to determine which of them is the most suitable for this purpose. Which in turn made it possible to identify risk situations and anticipate them through the implementation of preventive measures. To this end, a supervised learning approach was applied in the construction of the model, in which classification models were used to predict whether a given staff member might be subject to disciplinary sanctions in the future. One of the key aspects of this article was the optimization of the model's hyperparameters, as good accuracy and optimal performance were achieved. Different values of the hyperparameters were explored and those that allowed the best results to be obtained were selected. Finally, the model's measurement metrics were defined, in order to evaluate its accuracy and predictive capacity. The model designed in this article can provide a valuable tool for decision-making in the field of digital government and contribute to improving the efficiency and transparency in the performance of public officials.

1. Introduction

Public administration in Colombia is one of the most important activities for the country's development, and it is crucial that officials who hold popularly elected positions maintain the highest ethical standards and performance in their functions. However, sometimes situations of non-compliance or violation of the rules arise that can lead to disciplinary sanctions. Corruption and the misuse of public resources are problems that directly affect the well-being of the population and undermine trust in institutions.

In this sense, the objective of this research is to design a data analytics model [1] to predict possible disciplinary sanctions against officials who hold popularly elected positions in Colombia. The implementation of this model will make it possible to identify patterns and trends in the information available on the characteristics of officials, which in turn will make it possible to identify possible risk situations and anticipate them through the implementation of preventive measures.

The process of data exploration and the application of Machine Learning models will allow identifying patterns and trends in the available information. Optimizing the model's hyperparameters will be key to achieving optimal accuracy and performance, and the model's measurement metrics will be defined to assess its predictive capabilities.

The importance of this article lies in its potential to provide a valuable tool for decision-making in the field of digital government and contribute to improving the efficiency and transparency in the performance of public officials. In addition, the article has academic relevance in the field of engineering, as it combines concepts of data analysis, Machine Learning and digital government.

The methodology used in the article was descriptive and explanatory, and a process of documentary and field research was carried out. The problem was described and the general objective and specific objectives were formulated, and the delimitation and scope of the research article were defined. A normative and legal framework, a referential framework, a theoretical framework and a conceptual framework are presented that allowed the article to be contextualized in its environment.

Finally, the development of the model is presented, which will include the description of the data exploration process, the application of Machine Learning models, the optimization of hyperparameters, the definition of measurement metrics and the analysis of results. It concludes with a discussion of the findings of the article and the implications of the results obtained.

2. Materials and Methods

Review stage

Government entities often have large amounts of data from different sources, which in many cases are isolated databases. The integration of this data and the use of Machine Learning tools can allow the detection of patterns and trends that a priori could go unnoticed.

In Colombia, one of the main problems is the corruption that occurs in different municipalities and departments, which is partly due to the lack of transparency and ethics of some public servants, especially those who are popularly elected, such as mayors, governors, councillors, among others.

Corruption is a serious problem in Colombia and in the world. According to Transparency International's 2021 Corruption Perceptions Index (CPI), Colombia obtained 39 points out of 100, with 0 being very high corruption and 100 being the absence of corruption. The country ranks 87th out of 180 countries evaluated [2]. Between 2016 and 2020, the loss of $13.67 billion was reported in 284 acts of corruption [3].

To combat this problem, government watchdogs invest large sums of money in the fight against corruption. However, due to the large number of popularly elected officials in the country, it is not always easy to carry out effective surveillance over all of them. To get an idea, the following positions are currently elected in the regional elections.

32 governors.

418 deputies who will make up the departmental assemblies.

1,102 mayors.

12,072 councilors from all municipalities and cities in the country.

6,513 councillors who will make up the Local Administrative Boards (JAL).

Despite the efforts of the government and watchdogs, corruption remains a major obstacle to the country's development and prosperity.

For this reason, it is essential that effective measures are implemented to prevent, detect and punish corruption in all its forms. In particular, the early detection and punishment of popularly elected officials who engage in misconduct can have a significant impact on the prevention of corruption.

It is important to keep in mind that popularly elected positions are highly demanded and competitive, so it is essential to have tools that allow control entities to detect possible irregularities in the electoral process and in the performance of elected officials. In this way, timely and effective measures can be taken to ensure transparency and ethics in public administration.

Thus, by using Machine Learning techniques, a greater degree of precision and effectiveness is obtained in the early detection of possible misconduct and in the identification of officials that require greater attention from control entities with the implementation of several Machine Learning prediction models, specifically classification models (supervised learning). which will be fed by various sources of information or databases, such as disciplinary records, candidates' income, candidates' disqualifications, Terridata information from municipalities and departments, among others.

Final stage

The data sources that were used to collect the data include the use of APIs such as the Colombian government's Socrata open data, Excel files, and databases. It was ensured that all sources used are reliable and publicly available to ensure the transparency of the model.

In addition, a thorough review of the data was conducted to ensure its quality and consistency, eliminating incomplete or inconsistent data that may affect the accuracy and reliability of the model.

Python was used to process, analyze and interpret the data due to the ease that this programming language has to analyze large amounts of data and in general because of the multiple libraries it has for data analytics and Machine Learning such as pandas, numpy, SkyLearn, among others.

The population or universe of study are the popularly elected officials elected in the periods 2011, 2015 and 2019, as determined by the National Electoral Council [4].

3. Results

The process of data analysis in a research project is essential to guarantee the quality and reliability of the results obtained. To do this, it is necessary to follow a rigorous methodology that allows each of the phases of the process to be systematically addressed. In this chapter, the CRISP-DM methodology will be applied, which consists of six phases: understanding the business, understanding the data, preparing the data, modeling, evaluation and deployment. [1]

Understanding the business

The Office of the Attorney General of the Nation (PGN) is an autonomous entity of the Colombian State in charge of guaranteeing transparency and ethics in public service, as well as the defense of public assets and legality in general. It was created in 1830 as a dependency of the Ministry of Government, and was later reformed and transformed into its current form by the Constitution of 1991. [2]

The mission functions of the PGN are threefold:

The preventive function: It is one of the main responsibilities of the Office of the Attorney General of the Nation, since its objective is to prevent public servants from committing disciplinary offenses.

The intervention function: The Attorney General's Office intervenes before the different jurisdictions to defend fundamental rights and guarantees.

The disciplinary function: The entity is responsible for investigating and ruling on the corresponding sanctions in the event of disciplinary offenses committed by public servants and private individuals who exercise public functions or handle State money (Law 734 of 2002).

It is important to note that the Attorney General's Office not only focuses on electoral crimes committed by public servants, but also investigates and punishes individuals who violate electoral regulations or who collaborate in the commission of these crimes.

In Colombia, regional elections are held every 4 years, in which governors of the 32 departments of the country are chosen, 418 deputies of the departmental assembly, mayors of 1,102 municipalities, 12,072 councilors and 6,513 local councilors, these officials are of great importance for the Attorney General's Office, since they are in charge of making decisions and managing resources in their respective regions. The analytical model of this research project used the data collected in different databases to predict possible disciplinary sanctions against these elected officials.

Understanding the data

In order to carry out the analysis and prediction of possible disciplinary sanctions in popularly elected positions in Colombia, it was necessary to have updated and accurate information, so various sources of information were used to obtain a complete and detailed view of the disciplinary background, disqualifications, income and financiers of the candidates, as well as the data of the political parties and statistical information on the territories of the country. Below, in table No. 1, the 5 sources of information or databases that will be joined for this analysis are presented. [3]

Database	Fountain	Information system	Content
Disciplinary history	datos.gov.co	API Web	Certifiable disciplinary sanctions issued against public servants, former public servants and individuals who perform public functions.
Candidate income	cnecuentasclaras.gov.co	Excel file	Information regarding the income of candidates in the regional elections in Colombia, as well as data on their funders.
Disqualifications of candidates	Information system for the registration of sanctions and causes of disqualification	Excel file	Disqualifications of candidates for regional elections in Colombia.

Candidates registered in territorial elections	cnecuentasclaras.gov.co	Excel file	List with the data of the candidates registered for the regional elections in Colombia and the political parties to which they belong.
Terridata	National Planning Department DNP	Flat file	A dataset that provides territorial and statistical information on Colombia, which is organized into different geographical layers.

Table No. 1: Databases used in the analytical model

The information collected for the case of the databases of "Income of the candidates", "Disqualifications of the candidates" and "Candidates registered in territorial elections" corresponds to three different electoral periods: 2011, 2015 and 2019. [4]

1. Candidate Income: 27 columns

2011: 103,177 records
2015: 130,862 registrations
2019: 185,682 records

Column Name	Description
Corporation or Position	The position or position within the corporation to which the candidate is applying
Constituency	The electoral region to which the candidate belongs
Department	The department in which the candidate is applying
Municipality	The municipality in which the candidate is running
Locality	The location in which the candidate is running
Political Organization	The political party or coalition to which the candidate belongs
Candidate ID	The candidate's ID number
Candidate Name	The name of the candidate
Code	A code assigned to identify the income
Login Name	Name assigned to the type of income
Type Person	Indicates whether the donation was made by a natural or legal person
Name of Person	The name of the person or entity that made the donation
Value	The amount of money donated
Admission Department	The department in which the donation was made

City Entrance	The city in which the donation was made
Type of Identification	Indicates the type of identification used by the person or entity that made the donation
Identification Number	The identification number of the person or entity that made the donation
Record No.	The number of the record corresponding to the registration of the income
Pledge Value	Indicate whether the donation was pledged or not
Income Description	A detailed description of the source of the income
Remarks	Any additional observations related to the donation
Kinship	Indicate if the person or entity that made the donation is related to the candidate
Donation Type	Indicate the type of donation (cash, in-kind, etc.)
Coalition Party	The political party or coalition to which the person or entity that made the donation is affiliated
Movement Registration Date	The date the deposit was recorded
Internal Voucher Number	The internal voucher number corresponding to the entry record
Concept of Income	A brief description of the source of the income

Table No. 2: Description of the columns of the Candidate Income table

2. Candidate Disabilities: 35 columns
   2011: 236 records
   2015: 1,782 records
   2019: 3,702 records
3. Candidates registered in territorial elections: 28 columns
   2011: 100,159 records
   2015: 112,244 records
   2019: 117,160 records
4. Disciplinary history: 24 columns, 52,527 records
5. Terridata: 71 columnas, 1.102 registros

Data preparation

This is a critical stage in the data mining process, as this is where the cleaning, integration, selection and transformation of the data to be used in the analysis and machine learning models takes place.

Data integration

To integrate the data, the three election periods (2011, 2015 and 2019) were unified into a single period, in the case of the databases that were separated by these specific periods, such as "Candidates' income", "Candidates' disqualifications" and "Candidates registered in

territorial elections". In this way, a single table was obtained for each of the databases that contained all the data corresponding to the aforementioned periods.
Subsequently, these three databases were cross-referenced with the "Disciplinary Record" database. To do this, the candidate's ID column was used as a natural key, since this column was present in all the tables and allowed a relationship to be established between them.

As a result of this process, a table called "base officials" was obtained, which contained 31 columns and 713,961 records. Figure 1. Later, this table was integrated with that of Terridata, resulting in a table called "elected officials", Figure 2.

Figure 1- Integration of civil servant databases. In original Spanish language.

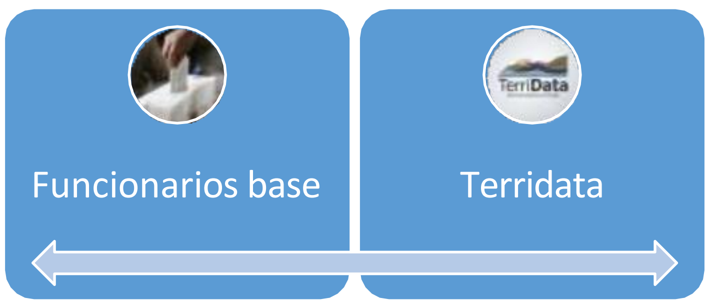

Figure 2- Integration of the civil servant database with Terridata. In original Spanish language.

Eliminate irrelevant and redundant variables

In this step, those variables that are not relevant to the analysis or that had a high correlation with other variables in the database were eliminated.

Data Cleansing

To clean the data, a filtering of the database of "base officials" was carried out, with the aim of leaving only the officials who were elected to their respective positions. This process was carried out by filtering the "Elected" column, leaving only those records whose value was different from "NO", Figure 3. In addition, the names of the records in this column were unified, since, when joining different databases, there were inconsistencies in their writing, some in lowercase and others in upper case, but with the same value.

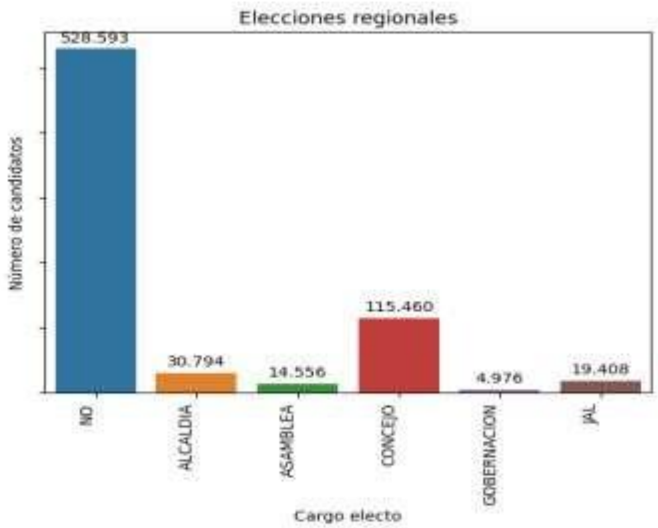

Figure 3- Ranking of candidates according to elected office. In original Spanish language.

Due to this first step in the cleaning process, a reduction in the number of registrations was achieved, leaving only elected officials for their respective positions. In this way, a table focused on the objectives of the project was obtained, which will allow a more efficient and accurate analysis of the data.

Creating New Variables

In order to improve the quality of the data, a new column was created that contained the full names of the elected officials in popularly elected positions. In this way, it was possible to eliminate four columns that contained the names and surnames of the official separately, Figure 4. This simplified the structure of the table and avoided duplication in the records.

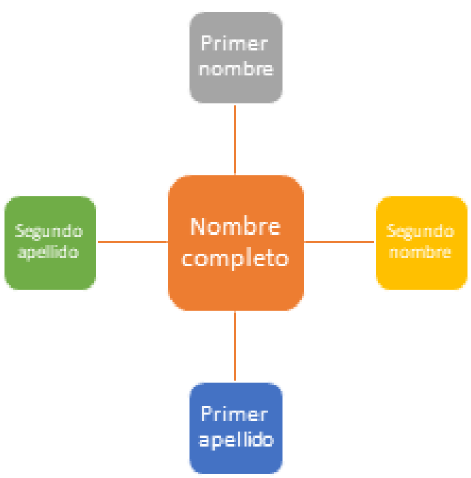

Figure 4- Column structure "Full name". In original Spanish language.

Similarly, a variable called "DIVIPOLA" was created in order to improve the structure of the table. This new variable made it possible to replace the columns of

"Department Code" and "Municipality Code", which were eliminated to simplify the structure of the table. Figure 5. In this way, greater efficiency was achieved in the analysis of the data, since the number of unnecessary columns was reduced and a cleaner and clearer table was generated.

Figure 5- Column structure "DIVIPOLA". In original Spanish language.

Exploratory analysis of the data

All the steps necessary to prepare the data from the "elected officials" database have been completed in advance. This database consists of 84 columns and 41,139 records.

The "numerical sanctions" column of the "elected officials" database falls into two categories:

- 0 - Not sanctioned
- 1 - Sanctioned

In the Figure 6, the distribution of the ages of elected officials in relation to the output variable "numerical sanctions" can be observed.

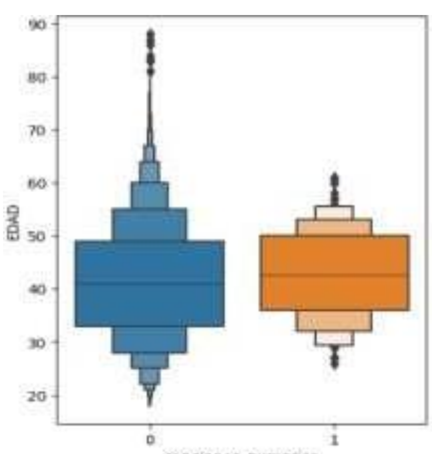

Figure 6- Age of elected officials VS exit variable "numerical sanctions".v

According to the Figure 6, most elected officials are in the age range between 32 and 50 years old. In addition, it can be observed that, in general, elected officials who have been sanctioned are slightly older than those who have not been sanctioned.

Figure 7 shows the relationship between the rural multidimensional poverty indicator and the output variable "numerical sanctions". It can be observed that sanctioned elected officials tend to come from municipalities with a higher rural multidimensional poverty index.

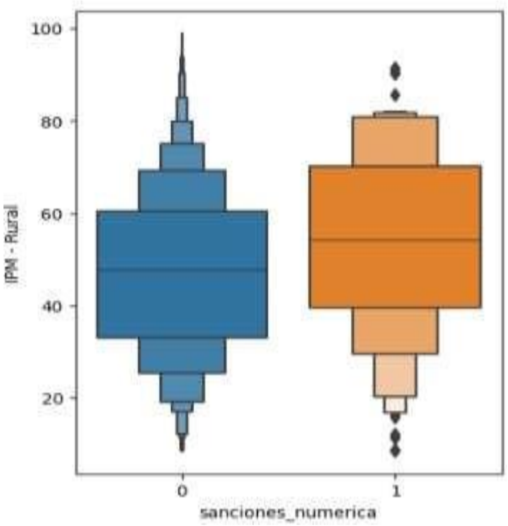

Figure 7- MPI - Rural VS output variable "numerical sanctions". In original Spanish language.

In the Figure *8-Number of sanctioned and non-sanctioned elected officials by office*8, a graph showing the number of elected officials who were sanctioned and the number of elected officials who were not sanctioned is presented, with respect to their position within the government. It is observed that, of the 27,876 councilors, 148 have been sanctioned, while, among mayors, 91 have received sanctions, which represents 3.05% of the total number of elected mayors.

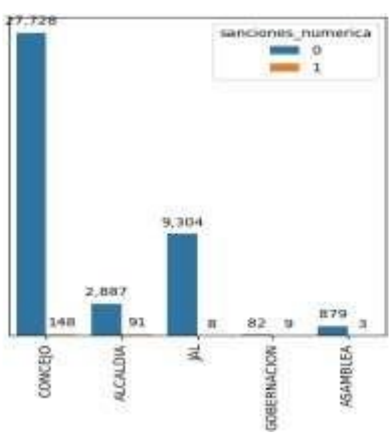

Figure 8-Number of sanctioned and non-sanctioned elected officials by office. In original Spanish language.

Reduction of variables

One of the variable reduction techniques used in this project was Principal Component Analysis (PCA), which can be used to reduce the dimensionality of the data and retain the most important features.

Data balancing

The parameter of class_weight='balanced' from the Python scikit-learn library was used in the models. This parameter automatically adjusts the weights of the classes based on how often each class appears in the data, so that samples from the minority class have a higher weight than samples from the majority class. This helps models to properly account for minority class samples during training.

Data Type Transformation

Categorical variable coding techniques were used to be used in Machine Learning models. To do this, the ColumnTransformer function of the sklearn.compose Python library was used.

A ColumnTransformer was created with two different transformers. The first used the one-hot coding technique with the handle_unknown parameter set to 'ignore', to encode the categorical variables: Corporation, position, Constituency, Region name, Party type, Political party name and Elected.

The second transformer also used the one-hot encoding technique, but with the drop parameter set to 'if_binary', to encode the binary variables: Gender and Disabled. In this way, categorical and binary variables were transformed into numerical variables to be used in machine learning models later on.

Modelling

Classification models were used to predict which popularly elected officials would be disciplined after their election. The problem was posed as a classification between sanctioned and non-sanctioned officials.

In addition to the classification models, clustering techniques were also used with the same purpose of identifying common patterns and characteristics among the sanctioned officials. Through the grouping analysis, we sought to identify the groups of sanctioned officials and understand the distinctive characteristics of each of them.

In this way, the combination of classification and clustering techniques allowed a more complete and detailed view of the sanctioned officials. While the classification made it possible to predict who would be disciplined, clustering allowed us to better understand the reasons behind these sanctions and group officials according to patterns of behavior and common characteristics.

The steps that were followed for the modeling were:

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The scikit-learn (also known as sklearn) library was used in Python. Scikit-Learn is an open-source machine learning library that provides a wide variety of tools for building machine learning models.

The train_test_split function was imported from the sklearn.model_selection library, which was used to divide the data into training and test sets.

The ColumnTransformer function in the sklearn.compose library was used to apply different transformations to different columns in the dataset. Data transformations in the models were also used, as is the case of OneHotEncoder from the sklearn.preprocessing library, to transform categorical variables into numerical variables.

Scaling methods were applied to normalize the data and improve the accuracy of the model, using MaxAbsScaler from the sklearn.preprocessing library. SimpleImputer from the sklearn.impute library was used to impute missing values in the data. Several classification models were tested, such as SVC, KNeighborsClassifier, DecisionTreeClassifier, LogisticRegression, and RandomForestClassifier from the sklearn library. To optimize the selection of hyperparameters, the GridSearchCV and RandomizedSearchCV functions of the sklearn.model_selection library were used.

For the sklearn.metrics library, the classification_report function was used to get a detailed report of the performance metrics of the classification model. This includes accuracy, recall, F1 scoring, and support for each class.

To reduce the dimensionality of the data, two techniques were used: UMAP and PCA from the umap and sklearn.decomposition libraries, respectively.

The KMeans and DBSCAN algorithms of the sklearn.cluster library were also applied to perform the clustering of the data. Clustering performance was evaluated using silhouette_score from the sklearn.metrics.cluster library.

Finally, Pipeline from the sklearn.pipeline library was used to create more complex modeling workflows and reduce the amount of code written.

Data separation

The data from the database of "elected officials" were divided into two DataFrames: "X" and "y", in which "X" is all the input data to the different Machine Learning models and "y" is the output variable, that is, the variable to be predicted "numerical sanctions".

The training and test data were separated, so that in the training 70% of the data were chosen and in the test the remaining 30%, this was done using the 'train_test_split' function to divide the dataset into two parts.

Transformer

The "transfomer" object of the ColumnTransformer class was created, which is used to transform different columns of a DataFrame into numerical features for use in machine learning models. In this case, three different transformers are used: **oh_encoder**, **oh_encoder_binary** and **pass**.

Climber

The "scalar" variable found in the code is an object of the MaxAbsScaler class, which is used to scale data in a range of [-1, 1] by dividing it by the absolute maximum value of each feature. This type of scaling is useful for sparse data and is invariant to any shift in the original distribution of the data.

Imputer

An object of the SimpleImputer class called "imputer" is created that is used to impute missing values in the data. The selected account assignment strategy is "most_frequent", which means that the missing values will be replaced with the most frequent value in the corresponding column. In other words, the most common value in each column will be used to replace the missing values in that column.

Selected Measurement Metric

In this case, the recall metric has been selected to evaluate the models.

Training classification models

Various supervised learning algorithms were used. Each of these models was trained using the pre-processed training dataset and their performance was evaluated using evaluation metrics such as accuracy and recall. Models used: SVC, KNeighborsClassifier, DecisionTreeClassifier, LogisticRegression and RandomForestClassifier.

Analysis of results

In the comparison of the results for SVC before and after hyperparameter optimization, it can be observed that the recall of class 0 decreased slightly from 0.84 to 0.80, while the recall of class 1 increased from 0.59 to 0.63, Table *3- SVC Metric Comparison Before and After Hyperparameter Optimization*3.

Metric	Before optimization	After optimization
Precision	1.00 / 0.02	1.00 / 0.02
Recall	0.84 / 0.59	0.80 / 0.63
F1-score	0.91 / 0.04	0.89 / 0.04
Accuracy	0.84	0.80
Macro avg	0.51 / 0.72	0.51 / 0.71
Weighted avg	0.99 / 0.84	0.99 / 0.80

Table 3- SVC Metric Comparison Before and After Hyperparameter Optimization

When training the model with the DecisionTreeClassifier algorithm, a recall of 0.99 was obtained for class 0 (non-sanctioned officials) and a recall of 0.10 for class 1 (sanctioned officials). However, when optimizing the hyperparameters, it was not possible to improve the performance in terms of class 1 recall. Instead, the class 0 recall went up to 1.00 after optimization, Table 4- *Comparison of DecisionTreeClassifier metrics before and after hyperparameter optimization*.

Metric	Before optimization	After optimization
Precision	0.99 / 0.07	0.99 / 0.24
Recall	0.99 / 0.10	1.00 / 0.06
F1-score	0.99 / 0.09	1.00 / 0.10
Accuracy	0.99	0.99
Macro avg	0.53 / 0.55	0.62 / 0.53
Weighted avg	0.99 / 0.99	0.99 / 0.99

Table 4- Comparison of DecisionTreeClassifier metrics before and after hyperparameter optimization

Using the LogisticRegression algorithm, a recall of 0.81 was obtained for class 0 (non-sanctioned officials) and a recall of 0.60 for class 1 (sanctioned officials). After the optimization of the hyperparameters, it was possible to maintain the same performance in terms of recall for both classes, i.e. the recall of class 0 remained at 0.81 and the recall of class 1 remained at 0.60, Table 5- *LogisticRegression metrics comparison before and after hyperparameter optimization*.

Metric	Before optimization	After optimization
Precision	1.00 / 0.02	1.00 / 0.02
Recall	0.81 / 0.60	0.81 / 0.60
F1-score	0.89 / 0.04	0.89 / 0.04
Accuracy	0.81	0.81
Macro avg	0.51 / 0.71	0.51 / 0.71
Weighted avg	0.99 / 0.81	0.99 / 0.81

Table 5- LogisticRegression metrics comparison before and after hyperparameter optimization

5. Conclusions

Having a robust and balanced dataset is paramount to accurate predictions, classifications, and clusters. The more balanced the data being analyzed, the more efficient the model will be able to learn, which translates into more accurate predictions.

Business and data understanding stages play a vital role in leveraging data. It is not enough to pre-process these and apply Machine Learning algorithms. Without a proper understanding of the functional needs of users, on the one hand, you risk reaching the wrong conclusions, and on the other hand, you could draw conclusions that lack business value.

Undoubtedly, the stage that demands the most effort and work in data mining is the preparation of the data. In the real world, data is usually mostly unstructured and is scattered across different databases and archive files. This stage requires careful extraction, transformation, and loading (ETL) of the data to achieve a coherent structure ready for further analysis.

The Colombian government's open data proved to be a valuable source of information for this research project. By combining them with various databases, it was possible to establish a solid initial structure for data analysis. This integration of diverse data sources allowed for a more complete and enriching view of the patterns and trends present in the data.

Although hyperparameter optimization played an important role in improving model performance, it was observed that the most determining factor in evaluating the models with the highest performance was data balancing. The balance between the classes in the dataset turned out to be a crucial variable for obtaining more accurate and reliable models. This underscores the importance of properly addressing the challenge of class imbalance when conducting analysis and predictions.

It is essential to note that Machine Learning algorithms, although powerful and effective, require subsequent review by functional experts. These experts are tasked with validating the outputs of the model and verifying the absence of bias or inaccurate information. Their experience and knowledge allow them to identify potential problems and ensure that the results of the model are consistent and reliable. This validation by experts is a best practice to ensure the quality and usefulness of the results obtained.

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