Revista ARACÊ
ISSN: 2358-2472

SENTIMENT ANALYSIS ON SOCIAL NETWORKS AS A TOOL TO SUPPORT DECISION MAKING IN REPUTATIONAL RISK MANAGEMENT IN THE BANKING SECTOR

ANÁLISE DE SENTIMENTO NAS REDES SOCIAIS COMO FERRAMENTA DE APOIO À TOMADA DE DECISÃO NA GESTÃO DE RISCO REPUTACIONAL NO SETOR BANCÁRIO

ANÁLISIS DE SENTIMIENTO EN REDES SOCIALES COMO HERRAMIENTA DE APOYO A LA TOMA DE DECISIONES EN LA GESTIÓN DEL RIESGO REPUTACIONAL EN EL SECTOR BANCARIO

https://doi.org/10.56238/arev7n10-149

Submission date: 09/13/2025 **Publication Date:** 10/13/2025

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ABSTRACT
The growing digital exposure of financial institutions highlights the need for effective reputational risk monitoring. This study proposes the development of a sentiment analysis model applied to texts collected from the X social network (formerly Twitter), aiming to automatically classify user comments based on emotional polarity (positive, neutral, or negative). The methodology includes data collection via API, text preprocessing, class balancing, and the implementation of the Naive Bayes algorithm through supervised learning

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techniques in Python. Results showed an overall accuracy of up to 69.27% in the original dataset, with performance improvements for minority classes using upsampling. The model proved most effective in detecting negative sentiments, which are crucial in managing reputational risk. The proposed solution is intended to support decision-making in the banking sector by enhancing institutional image monitoring and crisis prevention strategies

Keywords: Sentiment Analysis. Reputational Risk. Social Media. Financial Institutions. Machine Learning.

RESUMO
A crescente exposição digital das instituições financeiras destaca a necessidade de um monitoramento eficaz do risco reputacional. Este estudo propõe o desenvolvimento de um modelo de análise de sentimentos aplicado a textos coletados da rede social X (antigo Twitter), com o objetivo de classificar automaticamente os comentários dos usuários com base na polaridade emocional (positiva, neutra ou negativa). A metodologia inclui coleta de dados via API, pré-processamento de texto, balanceamento de classes e a implementação do algoritmo Naive Bayes por meio de técnicas de aprendizado supervisionado em Python. Os resultados mostraram uma precisão geral de até 69,27% no conjunto de dados original, com melhorias de desempenho para classes minoritárias usando upsampling. O modelo se mostrou mais eficaz na detecção de sentimentos negativos, que são cruciais na gestão do risco reputacional. A solução proposta visa apoiar a tomada de decisões no setor bancário, aprimorando o monitoramento da imagem institucional e as estratégias de prevenção de crises.

Palavras-chave: Análise de Sentimentos. Risco Reputacional. Mídias Sociais. Instituições Financeiras. Aprendizado de Máquina.

RESUMEN
La creciente exposición digital de las instituciones financieras pone de relieve la necesidad de una monitorización eficaz del riesgo reputacional. Este estudio propone el desarrollo de un modelo de análisis de sentimientos aplicado a textos recopilados de la red social X (anteriormente Twitter), con el objetivo de clasificar automáticamente los comentarios de los usuarios según su polaridad emocional (positiva, neutral o negativa). La metodología incluye la recopilación de datos mediante API, el preprocesamiento de texto, el balanceo de clases y la implementación del algoritmo Naive Bayes mediante técnicas de aprendizaje supervisado en Python. Los resultados mostraron una precisión general de hasta el 69,27 % en el conjunto de datos original, con mejoras de rendimiento para las clases minoritarias mediante sobremuestreo. El modelo demostró ser especialmente eficaz en la detección de sentimientos negativos, cruciales para la gestión del riesgo reputacional. La solución propuesta pretende apoyar la toma de decisiones en el sector bancario mediante la mejora del seguimiento de la imagen institucional y las estrategias de prevención de crisis.

Palabras clave: Análisis de Sentimientos. Riesgo Reputacional. Redes Sociales. Instituciones Financieras. Aprendizaje Automático.

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ISSN: 2358-2472

1 INTRODUCTION

The sustainability and growth of contemporary organizations is intrinsically linked to their ability to identify, assess and mitigate risks efficiently, because in this context, risk is understood as the possibility of events occurring whose outcomes differ from what is expected, which could compromise organizational stability, given that large corporations, especially in the financial sector, have institutional risk management guidelines, which guide the actions of employees in the face of adverse situations. Among the various types of risk, reputational risk stands out, which has a direct impact on the trust placed in the organization by stakeholders such as customers, suppliers, employees, regulatory bodies and society in general.

Reputational risk arises from the misalignment between institutional actions and the expectations of stakeholders. An emblematic example is the case of the company Hurb (formerly Hotel Urbano), which, by selling travel packages at affordable prices without being able to fulfill them, generated massive consumer dissatisfaction. The negative repercussions on social networks and in the press compromised the company's image, culminating in layoffs and financial losses, according to an article published on May 30, 2023 on the Seu Dinheiro portal.

Another episode with wide repercussions was that of Americanas S.A., which announced accounting inconsistencies in the order of R$20 billion, since the disclosure of the fraud triggered a crisis of confidence in the market, affecting consumers, suppliers, banking institutions and government agencies.

In the banking sector, the issue of reputation takes on even more sensitive proportions, given its strong regulation by the Central Bank of Brazil (BC) and its interdependence with the national economic system. A reputational shake-up can even trigger a bank run, like the historical phenomenon observed in the 1929 crisis when account holders tried to withdraw their funds simultaneously, leading to the insolvency of the institutions. Thus, continuous monitoring of elements that could impact public perception becomes imperative for maintaining the soundness and credibility of financial institutions.

This paper proposes an approach based on sentiment analysis applied to texts collected on social networks, using APIs and machine learning techniques. The aim is to develop a model that quantifies the polarity (positive, negative or neutral) of users' opinions about banks in Brazil, providing an aggregate indicator of the reputational status of these institutions that impacts on strategic decision-making.

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2 THEORETICAL BACKGROUND

This section aims to provide a theoretical basis for the central concepts of this work, with an emphasis on sentiment analysis. To do this, we discuss the conceptual basis of the main areas involved, their practical applications and interrelationships with Production Engineering, Information Technology and Computer Science. The construction of this framework also includes the presentation of related work that will serve as a subsidy for the development of the proposed work.

2.1 ARTIFICIAL INTELLIGENCE (AI)

Artificial Intelligence is a multidisciplinary field that encompasses the creation of systems capable of simulating aspects of human intelligence, such as decision-making, logical reasoning, problem-solving and learning. According to Russell and Norvig (2013), definitions of AI can be classified into four main approaches: thinking like humans, thinking rationally, acting like humans and acting rationally. Each of these approaches makes important contributions to the understanding and application of AI.

AI has various definitions that depend on the approach used, as can be seen in Table 1, taken from the renowned book Artificial Intelligence by Russell and Norvig (2013).

Table 1

Some definitions of AI, organized into four categories

Thinking like a human	Thinking rationally
"The new and interesting effort to make computers think (...) *machines with minds*, in the full and literal sense." (Haugelande, 1985) "[Automation of] activities that we associate with human thought, activities such as decision-making, problem-solving, learning..." (Bellman, 1978)	"The study of mental faculties through the use of computer models." (Charniak and McDermott, 1985) "The study of computations that make it is possible to perceive, reason and act. (Winston, 1992).
Acting like human beings	**Acting rationally**
"The art of creating machines that perform functions that require intelligence when performed by people." (Kurzweil, 1990)	"Computational Intelligence is the study of the design of intelligent agents." (Poole *et al.*, 1998) "AI... is related to intelligent performance of artifacts." (Nilsson, 1998)

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"The study of how computers can do tasks that today are best performed by people." (Rich and Knight, 1991)	

Source: Russel; Norvig (2013, p. 4).

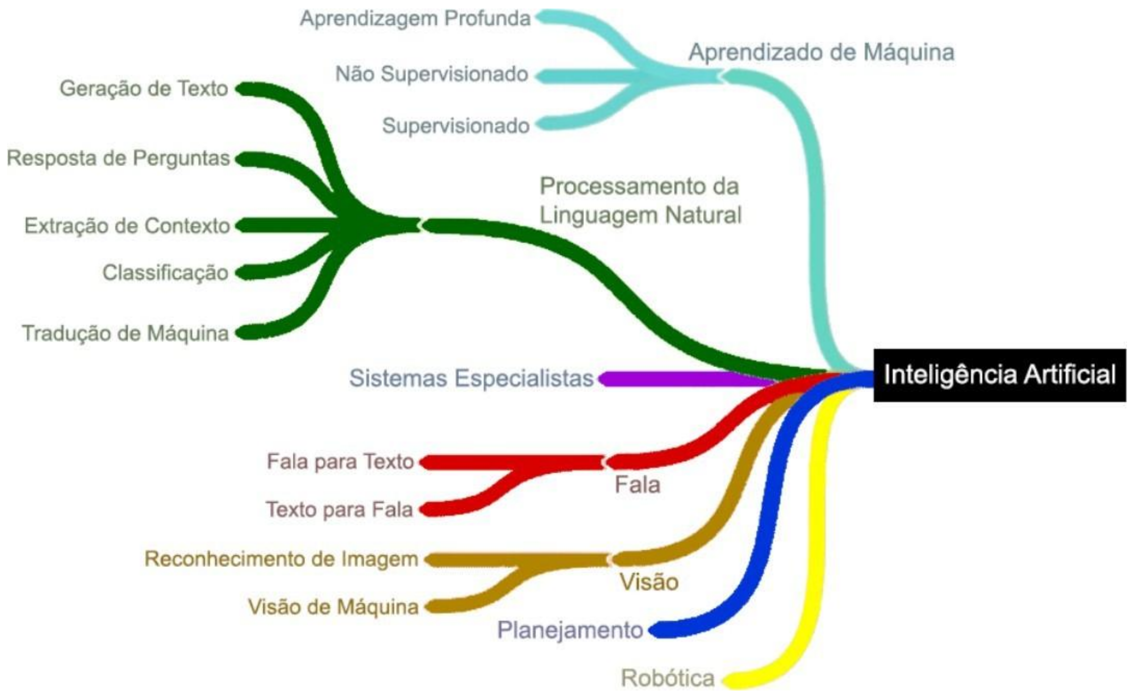
In general, AI can be defined as:

(...) an ingenuity capable of learning, as long as it is previously programmed through very well-defined algorithms given the complexity it is intended for, providing more effective decision-making, future predictions and interactions based on the data processed (Ferreira, 2022, p.18).

Below is Figure 1 of a mind map developed by Ferreira (2022, p.19) which illustrates how this science is subdivided.

Figure 1

Artificial Intelligence mind map



Source: Ferreira (2022, p.19).

The historical evolution of AI dates back to the work of McCulloch and Pitts (1943) with artificial neural networks and Turing (1950) with the Turing test, culminating in the consolidation of the term "artificial intelligence" by John McCarthy in 1956. Technological

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advances and access to large volumes of data have boosted the development of modern AI, which is now present in various solutions such as virtual assistants, recommendation systems and conversational models like ChatGPT.

2.2 MACHINE LEARNING (ML)

Machine learning is a sub-area of AI that allows computer systems to learn from data, identifying patterns and making predictions based on previous experiences. According to Ben-David and Shalev-Swartz (2014), machine learning refers to the automatic extraction of significant regularities in data.

ML techniques are generally classified into three categories: supervised, unsupervised and reinforcement learning. In supervised learning, models are trained on labeled data. In unsupervised learning, the aim is to find hidden structures in unlabeled data, as in clustering tasks. Reinforcement learning involves interacting with the environment to maximize rewards.

2.3 DEEP LEARNING (DL)

Deep learning is a more complex approach to machine learning, based on deep neural networks, which are made up of several processing layers. This hierarchical architecture allows abstract patterns to be represented from raw data, and is effective in tasks such as image, voice and text recognition.

Goodfellow et al. (2016) point out that deep learning is efficient at modeling complex phenomena through structures made up of simple concepts connected in multiple layers. This capability has considerably expanded the reach of AI in commercial and industrial applications.

2.4 NATURAL LANGUAGE PROCESSING (NLP)

Natural Language Processing is the area of AI that seeks to develop systems capable of understanding and manipulating human language. According to Allen (1995), it involves the use of computational techniques to analyze and interpret texts, speech and other forms of communication in natural language.

PLN applications include machine translation, syntactic and semantic analysis, summarization and, especially, sentiment analysis. NLP is essential for understanding opinions expressed in texts from social networks, blogs and other digital media.

2.5 SENTIMENT ANALYSIS

Sentiment analysis, also known as opinion mining, seeks to automatically identify and classify the emotions expressed in texts. Liu (2020) defines the practice as a methodology that aims to extract subjective feelings from natural language texts.

Sentiment analysis models categorize texts into positive, negative or neutral polarities, and can also use intensity scales. The techniques used vary between rule-based models, machine learning and hybrid approaches.

2.6 RISK MANAGEMENT

Risk management aims to mitigate uncertainties that could compromise organizational objectives. According to ABNT NBR ISO 31000:2018, risk is defined as the effect of uncertainty on objectives. Effective risk management must be integrated, structured, personalized, inclusive and guided by the best available information.

In the financial sector, risk management is fundamental to maintaining institutional stability and the system as a whole. The Central Bank of Brazil defines guidelines for classifying and treating financial and non-financial risks, including reputational risk.

Organizational reputation represents stakeholders' collective perception of the institution's credibility. An event that compromises this perception can generate significant losses. For Fombrun and Shanley (1990), reputation is a relational construct built on the organization's interactions with its stakeholders.

Menezes (2011) reinforces that reputation is based on past actions and expectations of future interactions. Proactive management of reputational risk requires monitoring mechanisms, agile response and the involvement of multiple organizational areas.

2.7 BANKING FINANCIAL INSTITUTIONS

Banks are essential agents in the intermediation of resources in the economic system. In Brazil, they are part of the National Financial System and are supervised by the Central Bank. Their activities range from credit operations to investment and foreign exchange services.

Financial institutions, especially commercial banks, have a direct impact on the economy and operate based on the trust of depositors. Reputational risk management is therefore vital to guaranteeing the stability of these organizations.

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2.8 REPUTATIONAL RISK IN BANKING INSTITUTIONS

Reputational risk in banks can compromise their ability to attract and maintain business relationships, access the interbank market and raise funds. According to Westphal (2012), this type of risk is triggered by negative stakeholder perceptions and can be aggravated by social, environmental and climate issues.

BC Resolution No. 4,557/2017 establishes specific guidelines for banks to integrate reputational risk management into their decision-making processes. In this context, tools such as sentiment analysis are emerging as promising solutions for monitoring this risk in real time.

2.9 DIGITAL SOCIAL NETWORKS

Social networks are virtual spaces that promote interaction between users, facilitating the exchange of opinions, experiences and perceptions. According to Boyd and Ellison (2007), these are systems that make it possible to build profiles and establish visible connections between members.

In the context of sentiment analysis, social networks provide a rich base of spontaneous textual data and are therefore relevant sources for monitoring institutional image.

2.10 BEHAVIORAL ANALYSIS

The analysis of human behavior seeks to understand the environmental stimuli that influence the actions of individuals. Skinner (1953) proposed that behavioral patterns are shaped by regular interactions between subject and environment, and can be observed and analyzed scientifically.

In the digital environment, such as social networks, users express their opinions more freely, making these environments rich in data on behavior, opinion and sentiment. Thus, the study of behavioral analysis complements the interpretation of the textual data used in this work.

3 METHODOLOGICAL ASPECTS

The methodology adopted in this work is based on biblioTableical research, with an exploratory approach and experimental development using machine learning algorithms. This section describes the procedures adopted throughout the research, detailing everything

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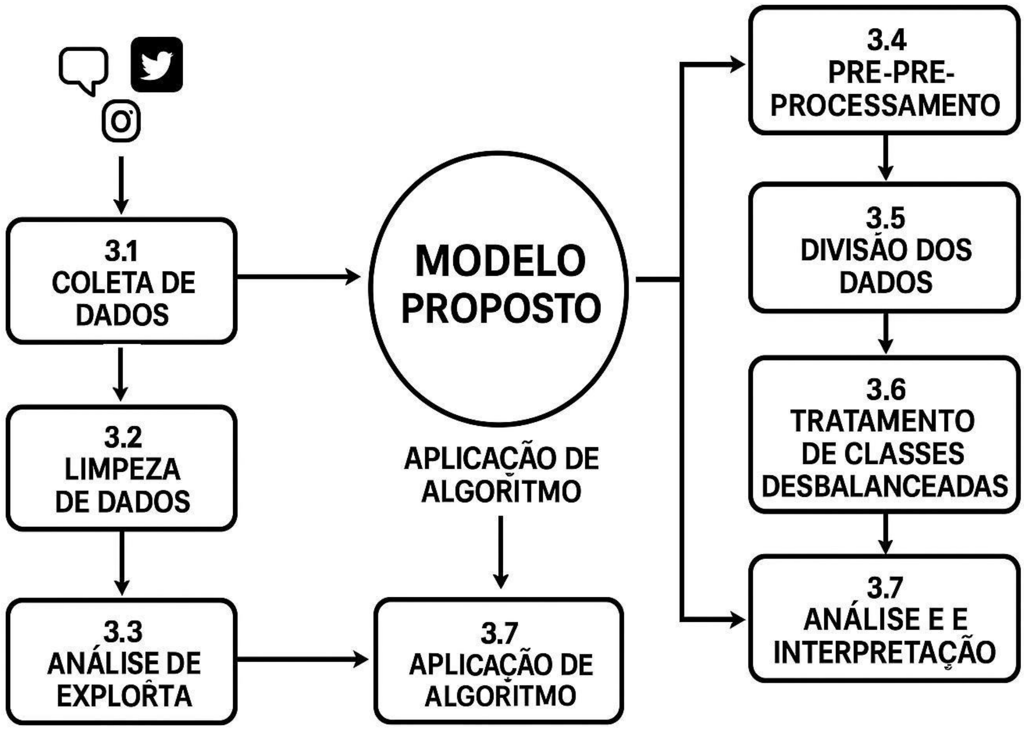
from data collection to the application of the predictive model, the purpose of which is to classify comments extracted from the social network X (formerly Twitter) according to their polarity: positive, negative or neutral. This classification aims to contribute to monitoring the reputational risk of banking financial institutions.

The stages of the research were inspired by the studies by Ferreira (2022) and Géron (2021) and follow the following structure: understanding the problem and delimiting the objectives; designing the research; defining the variables and collection instruments; acquiring, exploring, preparing and processing the data; applying the classification model; and, finally, analyzing the results.

Figure 2

Social network sentiment analysis model for reputational analysis



Source: Author's elaboration.

4 CASE STUDY

This research proposes as a solution for reputational risk management the automated classification of comments from the social network X, using a model based on the Naive Bayes algorithm. This is an established approach for text classification tasks, operating with supervised learning in the Python language. The proposed model aims to categorize

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comments according to their polarity (positive, negative or neutral), in order to provide support for risk management teams, especially in the banking sector.

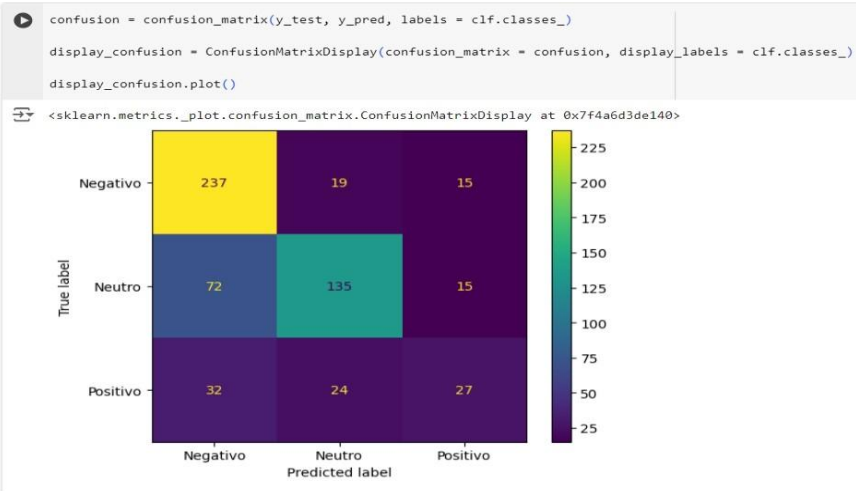
The expected result is the construction of a trained and tested model with satisfactory performance in identifying the polarity of texts, making a practical contribution to decision-making based on automated reputational analysis. The next section details the evaluation of the model according to specific performance metrics.

4.1 CONFUSION MATRIX

The confusion matrix made it possible to measure the classifier's performance by comparing the predictions with the actual values of the test data. There was greater accuracy in classifying negative comments (237 hits out of 271), while performance was lower for neutral comments (135 hits out of 222) and particularly low for positive comments (only 27 hits out of 83), as shown in Figure 2 below:

Figure 2

Confusion matrix



Source: Author's elaboration.

4.2 PREDICTION ERROR BY CLASS

The evaluation of classification errors showed that the model has a high error rate in the positive category (67.47%), followed by the neutral category (39.19%) and a more robust performance in the negative category (12.55%). These results were visualized using Tables generated with the Yellowbrick library, below are table 1, figure 3 and Table 2 referring to prediction errors by class.

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Table 2

Prediction errors by class

	Negative	Neutral	Positive
Errors by class	34	87	56
Total by class	271	222	83
Percentage by class	12,55%	39,19%	67,47%

Source: Author's elaboration.

Figure 3

Error prediction Table code by class

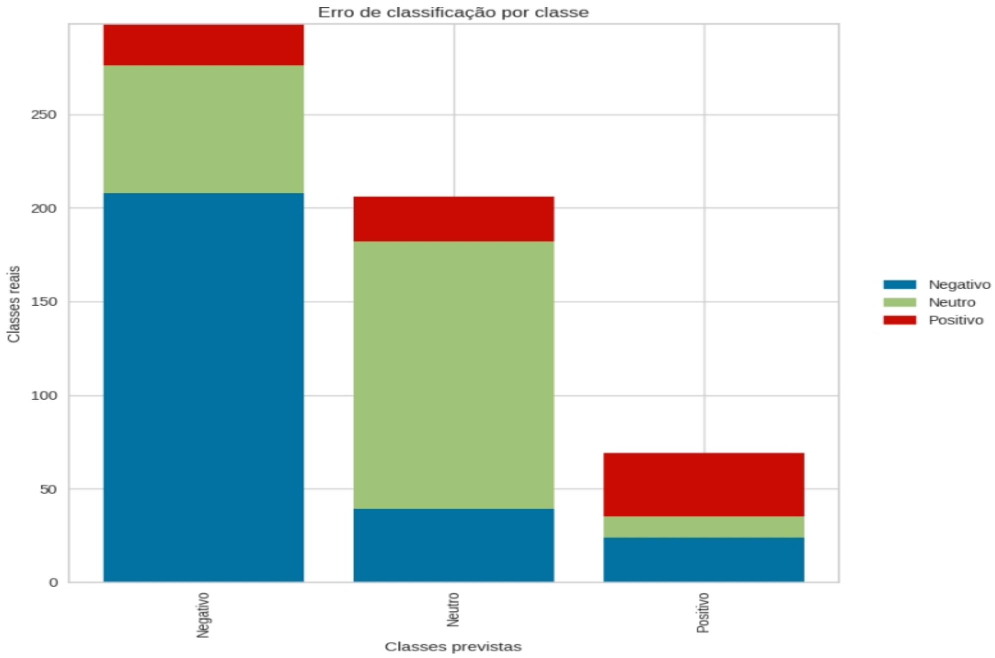
```
from yellowbrick.classifier import ClassPredictionError

fig, ax = plt.subplots(figsize = (10,10))
visualizer = ClassPredictionError(clf, classes = clf.classes_)
visualizer.score(x_test_dense, y_test)
visualizer.show(outpath = 'class_prediction_error.png')
visualizer.ax.set_title("Erro de classificação por classe")
visualizer.ax.set_xlabel("Classes previstas")
visualizer.ax.set_ylabel("Classes reais")
```

Source: Author's elaboration.

Figure 2

Classification errors by class



Source: Author's elaboration.

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4.3 ACCURACY

The overall accuracy of the model was approximately 69.27%. This value predominantly reflects the ability to classify negative comments, due to the imbalance in the distribution of classes. Therefore, although this metric is representative, it should be analyzed in conjunction with other indicators, due to its limitations in the face of unbalanced sets, see figure 4 below:

Figure 4

Result of the accuracy algorithm

```
[145] accuracy = accuracy_score(y_test, y_pred)
      accuracy

      0.6927083333333334
```

Source: Author's elaboration.

4.4 CLASS BALANCE ANALYSIS

The distribution of the data revealed a predominance of negative comments (47.02%), followed by neutral comments (38.52%) and, to a lesser extent, positive comments (14.46%). This disproportion had a direct impact on the model's performance, with high error rates in the minority classes.

To mitigate the effects of imbalance, upsampling (increasing minority classes) and downsampling (reducing majority classes) techniques were applied. The overall accuracy varied according to the approach: 69.27% (no upsampling), 68.75% (upsampling) and 64.76% (downsampling). The use of upsampling proved to be more promising as it partially preserved the accuracy of the majority class and improved the performance of the minority classes, as shown in the figures, Table and tables below:

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Figure 5

Code for plotting the class balance Table

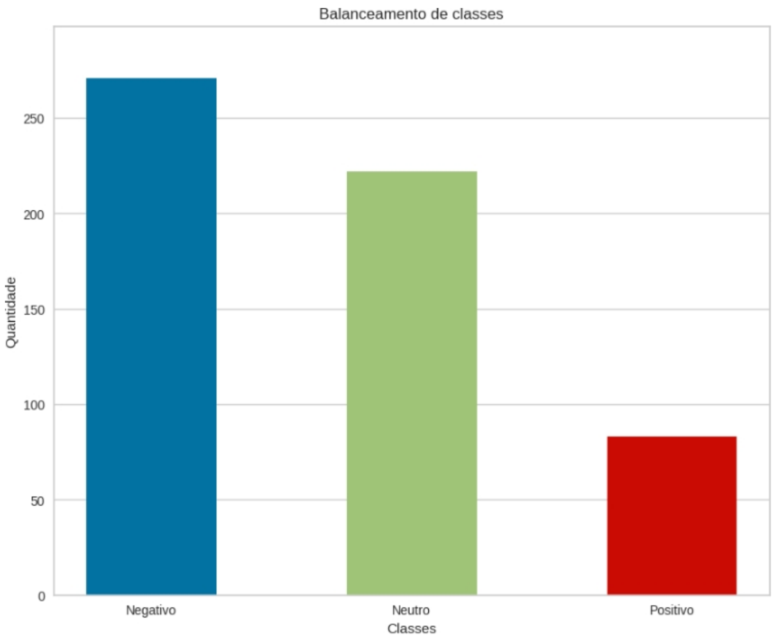
```
from yellowbrick.classifier import ClassBalance

fig, ax = plt.subplots(figsize = (10,8))
visualizer = ClassBalance(classes = clf.classes_)
visualizer.fit(y_test)
visualizer.show(outpath = 'class_balance.png')
visualizer.ax.set_title("Balanceamento de classes")
visualizer.ax.set_xlabel("Classes")
visualizer.ax.set_ylabel("Quantidade")
```

Source: Author's elaboration.

Figure 4

Class balance



Source: Author's elaboration.

Table 3

Percentage of errors per class

	Negative	Neutral	Positive
Percentage by class	47,02%	38,52%	14,46%
Percentage error	12,55%	39,19%	67,47%

Source: Author's elaboration.

Table 4

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Errors by type of class balancing

Errors	Negative	Neutral	Positive
Errors - unbalanced classes	12,55%	39,19%	67,47%
Errors - *downsampling*	22,51%	50,90%	34,94%
Errors - *upsampling*	16,61%	40,09%	55,42%

Source: Author's elaboration.

Table 5

Accuracy by type of class balancing

Accuracy	Negative	Neutral	Positive	Overall accuracy
Unbalanced classes	87,45%	60,81%	32,53%	69,27%
Balanced classes - *downsampling*	77,49%	49,10%	65,06%	64,76%
Balanced classes - *upsampling*	83,39%	59,91%	55,42%	68,75%

Source: Author's elaboration.

4.5 SOLUTION IMPLEMENTED

Based on the results obtained, a system is proposed that integrates: automated data collection via the X network API, storage in a database, textual pre-processing, separation into training and test sets, application of class balancing techniques, model training and deployment.

The solution should generate periodic reports that signal the presence of comments with a strong negative polarity, providing financial institutions with information to anticipate reputational crises. The proposal is to replace manual reading with an automated and responsive approach.

It can be seen that most of the messages captured have a negative connotation, which may be related to the perception that social networks are more effective spaces for expressions of dissatisfaction. In this scenario, the use of upsampling contributed to a better balance between the classes without severely damaging overall accuracy.

The proposed model should be subject to continuous updates and recurrent testing in a production environment, with a view to improving accuracy, stability and analytical relevance over time.

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5 FUTURE WORK AND FINAL CONSIDERATIONS

This work met the objective of developing a sentiment classification model applied to comments collected on the X social network, using supervised machine learning techniques. A variation of the Naive Bayes algorithm, implemented in Python, was used to categorize opinions into polarity classes (positive, neutral and negative).

The methodological execution, described in section 4, included the stages of data collection, cleaning and labeling, exploratory analysis, textual pre- processing, division into training and test bases, model training and performance evaluation. Among the challenges encountered was the limitation imposed by the X platform API, the free version of which does not include the type of query used, requiring the purchase of the basic plan, with a monthly cost of US$ 100.00. This factor restricted the sample to 2,476 comments, obtained from keyword searches related to the five largest commercial banks operating in Brazil, distributed over five collection periods.

Using Google Collaboratory computing resources and Jupyter notebooks, a model was developed with an overall accuracy of 69.27% using unbalanced classes, achieving a hit rate of up to 87.45% for negative comments. By applying upsampling techniques, there was a slight reduction in overall accuracy (68.75%), but a significant improvement in the classification of the positive class (from 32.53% to 55.42%). This approach proved to be more balanced and in line with the objective of minimizing reputational risks.

Given that detecting negative comments is a priority for reputational risk management, accuracy in identifying this class plays a strategic role. The presence of false negatives represents a threat to the efficiency of the system, implying a higher cost of manual analysis by specialized teams, so improving the predictive capacity of the model, especially in minority classes, is one of the avenues to be explored.

For future work, we suggest applying other classification algorithms, such as decision trees, k-NN, logistic regression, SVM and Random Forest, allowing systematic comparisons between performances. It is also advisable to expand the database by collecting data from other social networks or using web scraping, avoiding dependence on paid APIs and increasing the volume and diversity of the sample.

In addition, the model is expected to evolve with a focus on contextual treatment and improved semantic interpretation, especially in ambiguous or short texts. The expansion of the text corpus will enable more robust learning and greater generalization capacity.

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Finally, this work forms the basis for a scientific article to be submitted to journals or academic events in the areas of Production Engineering, Computer Engineering, Data Science and Software Engineering. It is hoped that the results presented here will serve as an incentive for the development of innovative solutions in automated opinion analysis and institutional reputation management.

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