ISSN: 1692-7257 - Volume 2 – Number 44 - 2024

RCTA
Revista Colombiana de Tecnologías de Avanzada
UNIPAMPLONA

Digital Object Identifier: 10.24054/rcta.v2i44.3018

Optimizing audit reporting using natural language processing: a data-driven approach from quality audits in higher education

Optimización de la generación de informes de auditoría mediante procesamiento de lenguaje natural: un enfoque basado en datos de auditorías de calidad en educación superior

MSc. Alveiro Rosado Gómez [1], PhD. Claudia Marcela Duran Chinchilla [2], MSc. Deccy Arias Rodríguez [3]

[1] ***Universidad Francisco de Paula Santander,*** *Facultad de Ingeniería, Grupo de Investigación en Desarrollo Tecnológico en Ingeniería (GITYD), Ocaña, Norte de Santander, Colombia.*
[2] ***Universidad Francisco de Paula Santander,*** *Departamento de Humanidades, Grupo de Investigación de la Facultad de Educación, Artes y Humanidades (GIFEAH), Ocaña, Norte de Santander, Colombia.*
[3] ***Universidad Francisco de Paula Santander,*** *Facultad de Ciencias Agrarias y del Ambiente, Especialización en Sistemas de Gestión Integral HSEQ, Ocaña, Norte de Santander, Colombia.*

Correspondence: *aarosadog@ufpso.edu.co*

Received: *january 21, 2024.* ***Accepted:*** *june 11, 2024.* ***Published:*** *july 23, 2024.*

How to cite: *A. A. Rosado Gómez, C. M. Duran Chinchilla, and D. Arias Rodríguez, "Optimizing audit reporting using natural language processing: a data-driven approach from quality audits in higher education", RCTA, vol. 2, no. 44, pp. 89–96, Jul. 2024. Recovered from* https://ojs.unipamplona.edu.co/index.php/rcta/article/view/3018

Abstract: This research focused on automating the understanding and semantic identification of findings for classification in internal audits using natural language processing techniques. Internal audit reports were analyzed to extract texts linked to non-conformities, strengths, and opportunities for improvement. To optimize text presentation for various algorithms, methods such as bag-of-words (BoW), term frequency-inverse document frequency (TF-IDF), and text representations via embedded word vectors such as Word2Vec and FastText. The best combination of performance was determined to come from a linear classifier, which uses data transformed by word embeddings and balances oversampled classes. This model bases its classifications on words that adequately capture the meaning and context of the analyzed finding.

Keywords: Machine learning, internal audit, supervised learning, artificial intelligence, natural language processing.

Resumen: Esta investigación se centró en la automatización de la comprensión e identificación semántica de hallazgos para su clasificación en auditorías internas, utilizando técnicas de procesamiento de lenguaje natural. Se analizaron informes de auditorías internas para extraer textos vinculados a no conformidades, fortalezas y oportunidades de mejora. Para optimizar la presentación del texto para diversos algoritmos, se examinaron métodos como bolsa de palabras (BoW), frecuencia de término-frecuencia inversa de documento (TF-IDF), así como representaciones de texto a través de vectores de palabras incrustadas como Word2Vec y FastText. Se determinó que la mejor combinación de rendimiento provino de un clasificador lineal, que utiliza datos transformados mediante palabras incrustadas y equilibra las clases con sobre-muestreo. Este modelo fundamenta sus clasificaciones en palabras que capturan adecuadamente el sentido y contexto del hallazgo analizado.

Palabras clave: Aprendizaje automático, auditoría interna, aprendizaje supervisado, inteligencia artificial, procesamiento del lenguaje natural.

1. INTRODUCTION

Organizations are groupings of individuals with legal identities who collaborate under specific rules to achieve shared objectives, mainly focused on providing services and products to society [1]. In management, these entities face continuous challenges, including the quality of their products or services, regulatory compliance, customer satisfaction, and the constant search for improvement. Organizations define fundamental elements such as guidelines, goals, and procedures to address these challenges. However, the complexity of structuring and implementing these components often leads them to rely on management systems [2]. A quality management system (QMS) represents how an organization guides and monitors its activities to achieve desired results [1]. This system encompasses various organizational aspects, planning, processes, and resources focused on quality framed within the quality policy that maintains internal product conformity standards [3]. In this context, ISO 9001 is an essential alternative because it focuses on quality criteria in management, promoting the implementation of requirements and standards [4].

The ISO 9001 standard requires tools to determine whether the quality management system complies with its requirements. To achieve this, systematic and independent evaluations called audits are carried out, which can be internal, carried out by the organization's personnel, or external, carried out by independent entities such as certification bodies [2] [4]. The results derived from the evaluation of the evidence gathered during the audit in comparison with the established standards are called audit findings, which cover both conformity and nonconformity with the audit criteria and possible areas for improvement [5].
The audit findings are the basis for the improvement plans made by the processes that failed to comply with some of the requirements of the standard; therefore, the way they are written is related to the importance and scope of the solution [1] [3]. These texts should clearly express the problems and their implications, seeking a balance between providing sufficient details to support the findings in a logical and coherent manner with syntheses that allow an effective reading [6].

Identifying and communicating findings in an audit report requires a classification into three categories: when the finding is positive, when it is negative, or when there is room for improvement. When highlighting strengths, achievements, and effective practices that contribute to both organizational objectives and the management system are described. About nonconformities, a structure is proposed that begins with a clear identification of the nonconformity, followed by specific details and evidence, and analyzes how it affects processes, quality and objectives. In exploring opportunities for improvement, emphasis is placed on describing areas with potential for positive change, presenting practical recommendations, and the expected benefits to the organization in terms of performance and goal achievement [7].

Auditors must deliver the audit report to the person or role responsible for consolidating and reviewing the information to evaluate its quality, clarity, and relevance. This stage involves a significant investment of time and administrative effort since, in addition to the duration of the evaluation process, the auditor also needs time to implement the required corrections in the audit report. This generates a longer delay in the conclusion of the audit process and in the initiation of the corresponding improvement plan [1] [2] [5]. This situation invites advanced actions to reduce the time and resources involved in quality assurance in the organization's management. Therefore, one option proposed is the application of technology that automates the process of understanding the results of the audit [8] [7].

From an automation perspective, intelligent technological solutions capable of handling unstructured data are necessary to identify relevant audit information [8]. Through natural language processing (NLP), it is possible to extract data from these formats, automating, to a large extent, the evaluation and validation of textual quality [9]. For this reason, this research aimed to incorporate NLP techniques in evaluating the findings recorded in audit reports, reducing the time and the incidence of human errors in the drafting and categorization of the findings [8].

2. METHODOLOGY

The dataset used corresponds to the results of the audits performed in a higher education institution certified in ISO 9001: 2015. The dataset contained two columns, one with a description of the finding and the other with its finding label; the latter column contained three values: Non-conformity (NO CONFORMIDAD), which was used when a standard requirement was not met. Strength (FORTALEZA) is when the process shows a degree of maturity higher than that required by the standard and in favor of management. The third value is an opportunity for improvement (OPORTUNIDAD DE MEJORA), which refers to compliance with the standard in an acceptable manner or non-compliance with the institution's internal standards. Table 1 shows the distribution of the 864 records used.

***Table 1**: distribution of class*

Class	Quantity
FORTALEZA	294
NO CONFORMIDAD	78
OPORTUNIDAD DE MEJORA	492

***Source**: author's elaboration*

In the Machine Learning (ML) domain, the supervised learning approach starts with an input dataset to which output labels are assigned. These labels represent the desired results and allow the model to generalize and learn through the relationships between the inputs, the original labels, and the resulting classifications [10] [11]. The unstructured nature of text-type attributes demands some kind of transformation to a form suitable for ML, such as numerical and categorical formats [12] [13].

This research used several ways of processing text to select the presentation that produced the best performance for different algorithms. The Bag of Words (BoW) approach uses a textual representation technique that converts the content into a numeric vector. Each word in the text is converted into a token and transformed into a vector in which each value reflects the frequency of occurrence of a specific word [12] [14]. Also, the text was processed using Term Frequency-Inverse Document Frequency (TF-IDF), which is a strategy that gives weight to words in a document according to their relevance.

Words that are repeated more frequently in a document but are sparse in the total set are considered more meaningful [12] [15] [16]. Additionally, text representations using word vectors with context were used, one of which is Word2Vec, which is a word embedding technique that employs neural networks to learn vector representations to capture the semantics and relationships between words by observing how they are distributed in a text corpus [17] [18]. The other type of representation used was FastText, which allows it to represent word assets of character substrings and interpret words that are not in the original vocabulary [19].

Each data set generated by the transformation of text into numerical format was divided into a training set (80%) and a test set (20%), and then used with different classifiers in order to select the best performing combination of data and algorithm to be produced. Classifiers families such as Support Vector Machines (SVM), which are characterized by searching for optimal hyperplanes to separate classes in high-dimensional spaces, were used. Ensemble Methods, which combine multiple classifiers to improve overall performance, were used. Another family that was worked on was Generalized Linear Models (GLM) which include models such as logistic regression and Ridge to fit relationships between features and objectives. K-Nearest Neighbors (K-NN) assign classes based on nearest neighbors, while Decision Trees divide spaces according to features. Discriminant Analysis, searches for a projection of the original features into a new space in which the classes are better separated, and XGBoost employs boosting combined with residuals to train new trees and regularization to avoid overfitting [14] [20] [21] [22].

Then, the best algorithm was selected by type of transformation; these algorithms and datasets were given interventions such as class balancing, using Random under sampling (RUS) to reduce instances of the majority class, affecting the generalization of the model. Random oversampling (ROS) replicates instances of the minority class. The synthetic minority oversampling technique (SMOTE) creates synthetic instances of the minority class from near neighbors, improving the equilibrium and generalization of the model [21]. Additionally, parallel hyperparameter fitting was performed using the Mango library [23].

From these interventions, the model with the highest F1 value was selected as the criterion for the best combination of accuracy (percentage of correct predictions among positive predictions) and sensitivity (percentage of positive instances correctly identified) [24]. Since this was a multi-class problem, the initial selection of the best models was made by averaging the value of each metric [25].

3. RESULTS

Table 2 shows the distribution of the results for each method used in transforming the text to a numerical representation. Both BoW and TF-IDF coincide in the same number of attributes due to how the words are presented. However, the content of each value within the result matrix is different because it depends on how these values are calculated within the matrix and how these values are weighted according to the frequency and rarity of the words in the corpus [26]. The vector space dimension in which the words will be represented was defined to be 500 for Word2Vec and FastText. It can be observed how the methods based on frequency of occurrence provide a higher dimensionality to the dataset, while the methods based on vector representation are configurable and can be lower [27].

***Table 2**: Data by representation*

Class	Attributes
BoW	1432
TF-IDF	1432
Word2Vec	500
FastText	500

***Source**: author's elaboration*

Table 3 presents the outstanding results for each text processing technique. The results are shown for implementing the classifiers without balancing the data. It can be seen how vocabulary-based datasets perform better with linear algorithms than vector-based ones. Additionally, it is highlighted that word embeddings achieve better performance when combined with the XGBClassifier algorithm.

***Table 3**: Metrics by model*

Algorithm	F1	Technique
LogisticRegressionCV	0.905	tfidf
PassiveAggressiveClassifier	0.900	bow
XGBClassifier	0.846	word2vec
XGBClassifier	0.802	fasttext

***Source**: author's elaboration*

Analyzing the F1 value for each class, as shown in Table 4, all the algorithms perform better in identifying nonconformities (NC) and lower in strengths (FO). For opportunities for improvement (OP), the results vary slightly among the algorithms. Similar to the averaged results, when reviewing the output by class, the data's performance based on word vocabulary is still considered.

***Table 4**: F1 by model*

Algorithm	FO	NC	OM
LogisticRegressionCV	0.824	1	0.891
PassiveAggressiveClassifier	0.833	0.960	0.893
XGBClassifier	0.755	0.916	0.867
XGBClassifier	0.716	0.846	0.843

***Source**: author's elaboration*

Table 5 presents the outstanding results for each text processing technique. The classifiers were trained with the data sets using different class-balancing techniques. In order to achieve the best model, the classifier family representations were run. For all classifiers, the combination with ROS produced the best output, and better F1 results were achieved without any intervention on the dataset. However, the classifiers for three of the techniques changed while maintaining the vocabularies-based techniques, allowing better text generalization, especially TF-IDF.

Table 5. Balanced classes

Algorithm	F1	Technique
LogisticRegressionCV	0.917	tfidf
RandomForestClassifier	0.911	bow
LogisticRegressionCV	0.909	word2vec
GradientBoostingClassifier	0.818	fasttext

***Source**: author's elaboration*

We then proceeded to train the classifiers that showed the best performance for each variant of text processing. These models were adjusted using balanced data using previously identified techniques, and hyper-parameter optimization was performed. Outstanding, only the LogisticRegressionCV algorithm, when working with the dataset processed using word2vec and applying class balancing with ROS, improved its F1 score, increasing to 0.918. In contrast, the performance of the other models decreased when implementing the new hyper-parameters.

To explain why a model made a particular prediction, LimeTextExplainer is a part of the Lime library that allows understanding of how text classification models work by introducing minor modifications to the original text and creating a simpler model that facilitates generating explanations that highlight keywords in a text instance [28]. The instances that were used are related to the frequent words in each of the classes. For example, in strengths, words such as allowed are repeated 63 times; for improvement opportunity, the word review is repeated 61 times; and in nonconformity, the numeral is repeated 30 times. Other words related to empty words were not counted since these were not included in the vocabularies-based datasets.

Figure 1 illustrates the explanation of a specific instance of the test data set that was classified as "strength." In this explanation, the keywords "because" and "allowed" are highlighted, which significantly influenced the resulting prediction.

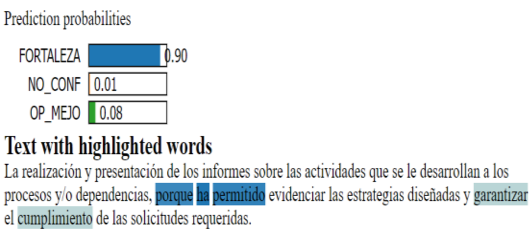

Fig. 1. *Rating strength.*
Source: *author's elaboration.*

Figure 2 presents the model output for an instance of an improvement opportunity. In this visualization, words such as "review," "update," and "stakeholder" are evident, which had a positive contribution to the classification of this instance.

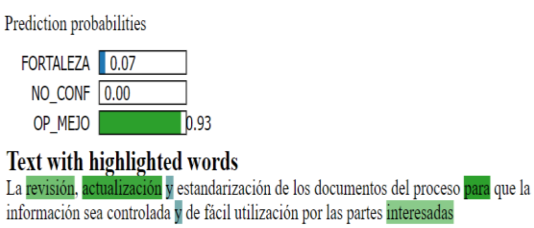

Fig. 2. *Improvement opportunity rating.*
Source: *author's elaboration.*

Related to the nonconformities shown in Figure 3, the word No is very significant for its color intensity, and the words evidence and numeral positively contribute to the classification.

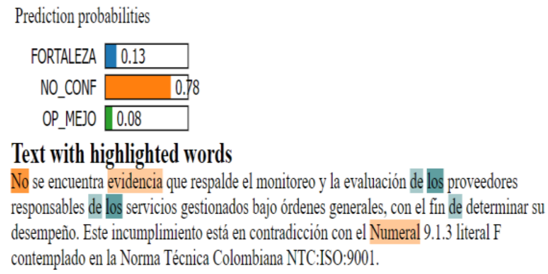

Fig. 3. *Non-conformity classification.*
Source: *author's elaboration.*

The appearances in Figures 2 and 3 of empty words suggest the use of these words in the argumentation of strengths, and this is how the model understands it, where the local explanatory model used these words present in the disturbed instances to generate their respective classifications of the original model.

4. DISCUSSION

This research followed the recommendations proposed in the literature related to text processing, especially during preprocessing, where approaches such as Bag-of-Words (BoW) and TF-IDF require the removal of uninformative words, such as joint or infrequent stopwords, in order to improve the efficiency of these methods [12]. The BoW and TF-IDF approach, as reported by Gasparetto, Marcuzzo, Zangari, & Albarelli [29], resulted in high dimensionality vectors (1432 attributes). In contrast, word2vec and FastText generate vectors with fixed dimensions regardless of vocabulary size, preserving the original order and capturing semantic patterns and relationships between words more accurately [29]. Despite the problems that high dimensionality can generate in the generalization of the objective function presenting the data [30], this research showed that, for all the text representation transformation methods used, the trained models generated F1 metrics above 80% [31].

The combination used with LogisticRegressionCV, trained using Word2Vec in text processing and applying the Random Oversampling (ROS) technique for class balancing, proved effective in classifying findings identified in internal audits. The chosen model's characteristics focus on using the LogisticRegressionCV classifier, which employs cross-validation to optimize regularization. When trained on data transformation using Word2Vec, this approach allowed the capture of the semantic relationships present in the text. In addition, including the class oversampling technique with ROS facilitated better performance in classifying different classes [32] [33].

The output of the constructed model showed that words acquire meaning depending on the reported finding [34]. The term allowed (permitido), frequently used in the wording of strength, denotes actions aimed at complying in the best possible way with established requirements, regulations, or standards in a quality context [35].

The term upgrade (actualización) stands out from the classification of improvement opportunities, which denotes making changes or improvements to something to align with newer information or technology. In quality, it can imply keeping methods and processes up to date. It connotes adaptation, innovation, and progress. It also suggests the exploration of excellence and a willingness to stay relevant in an ever-changing environment. The word review refers denotatively to a thorough and critical analysis of something to assess its quality, accuracy, and adequacy. In the context of quality, it is about examining processes and results for possible improvements. It connotes introversion, detailed analysis, and search for possible areas of strength and weakness [1].

The terms used in a nonconformity context are evidence (evidencia) and numeral (numeral), which are essential to fully understanding each term's nature and scope. Evidence denotatively refers to data, facts, or information supporting or corroborating an assertion, hypothesis, or conclusion. In the context of a nonconformity, evidence can be crucial to identify and understand the problem. It connotes objectivity, substantiation, and a solid foundation. A numerical term denotes a section or clause in a policy or regulation. It connotes specificity, detail, and formality in the presentation of information [36].

Finally, the research took advantage of the resources provided by natural language processing to achieve a semantic identification and understand the meaning of the wording of the findings within a particular linguistic and cultural context [37] [38]. The results demonstrated the effectiveness of the combination of the embedded words, with class balancing through oversampling, to train a model for classifying findings detected in internal audits, which will optimize time and resources in the continuous improvement processes of the organization.

5. CONCLUSIONS

This research highlighted the importance of automation in understanding and classifying findings in internal audits. By means of natural language processing techniques, it is possible to effectively analyze and categorize the results of audits, which facilitates decision making and opens the possibilities to evaluate the quality of a text according to how the model classifies it.

Although Word2Vec was selected as the dataset that best generalized the data, other text processing techniques, such as Bag-of-Words (BoW), TF-IDF, and FastText, also generate results close to the selected one, suggesting that there is no dominance between vocabulary-based methods and methods based on embedded word vectors. Additionally, machine learning techniques such as class balancing and hyperparameter optimization can improve model performance once the text has been processed and converted to numerical values.

The results indicate how applying natural language processing can help improve the understanding of audit reports since the words used in the findings acquire specific meanings depending on the category (strengths, nonconformities, or opportunities for improvement). This indicates that the model adequately identified the semantics and linguistic context used by the auditors by using words specific to each finding to make the classification.

REFERENCES

[1] N. Calso, Guia practica para la integracion de sistemas de gestion. ISO 9001, ISO 14001 e ISO 45001, Madrid: AENOR - Asociacion Espanola de Normalizacion y Certificacion, 2018.

[2] M. Espino, Fundamentos de auditoría, México: Grupo Editorial Patria, 2015.

[3] AENOR, ISO 9001: 2015 para la pequeña empresa: recomendaciones del ISO/TC 176, Madrid: AENOR Internacional, 2016.

[4] J. Cortés, Sistemas de gestión de calidad (ISO 9001:2015), Málaga: Interconsuttmg Bureau, 2017.

[5] T. Sevilla, Auditoría de los sistemas integrados de gestión ISO 9001:2015, ISO 14001:2015, ISO 45001:2018, Madrid: FC Editorial, 2019.

[6] M. Vásquez, 6 pecados con la ISO 9001, Santa Cruz de la Sierra: El Cid Editor, 2020.

[7] T. Xiao, C. Geng y C. Yuan, «How audit effort affects audit quality: An audit process

and audit output perspective,» *China Journal of Accounting Research*, pp. 109-127, 2020.

[8] G. Boskou, E. Kirkos y C. Spathis, «Classifying internal audit quality using textual analysis: the case of auditor selection,» *Managerial Auditing Journal*, pp. 925-950, 2019.

[9] D. Khurana, A. Koli, K. Khatter y S. Singh, «Natural language processing: state of the art, current trends and challenges,» *Multimedia Tools and Applications*, p. 3713–3744, 2023.

[10] R. Stuart y P. Norvig, Artificial Intelligence: A Modern Approach, Englewood Cliffs: Prentice Hall, 1995.

[11] J. Han, M. Kamber y J. Pei, Data Mining Concepts and Techniques, Tercera ed., Waltham: Morgan Kaufmann, 2012.

[12] V. Lakshmanan, S. Robinson y M. Munn, Machine Learning Design Patterns, Sebastopol: O'Reilly Media, 2020.

[13] F. K. Khattak, S. Jebleea, C. Pou-Proma, M. Abdalla, C. Meaney y F. Rudzicz, «A survey of word embeddings for clinical text,» *Journal of Biomedical Informatics*, 2019.

[14] A. Müller y S. Guido, Introduction to Machine Learning with Python, Sebastopol: O'Reilly, 2017.

[15] T. Verdonck, B. Baesens, M. Óskarsdóttir y S. Broucke, «Special issue on feature engineering editorial,» *Machine Learning*, 2021.

[16] S. Raschka y V. Mirjalili, Python Machine Learning Third Edition, Birmingham: Packt, 2019.

[17] T. Mikolov, K. Chen, G. Corrado y J. Dean, «Efficient Estimation of Word Representations in Vector Space,» *arXiv*, pp. 1-12, 2013.

[18] T. Mikolov, I. Sutskever, K. Chen, G. Corrado y J. Dean, «Distributed Representations of Words and Phrases and their Compositionality,» *arXiv*, pp. 1-9, 2013.

[19] P. Bojanowski, E. Grave, A. Joulin y T. Mikolov, «Enriching Word Vectors with Subword Information,» *arXiv*, 2016.

[20] A. Géron, Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow, Sebastopol: O'Reilly, 2019.

[21] M. Galar, A. Fernández, E. Barrenechea, H. Bustince y F. Herrera, «A Review on Ensembles for the Class Imbalance Problem: Bagging-, Boosting-, and Hybrid-Based Approaches,» *IEEE Trans Syst Man Cybern Part C*, p. 463–484, 2012.

[22] M. Lango y J. Stefanowski, «Multi-class and feature selection extensions of Roughly Balanced Bagging for imbalanced data,» *Journal of Intelligent Information Systems*, p. 97–127, 2018.

[23] S. Sandha, M. Aggarwal, I. Fedorov y M. Srivastava, «Mango: A Python Library for Parallel Hyperparameter Tuning,» de *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Barcelona, 2020.

[24] A. Zheng, Evaluating Machine Learning Models, Sebastopol: O'Reilly Media, 2015.

[25] I. Witten, E. Frank, M. Hall y C. Pal, Data Mining: Practical Machine Learning Tools and Techniques, Burlington: Morgan Kaufmann, 2017.

[26] S. Ahmed, M. Singh, B. Doherty, E. Ramlan, K. Harkin, M. Bucholc y D. Coyle, «An Empirical Analysis of State-of-Art Classification Models in an IT Incident Severity Prediction Framework,» *Applied Sciences*, pp. 1-27, 2023.

[27] W. Zhou, H. Wang, H. Sun y T. Sun, «A Method of Short Text Representation Based on the Feature Probability Embedded Vector,» *Sensor*, 2019.

[28] A. Bhattacharya, Applied Machine Learning Explainability Techniques: Make ML models explainable and trustworthy for practical applications using LIME, SHAP, and more, Birmingham: Packt, 2022.

[29] A. Gasparetto, M. Marcuzzo, A. Zangari y A. Albarelli, «A Survey on Text Classification Algorithms: From Text to Predictions,» *Information*, pp. 1-39, 2022.

[30] S. Galli, Python Feature Engineering Cookbook, Birmingham: Packt Publishing, 2020.

[31] Z. Zhao, G. Feng, J. Zhu y Q. Shen, «Manifold learning: Dimensionality reduction and high dimensional data reconstruction via dictionary learning,» *Neurocomputing*, p. 268–285, 2016.

[32] A. Akkasi y M.-F. Moens, «Causal relationship extraction from biomedical text using deep neural models: A comprehensive survey,» *Journal of Biomedical Informatics*, pp. 1-12, 2021.

[33] K. Ghosh, A. Banerjee, S. Chatterjee y S. Sen, «Imbalanced Twitter Sentiment Analysis using Minority Oversampling,» de *International Conference on Awareness Science and Technology (iCAST)*, Morioka, 2019.

[34] M. García , «La polisemia en el lenguaje cotidiano,» *Revista de Linguistica Moderna 7(2)* , pp. 45-58 https://doi.org/10.12345/rlm.2015.7.2.45 , 2015.

[35] P. Robayo, «La innovación como proceso y su gestión en la organización: una aplicación para el sector gráfico colombiano,» *Suma de Negocios,* pp. 125-140, 2016.

[36] C. Zheng, B. Huang, A. Agazaryan, B. Creekmur, T. Osuj y M. Gould, «Natural Language Processing to Identify Pulmonary Nodules and Extract Nodule Characteristics From Radiology Reports,» *Chest,* pp. 1902-1914, 2021.

[37] J. Smith, Semántica y significado, Editorial Lingua , 2010.

[38] R. García y M. Huerta , «Significado y sociedad,» *Sincronía, núm. 77. Disponible en: https://www.redalyc.org/articulo.oa?id=513862147026,* pp. 530-544, 2020.

[39] M. Schonlau y R. Y. Zou, «The random forest algorithm for statistical learning,» *The Stata Journal*, pp. 3-29, 2020.