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Accurate Voice of the Customer Interpretation Via Hybrid Fuzzy – Decision Tree Classification

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***Abstract* - Managing, analyzing, and interpreting the results of student surveys is a complex process that involves analyzing a large amount of data. In this article, the authors propose to develop an intelligent system for classifying students' responses to identify the "Voice of the Customer." The study suggests addressing the issue of feedback analysis by considering the ambiguity of natural language and implementing an accurate and efficient method of classifying students' responses.**

The research is conducted using the BERT algorithm that utilizes lexical features enhanced with intensifiers and superlatives identified in the Spanish language to implement sentiment analysis. The authors also apply fuzzy logic and decision-making rules to introduce membership functions that estimate the feedback's polarity and classify it. Finally, the article describes the Business Intelligence dashboard that allows monitoring the key metrics in real time.

As a result, the methodology identifies that using fuzzy sets and recognizing superlatives in natural language can improve the accuracy of classification by reducing the number of false discoveries and omissions.

Keywords: Fuzzy, Logic, Interpretation, Classification, Comments.

I. INTRODUCTION

Nowadays, it is necessary for the customer to express his feelings about the experience he has with the product or service he is acquiring. It is extremely important for companies to know the opinions and provide them with a punctual follow-up to improve the experience and contribute to customer retention and to increase the acquisition of new customers. In the academic field, educational institutions receive feedback from their students, such action is aimed at student satisfaction and continuous improvement of the services they receive. In addition to offering an overview of the educational experience, the comments made by students provide insight into areas of opportunity, strengths and weaknesses of the institution.

However, manual management and analysis makes it a tedious, inaccurate, error-prone and costly process, since large volumes of information are handled. The above motivates the need to develop an automated computer system that achieves proper classification and interpretation of the collected comments (Nasim *et al.*, 2017).

The Universidad del Valle de México, like other institutions in the country, faces the challenge of handling many comments from students, ranging from the courses they enroll in, the professors who teach them, the school's facilities and infrastructure, to suggestions for administrative services. Currently, this field has gained great relevance and interest for data scientists due to the proliferation and interaction with digital platforms where users can express their opinions and feelings based on previous experience.

To implement the pertinent improvements to each of the evaluated items, the educational institution requires a correct interpretation of the comments issued and an effective classification for subsequent follow-up. In simple words, it will contribute to improving the overall educational quality (Chen & Zou, 2020). In addition, it is necessary to consider the unstructured and subjective nature of natural human language displayed in the comments issued by students.

In the context described above, the need arises to develop an intelligent system capable of minimizing uncertainty and ambiguity, inherent characteristics of natural language. An alternative that has the necessary sufficiency to meet the requirements of accurate interpretation and classification is the fuzzy logic defined by Zadeh. This technique proposes a reliable and accurate interpretation since it is characterized by its ability to decode vague information that could be considered ambiguous. To classify the comments and analyze the unstructured (or loosely structured) text of each uttered comment, membership functions are used that help improve the accuracy of the analysis, facilitate the identification of patterns and can show trends regarding student feedback (Lee & Wang, 2011).

What is sought with the fuzzy logic-based computerized feedback rating system is for universities to embrace

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significant potential to transform the way they manage student feedback. Real-time automation of such management is intended to convert data into valuable information that supports decision making quickly and efficiently. This is relevant because students' educational experience should depend on immediate response to their concerns and suggestions (Chen *et al.*, 2020).

The use of fuzzy logic allows the adaptability of the system to different contexts and types of unstructured comments. When we say "unstructured comment" we refer to comments that lack a predetermined structure and prior classification. In the tests we will make use of triangular and trapezoidal membership functions that are useful for modeling qualitative and subjective information, while Gaussian and sigmoidal functions provide superior flexibility that allow capturing intensity in the comments (Zadeh, 1965). Combining the previously techniques will allow an accurate, complete and nuanced interpretation of the comments issued which, in turn, will improve the quality of feedback-based decisions.

II. TECHNICAL BACKGROUND

Comment analysis is also known as opinion mining and consists of a process that makes use of natural language processing (NLP) and data analysis techniques to delimit and extract subjective information from a text, as in this case, the students' comments.

The main objective of the analysis is to show the polarity of the text, i.e., whether it is positive, negative or neutral. There are different techniques that allow us to achieve polarization, some use advanced approaches such as machine learning and deep neural networks (Medhat, Hassan, & Korashy, 2014). Others make use of lexicon-based methods in which dictionaries are created with scores assigned to words based on the intensity of their meaning. For example, the comment "The school administration is bad" is negative, but the comment "The school administration is nefarious" is even more negative so it is necessary to punctuate the words (Pang & Lee, 2008).

On the other hand, fuzzy logic is an extension of Boolean logic. While Boolean logic represents only false or true values in a categorical manner, fuzzy logic represents values between these two limits, which allows it to analyze imprecise and ambiguous information. Mathematically speaking, fuzzy logic allows variables to adopt values from a continuous range between 0 and 1.

Under the context of sentiment and opinion analysis, fuzzy logic is used to model the uncertainty and subjectivity that are inherent in natural language. The membership functions will be the ones who help to nuance the different sentiments and thus classify them accurately (Ross, 2010).

It is possible to note that the integration of fuzzy logic techniques in sentiment analysis provides a robust methodology for handling ambiguity and impressionability of comments that lack a concrete structure. They enable flexible and adaptive classification with respect to sentiments providing useful results for optimal decision making (Lee & Wang, 2011).

Moreno, Torres and Boucheneb (2020) implemented a sentiment analysis system in social networks using deep learning and fuzzy logic techniques. Their study demonstrated how the combination of techniques substantially improves sentiment classification accuracy on platforms such as Twitter (now X) especially in its relation to sarcasm and irony. Wang, T., and Chen, J. (2020) demonstrated the ability of such techniques to handle subjectivity in identifying emotions in literary texts.

III. SYSTEM DESIGN AND RESULTS

Figure 1 shows the process of handling comments, from acquisition to scoring. Each of the steps is detailed below:

Step 1: Consists of the collection of opinions from the students. To accomplish the above, an online survey was designed to allow students to express their comments and opinions regarding the academic and administrative services they receive from the institution. The instrument contains open-ended questions so that students can describe, in their own words, their experiences and perceptions. The data collected is stored in a structured database in the following format:

a) Opinion ID: This is the unique identifier for each opinion. In database terms it is referred to as the primary key.
b) Date: It houses the time stamp regarding the moment when the opinion was registered. This field can be useful for temporal analysis and tracking changes and improvements over time.
c) Commentary: Contains the opinions expressed by the students in free text format. It should be noted that the comments to be analyzed are in Spanish, since it is the official language of Mexico.

Table 1 shows the hosting structure of the information collected in the database.

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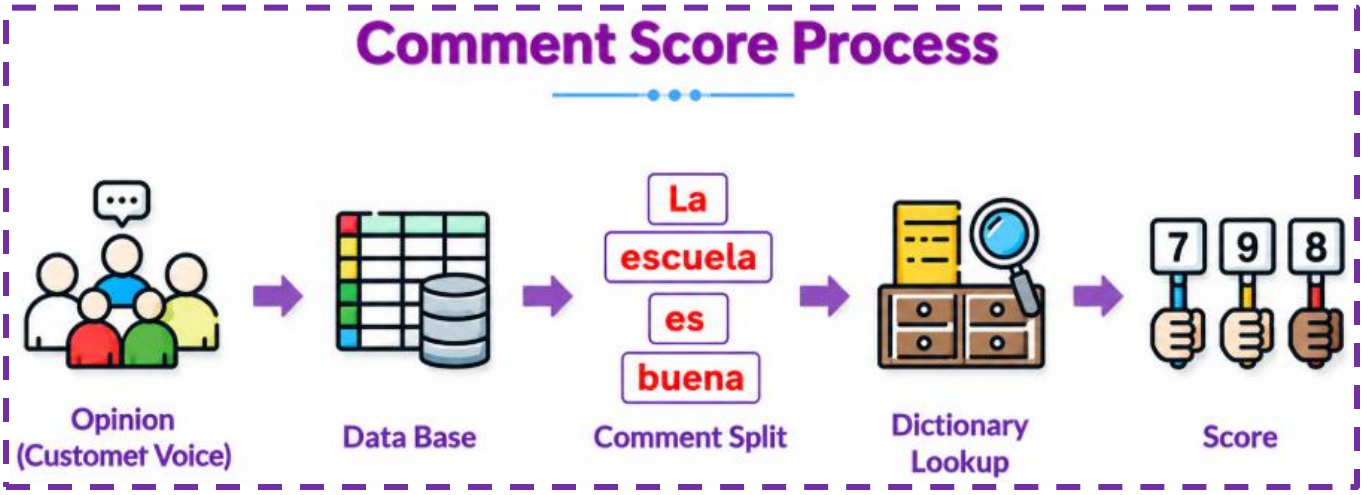

Figure 1: Comment Score Process

Table 1: Structural example of the database

Opinion ID	Date	Commentary
1	22/7/2026 0:03:06	Las clases son muy interesantes.

Step 2: Once the students' comments have been collected, it is time to analyze their content to score them. For this purpose, the BERT (Bidirectional Encoder Representations from Transformers) algorithm is used. Said algorithm is a pre-trained model developed by Google that has demonstrated its effectiveness in natural language processing tasks due to its bidirectional analysis capacity in texts (Devlin et al., 2019). But how does BERT work?

Each comment is divided by words, these smaller units are called tokens. This process is crucial because the BERT model analyzes word-by-word (and even sentence-by-sentence).

Mathematically:

$$\text{Tokenize}(C_i) = \{t_{i1}, t_{i2}, \ldots, t_{im}\} \qquad (1)$$

For example, for the comment “Las clases son muy interesantes”, the token set could be {“Las”, “clases”, “son”, “muy”, “interesantes”}.

After the comments are tokenized, each token is converted into a numerical representation; that is, they are encoded capturing both the meaning of the words and their context in the sentence.

The process described above involves assessing the sentiment associated with each comment, which can be positive, negative or neutral.

To calculate the total score for each comment, we make use of the following equation:

$$S(C_i) = \frac{1}{m}\sum_{j=1}^{m} s(t_{ij}) \qquad (2)$$

In Equation 2, “m” represents the number of tokens in the comment “C_i” and “$s(t_{ij})$” is the sentiment score corresponding to the token “t_{ij}”. As an example to our comment “The classes are very interesting” we obtain the following scores: {“Las”=0, “clases”=0.2, “son”=0, “muy”=0.5, “interesantes”=0.8}. Therefore, the sentiment score for the total comment would be:

$$S(C_i) = \frac{1}{5}(0 + 0.2 + 0 + 0.5 + 0.8) = 0.3 \qquad (3)$$

In this section we emphasize the monosyllable “muy”. The dictionary on which we base the punctuation of Spanish words does not consider the superlatives.

As can be seen in the example of equation 3, we have considered the called superlatives. A superlative is considered as a grammatical form used to express the highest degree of a quality.

Step 3: To give value to each token (word) we made use of a dictionary marked with emotions and weighted for the Spanish language. This dictionary was designed under basic emotional categories: joy, anger, fear, sadness, surprise and repulsion in Spanish language.

Step 4: The valuation of each word was labeled using percentages of probability of being used under an emotional sense. We use a measure that gives the words a weight factor, the affective use probability factor (APF).

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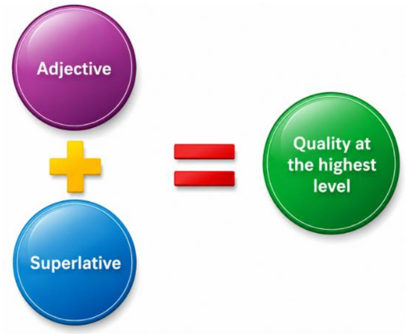

Figure 2: Purpose of superlative

For the above there are two forms of expression:

a) Absolute superlative: it results from the addition of suffixes "ísimo/a/os/os/as" to the adjective. Although it can also be formed by using adverbs such as "muy", "sumamente", "extremadamente" before the adjective (this is the superlative used in the example).
b) Relative superlative: compares an element with all the others in its group by using the words "the more/the more/less" followed by the adjective.

That is, to the dictionary consulted we add superlatives that, under the context of each comment, would act as enhancers of an emotion granting a feeling with more strength and that, therefore, would mean a higher score to that comment that could lead to positivism or negativism of the scale.

To make clear the inclusion of superlatives as enhancers of the sentiment given by a word, we created a sentimetometer. This instrument consists of a visual tool that represents the sentiment scores implicit in the comments, which allows for an effective and accurate assessment of the sentiment that students wish to express. Figure 3 shows the sentimetometer.

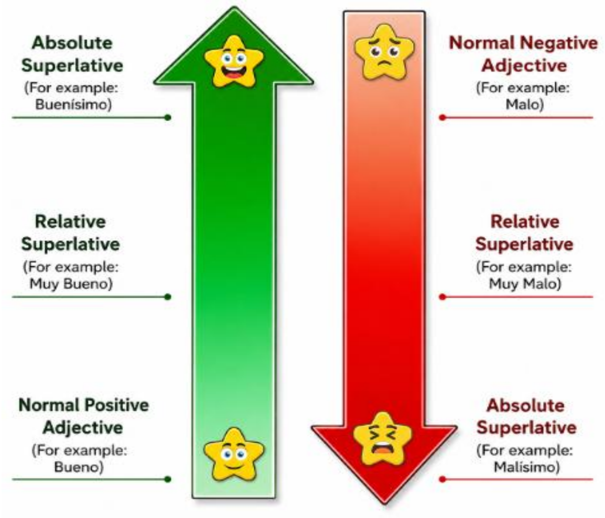

Figure 3: Sentimetometer

In conclusion, the main purpose of a superlative is to maximize the gradation of the adjective and thus give greater emphasis to the quality we want to express. For example, "buenísimo" is the highest gradial expression of "bueno" and the same for negative expressions, they give more strength to adjectives.

It is worth mentioning that the implementation of superlative detection will allow the algorithm to classify comments more accurately and thus ensure a decrease in false positives or false negatives.

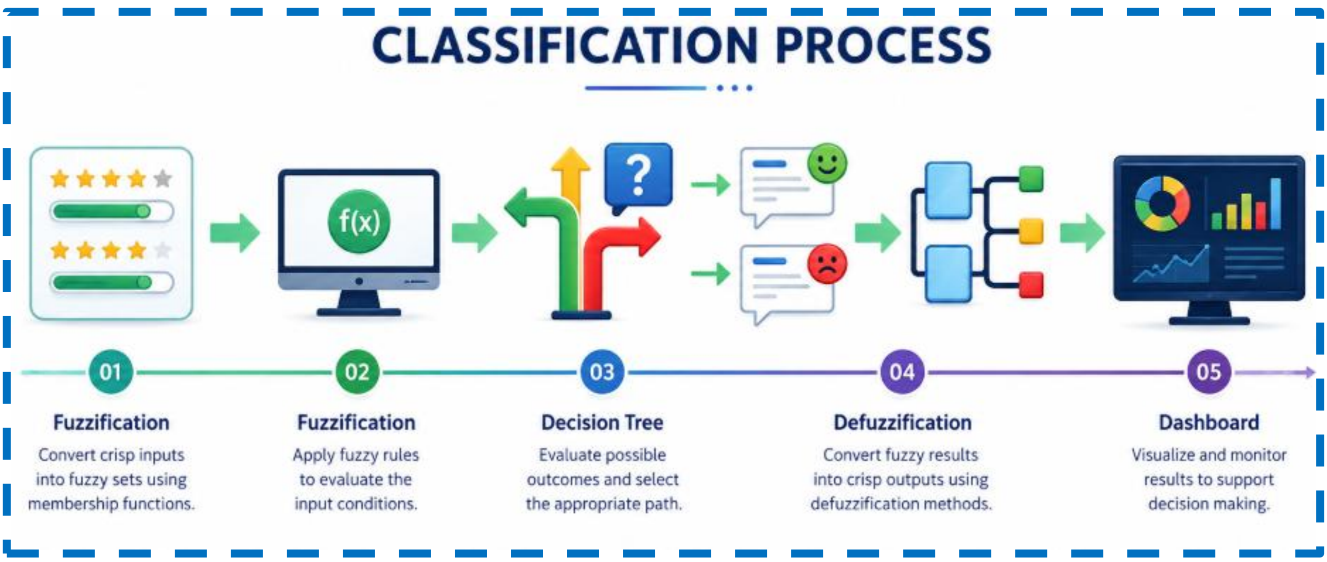

Figure 4: Classification Process

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Once the comments have been quantified with respect to their location in the sentimetometer, it is time to apply the classification process to now also classify by sentiment and by the area to which each comment is oriented. The first step is fuzzification, which consists in the manipulation of partial truth concepts working with degrees of freedom instead of a sharp classification. We define fuzzy input and output variables:

a) Input variables: words from student comments converted into fuzzy linguistic variables, e.g., "queja", "elogio".
b) Output variables: the constituent areas of the academic institute, e.g., "Administración", "Becas", "Biblioteca".

In other words, relevant and meaningful information is first extracted from the comment. The goal is to identify characteristics such as:

a) Overall sentiment
b) Emotional intensity
c) Presence of positive words
d) Presence of negative words
e) Topic of the comment
f) Length
g) Level of satisfaction
h) Polarity

It is crucial to identify and interpret the emotions that are indirectly conveyed in the comments, as well as the overall tone of the review, so that the classification accurately reflects the customer's intended meaning. The dictionary we have created will allow us to rate the intensity of the words used.

For example, based on the comment in Figure 1, "La escuela es buena", the following information was obtained:

Table 2: Variables extracted from a comment

Variable	Result obtained
Sentiment	Positive
Positivity	0.85 ~ 0.95
Negativity	0 ~ 0.10
Emotion	Satisfaction
Topic	Institution Quality

After that, it is necessary to apply the rules that will represent human interpretation and that will fully define the classification of the comment. It is important to note that several rules may apply at the same time, especially when there is a "but" in the comment.

In practice, the analysis of comments is based on the following criteria:

1. Sentiment: This analyzes whether the comment is positive, negative, or neutral.
2. Positivity: This measures how positive the opinion is based on a scale.
3. Negativity: This measures how negative the opinion is, but it's important to note that it is not the opposite of positivity, since some comments are classified as neutral.
4. Emotion: This identifies the predominant human emotion.
5. Topic: This identifies the subject being discussed.

Finally, the results are stored so that indicators and metrics such as the following can be viewed via a dashboard:

a) Percentage of positive comments.
b) Percentage of negative comments.
c) Frequent topics.
d) Periodic trends.
e) Recurring issues.
f) Satisfaction by region.
g) Satisfaction by product and/or service.
h) Predominant emotions.
i) Trends.

Below is a step-by-step guide to categorising the comment in Spanish:"La escuela tiene excelentes profesores, pero el proceso de inscripción fue demasiado lento."

1. Each comment is stored in a database. Figure 5 shows the Python code for this process:

```
database = [
    {
        "id": 1,
        "comment": "La escuela tiene excelentes..."
    }
]
```

Figure 5: Database

2. After that, each comment is split into individual words. Figure 6 shows the Python code for this process:

```
import re

comment = "La escuela tiene excelentes profesores ..."

words = re.findall(r'\b[\wáéíóúüñ]+\b', comment.lower())

print(words)
```

Figure 6: Word segmentation process

3. It is important to bear in mind that not all words carry the same weight in sentiment analysis. Figure 7 shows a breakdown of some of the words in the sentence used at the start of the example, along with the validation for each one.

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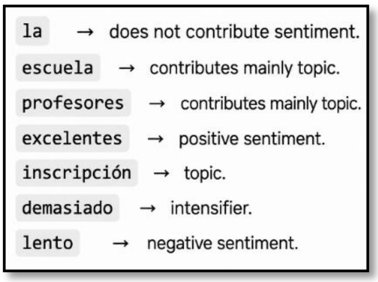

Figure 7: Interpretation and evaluation of words

4. The next step is to read through the comments in order to assess each word. It is important here to take into account intensifiers and superlatives, as these can heighten or dampen the sentiment and emotion conveyed in each comment. To do this, we use a Spanish-language lexical dictionary that was created specifically for this project. It is worth noting that the intensifiers and superlatives included are those that are commonly used in the Spanish language.The dictionary created contains the following elements:

- ✓ Positive and negative words
- ✓ Polarity from -1 to +1
- ✓ Intensifiers: muy, demasiado, extremadamente, súper, etc.
- ✓ Mitigators: algo, ligeramente, poco, etc.
- ✓ Negatives: no, never, ever, etc.
- ✓ Superlatives: buenísimo, lentísimo, pésimo, rapidísimo, etc.
- ✓ Adversative connectors: pero, sin embargo, aunque, etc.
- ✓ Emotion: satisfacción, frustración, enojo, decepción, alegría, etc.
- ✓ Topic: profesores, inscripción, administración, infraestructura, tecnología, atención, etc.
- ✓ Headword for each term to enable word standardisation.
- ✓ A column of usage notes to explain how to interpret each type.

Table 3 shows an example of the list of words that make up the dictionary. If you wish to download the complete dictionary, it is available at the following link: https://tinyurl.com/LexicalDictionary

In the example under analysis, we can identify two predominant expressions:

a) "Excelentes maestros"; for the word 'Excelentes', we have a weighting of +1.0
b) "Demasiado lento"; here, intensifiers are used as multiplicative factors; that is to say, 'Demasiado' would have a weighting of 1.25 and 'Lento' a value of -1. Therefore, the expression would be weighted as -1.25.

Adding both weights together gives us P = -0.25. This allows us to conclude that the negative expression has slightly greater intensity.

The final step is to assign a score to the overall expression. This score must satisfy the following condition: 0 <= Score <= 100, and we use the following expression:

$$Score = 50 + 50P \qquad (4)$$

Table 3: Lexical dictionary of Spanish terms and expressions

Term	Type	Polarity	Multiplier	Sentiment	Emotion	Topic
excelente	sentiment_word	1.00	1.00	positive	satisfacción	calidad
pésimo	sentiment_word	-1.00	1.00	negative	enojo	calidad
lento	sentiment_word	-0.70	1.00	negative	frustración	tiempo
muy	intensifier	0.00	1.25	modifier	—	general
demasiado	intensifier	0.00	1.35	modifier	—	general
ligeramente	attenuator	0.00	0.60	modifier	—	general
buenísimo	superlative	0.95	1.00	positive	alegría	general
lentísimo	superlative	-0.95	1.00	negative	frustración	general
no	negation	0.00	-1.00	modifier	—	general
pero	contrast_connector	0.00	1.25	modifier	—	general
profesores	topic_term	0.00	1.00	neutral	—	docentes
inscripción	topic_term	0.00	1.00	neutral	—	administración

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Applying formula 4 gives us a result of 37.5%, which is interpreted to mean that the negative aspect of the comment carries slightly more weight or leans more towards that sentiment, in contrast to the positive aspect of the comment.

At this stage, we already have the comment ranked with a unique value. It is now time to carry out the classification process, following the steps shown below:

For fuzzification, we need to define three sets that will help us categorise the measure with which we began this process (the score). We define the low level as 0 to 30, the medium level as 31 to 70 and the high level as 71 to 100. We will refer to these levels as membership functions.

For the lower membership function, we define the following mathematically:

$$\mu_{lower} = \begin{cases} 1 & x \le 30 \\ \dfrac{50 - x}{20} & 30 < x < 50 \\ 0 & x \ge 50 \end{cases} \qquad (5)$$

For the score obtained (37.5), we are left with:

$$\mu_{lower}\,(x) = \frac{50 - x}{20}$$

$$\mu_{lower}\,(37.5) = \frac{50 - 37.5}{20}$$

$$\mu_{lower}\,(37.5) = 0.625$$

This is interpreted to mean that the comment analysed shows a 62.5% tendency towards the low level established at the outset.

For the medium membership function, we define the following mathematically:

$$\mu_{medium} = \begin{cases} 0 & x \le 30 \\ \dfrac{x - 30}{20} & 30 < x < 50 \\ \dfrac{70 - x}{20} & 50 \le x < 70 \\ 0 & x \ge 70 \end{cases} \qquad (6)$$

In the case of the example, the result would be μ_{medium} = 0.375.

For the higher membership function, we define the following mathematically:

$$\mu_{higher} = \begin{cases} 0 & x \le 50 \\ \dfrac{x - 50}{20} & 50 < x < 70 \\ 1 & x \ge 70 \end{cases} \qquad (7)$$

In the case of the example, the result would be μ_{higher} = 0. The next step is to apply the fuzzification rules:

1. If the score is low, the sentiment is negative.
2. If the score is medium, the sentiment is neutral.
3. If the score is high, the sentiment is positive.

Figure 8: Customer Voice Dashboard

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In this example, the comment is 62.5% negative, 37.5% neutral and 0% positive. We then proceed to defuzzification using the mathematical technique of weighted averaging, assigning a value of 25 to negative, 50 to neutral and 75 to positive. Calculating the weighted average:

$$Output = \frac{(0.625)(25) + (0.375)(50) + (0)(75)}{0.625 + 0{,}375 + 0}$$

$$Output = 34.47\%$$

This tells us that the comment can be classified as neutral but with a negative slant, as it leans more strongly towards that classification. We can therefore conclude that attention span is an area with potential for improvement.

Figure 8 shows the Voice of the Customer Dashboard, which provides a visual and summarised overview of the key findings from the analysis of numerous comments made by the school community regarding the services and support they receive at the school. It incorporates sentiment indicators, as well as the identification of recurring themes, areas requiring attention, areas of opportunity and areas of outstanding performance.

Through charts, indicators and trends, it enables a quick assessment of what is working well, which aspects require attention and how customer opinions evolve over time. Its main value lies in transforming large volumes of feedback into actionable information for decision-making. Ratherthan reviewing each piece of feedback individually, managers can quickly identify:

- ✓ Strengths: areas of high satisfaction.
- ✓ Areas for attention: recurring problems or negative experiences.
- ✓ Areas of opportunity: aspects that can be improved.
- ✓ Trends: changes in customer perception throughout the time.
- ✓ Priority topics: issues that attract the highest number of comments.
- ✓ Impact: where resources and improvement measures should be directed.

Therefore, the dashboard not only displays data but also functions as a Business Intelligence tool to transform the Voice of the Customer into concrete decisions for improvement.

IV. CONCLUSION

This paper introduces an intelligent system for the accurate interpretation and classification of the 'Voice of the Customer' (VoC) in educational settings, overcoming the difficulties posed by the ambiguity, subjectivity and lack of structure inherent into natural language. By using a hybrid approach combining the BERT algorithm for contextual tokenisation, a lexical dictionary adapted to Spanish and fuzzy logic it has been possible to correctly model the emotional intensity conveyed by students' opinions.

One of the most interesting contributions of this model is the inclusion of intensifiers and superlatives (absolute and relative) in the lexical analysis, reflected in the Sentimetometer. These allowed high-impact adjectives (for example, 'really great' or 'really slow') and adversative connectors to be weighted more correctly and reduce significantly the number of false positives and false negatives in the assignment of polarity scores.

In addition, the application of membership functions during the fusion phase and their subsequent defusion using weighted averaging proved absolutely effective in classifying ambiguous or mixed comments (for example the example analysed with the 37.5% scoring formula, resulting in a 62.5% inclination towards a low level and finally classified as neutral with a negative bias).This type of quantitative detail allows the institution to correctly assess not only the direction of opinion, but also the degree of user dissatisfaction or satisfaction.

Finally, the inclusion of these results in the Voice of the Customer dashboard makes it possible to transform large amounts of unstructured text into a Business Intelligence resource. By consolidating metrics on overall sentiment, by subject area (such as lecturers or enrolment processes) and periodic trends, it can provide senior management with a clear and immediate overview for strategic decision-making, funneling institutional resources to solve recurring issues and consolidating its operational and academic strengths.

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Through this message, we wish to express our most sincere gratitude to our beloved institution for the constant support that it has provided to us. The academic excellence as well as the solid educational foundation that the IPN has provided us with, throughout our journey, are the pillars that have allowed us to base our professional and personal development.

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REFERENCES

[1] Z. Nasim, Q. Rajput, and S. Haider, "Sentiment analysis of student feedback using machine learning and lexicon based approaches," *in Proc. 2017 5th Int. Conf. Research and Innovation in Information Systems (ICRIIS)*, 2017, pp. 1–6, doi: 10.1109/ICRIIS.2017.8002475.

[2] X. Chen, H. Xie, D. Zou, and G. J. Hwang, "Application and theory gaps during the rise of Artificial Intelligence in Education," *Computers and Education: Artificial Intelligence*, vol. 1, Art. no. 100002, 2020, doi: 10.1016/j.caeai.2020.100002.

[3] J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," *in Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics: Human Language Technol., Minneapolis, MN, USA*, Jun. 2019, pp. 4171–4186.

[4] E. Zaitseva, B. Tucker, and E. Santhanam, Eds., Analysing Student Feedback in Higher Education Using Text-Mining to Interpret the Student Voice. *London, U.K.: Routledge*, 2022.

[5] C. N. Dang, M. N. Moreno-García, and F. de la Prieta, "Hybrid deep learning models for sentiment analysis," *Complexity*, vol. 2021, Art. no. 9986920, 2021, doi: 10.1155/2021/9986920.

[6] L.-G. Moreno-Jiménez, J.-M. Torres-Moreno, H. Boucheneb, and R. S. Wedemann, "FLE: A fuzzy logic algorithm for classification of emotions in literary corpora," *in Proc. 12th Int. Joint Conf. Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K)*, 2020, pp. 202–209, doi: 10.5220/0010110902020209.

[7] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications: A survey," *Ain Shams Engineering Journal*, vol. 5, no. 4, pp. 1093–1113, 2014.

[8] B. Pang and L. Lee, "Opinion mining and sentiment analysis," *Foundations and Trends in Information Retrieval*, vol. 2, no. 1–2, pp. 1–135, 2008.

[9] J. Using Sentiment Analysis, "Using sentiment analysis to analyze the feedback of students with open-ended questions," *Journal of Humanities and Social Sciences*, 2020.

[10] L.-G. Moreno-Jiménez, J.-M. Torres-Moreno, H. Boucheneb, and R. S. Wedemann, "FLE: A fuzzy logic algorithm for classification of emotions in literary corpora," *in Proc. 12th Int. Joint Conf. Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K)*, 2020, pp. 202–209, doi: 10.5220/0010110902020209.

[11] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, no. 3, pp. 338–353, 1965.

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