Sentiment-Enriched AI for Toxic Speech Detection: A Case Study of Political Discourses in the Valencian Parliament

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Abstract: The increasing prevalence of toxic speech across various societal domains has raised significant concerns regarding its impact on communication and social interactions. In this context, the analysis of toxicity through AI techniques has gained prominence as a relevant tool for detecting and combating this phenomenon. This study proposes a novel approach to toxic speech detection by integrating sentiment analysis into binary classification models. By establishing a confusion zone for ambiguous probability scores, we direct uncertain cases to a sentiment analysis module that informs final classification decisions. Applied to political discourses in the Valencian Parliament, this sentiment-enriched approach significantly improves classification accuracy and reduces misclassifications compared to traditional methods. These findings underscore the effectiveness of incorporating sentiment analysis to enhance the robustness of toxic speech detection in complex political contexts, paving the way for future research in this relevant area.

1 INTRODUCTION

The growing prevalence of toxic speech across diverse societal domains has become a significant concern due to its harmful effects on communication, social cohesion, and trust within communities. Toxic speech, characterized by offensive, inflammatory, or demeaning language, not only disrupts civil discourse but also fosters polarization, harassment, and exclusion (Buitrago López et al.,). In an era where digital platforms amplify such speech and where transcripts of public interactions are increasingly available, the urgency of developing robust mechanisms for detecting and mitigating toxic content has escalated.

Artificial intelligence has emerged as a powerful tool in this context, enabling automated detection and analysis of toxic speech (Chhabra and Vishwakarma, 2023). Traditional binary classification models have been widely used for this task, offering a straightforward approach to categorizing content as toxic or non-toxic. However, these models often face limitations when confronted with ambiguous cases—instances where the likelihood of toxicity is unclear (Islam et al., 2021). This ambiguity, which typically occurs when a speech's toxicity is contextually or sentimentally nuanced, can lead to misclassification, hindering efforts to foster healthier communication, especially in complex environments such as political discourse.

To overcome these challenges, this study presents a novel framework that enhances toxic speech detection by incorporating sentiment analysis into conventional binary classification models. By defining a "confusion zone" for ambiguous classification probabilities, our approach directs uncertain cases to a sentiment analysis module. This added layer of contextual understanding helps refine classification decisions, ensuring greater accuracy in identifying toxic content.

Our methodology is particularly tailored to political discourse, where the impact of toxic language is profound, influencing public perception, societal norms, and behavior. We apply this approach to

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speeches from the Valencian Parliament, a bilingual legislative body, to evaluate its effectiveness in detecting nuanced toxic speech in a politically charged environment. By improving accuracy and reducing misclassification, this research contributes to ongoing efforts to enhance the detection of toxic speech and promote more respectful and constructive communication in complex social contexts.

2 RELATED WORK

The detection of toxic speech—defined as language that is rude, disrespectful, or likely to disrupt conversations and alienate users (Arab and Díaz, 2015)—has become increasingly important in the digital era, where online discourse is widespread and often volatile. Toxic speech detection has evolved significantly, starting with basic rule-based systems and keyword filtering approaches. These early methods struggled to capture the nuances of language, often leading to high rates of false positives and negatives, as they were unable to understand context or infer meaning from subtle linguistic cues (Bonetti et al., 2023).

The introduction of machine learning represented a major leap forward, with models like Support Vector Machines and Naive Bayes improving detection accuracy by leveraging features extracted from text, such as word frequencies and n-grams (Subramanian et al., 2023). While these models offered better generalization than rule-based approaches, they still encountered difficulties when dealing with more complex, context-dependent cases of toxicity.

The rise of deep learning further revolutionized the field, offering more sophisticated techniques for detecting toxic speech. Convolutional Neural Networksand Recurrent Neural Networks became popular for their ability to automatically learn and represent features from raw text data (Garg et al., 2023). Models like Long Short-Term Memory networks and Transformer-based models such as Bidirectional Encoder Representations from Transformers (BERT) have proven especially effective by capturing intricate semantic relationships and understanding the subtleties of language (Malik et al., 2021). However, despite their improved performance, these models are resource-intensive, requiring large annotated datasets and significant computational power to train and finetune (Subramanian et al., 2023).

One of the most pressing challenges in toxic speech detection is the multilingual and culturally nuanced nature of global communication. Toxicity is contextually dependent not only on language but also on cultural values and norms, making cross-linguistic detection particularly complex (Leite et al., 2020). Recent studies have shown that sentiment analysis can be an effective tool for addressing these challenges, especially in multilingual contexts. For example, research by Proksch et al. (Proksch et al., 2019) demonstrated how sentiment analysis applied to legislative debates across different languages could capture underlying political conflicts and nuances, suggesting that sentiment-aware models could enhance toxicity detection by providing additional contextual information.

Despite these advances, handling ambiguous cases in toxicity detection remains a significant challenge. Ambiguity often arises when language is neither clearly toxic nor benign, complicating classification efforts. Sheth et al. (Sheth et al., 2022) highlighted the difficulty of defining the boundaries between toxic and non-toxic speech, while Subramanian et al. (Subramanian et al., 2023) discussed the limitations of current models in addressing these borderline cases. Approaches such as multi-channel CNNs have been proposed to address this issue, but accurately classifying ambiguous content continues to pose difficulties.

Building on these advancements, our proposed methodology integrates sentiment analysis with traditional binary classification models to address the challenge of ambiguous cases. By introducing a confusion interval for uncertain toxicity scores, our model redirects these cases to a sentiment analysis module, which enriches the classification process with additional emotional and contextual information. This dual-layered approach improves the robustness and accuracy of toxic speech detection, particularly in complex, politically charged environments where nuance and sentiment play a critical role.

3 PROPOSAL ARCHITECTURE

To ensure robust and accurate detection of toxic speech, we propose a comprehensive, modular framework that integrates multiple components to enhance the precision, adaptability, and reliability of toxicity inference. This architecture is designed to handle the challenges posed by complex, multilingual, and nuanced content, making it well-suited for both digital platforms and politically charged environments. The following section details the methodology and system architecture, which together form the backbone of our proposed solution.

3.1 Data Acquisition Module

The first step in the process is the *Data Acquisition Module*, which is responsible for the automatic retrieval of textual data from diverse sources, including digital platforms (social media, online forums) and transcriptions of spoken interactions (e.g., parliamentary debates). This module is designed to process various types of input data, ensuring scalability and adaptability to different environments and languages. By encompassing multiple sources, it allows the framework to operate on both real-time streams and historical archives, making it applicable to a wide range of use cases, from online content moderation to retrospective analysis of political speeches.

The acquisition process includes mechanisms to handle noise in the data, such as filtering non-relevant content and pre-processing steps like tokenization and removal of stop words. This ensures that only pertinent text data are fed into subsequent modules, improving the overall efficiency and accuracy of the system.

3.2 Language Unification Module

Given the multilingual nature of modern discourse, particularly in political settings such as the Valencian Parliament, the *Language Unification Module* plays a crucial role in standardizing text data before further processing. This module automatically detects the language of incoming text and translates it into a unified language format (in this case, Spanish), enabling consistent and reliable analysis.

The challenge of multilingual text is twofold: lexical variations across languages and the differing cultural connotations of certain words. The Language Unification Module addresses both by leveraging state-of-the-art machine translation models that are sensitive to context. This ensures that translations maintain the semantic integrity of the original speech, preserving subtle nuances that are essential for accurate toxicity detection. By addressing linguistic discrepancies at this early stage, the framework is able to avoid errors that might arise from handling multiple languages simultaneously, ensuring a more coherent and reliable toxicity assessment downstream.

3.3 Toxic Detection Module

The *Toxic Detection Module* serves as the core component of the framework, responsible for evaluating the toxicity of the standardized text. This module utilizes advanced AI techniques, specifically binary classification models, to determine whether a given piece of text is likely to be toxic. In this study, we employed the pre-trained Detoxify model (Hanu and Unitary, 2023), which has demonstrated strong performance in various toxic speech detection tasks.

Detoxify assigns a probability score to each text sample, representing the likelihood that the content is toxic. A score close to 0 indicates non-toxic content, while a score closer to 1 suggests toxic speech. However, despite its effectiveness, the module can sometimes produce ambiguous results, especially when the probability score falls within a certain range where the classification is not definitively clear. To address this, we introduce a predefined "confusion zone," typically ranging between 42% and 58%. Texts with scores within this zone are neither clearly toxic nor clearly non-toxic, indicating a need for further analysis to reach a confident conclusion.

This confusion zone is particularly relevant in the context of political discourse, where language is often nuanced and may involve sarcasm, rhetorical devices, or indirect speech. Such complexities can make it difficult for the model to assign a clear classification, resulting in borderline cases. To handle these, the system flags these texts for additional processing by the Sentiment Analysis Module, which provides further contextual understanding to improve classification accuracy.

3.4 Sentiment Analysis Module

To handle these uncertain cases, we introduce a second layer of analysis: the *Sentiment Analysis Module*. Once a text is flagged by the Toxic Detection Module as ambiguous, it is redirected to this module for further evaluation. The Sentiment Analysis Module performs a deeper analysis of the emotional tone, providing additional context to aid in the final classification.

By assessing the emotional valence of the text, the sentiment analysis adds a nuanced layer of interpretation that binary classifiers typically overlook. For instance, a politically charged statement with a highly negative sentiment score is more likely to be toxic, even if the initial classifier was uncertain. On the other hand, a text with low sentiment intensity may indicate sarcasm or rhetorical neutrality, reducing the likelihood of it being classified as toxic.

This dual-layered approach—combining toxicity classification with sentiment analysis—enables the system to handle complex and ambiguous language more effectively. Texts with strong negative sentiment are reclassified as toxic, while those with more neutral or positive sentiment are deemed non-toxic, thus significantly reducing false positives and negatives in the overall classification process.

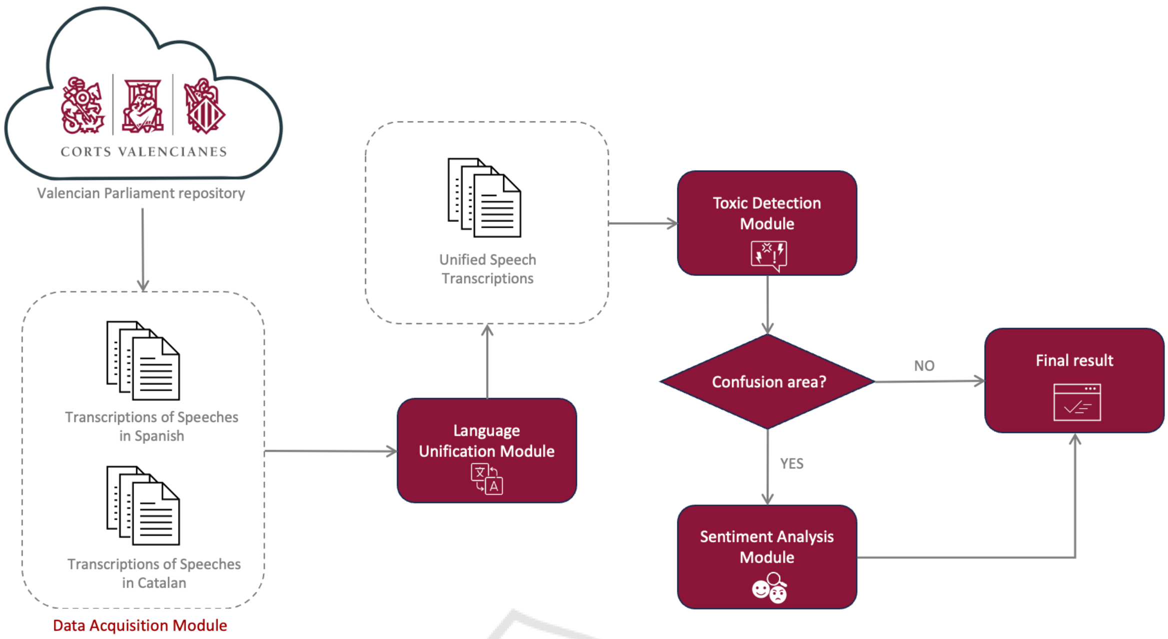


Figure 1: Architecture diagram of the proposed toxic speech detection framework.

3.5 System Integration and Scalability

The integration of the aforementioned modules forms a robust system capable of accurately detecting toxic speech across a wide variety of linguistic and contextual scenarios. The modular design allows for flexibility, as each component can be updated or replaced as new models and techniques become available. For example, the Sentiment Analysis Module can be easily swapped with more advanced models like transformer-based sentiment classifiers as they evolve.

Fig. 1 shows a general schematic of the proposed solution, instantiated with the use case of the Valencian Parliament. The proposed architecture not only addresses the challenges of ambiguous toxicity inference but also paves the way for future advancements in the field of toxic speech analysis.

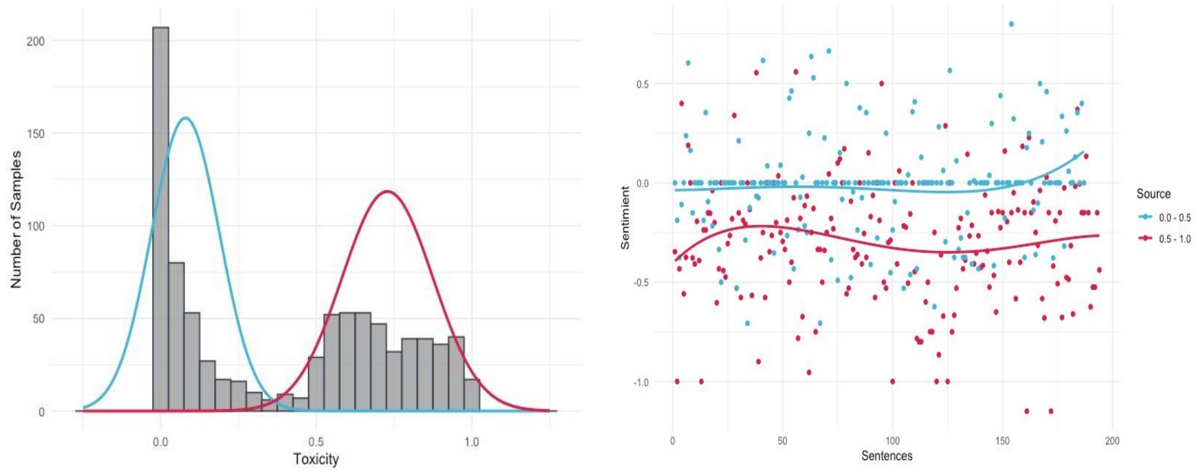
4 CASE STUDY: THE VALENCIAN PARLIAMENT

The Valencian Parliament, known as Les Corts Valencianes, provides an ideal case study for analyzing toxic speech detection, primarily due to its dual-language environment (Spanish and Catalan) and the increasing focus on monitoring political discourse. As a legislative body where formal and respectful discourse is generally expected, parliamentary debates often reflect broader societal trends, including polarized speech and contentious rhetoric. This makes Les Corts a valuable setting for studying the dynamics of toxic speech and its impact on public perception and societal attitudes.

Les Corts Valencianes serves as the legislative body of the Valencian Community in Spain, where both Spanish and Catalan hold official language status. This bilingual context introduces unique challenges for toxic speech detection, as language-specific nuances can affect how speech is perceived. Consequently, robust language processing capabilities are required to accurately assess toxic speech in such a complex setting.

In this study, we applied a combination of the pre-trained Detoxify model (Hanu and Unitary, 2023) and the sentimentR library (Rinker, 2016) to enhance toxicity detection. The Detoxify model was chosen for its strong performance in toxic speech detection, and we integrated sentiment analysis to handle the complexities inherent in political discourse. The combination allowed us to create a more refined system capable of distinguishing between overtly toxic language and subtler, context-dependent forms of toxicity common in political settings.

Our experiment involved analyzing ten plenary sessions from the Valencian Parliament. The speeches were segmented into individual sentences, which were then used as samples for toxicity analysis. The initial toxicity inference using Detoxify revealed that the average level of toxicity across these sessions ranged from 0.50% to 0.89%, indicating a generally



(a) Samples distribution.

(b) Sentiment analysis results.

Figure 2: Distribution of samples and sentiment analysis results.

low but present occurrence of toxic speech in this formal setting.

For this study, we selected 870 samples, half of which (435) had a toxicity score greater than 50%, indicating a higher likelihood of toxicity. The other half had a toxicity score below 50%. These samples were used to evaluate the performance of our sentiment-enriched approach. The distribution of these samples is shown in Fig. 2a, while the results of the sentiment analysis are depicted in Fig. 2b.

From these 870 samples, we chose a subset of 80 for manual validation. The remaining samples were divided into intervals based on their toxicity inference, with one group having scores below 0.25 and another above 0.75. Fig. 2b shows two distinct clusters in the sentiment analysis: one centered near a sentiment score of 0 (indicating neutral or non-toxic content) and the other near -0.33 (indicating toxic content).

For validation, we defined a confusion zone for toxicity inference between 42% and 58%, representing ambiguous cases where classification was uncertain. We compared the performance of the Detoxify model alone against our sentiment-enriched model using this confusion zone. A group of three experts (two in philology and one in sociology) manually labeled the samples for further validation.

The results indicated that without the confusion zone, our model achieved an accuracy of 80.35%. However, when the confusion zone was incorporated, along with sentiment reassignment, accuracy improved significantly to 87.89%. This demonstrates the effectiveness of adding a sentiment layer to refine toxic speech detection, particularly in politically charged and linguistically complex contexts such as the Valencian Parliament.

To further benchmark our model, we compared its performance against several other state-of-the-art models, including Logistic Regression, BERT, and HateBERT (Caselli et al., 2021). Table 1 provides a comparison of key performance metrics, including accuracy, precision, recall, and F1-score.

As shown in Table 1, our sentiment-enriched model outperformed baseline models in all metrics, achieving an accuracy of 88%, a precision of 86%, a recall of 87%, and an F1-score of 86%. The inclusion of the confusion zone significantly improved the overall performance, demonstrating the advantage of using sentiment analysis to handle ambiguous cases.

5 CONCLUSION AND FUTURE WORK

In this preliminary study, we introduced a novel approach to toxic speech detection by integrating sentiment analysis into traditional binary classification models. The proposed sentiment-enriched framework significantly enhances the accuracy and robustness of toxicity inference, particularly in handling ambiguous cases where traditional models often struggle. By adding a sentiment analysis layer, our approach offers a more nuanced understanding of the emotional and contextual elements of speech, which is critical in complex and politically charged environments like the Valencian Parliament.

The results from this study underscore the potential of combining toxicity detection with sentiment analysis, especially in domains where language carries significant emotional weight and subtlety, such

Table 1: Comparison of performance metrics across different models. The table compares accuracy, precision, recall, and F1-score for various models, showing the effectiveness of our sentiment-enriched model with and without the confusion zone.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Logistic Regression	0.75	0.72	0.68	0.70
BERT	0.84	0.82	0.83	0.82
HateBERT	0.87	**0.85**	0.86	0.85
Our Model (without confusion zone)	0.80	0.78	0.79	0.78
Our Model (with confusion zone)	**0.88**	0.85	**0.87**	**0.86**

as political discourse. Our method not only improves detection accuracy but also reduces the likelihood of misclassifying borderline cases that often fall within the "confusion zone" of probability scores.

One of the key areas for future improvement is the sentiment analysis component. While the current study utilized the sentimentR library, more sophisticated techniques, such as transformer-based models (e.g., BERT or GPT-like models) specifically fine-tuned for sentiment analysis, could offer significant improvements. Transformer models have shown exceptional capabilities in capturing the intricacies of language, including context, irony, and sentiment polarity, making them ideal candidates for refining this aspect of the framework. Fine-tuning such models on domain-specific datasets, such as political speeches or social media conversations, could further boost accuracy and adaptability.

Another promising direction for future work involves the integration of additional contextual features that go beyond the sentiment of the text itself. For instance, speaker intent, tone, and audience reaction could provide valuable cues for determining toxicity. Analyzing speaker history (e.g., previous inflammatory remarks or speech patterns) and audience engagement (e.g., applause, boos, or online sentiment in response to a speech) could offer deeper insights into whether a statement is likely to be toxic or merely provocative. Leveraging these contextual features could enhance the model's ability to distinguish between different forms of aggressive or inflammatory speech.

A further potential area of research is exploring cross-modal toxicity detection, where textual data is combined with other modalities such as audio, video, or even social media interactions (Maity et al., 2024). In many cases, tone of voice, body language, or visual cues may reveal toxicity that is not explicitly present in the text itself. For example, integrating acoustic analysis from speeches or debates could capture variations in tone that indicate sarcasm, anger, or passive aggression—key indicators of underlying toxicity. Video analysis of facial expressions or gestures could similarly add depth to toxicity inference, particularly in live debates or interviews.

In parallel with advancing technical capabilities, ensuring that these models are explainable and ethically sound is crucial. As toxic speech detection systems are increasingly used in sensitive domains, such as political discourse or online moderation, it is important to make sure that the decision-making process is transparent and justifiable (Mahajan et al., 2021). Further research should explore methods for making these models interpretable, allowing users or moderators to understand why a particular piece of content was flagged as toxic. Incorporating fairness measures to prevent biases related to gender, race, or political ideology will be vital for building trust and ensuring that the models do not inadvertently perpetuate discrimination.

In conclusion, this preliminary study presents a promising approach for improving toxic speech detection by integrating sentiment analysis with binary classification models. While the current implementation has demonstrated success in a political context, particularly within the Valencian Parliament, there are ample opportunities for refinement and broader application. As toxic speech continues to be a pressing issue in both political and digital spaces, advancing this methodology will contribute to fostering healthier communication environments. Through further validation, the integration of advanced sentiment models, contextual features, and multi-modal data, this approach has the potential to lead the way in addressing the challenges of toxic speech detection and promoting constructive dialogue in complex social settings.

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