Unveiling Hope in Social Media: A Multilingual Approach Using BERT

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***Abstract*—This article presents research on the topic of detecting hope speech in English and Spanish on social media platforms. The study explores the significance of hope speech in fostering equality, diversity, and inclusion, as well as its implications for individuals' mental well-being and resilience. Leveraging advanced natural language processing (NLP) techniques, including BERT and transformer models, the research develops robust methodologies for binary and multiclass hope speech detection tasks. The methodology encompasses data preprocessing, model selection, fine-tuning, training, and evaluation stages, aiming to accurately identify expressions of hope across diverse linguistic contexts. Furthermore, the paper discusses the challenges and opportunities associated with analyzing hope speech on social networks, emphasizing the ethical considerations and practical implications for various fields, such as psychology, sociology, and public health. The results demonstrate promising performance in accurately detecting hope speech in both binary and multiclass settings across English and Spanish languages, underscoring the potential of NLP approaches in understanding and promoting positive communication dynamics on social media platforms.**

***Index Terms*—Natural language processing, hope speech, social media, analysis.**

I. Introduction

Nowadays, social networks are an integral part of our lives. People often express their thoughts there. The growth of social networks such as Instagram and Twitter has been driven by their key characteristics: they are quickly adopted, cost-effective, easily accessible, and provide a certain degree of anonymity [5]. These platforms have become an integral part of people's lives, serving not only as spaces for social interaction but also as rich sources of data for various scientific studies, especially in the field of Natural Language Processing (NLP) [8].

Hate speech [18, 3], sentiment analysis, fake news [19] detection, and hope speech identification are pivotal tasks in natural language processing (NLP) [13], aimed at discerning the nuanced aspects of human communication. They are addressed through various models, including traditional machine learning, deep learning [1], and transformer-based approaches. Traditional machine learning methods employ algorithms like SVMs, Naive Bayes, and logistic regression, often relying on handcrafted features. Deep learning techniques, such as recurrent neural networks (RNNs), convolutional neural networks (CNNs), and LSTM networks, excel at capturing intricate patterns in text data. Transformer-based models, exemplified by BERT, have revolutionized NLP tasks by leveraging attention mechanisms and contextual embeddings, achieving state-of-the-art performance in many domains.

Social networks, with their extensive user base and diverse content, provide researchers with unprecedented opportunities to study human behavior and communication models [17]. By analyzing the language used in posts, comments, and messages, researchers can gain insight into various aspects of human psychology, including emotions, relationships, and beliefs [15].

Moreover, social media data allows for real-time insights into social trends, cultural shifts, and public sentiments, making them valuable resources for sociological and psychological research [14]. One area of particular interest in social media analysis is the study of hope. Hope, defined as the expectation of positive outcomes in the future, plays a crucial role in shaping human thoughts, feelings, and actions [6]. On social networks, people often openly express their hopes, dreams, and aspirations, providing researchers with a wealth of data to study.

Hope is when we can anticipate what might happen in the future and what outcomes we expect. It affects our feelings and behavior, even if what we expect may be unlikely. Hope is a positively colored emotion that arises from tense anticipation of the fulfillment of a desired outcome and anticipates the possibility of its achievement; a philosophical, religious, and cultural concept related to understanding the state of a person experiencing this emotional process.

Understanding how hope is expressed and perceived on social networks can provide valuable information about people's well-being and resilience. By studying the language and content of hopeful messages, researchers can identify patterns related to goal setting, mechanisms for overcoming difficulties, and reactions to adversity. Additionally, examining the dynamics of hope in online communities can shed light on factors that contribute to people's ability to cope with setbacks and life challenges.

Furthermore, analyzing hope in social networks can have practical implications for various fields, including psychology, sociology, and public health. For example, identifying linguistic markers of hopelessness or despair in online discourse can help in early detection of mental health problems and facilitate targeted interventions [16]. Similarly, understanding the factors that instill hope and optimism in virtual communities can aid in developing strategies to enhance resilience and well-being in offline settings.

Despite the potential benefits of studying hope in social networks, there are also challenges and limitations to consider.

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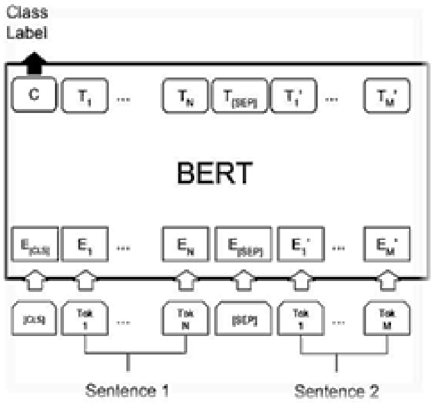

Fig. 1. Example of pre-trained BERT model for sequence classification tasks

For example, the enormous volume of data generated on these platforms poses challenges in terms of data processing and analysis. Moreover, the public nature of interaction on social networks raises ethical concerns regarding confidentiality, consent, and data usage. Researchers must carefully address these issues to ensure that their studies are conducted in accordance with ethical norms such as fear, joy, and depression, and how they communicate with each other, including hostile language.

Over the past few years, several researchers have studied psychological traits and other tasks in social media analysis, such as emotion analysis (fear, anger, happiness, depression), hate speech language, identifying offensive languages, and detecting misogyny using NLP techniques [4]. However, hope speech in social networks is yet to be studied as an NLP task. As far as we know, there are only two available corpora for detecting hope speech: the Hope Speech for Equality, Diversity, and Inclusion (HopeEDI) dataset [9] and the corpus presented by Palakodety, KhudaBukhsh, and Carbonell [11], both of which include multilingual examples in English.

II. Related Work

The paper [6] introduces a novel dataset for hope speech detection in English tweets, marking a significant contribution to the field, as hope has been relatively understudied in social media analysis tasks. The dataset classifies tweets into’ Hope’ and ’Not Hope’ categories, further categorizing hope tweets into three fine-grained classes: ’Generalized Hope’, ’Realistic Hope’, and ’Unrealistic Hope’.

The annotation process employed a rigorous selection of annotators and detailed guidelines, resulting in high inter-annotator agreement scores. Baseline experiments using various learning approaches, including traditional machine learning and deep learning models, highlighted the challenge of multiclass hope speech detection. While simpler machine learning models performed well in binary classification, neural network models, particularly transformers, showed superior performance in multiclass classification. The paper underscores the potential of hope speech detection in various NLP applications and proposes future directions for research, including expanding the dataset size and exploring different languages and social media platforms.

In the paper [12], a convolutional neural network (CNN) model is proposed for the detection of hope speech in short texts, addressing the HOPE 2023 shared task at IberLEF 2023. The study emphasizes the importance of automatically detecting hope speech to mitigate hostile environments and alleviate illnesses like depression. The approach utilizes lexical features and a preprocessing step to handle special characters and tokenization.

By training a 5-layered CNN using Keras, the model aims to learn relevant lexical features related to hope in both Spanish tweets and English YouTube comments. However, the study identifies opportunities for improvement in the datasets, particularly regarding the presence of certain lexical features contradicting the definition of hope speech and issues with incorrect labeling in the English dataset, which contributed to dataset imbalance. The paper contributes to the field by presenting a method capable of learning features associated with hope in short texts, despite the challenges encountered with dataset quality and imbalance. This paper examines an approach using a pretrained BERT model for sequence classification tasks aimed at detecting hope in English and Spanish texts.

III. Methodology

The methodology for detecting hopeful speech in the HOPE datasets in English and Spanish using a pre-trained BERT model for sequence classification is as follows (Figure 1). The model is based on the BERT model, which includes multiple transformer layers, allowing it to effectively capture contextual information from input sequences. The model is configured for sequence classification by adding a classification layer on top of the base BERT model. During training, the model is finetuned for a specific classification task using a labeled dataset.

In the script, the input data is preprocessed by tokenizing text sequences, encoding them into input IDs, and creating attention masks to distinguish real words from padding tokens. The training process involves optimizing model parameters using the AdamW optimizer and a linear learning rate scheduler. The trained model is then evaluated on a separate test dataset, and its performance is assessed using metrics such as accuracy and a classification report. Finally, the predicted labels are mapped back to their original categories and saved to a file for further analysis. The goal of the model is to explore relevant lexical features related to hope in both Spanish tweets and English YouTube comments. However, opportunities for improving the datasets were identified during the study, particularly regarding the presence of certain lexical features contradicting the definition of hopeful speech and issues with incorrect labeling in the English dataset, contributing to dataset imbalance. The work contributes to the field by presenting a method capable of exploring features associated with hope in short texts, despite challenges with data quality and imbalance.

A. *Core Methodology*

The methodology encompasses two primary tasks: binary classification (hope vs. non-hope) and multiclass classification (Generalized Hope, Unrealistic Hope, Realistic Hope). The following steps outline the proposed approach:

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Data Preparation:

1 The dataset comprising English and Spanish tweets is preprocessed to handle text normalization, including tasks such as removing special characters, punctuation, and tokenization.
2 The dataset is divided into training, validation, and test sets for both binary and multiclass classification tasks, ensuring language-wise stratification to maintain data integrity.

Model Selection and Fine-Tuning:

1 BERT (Bidirectional Encoder Representations from Transformers) and transformer-based models are chosen for their effectiveness in capturing contextual information in text.
2 Pretrained BERT models, such as bert-base-multilingual-cased, are fine-tuned on the hope speech detection task using transfer learning. The models are initialized with weights pretrained on large-scale language modeling tasks to leverage their contextual understanding capabilities.
3 For binary classification, the final layer of the BERT model is adapted to a binary classification output, whereas for multi-class classification, modifications are made to accommodate the multiple classes.

Training and Evaluation:

1 The fine-tuned BERT models are trained on the training data for both binary and multiclass classification tasks, employing appropriate loss functions (e.g., binary cross-entropy for binary classification and categorical cross-entropy for multiclass classification) and optimization techniques (e.g., Adam optimizer).
2 Model performance is evaluated on the validation set using evaluation metrics such as accuracy, precision, recall, and F1-score. Hyperparameter tuning may be performed to optimize model performance.
3 The best-performing models are selected based on validation set performance and further evaluated on the test set to assess their generalization capabilities.

B. Extended Methodology

In addition to the core methodology outlined above, several extensions and enhancements can be incorporated to further improve the hope speech detection task:

Language-specific Fine-Tuning: Given the linguistic nuances between English and Spanish, separate fine-tuning of BERT models can be performed for each language to better capture language-specific contextual information. This involves training language-specific BERT models on the respective datasets to enhance classification performance.

Ensemble Learning: Ensemble learning techniques, such as model averaging or stacking, can be employed to combine predictions from multiple BERT and transformer-based models trained with different architectures or pretrained embeddings. This ensemble approach can mitigate the risk of overfitting and improve classification accuracy by leveraging diverse model representations.

Data Augmentation and Balancing: Techniques such as data augmentation, including back translation and synonym replacement, can be utilized to augment the training data and address class imbalances, particularly in the multiclass classification task where certain classes may be underrepresented. Additionally, oversampling or under sampling strategies can be employed to balance class distributions and improve model robustness.

TABLE I
DATA SET IN ENGLISH AND SPANISH LANGUAGES

Train Sets			
Data sets	**Category of data**	**Spanish**	**English**
Binary-Test	Hope	379	541
	Not Hope	773	491
Multiclass-Test	Generalized Hope	206	309
	Realistic Hope	77	124
	Unrealistic Hope	96	108
Test Sets			
Binary-Test	Category of data	2,553	3,634
	Hope	5,500	3,590
Multiclass-Test	Not Hope	1,337	2,026
	Generalized Hope	579	585
	Realistic Hope	637	750

C. Task Overview

The first task [10] centers on fostering Equality, Diversity, and Inclusion by identifying hope speech within Spanish tweets. It addresses the crucial role of hope speech in mitigating hostility and providing inspiration, particularly for vulnerable groups such as the LGTBI community, racial minorities, and individuals with disabilities. Social media interactions significantly shape individuals' perceptions and attitudes towards society, making the detection of hope speech essential for promoting inclusion and support. This task includes two subtasks:

1.a. focuses on detecting hope speech within the LGTBI domain, while 1.b extends the analysis to identify hope speech in unknown domains.

The second task [7] delves into the concept of hope as expectations and aspirations, exploring its impact on individuals' mental states and behaviors within English and Spanish texts. It acknowledges the significance of social media plat forms in shaping individuals' expressions and provides insights into well-being and goal-directed behaviors. This task involves binary and multiclass hope speech detection, aiming to distinguish between expressions of hope and non-hope across various domains. Subtask 2.a focuses on binary hope speech detection, while Subtask 2.b expands the classification to include multiple categories of hope speech.

D. Datasets

The dataset consists of two collections of data, one in Spanish and the other in English, which were collected from 2019 to 2022 [10].

The table provides an overview of the dataset used in the study, categorized into train and test sets for binary and multiclass hope speech detection tasks in both Spanish and English.

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TABLE II
APPLICATION RESULTS OF THE PROPOSED MODEL

Tasks	M Pr	M Re	M F1	W Pr	W Re	W F1	Acc
PolyHope Binary (English)	0.848	0.844	0.845	0.848	0.846	0.846	0.846
PolyHope Multiclass (English)	0.642	0.668	0.652	0.732	0.718	0.723	0.718
PolyHope Binary (Spanish)	0.802	.0814	0.807	0.831	0.826	0.828	0.826
PolyHope Multiclass (Spanish)	0.642	0.645	0.640	0.793	0.788	0.789	0.788

TABLE III
COMPARISON OF THE RESULTS OF APPLYING SIMILAR METHODS (ON ENGLISH DATASET)

2*Methods	**PolyHope Binary**							**PolyHope Multiclass**						
	M Pr	**M Re**	**M F1**	**W Pr**	**W Re**	**W F1**	**Acc**	**M Pr**	**M Re**	**M F1**	**W Pr**	**W Re**	**W F1**	**Acc**
Method 1	0.846	0.845	0.846	0.846	0.846	0.846	0.846	0.665	0.678	0.671	0.743	0.736	0.739	0.736
Method 2	0.846	0.845	0.846	0.846	0.846	0.846	0.846	0.665	0.678	0.671	0.743	0.736	0.739	0.736
Proposed method	0.848	0.844	0.845	0.848	0.846	0.846	0.846	0.642	0.668	0.652	0.732	0.718	0.723	0.718
Method 3	0.736	0.737	0.736	0.737	0.736	0.737	0.736	0.543	0.442	0.453	0.575	0.586	0.560	0.586

The train sets include counts of samples labeled as “Hope” and “Not Hope” for binary classification and further divided into “Generalized Hope, “Realistic Hope,” and “Unrealistic Hope” for multiclass classification. Similarly, the test sets display the distribution of samples across the same categories for evaluation. For instance, the binary test set contains a total of 2,553 “Hope” samples and 5,500 “Not Hope” samples in Spanish, and 3,634 “Hope” samples and 3,590 “Not Hope” samples in English. Likewise, the multiclass test sets show the counts for each subclass within the “Hope” category for both languages.

IV. RESULTS

Table 2 shows the results of applying the proposed model to English and Spanish datasets. In the English binary hope speech detection task, the model achieved precision, recall, and F1-score of 0.848, 0.844, and 0.845 respectively. The weighted precision also stands at 0.848, with recall and F1-score at 0.846, indicating a well-balanced performance across classes. Similarly, in the English multiclass hope speech detection task, the model attained precision, recall, and F1-score of 0.642, 0.668, and 0.652. The weighted precision, recall, and F1-score were 0.732, 0.718, and 0.723 respectively. Transitioning to the Spanish dataset, the binary hope speech detection model exhibited precision, recall, and F1-score of 0.802, 0.814, and 0.807. The weighted precision, recall, and F1-score were also 0.831, 0.826, and 0.828 respectively. For the multiclass hope speech detection in Spanish, the precision, recall, and F1-score were 0.642, 0.645, and 0.640. The weighted precision, recall, and F1-score stood at 0.793, 0.788, and 0.789 respectively.

Transitioning to the Spanish dataset, the binary hope speech detection model exhibited precision, recall, and F1-score of 0.802, 0.814, and 0.807. The weighted precision, recall, and F1-score were also 0.831, 0.826, and 0.828 respectively. For the multiclass hope speech detection in Spanish, the precision, recall, and F1-score were 0.642, 0.645, and 0.640. The weighted precision, recall, and F1-score stood at 0.793, 0.788, and 0.789 respectively.

The model’s performance in accurately identifying hope speech in both binary and multiclass settings across two languages is demonstrated in the table, with reasonably high precision, recall, and F1-scores.

Metrics used for assessing the results include Macro Precision (M Pr), where precision for each class is calculated independently and then averaged to obtain the macro-precision; Macro Recall (M Re), where recall for each class is calculated independently and then averaged to obtain the macro-recall; and Macro F1-score (M F1), where F1-score for each class is calculated independently and then averaged to obtain the macro-F1-score. Additionally, Weighted Precision (W Pr), Weighted Recall (W Re), and Weighted F1-score (W F1) were utilized. In this context, precision, recall, and F1-scores are calculated for each class independently and then weighted by the number of examples of each class to obtain the respective weighted metrics. These evaluations are performed for both binary and multiclass classification tasks, allowing assessment of the model’s accuracy, recall, and balance across different classes.

E. *Analysis of the Use of Similar Methods*

To assess the effectiveness of the chosen model, a comparison of the results obtained from applying various methods on English and Spanish datasets, focused on detecting the “Poly-Hope” sentiment in social media, has been conducted.

The table 3 provides a comparison of the results obtained from applying various methods on an English dataset. The methods are evaluated based on their performance in two scenarios: PolyHope Binary and PolyHope Multiclass. Each method’s performance is measured using precision (Pr), recall (Re), F1-score (F1), and accuracy (Acc).

For the PolyHope Binary scenario, Method 1 achieves a high precision, recall, F1-score, and accuracy, all consistently at 0.846. Method 2 also performs consistently across these metrics at 0.846. The proposed method shows a slightly higher precision of 0.848 but with a slight decrease in recall and F1-score compared to Method 1 and Method 2. Method 3, however, demonstrates notably lower performance across all metrics compared to the other methods.

In the PolyHope Multiclass scenario, Method 1 again exhibits the highest precision, recall, F1-score, and accuracy, with values of 0.665, 0.678, 0.671, and 0.736, respectively. Method 2 achieves identical performance metrics to Method 1 in this scenario.

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TABLE IV
COMPARISON OF THE RESULTS OF APPLYING SIMILAR METHODS (ON SPANISH DATASET)

2*Methods	PolyHope Binary							PolyHope Multiclass						
	M Pr	**M Re**	**M F1**	**W Pr**	**W Re**	**W F1**	**Acc**	**M Pr**	**M Re**	**M F1**	**W Pr**	**W Re**	**W F1**	**Acc**
Proposed method	0.802	0.814	0.807	0.831	0.826	0.828	0.826	0.642	0.645	0.640	0.793	0.788	0.789	0.788
Method 1	0.820	0.774	0.790	0.825	0.826	0.820	0.826	0.507	0.437	0.441	0.670	0.689	.0669	0.689
Method 2	0.820	0.774	0.790	0.825	0.826	0.820	0.826	0.507	0.437	0.441	0.670	0.689	0.669	0.689
Method 3	0.707	0.715	0.710	0.745	0.739	0.741	0.738	0.467	0.301	0.297	0.599	0.657	0.694	0.657

The proposed method performs slightly worse compared to Method 1 and Method 2, with precision, recall, F1-score, and accuracy values of 0.642, 0.668, 0.652, and 0.718, respectively. Method 3 trails significantly behind the other methods in terms of precision, recall, F1-score, and accuracy. Overall, Method 1 and Method 2 demonstrate strong and consistent performance across both scenarios, with the proposed method showing competitive results, albeit slightly lower in some metrics. Method 3 lags behind significantly in performance compared to the other methods.

Table 4 presents a comparison of results obtained from different methods applied to a Spanish dataset, focused on detecting the “PolyHope” sentiment in social media. The evaluated methods include the proposed method as well as three other competing approaches labeled as Method 1, Method 2, and Method 3.

The performance of each method is measured across various metrics, including precision (Pr), recall (Re), and F1-score (F1), calculated both for micro-averaged (M) results and weighted (W) results. Additionally, accuracy (Acc) is provided as an overall measure of performance. The method proposed in this paper demonstrates competitive performance in both binary and multiclass classifications of “PolyHope.” In the binary classification task, the proposed method achieves an F1-score of 0.807 (micro-averaged) and 0.828 (weighted), with an accuracy of 0.826. Similarly, in the multiclass classification task, the proposed method achieves an F1-score of 0.640 (micro-averaged) and 0.789 (weighted), along with an accuracy of 0.788.

Comparatively, Method 1 and Method 2 exhibit similar performance patterns across the evaluated metrics, with slightly lower F1-scores and accuracies compared to the proposed method. These methods achieve F1-scores ranging from 0.790 to 0.441 (micro-averaged) and from 0.820 to 0.669 (weighted). The accuracy values for Method 1 and Method 2 closely align with those of the proposed method.

In contrast, Method 3 demonstrates significantly lower performance across all metrics, with micro-averaged F1-scores of 0.710 and 0.297 for the binary and multiclass classifications, respectively. Similarly, weighted F1-scores for Method 3 are reported as 0.741 and 0.594, with corresponding accuracies of 0.738 and 0.657.

The obtained results indicate that the proposed method outperforms competing methods in terms of F1-score and accuracy, highlighting its effectiveness in detecting “PolyHope” sentiment in Spanish social media.

The comparison of results obtained from different methods applied to English and Spanish datasets, focused on detecting the “PolyHope” sentiment in social media, reveals intriguing insights into the effectiveness of various approaches across languages. When analyzing the English dataset, Method 1 and Method 2 consistently demonstrate robust performance metrics, achieving high precision, recall, F1-score, and accuracy in both the PolyHope Binary and PolyHope Multiclass scenarios. The proposed method also shows competitive results, albeit with slightly lower performance compared to Methods 1 and 2.

However, Method 3 exhibits notably lower performance across all metrics on the English dataset, indicating its inefficacy in capturing the nuanced “PolyHope” sentiment in English social media content.

In contrast, when evaluating the same methods on the Spanish dataset, Method 1 continues to exhibit strong performance, showcasing high precision, recall, F1-score, and accuracy in both PolyHope Binary and PolyHope Multiclass scenarios. Method 2 mirrors its performance closely to that of Method 1 on the Spanish dataset as well. Interestingly, the proposed method demonstrates a slight improvement in performance on the Spanish dataset compared to its performance on the English dataset, indicating potential adaptability across languages. However, Method 3 still trails significantly behind the other methods on the Spanish dataset, further emphasizing its limited effectiveness in detecting the “PolyHope” sentiment in Spanish social media content.

Overall, the comparative analysis underscores the importance of considering language-specific nuances and challenges when developing methods for sentiment detection in social media. While some methods exhibit consistent performance across both English and Spanish datasets, others may require adaptation or refinement to effectively capture sentiment across different languages.

V. CONCLUSION

In conclusion, this study contributes to the growing body of research on hope speech detection in social media contexts, particularly in English and Spanish languages. By leveraging advanced NLP techniques, including BERT and transformer models, we have developed robust methodologies for binary and multiclass classification tasks, achieving promising results in accurately identifying expressions of hope. Our findings underscore the importance of understanding and promoting positive communication dynamics on social media platforms, especially in fostering equality, diversity, and inclusion, and enhancing individuals’ well-being and resilience.

Despite the challenges associated with data processing, linguistic nuances, and ethical considerations, our research highlights the potential of NLP approaches in uncovering valuable insights into human behavior and communication patterns. Moving forward, further research is warranted to explore additional languages, domains, and social media platforms, as well as to address ongoing challenges in dataset

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quality, model generalization, and ethical data usage. By continuing to advance our understanding of hope speech and its impact on society, we can better support individuals and communities in navigating the complexities of modern communication landscapes.

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