

# CIC@LT-EDI-ACL2022: Are transformers the only hope? Hope speech detection for Spanish and English comments

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## Abstract

Hope is an inherent part of human life and essential for improving the quality of life. Hope increases happiness and reduces stress and feelings of helplessness. Hope speech is the desired outcome for better and can be studied using text from various online sources where people express their desires and outcomes. In this paper, we address a deep-learning approach with a combination of linguistic and psycholinguistic features for hope-speech detection. We report our best results submitted to LT-EDI-2022 which ranked 2<sup>nd</sup> and 3<sup>rd</sup> in English and Spanish respectively.

## 1 Introduction

Automatic detection of hope-speech has recently grabbed the attention of Natural Language Processing (NLP) researchers (Chakravarthi, 2020; Chakravarthi and Muralidaran, 2021). Social media platforms have opened doors for linguists, computer scientists and psychologists to dive deep into multiple forms of human expression (Ashraf et al.; Ameer et al., 2020) i.e. hate, sadness, joy and love (Sampath et al., 2022; Ravikiran et al., 2022; Chakravarthi et al., 2021, 2022b; Bharathi et al., 2022; Priyadharshini et al., 2022). Similar to detecting other forms of expression, hope-speech allows us to understand the human desire for an outcome.

The definition of hope (Snyder et al., 2002) used in past computational studies, explains the association of hope with potential, reassurance, support, inspiration, suggestions and promise during times of misfortune. Hope, however, cannot be limited to the understanding of positivity as a sentiment alone, as hope is not “optimism” (Bryant and Cven-gros, 2004). Understanding hope in its complete form can help us understand the desired outcomes of a certain person, community, gender or ethnicity. The first step towards the understanding of hope is to distinguish hope from neutral and not-hopeful

sentences. To help that, many computational approaches have been tested on hope-speech detection using deep learning/transformer methods and a variety of linguistic features (Balouchzahi et al., 2021a; Junaida and Ajees, 2021; Dowlagar and Mamidi, 2021).

This paper gives a system report of Task 1: Shared Task on Hope Speech Detection for Equality, Diversity and Inclusion at “LT-EDI 2022” (Chakravarthi et al., 2022a). The shared task is an extension of last year’s shared task on hope speech detection (Chakravarthi and Muralidaran, 2021). This year the task is converted to a binary classification problem that aims to detect “Hope” and “Non-Hope” classes from Youtube comments. We attempted the task in only English and Spanish for thorough experimentation. Our model comprises a basic sequential neural network with a combination of features including Linguistic Inquiry and Word Count (LIWC) and n-grams.

The paper contributes by developing a deep learning approach that ranked 2<sup>nd</sup> in English and 3<sup>rd</sup> in Spanish for hope speech detection. we also identified psycho-linguistic and linguistic features that work the best for the two languages. The following section gives a detailed description of the methods used in the previous year’s shared task. Section 3 and 4 explain the dataset statistics and the methodology used to obtain the results. While Section 5 and 6 elaborate on the results and conclusions drawn from the paper.

## 2 Literature Review

Early research (Palakodety et al., 2020) on identifying hope highlighted the potential of hope in the situation of war through Youtube comments. These comments were extracted multilingually (*Hindi/English*) in Devanagari and Roman scripts. The study used 80/10 train test

spit using logistic regression with l2 regularization. The used N-grams (1, 3), sentiment score and 100 dimensional polyglot FastText embeddings as features. A combination of all features gave an  $F - 1$  score of 78.51 ( $\pm 2.24\%$ ). In 2021, the shared-task (Chakravarthi and Muralidaran, 2021) for Hope speech detection was presented at “LT-EDI-2021”. The task was built on the code-mixed imbalance dataset (?) comprised of Youtube comments in English, Malayalam, and Tamil. The English dataset was divided into three classes namely: “Hope” with 2484 comments, “Non-Hope” with 25,950 comments and “Other language” with 27 comments. The literature review only highlights the methodologies and results proposed for Hope-Speech detection at “LT-EDI-2021” in English.

A majority voting ensemble approach (Upadhyay et al., 2021) with 11 models and fine-tuned pre-trained transformer models (RoBERTa, BERT, ALBERT, IndicBERT) gave us the F-1 score of 0.93%. The same results were achieved in the study, which used a combination of contextualized string embedding (Flair), stacked word embeddings and pooled document embedding with Recurrent Neural Network (RNN) (Junaida and Ajees, 2021). Transformer methods all scored F-1 score of 0.93% consistently with many fine-tuned methods such as RoBERTa (Mahajan et al., 2021), XML-R (Hossain et al., 2021), XLM-RoBERTa (Ziehe et al., 2021), XLM-RoBERTa with TF-IDF (Huang and Bai, 2021), ALBERT with K-fold cross-validation (Chen and Kong, 2021) and multilingual-BERT model with convolution neural networks (CNN) (Dowlagar and Mamidi, 2021). However, these weighted F1-Scores present an incomplete picture of the hope speech detection models as none of the models gave us an F-1 score of more than 0.60% in the “Hope” class. These high weighted F-1 scores were majorly contributed by the “Non-hope” class which had more than 10X times more comments than the “Hope” class.

We saw a slightly different language model approach in (Chinnappa, 2021), where the authors used FNN, SBERT and BERT to classify the labels after initial detection of the language using multiple language identifiers such as Compact Language Detector 2, langid etc. The approach got achieved 0.92% F-1 score with extremely poor performance on the third label “Not language”, which was expected due to the imbalance instances in the class label. The best models seen were the

ones that performed slightly better in the hope-speech class. Since, the shared task was code-mixed, only (Balouchzahi et al., 2021a) provided a solution catering to the sentences combined with char sequences for words with Malayalam-English and Tamil-English code-mixed texts and a combination of word and char n-grams along with syntactic word n-grams for English text. The proposed approach got an F-1 score of 0.92% in English and was also robust in the low resource languages.

The related studies show a huge gap in the understanding of “Hope” class as a whole and hence, more impactful features and methods need to be explored.

### 3 Dataset

The dataset comprises of Youtube comments for English and Tweets for Spanish. The table 1 shows the dataset statistics and the imbalance between the two binary classes in the English dataset. The number of tweets in Spanish are balanced but also visibly less than in English. The table 2 shows the structure of the train and development sets without ids for both English and Spanish. The predictions were made on the training set comprising of 389 English comments and 330 Spanish tweets.

Train Set		
Categories	English	Spanish
Hope speech	1962	491
Not hope speech	20778	499
Development Set		
Hope speech	272	169
Not hope speech	2569	161

Table 1: Label distribution over datasets

Language	Comments and Tweets	Class
En	It’s not that all lives don’t matter	NHS
En	God accepts everyone	HS
Es	¿Quien me puede explicar que tiene que ver el desgraciado crimen de Samuel en A Coruña con la #homofobia y la #LGTBI?	NHS
Es	El Tribunal Supremo israelí da luz verde a la gestión subrogada de parejas del mismo sexo. #LGTBI	HS

Table 2: Examples from the trainset in English (En) and Spanish (Es) with labels Hope speech (HS) and Non-hope speech (NHS)

## 4 Methodology

The proposed methodology contains two main phases, namely: Feature Engineering, and Model Construction. Each phase is described below:

### 4.1 Feature Engineering

The feature engineering steps are shown in Figure 1 and described below:

#### 4.1.1 Data Cleaning

This phase includes emoji to text conversion using UNICODE\_EMO() (handles the graphical emojis) and EMOTICONS() (handles text-based emojis, e.g., :-) :-)) functions from emot<sup>1</sup> library. Once emojis were converted to texts, all texts were lower-cased and all digits, unprintable characters and non-alphabet characters along with stopwords were removed.

#### 4.1.2 Feature Extraction

Two types of features, namely: Psychological and linguistic features were used for the study. Psychological features in the current work were taken from Linguistic Inquiry and Word Count (LIWC) (Tausczik and Pennebaker, 2010). LIWC is the gold standard lexicon that categorizes the words in the tweets in their respective psychological categories. We utilized all categories provided in LIWC 2015. Furthermore, we used character and word n-grams each in the range of (1, 3) for experiments. Later, TF-IDF Vectorizer was used to vectorize the obtained n-grams and 30,000 most frequent from each (char and word n-grams) and transferred for the next step (Feature Selection).

#### 4.1.3 Feature Selection

A large number of features does not always generate the highest performance and might cause more processing time and overfitting (Balouchzahi et al., 2021b). Therefore, a feature selection step is deemed useful to further reduce the dimension of feature vectors keeping only the most impactful features for the classifier. Similar to the ensemble concept in model construction, two DecisionTree (DT) and one RandomForest (RF) classifiers were ensembled to produce feature importance for the extracted features. The soft voting of produced collective features from all three classifiers was transferred as the input. Feature importance of each feature indicates how much a feature contributes

<sup>1</sup><https://pypi.org/project/emot/>

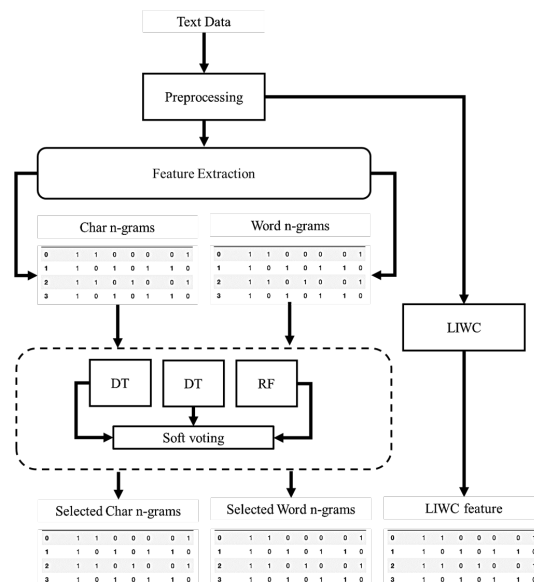


Figure 1: Feature Engineering phase

to the solving classification problem for the current task (Balouchzahi et al., 2021b). Eventually, the features are sorted based on higher feature importance and the top 10,000 features are selected for classification. Only linguistic features are gone through feature selection due to high dimensions in extracted word and char n-grams features. The total number of features is given in Table 3.

Language	LIWC	Char n-grams	Word n-grams
English	93	2437500	499036
Spanish	93	238940	44339

Table 3: Total number of features for each feature type

## 4.2 Model Construction

Since the main focus of current work is on exploring the impact of Psycho-linguistic features on hope speech, a simple but effective Keras<sup>2</sup> Neural Network architecture has been borrowed from (Balouchzahi et al., 2021a). This enables us to compare the performance of the proposed feature set to subwords n-grams generated through char sequences and syntactic n-grams used in previous work (Balouchzahi et al., 2021a). The graphical representation of the model used in the current task is detailed in Figure 2. The model was trained with four different feature combinations and the results are analyzed in Section 5.

<sup>2</sup><https://keras.io/>

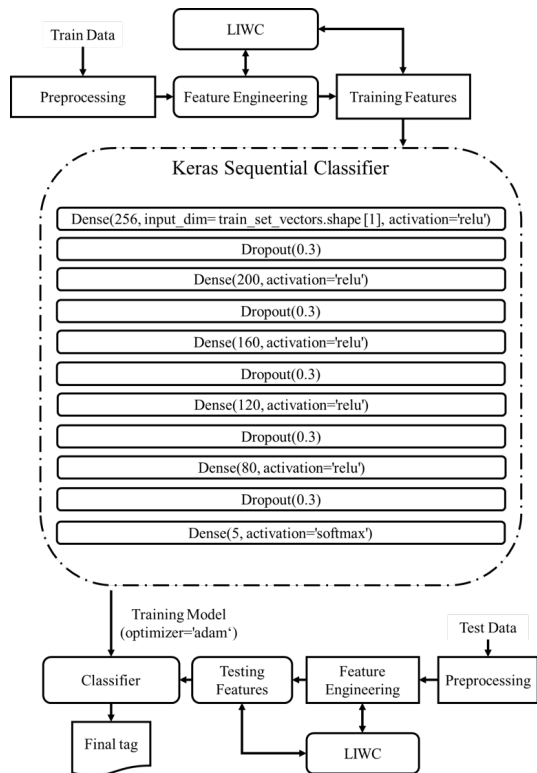


Figure 2: Keras Neural Network architecture

## 5 Results

The best performing results for the both languages were with the combination of n-grams with LIWC features. The study reports Macro\_F1 score, which reports the F1\_score per class giving equal weight to each class, whereas, Weighted\_F1 score gives an insight on the F1 score per class by keeping in mind the proportion of each class.

Even though Weighted\_F1 scores are more helpful for evaluating the imbalanced classes, the evaluation of the rankings were done with the Macro\_F1 scores. The table 4 shows the comparison of the submitted models with the top two models. Our model performed better than the first ranked model in the Weighted\_F1 (0.870) and was only lower than one model (0.880) in the ranking. Our model with only LIWC features achieved the second rank for hope speech detection in English (W\_F1 = 0.870), while, our model with the combination of LIWC, word and char n-grams achieved the third rank (W\_F1 = 0.790) for the Spanish text. The char embeddings created a significant difference in the Spanish text when combined with the LIWC features.

The overall Macro\_F1 scores achieved in the English task was significantly lower than the

Team name	M_F1-score	W_F1-score	Rank
IITSurat	0.550	0.880	1
MUCIC	0.550	0.860	1
ARGUABLY	0.540	0.870	2
CIC.LIWC	0.530	0.870	2
CIC.LIWC + words	0.530	0.870	3
CIC.LIWC + char	0.500	0.860	5

(a) English

Team name	M_F1-score	W_F1-score	Rank
ARGUABLY_Spanish	0.810	0.810	1
AbliMet_Spanish	0.800	0.800	2
CIC.LIWC + Words + Char	0.790	0.790	3

(b) Spanish

Table 4: Comparison of team submissions with the top 2 ranks in the competition

Weighted\_F1 score because of the imbalanced classes contrary to Spanish texts where the classes were balanced.

## 6 Conclusion

In this paper, we reported the impact of psycho-linguistic and linguistic features on hope speech detection using a non-complex deep learning algorithm. Our approach showed that even simple deep learning models can outperform complex language models with a combination of linguistic and psycho-linguistic features. Psycho-linguistic features were efficient in both English and Spanish tasks which can be due to the nature of hope targeted in the dataset which comprised of only positive comments. Our best models ranked 2<sup>nd</sup> and 3<sup>rd</sup> in English and Spanish respectively.

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