.

HOPE@IberLEF 2024: Beyond Binary Bounds—Classifying Hope in Online Discourse

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Abstract
This study uses binary classification algorithms to investigate the detection of "hope speech" in Twitter messages. Hope speech expresses the possibility of positive outcomes in the face of difficulties in an effort that fosters optimism and resilience. We studied the dataset provided to us and used logistic regression, support vector machines, and deep neural networks to distinguish between hopeful and non-hopeful remarks. As part of the collaborative effort for HOPE at IberLEF 2024, we conducted our study primarily using a Twitter dataset, which guaranteed a comprehensive analysis of context influence and the application of ethical principles.The highest accuracy we achieve is 0.72, 0.73 macro average, 0.72 recall, and 0.72 f1-score. These findings contribute to our comprehension of how technology might facilitate constructive online discourse to foster a friendly online forum.

Keywords
Hope Speech, Binary Classification, Natural Language Processing, Machine Learning, Online Communication, Twitter Dataset, Deep Learning, Support Vector Machines, Logistic Regression

1. Introduction

Online interactions, which show a variety of emotions and goals, are a part of global communication in today's age of technology. 'Hope speech' is a distinctive communication style that promotes optimism, inspiration, and improvement in communities [1]. Since the internet is an environment for conversation, valuing and promoting, hope speech is key to building an optimistic online community. This research investigates the detection of hope speech in text, focusing on binary classification algorithms that may differentiate between comments that are hopeful and those that are not.

'Hope speech' is not to be mistaken with other forms of positive communication, such praises or words of support. It primarily relates to claims that, in the face of difficulties, suppose an opportunity of favorable results [2]. This could be anything from social resilience projects to personal affirmations of support. It is a complicated process involving a solid understanding of linguistic specifics to consider, cultural background, and the psychological knowledge [**?**] of hope for automatic identification of this type of speech.

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From an academic viewpoint, different problems that go beyond standard sentimental analysis have to be addressed in identifying hope speech. Hope speech detection requires a more sophisticated approach than sentiment analysis, which organizes phrases into broad categories of positive, negative, and neutral attitudes [3]. It requires understanding between different kinds of affirmative speech and accurately identifying the emotional and contextual cues that convey hope. This demands the use of cutting-edge machine learning models that can learn from massive datasets along with better natural language processing approaches.

We use binary classification models to tackle the task of hope speech detection in this paper. The reason binary classifiers are used for decision-making situations is that they are effective in quickly classifying material as either "hopeful" or "non-hopeful." We did thorough research on the dataset provided to us and used various kinds of algorithms, including logistic regression, support vector machines, and deep neural networks. Additionally, we explore a number of feature extraction methods, including word embeddings and n-grams, which are adept at detecting the variations of linguistic expression that are essential for correct categorization.

Our approach includes a detailed review of the labeled dataset that we used to train our models; this dataset was obtained from Twitter as part of the shared challenge in HOPE at IberLEF 2024 [4]. We made sure that this one data source was thoroughly examined because we understood how important context is. We also carefully address potential biases and ethical issues that arise during model training and implementation, demonstrating that we are committed to promoting accessibility and fairness in our process.

This research helps the field of hope speech detection and improves the overall objective of further improvement in online communication quality. In order to create a more positive and affirmative online environment, we hope that our research can throw light on the ways in which technology can be employed to detect and magnify positive speech in digital contexts.

2. Related Work

Extensive research is going on to detect activities on social media and e-commerce platforms and to build the most efficient and robust models, which range from multi-layer models (MLMs) to natural language processing (NLP) models. One such social media activity that is under research is hope. Hope has been called the "lifeblood of the soul," an indispensable condition for human existence. [5] Yet, hope is constituted following cultural norms, and hence it may vary fundamentally from one society to another.

[6] and [7] were the first to present hope speech identification as a natural language processing task. They proposed two multilingual corpora that categorize YouTube remarks into two groups: Hope and Not Hope. The transformer model, ALBERT, was utilized in research by Vijayakumar et al. (2022) to perform hope speech detection in the languages of Tamil, Malayalam, Kannada, and English. In 2022, Chakravarthi introduced a new model based on convolutional neural networks (CNNs) that performed better at detecting hope speech than previous conventional models. The corpora presented by [8] for Hope Speech identification is in Hindi and English. Hope detection is modeled by both corpora as a binary text classification with two classes: "Hope" and "Not Hope." There might be several kinds of hope in the texts. Thus, texts that fall under the "hope" class can also be categorized under "realistic and wishful hopes" or "rational

and irrational [9]."

[10] used a variety of transformer models to detect hope speech in Malayalam, Tamil, and English. The IndicBERT, multilingual m-BERTcased, and XLM-Roberta (XLMR) models were used. The model with the m-BERT casing has the best F1 score out of all of them. Hope detection was carried out for three language data sets—Tamil, English, and Malayalam—by [11]. Among the language models they used were langid, textblob language detector, langdetect, and compact language detectors 2 and 3. The findings of the experiment indicated that it is challenging to identify hope from text, particularly when dealing with code-mixed data.

A deep learning model consisting of a simple sequential neural network with features like n-grams and Linguistic Enquiry and Word Count (LIWC) was developed by [12], who took part in determining the English and Spanish Hope Speech categories at CIC@LT-EDI-ACL2022. [13] employed two categorization methods for hope speech: binary and multi-class. The binary task only needed two labels, whereas the multi-class problem required three. Several deep learning, transformer, and traditional models were applied to the dataset.

The extensive study discussed in this section demonstrates the creative and developing methods for employing cutting-edge algorithms to recognize and analyze expressions of hope on social networking platforms. They highlight the ability of natural language processing (NLP) technology to identify and classify human emotions, a task made difficult by the personal and culturally variable nature of views like hope.

3. Task and Data Description

The shared task on Hope Speech, namely "Task 2: Hope as Expectations," as outlined by [13], aims to classify text using two different approaches:

3.1. Subtask 2

- a: Binary Hope Speech Detection from English and Spanish texts
- b: Multiclass Hope Speech Detection from English and Spanish texts.

We participated in one of the two available subsets of this task, specifically focusing on "Binary Hope Speech Detection from English and Spanish Texts." However, our submission was limited to the English dataset only. The emphasis of this task was on identifying expectations and differentiating between facts in the material that are hopeful and un-hopeful. The information was organized into two fields: text and labels, and the data was sourced from Twitter [14].

3.2. Data Composition

- Training Dataset: Composed of approximately 6,192 tweets, split almost evenly with 3,104 labeled as hope speech and 3,088 as non-hope speech.
- Development Dataset: Included 1,032 tweets, with 530 categorized as hope speech and 502 as non-hope speech.
- Testing Dataset: It also contained 1,032 tweets, among which 527 were identified as hope speech and 484 as non-hope speeches.

This methodical approach to gathering and classifying data made it easier to analyze in detail the way expressions of hope appear in social media discourse, particularly when it comes to English-language content [15].

Table 1

Table 1: Task 2 Dataset Split (Binary English)

Label	Train	Development	Test
Hope	3104	530	527
Not Hope	3088	502	484
Total	6192	1032	1032

4. Methodology

Our study examined both conventional machine learning and contemporary deep learning techniques, as shown in Figure 1, to determine which model performed the best for hope speech detection. Below is a summary of each model's experimental designs.

4.1. Traditional Machine Learning Approach: Random Forest Classifier

- Model Description: Using several decision trees, Random Forest is an ensemble learning technique that produces reliable predictions. The majority vote from each decision tree is used to establish the final class.
- Configuration: We started our Random Forest model with a random state of zero (random-state=0) and configured it with 200 decision trees (n-estimators=200).
- Training: By fitting the data to the ensemble of decision trees, we were able to train the model to categorize text using our dataset.
- Evaluation: On the test dataset, the model's overall accuracy was a moderate 51 %. This finding indicates that although the Random Forest model can categorize hope speech to a certain extent, there is a great deal of space for model refinement and parameter modification.

4.2. Deep Learning Approach: Long Short-Term Memory (LSTM) Network

- Model Description: LSTM networks are a sort of recurrent neural network (RNN) that are well-suited for processing sequences like text because they can capture long-term dependencies.

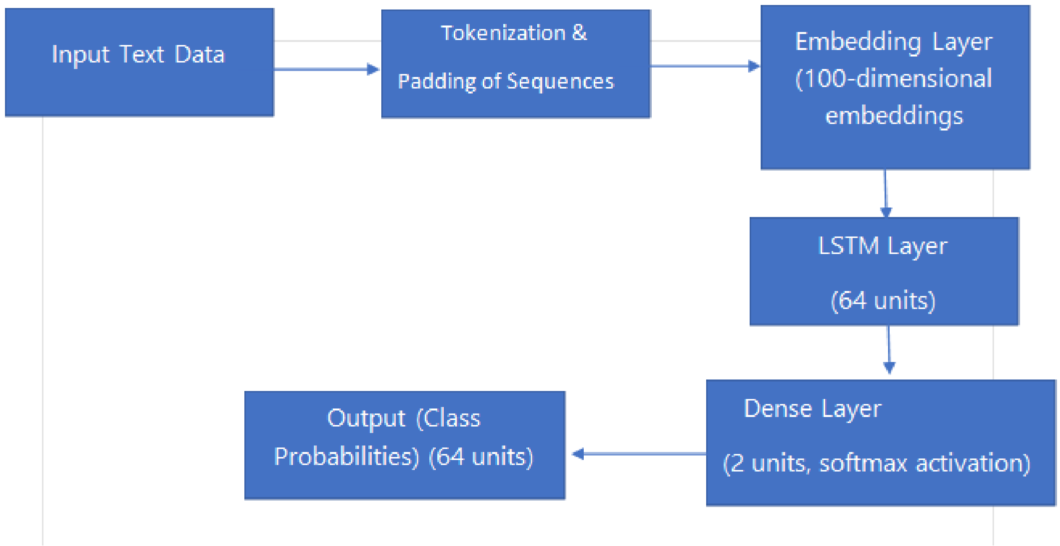

Figure 1: Methodology

- Architecture:
  - Embedding Layer: This layer transforms input text into fixed-size, dense vector representations. With the embedding dimension set to 100.
  - LSTM Layer: A collection of 64 units that process text data sequentially and detect temporal relationships.
  - Dense Layer: A completely linked layer with a softmax activation function that yields probabilities for each class (hope or non-hope).
- Training: The LSTM was trained with a batch size of 64 over 10 epochs, using 20% of the training data as a validation split to monitor performance adjustments.
- Evaluation: Evaluation: Following training, the model was evaluated on the test dataset, with its performance quantified using the Keras evaluate function, which analyzed test loss and accuracy.

5. Results

In this study, we employed two primary methodologies to address the task of binary hope speech detection from a dataset of English tweets. Our experiments aimed to identify which model—random forest or LSTM—would demonstrate superior performance in classifying tweets as hope or non-hope speech.

5.1. Random Forest Classifier Results

The first model to be assessed was the Random Forest Classifier, which had 200 decision trees developed. On the test dataset, an overall accuracy of 51% was attained. While Random Forest can classify the tweets to some extent, as evidenced by this reasonable performance, moreover half of the predictions did not match the labels appropriately, suggesting that there may be problems with either overfitting or underfitting in the model.

5.2. LSTM Model Results

Several important measures were used in our work to assess the effectiveness of the LSTM model, including precision, recall, F1-score for each class, and total accuracy. With a macro-average precision of 0.73 , a recall of 0.72, an F1-score of 0.72 , and an accuracy of 0.72 in tests, the LSTM model performed well. The 'hopeful' and 'non-hopeful' categories of the text data were appropriately classified by the LSTM model, according to these results.

6. Analysis

6.1. Comparison of Models

Several important insights into the nature of hope speech detection are revealed by this study's comparative investigation of the Random Forest and LSTM models:

6.1.1. Model Suitability

Model Suitability: Neural network approaches are more appropriate for text classification tasks, particularly when natural language data is involved, as demonstrated by the LSTM model's better results over the Random Forest model. The capacity of the LSTM algorithm to extract temporal connections from the data seems to be essential for comprehending the complex expressions of hope found in brief texts such as tweets.

6.1.2. Difficulties with Conventional Models

Based on the Random Forest model's average results, it appears that conventional machine learning models may have trouble capturing the depth and variety of natural language, especially when it comes to analyzing emotions where subtle understanding is crucial. Even though the ensemble method is resistant to overfitting, it may not be able to capture the deeper semantic layers required for hope speech categorization to be effective.

6.1.3. Implications for Hope Speech Detection

Contextual and cultural variations have a crucial influence on speech recognition, which is hard due to the diversity in model performance. Hope can differ significantly between cultural contexts, as the associated work shows, which could have an impact on model performance and the generalizability of findings.

7. Further Considerations

There are several actions that could be taken to improve the performance of hope speech detection models:

7.1. Model Tuning and Experimentation

By fine-tuning the hyperparameters of both models, better outcomes may be obtained. Furthermore, experimenting with alternative neural network designs, including transformer-based models (like BERT), could make use of recent developments in NLP to produce possibly better results.

7.2. Expanded Data and Multilingual Models

Larger and more varied datasets, including multilingual corpora, might be added to the models to increase their accuracy and resilience. This extension would also contribute to a more thorough knowledge of the cultural layers of hope expression.

7.3. Interdisciplinary Approaches

The constraints identified in previous research may be addressed by incorporating knowledge from psychology and cultural studies into the model training process, which could improve models' accuracy in identifying various hope expressions.

8. Conclusion

To sum up, although the LSTM model showed promise for identifying hope speech in English tweets, more study and advancement are needed to fully realize the potential of NLP approaches for comprehending intricate human emotions like hope in social media settings.

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