ML&AI_IIIT Ranchi@LT-EDI-2023: Identification of Hope Speech of YouTube comments in Mixed Languages

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Abstract

Hope speech analysis refers to the examination and evaluation of speeches or messages that aim to instill hope, inspire optimism, and motivate individuals or communities. It involves analyzing the content, language, rhetorical devices, and delivery techniques used in a speech to understand how it conveys hope and its potential impact on the audience. The objective of this study is to classify the given text comments as Hope Speech or Not Hope Speech. The provided dataset consists of YouTube comments in four languages: English, Hindi, Spanish, Bulgarian; with pre-defined classifications. Our approach involved pre-processing the dataset and using TF-IDF (Term Frequency-Inverse Document Frequency) as well as BOW(Bag Of Words) feature vectors on various machine learning algorithms. Our approach also involved fine-tuning of DistilROBERTa, a pre-trained model by hugging face.

1 Introduction

In a world full with problems, uncertainties, and moments of despair, the power of hope becomes an urgent appeal for resilience and transformation. Hope speeches, a distinct mode of communication, have evolved as a powerful tool for instilling optimism, inspiring action, and fostering a renewed feeling of possibilities in individuals and communities. These speeches capture the spirit of optimism by combining words, emotions, and ideas of a brighter future.

Hope talks overcome linguistic boundaries, reaching audiences of all cultures and languages. They have an extraordinary power to touch hearts, ignite emotions, and motivate people for positive change. This study work tries to uncover the universal characteristics that underlying these messages through the analysis of hope speeches in four different languages; English, Hindi, Spanish, and Bulgarian.

This study examines the tremendous impact of hope speeches on individuals and societies, drawing on studies undertaken by several research institutes. The Institute of Hope Studies at the University of Oklahoma has conducted research that demonstrates the transforming power of hope in improving mental well-being, increasing resilience, and improving outcomes in a variety of circumstances. Furthermore, the University of Oklahoma's Centre for Hope Studies provides unique insights into the psychological and social implications of hope speeches in various cultural contexts.

We faced some difficulties while analysing hope speech text snippets. The subjective nature of hope was one such obstacle. The distinctive emotional and psychological responses of individuals within a certain cultural and linguistic framework has to be considered when determining the effectiveness of a hope speech. Another difficulty was translating and interpreting hope speeches across languages, as variations, cultural allusions, and rhetorical strategies may differ, potentially changing the impact on varied audiences.

In this study we have attempted to provide a greater knowledge of hope speech analysis by looking into these difficulties. We aimed to develop a viable system that could detect and categorise hope speech in this language by leveraging several machine learning and deep learning approaches. Our experiments involved training and fine-tuning models applying cutting-edge methodologies. By fine-tuning DistilRoBERTa, a language model trained on numerous languages, we hoped to improve the accuracy and effectiveness of our categorization system.

Our experiment produced encouraging results, with a Precision-Score of 0.66. This performance displayed the effectiveness of our strategy as well as the efforts put in in tackling the obstacles unique to the English language. We improved our system's

LT-EDI 2023 – Third Workshop on Language Technology for Equality, Diversity and Inclusion, pages 214–222, Varna, Bulgaria, Sep 7, 2023.
https://doi.org/10.26615/978-954-452-084-7_033

capabilities and got commendable results in detecting and categorising hope speech by leveraging the power of transfer learning and combining it with domain-specific fine-tuning.

In conclusion, hope speech analysis, particularly text analysis, provides vital insights regarding their universal significance. We can learn how these speeches inspire optimism and resonate with varied audiences by evaluating linguistic and rhetorical aspects such as metaphors, imagery, and narrative frameworks. Text analysis allows us to delve into the complexities of language, revealing the tactics used by speakers to provoke emotions and transmit positive messages. However, difficulties arise in the subjective interpretation and translation of hope speeches, highlighting the importance of taking cultural settings and language variations into account. By negotiating these intricacies, we gain a better grasp of hope speech analysis, allowing us to use words to inspire good change in individuals and communities alike.

Our Work has been organized in a step–by–step to represent our work in a much efficient way. Section 2 describes work done in the related field, Section 3 & 4 identifies the outlines of the task and dataset description, Section 5 mentions the various methodologies adapted and their results on validation dataset. Lastly, we have discussed the result and concluded in Section 6 and 7 respectively.

2 Related Works

For the purpose of fostering hope and uplifting individuals, researchers and organizations involved in hope speech analysis have recognized the importance of exploring and developing effective methodologies and models. In order to inspire and empower individuals, studies have been conducted to examine various approaches to hope speech analysis across different fields. Just as social media companies have been obligated to support sentiment analysis research for the protection of users from cyberbullying, researchers in hope speech analysis strive to enhance their understanding of the key components that instill hope and promote optimism. Through the examination of different methodologies and models, researchers of (Kumaresan et al., 2023) seek to uncover the most impactful elements that contribute to the effectiveness of hope speeches. By investing in hope speech analysis research, scholars and organizations aim to unlock the potential for positive change, resilience, and motivation in individuals and communities.

The authors of (Kumar et al., 2022) used YouTube comments to do opinion mining and trend analysis. The researchers examined attitudes to determine trends, seasonality, and projections; user sentiments were discovered to be highly associated with the impact of real-world events. The research (Severyn et al., 2014) conducted a thorough study of opinion mining using YouTube comments. The authors created a comment corpus with 35K hand labelled data in order to predict the opinion polarity of the comments using tree kernel models.

The works (Chakravarthi, 2022; Chakravarthi et al., 2022; Chakravarthi, 2020) used a social network analysis and mining approach to find hope speech in YouTube comments. Their study emphasises the role of hope within online networks and its potential impact on human well-being. They create a framework specifically designed to identify instances of hope speech using sentiment analysis and natural language processing techniques. They successfully extract relevant patterns and features for accurate detection by employing data mining techniques and taking into account linguistic, visual, and social elements. Their study contributes to a better understanding of the role of hope in digital communities by providing significant insights into the detection of hope speech in online platforms. The researchers of (Palakodety et al., 2019) investigate the application of computational approaches to analyse peace discourse in the context of Kashmir in their research. Through computer analysis, their research provides unique insights into the dynamics of peace-related communication. They use powerful computational approaches to shed light on the voices advocating for peace in the region.

The work (Maas et al., 2011) explored using deep learning, specifically Convolutional Neural Networks (CNNs), for sentiment analysis. They investigate various word vector representations' effectiveness and advances understanding of using neural networks for discerning sentiment in text data. The works (Aurpa et al., 2022; Lucky et al., 2021) employed deep neural network models based on transformers to detect offensive remarks in Bangla social media. BERT (Bidirectional Encoder Representations from Transformers) and ELECTRA (Efficiency Learning an Encoder that Classifies Token Replacements Accurately) pretraining language architectures are used in tandem.

The authors constructed a one-of-a-kind dataset that includes 44,001 comments from a wide range of Bangla-language Facebook postings.

Hence, the existing literature on hope speech analysis includes a diverse set of ideas and methodologies. The evaluated works in this subject stress the importance of experimenting with various data mining techniques, using benchmark datasets, leveraging deep learning models, and conducting comparative studies. These findings highlight the necessity of building thorough frameworks, using credible datasets, and using lessons from prior research in order to progress the area of hope speech analysis. The proposed approaches, benchmark datasets, and findings from these studies are useful tools for scholars and practitioners interested in developing successful computational strategies for instilling hope and optimism. Building on these references, our work in hope speech analysis intends to be inspired by proven methodology and to perform a comparative research of our dataset in order to uncover and develop effective ways. We intend to contribute to the development of strong approaches in hope speech analysis that can empower individuals and communities, create resilience, and inspire positive change by incorporating insights from prior studies and utilising our own comparative analysis.

3 Task Description

The primary objective of this task is to perform Hope Speech analysis on YouTube comments in four different languages, which are English, Hindi, Spanish and Bulgarian. Health professionals believe that hope is important for human well-being, healing, and repair. Hope speech represents the notion that one may uncover and get motivated to employ pathways to one's desired goals. Our approach strives to shift popular thinking away from preoccupations with prejudice, loneliness, or the negative aspects of life and towards fostering confidence, support, and positive traits based on individual comments.

Hope speech analysis refers to the examination and evaluation of speeches or messages that aim to instill hope, inspire optimism, and motivate individuals or communities.It entails analysing a speech's content, language, rhetorical devices, and delivery tactics to determine how it transmits hope and its potential impact on the listener.

Participants are presented with training, development, and test datasets in four languages (Hindi, English, Spanish, Bulgarian), some of them being code-mixed. The datasets are annotated at the comment/post level. A comment or post may contain more than one sentence, although the corpus's average sentence length is one. Participants can opt to classify one or more code-mixed languages. Each language's leaderboard results were released.

We address this problem using a variety of machine learning approaches and methodologies. These include typical machine learning algorithms, deep learning models, or a combination of the two. By training and fine-tuning such models on the available information, we hope to develop a robust classifier capable of accurately predicting the level of depression displayed in unseen social media posts.

4 Dataset Description

The dataset utilized for the Hope Speech Analysis task in multiple languages comprises a diverse collection of YouTube comments. It is segmented into three distinct subsets: a training dataset, a development dataset, and a test dataset. The dataset consists of 2 labels, which differ for the languages. For English, "Hope speech" is used for Hope Speech and "Non hope speech" for Not Hope Speech. For Hindi, "Hope" is used for Hope Speech and "Not-Hope" for Not Hope Speech. For Spanish, "HS" is used for Hope Speech and "NHS" for Not Hope Speech. For Bulgarian, "TRUE" is used for Hope Speech and "FALSE" for Not Hope Speech.

Table 1 shows samples of text excerpts together with their corresponding labels to help the reader understand the dataset. These examples from the dataset demonstrate the wide range of postings to which each label can be applied.

The dataset was separated into three parts for the competition: the training set, the development set, and the test set. The labels for the test set were hidden by the competition's administrators because this section was exclusively utilised to evaluate the competitors' solutions.

The training dataset provided to us contains a large number of YouTube comments composed in many languages and code-mixed format. Each post in the training dataset is labelled with a label indicating whether it is a hope or non-hope comment. These labelled annotations served as the basis for training classification models, helping the construction and refining of machine learning

Table 1: Text Excerpts from Dataset

Text	Label	Dataset	Language
Totally agree! All Lives matter!	Hope_Speech	Train	English
Uggghhhhh so vile and ego out of control he	Non_Hope_Speech	Dev	English
LGBTQ+ means Lets Get Biden To Quit plus Kamal..	Non_Hope_Speech	Test	English
Syndrome bolte kya	Not_Hope	Train	Hindi
Bahut kam nahi hote he sir.....bas log open ho..	Hope	Dev	Hindi
Sir I have always watched your videos and I appre..	Hope	Test	Hindi
Todas ellas coinciden, además, en que la p..	HS	Train	Spanish
¿Quien me puede explicar que tiene que..	NHS	Dev	Spanish
Si no apoyas el avance de ley trans, eres transfobicx y punto	NHS	Test	Spanish
Velik si.. s takiva klipove :D	TRUE	Train	Bulgarian
Tova ne sa drekhi za makhane i slagane..	FALSE	Dev	Bulgarian
che se pravyat na tezhkari i biyat vsichki	FALSE	Test	Bulgarian

Table 2: Dataset Distribution

Language	Train	Dev	Test	Total
English	18192	4548	4805	27545
Hindi	2563	320	321	3204
Spanish	1312	300	547	2159
Bulgarian	4671	589	599	5859

or deep learning models. The dev dataset, also known as the validation dataset, supplements the labelled data provided. It enabled us to analyse model performance and fine-tune hyperparameters during the development period. The labelled information in the development dataset aids in determining whether the algorithms are accurate in categorising social media text as original or fake news.

Table 2 provides an overview of the distribution in the dataset and lists the number of instances for each language. The training set has a greater number of instances than the development set. This size disparity allows for more effective fine-tuning of hyperparameters in both machine learning algorithms and deep learning neural networks. A bigger training set allows for more robust model optimisation, which leads to enhanced performance and generalisation capabilities.

5 Methodology

In our study, we used a variety of approaches on the development dataset to determine the most successful approach for making predictions on the test dataset. numerous methodologies were used in the experiments carried out during the inquiry. These included data preprocessing, TF-IDF based classification and bag of words classification.

The raw English social media postings were processed through a range of text cleansing processes during the initial data pre-processing step. To standardise the textual data, these include the removal of punctuation, stop words, and special characters, as well as tokenization and stemming procedures. This stage of pre-processing ensures that the text is properly prepared for further analysis.

Following that, TF-IDF-based classification is implemented. Each document, i.e., YouTube comment, is represented as a numerical feature vector using the TF-IDF (Term Frequency-Inverse Document Frequency) approach. The methodology involves bag of words classification after TF-IDF-based classification. The text data is represented using a bag of words model, which creates a vocabulary comprised of unique words extracted from the corpus.

Following this methodology, which includes data pre-processing, TF-IDF and bag of words classification, a comprehensive and effective approach for accurately categorising code-mixed YouTube comments was developed.

5.1 Data Pre-processing

We began our task preparations by performing data pre-processing and visualisation. We began by inspecting the data for any occurrences of null or missing values. We performed a text statistical study after establishing the lack of such values. This entailed assessing the word count, character count, and word density per phrase.

$$\textbf{WordCount(T)} = |\textbf{words}(\mathrm{T})|$$
$$\textbf{CharacterCount(T)} = |\textbf{characters}(\mathrm{T})|$$
$$\textbf{WordDensity(T)} = \frac{\textbf{WordCount}(T)}{\textbf{SentenceCount}(T)}$$

The initial step entailed removing punctuation marks, Emojis, and alphanumeric characters to reduce noise and assure a better depiction of the textual information. Following that, we removed stopwords, which are frequently occurring words that do not contribute significantly to the overall meaning of the text. Furthermore, we concentrated on expanding any contracted terms to their full forms, allowing for a more comprehensive study of the text.

The next step in the data pre-processing pipeline was tokenization, which involves breaking down the text into discrete units such as words or subwords. By providing a structured representation of the text data, this method makes subsequent analysis and modelling activities easier. Furthermore, we used lemmatization to reduce inflected or variant words to their base or dictionary form, increasing consistency and coherence within the dataset.

We obtained a cleaner and more refined version of the text suitable for additional feature representation through these systematic and formalised data pre-processing methods. These activities set the groundwork for our task's later stages of feature extraction, categorization, and analysis.

We hoped to improve the quality and dependability of the text data by meticulously implementing these data pretreatment techniques, preparing it for subsequent analysis and classification jobs. Following the extraction of features step, we performed the classification job using a variety of machine learning models and deep learning techniques. The specific methodologies used are addressed in the following subsections of this study, emphasising the complexities and nuances connected with each methodology.

5.2 Classification using TF-IDF

In this research study, we began experimenting with the TF-IDF (Term Frequency-Inverse Document Frequency) technique for machine learning-based classification problems. The primary goal of our study was to evaluate the performance of TF-IDF-based techniques for text classification.

TF-IDF is a popular natural language processing method that assigns weights to individual terms based on their frequency of occurrence within a given text and their rarity over the entire corpus. TF-IDF identifies discriminative features important for classification by taking into account the particular significance inside a document and its wider distinctiveness across the corpus.

$$\textbf{TF-IDF}: \textbf{TF-IDF}(t, d, D) = \textbf{tf}(t, d) \times \textbf{idf}(t, D)$$
$$\textbf{Max Document Frequency (max\_df)} = 0.9$$
$$\textbf{Min Document Frequency (min\_df)} = 5$$

where
t is the term (word)
d is the document
D is the entire corpus or collection

To perform the TF-IDF-based classification, we applied a variety of machine learning methods, including the random forest classifier and the gradient boosting classifier. These algorithms are well-known for their ability to handle text categorization jobs. In addition, we investigated other similar algorithms to assess their effectiveness and compare the findings acquired.

For the TF-IDF method, we used a value of 0.9 for max_df, indicating that we ignored terms appearing in more than 90% of the texts. Furthermore, min_df was set to 5, suggesting that terms appearing in fewer than five documents would be excluded. This parameter selection attempted to achieve a balance between capturing rich vocabulary and avoiding computational complexity. We sought to ensure robust classification performance while managing the dimensionality of the feature space by limiting the dictionary to the most common and informative terms. Tables 4, 6, 8 and 10 summarise the results of utilising several machine learning methods on the training and development datasets.

Table 3: Hyperparameters

Hyperparameters	Values
Number of Layers	4
Activation Function(s)	ReLU, Swish, Sigmoid
Dropout Rate	0.4
Optimizer	Adam
Number of Epochs	13

Table 4: TF-IDF Features based Results on Training and Validation Datasets for English Language

Classifier	Macro F1	Macro Precision	Macro Recall
Ridge-Classifier	0.427	**0.681**	0.391
Perceptron-Classifier	0.467	0.533	0.43
SGD-classifier	0.499	0.641	0.449
Passive-Aggressive-Classifier	0.51	0.536	0.489
Decision-Tree-Classifier	0.458	0.457	0.46
Random-Forest-Classifier	0.519	0.548	**0.494**
AdaBoost-Classifier	0.519	0.548	**0.494**
Gradient Boosting-Classifier	0.479	0.617	0.432
SVM Classifier	**0.521**	0.614	0.473

Table 5: BOW Features based Results on Training and Validation Datasets for English Language

Classifier	Macro F1	Macro Precision	Macro Recall
Ridge-Classifier	0.48	0.5	0.463
Perceptron-Classifier	0.398	0.507	0.359
SGD-classifier	0.492	0.507	0.49
Passive-Aggressive-Classifier	0.482	0.46	**0.508**
Decision-Tree-Classifier	0.471	0.465	0.478
Random-Forest-Classifier	0.425	0.664	0.403
AdaBoost-Classifier	**0.51**	0.559	0.478
Gradient Boosting-Classifier	**0.51**	0.559	0.478
SVM Classifier	0.478	**0.612**	0.434

Table 6: TF-IDF Features based Results on Training and Validation Datasets for Hindi Language

Classifier	Macro F1	Macro Precision	Macro Recall
Ridge-Classifier	0.489	**0.699**	0.507
Perceptron-Classifier	0.616	0.59	**0.654**
SGD-classifier	0.585	0.617	0.571
Passive-Aggressive-Classifier	0.557	0.558	0.557
Decision-Tree-Classifier	0.576	0.571	0.583
Random-Forest-Classifier	0.549	0.629	0.541
AdaBoost-Classifier	**0.632**	0.653	0.617
Gradient Boosting-Classifier	0.565	0.622	0.552
SVM Classifier	0.589	0.655	0.57

5.3 Bag-Of-Words Feature Classification

In the field of natural language processing, Bag-of-Words (BOW) text classification has developed as a popular method for representing text documents as numerical feature vectors. In this research project, we also used BOW-based text classification in conjunction with machine learning algorithms to effectively analyse and classify textual data.

The first step in the BagOfWords-based text classification method was to create a list or glossary of unique words or phrases. This vocabulary was used to lay the groundwork for presenting the documents. To achieve complete coverage, we developed a vocabulary of 10,000 terms that included the most frequent and informative terms from the training dataset.

After forming the dictionary, each document was converted into a sparse vector representation. Using techniques such as term frequency-inverse document frequency (TF-IDF), this representation recorded the presence or absence of dictionary words inside the document, as well as their corresponding frequencies or weighted values.

We used a variety of machine learning algorithms to help with the training and classification of the BOW representations, including well-known models like logistic regression, support vector machines, random forests, and decision trees. These algorithms were trained using a labelled dataset of documents and their associated class labels.

The machine learning algorithms discovered the underlying patterns and correlations between the BOW characteristics and their related classes during the training phase. Following that, we assessed the trained models' effectiveness and generalization capabilities using performance metrics including Macro Precision, Macro Recall, and Macro

F1-score on a separate development dataset.

6 Results

Table 7: BOW Features based Results on Training and Validation Datasets for Hindi Language

Classifier	Macro F1	Macro Precision	Macro Recall
Ridge-Classifier	0.606	0.695	0.581
Perceptron-Classifier	0.634	0.587	**0.721**
SGD-classifier	0.624	0.634	0.617
Passive-Aggressive-Classifier	0.611	0.647	0.591
Decision-Tree-Classifier	0.608	0.615	0.601
Random-Forest-Classifier	0.547	**0.762**	0.54
AdaBoost-Classifier	**0.636**	0.663	0.619
Gradient Boosting-Classifier	0.619	0.718	0.591
SVM Classifier	0.598	0.623	0.585

Table 8: TF-IDF Features based Results on Training and Validation Datasets for Spanish Language

Classifier	Macro F1	Macro Precision	Macro Recall
Ridge-Classifier	**0.794**	**0.797**	**0.794**
Perceptron-Classifier	0.696	0.762	0.644
SGD-classifier	0.761	0.761	0.761
Passive-AggressiveClassifier	0.737	0.74	0.733
Decision-Tree-Classifier	0.67	0.672	0.671
Random-Forest-Classifier	0.787	0.789	0.773
AdaBoost-Classifier	0.705	0.705	0.705
Gradient Boosting-Classifier	0.749	0.754	0.748
SVM Classifier	0.789	0.789	0.789

Table 9: BOW Features based Results on Training and Validation Datasets for Spanish Language

Classifier	Macro F1	Macro Precision	Macro Recall
Ridge-Classifier	0.782	0.784	0.782
Perceptron-Classifier	0.601	0.842	0.472
SGD-classifier	0.776	0.758	0.795
Passive-AggressiveClassifier	**0.804**	0.8	**0.807**
Decision-Tree-Classifier	0.686	0.687	0.686
Random-Forest-Classifier	0.775	0.787	0.769
AdaBoost-Classifier	0.761	0.762	0.761
Gradient Boosting-Classifier	0.780	0.787	0.779
SVM Classifier	0.801	**0.803**	0.801

Table 10: TF-IDF Features based Results on Training and Validation Datasets for Bulgarian Language

Classifier	Macro F1	Macro Precision	Macro Recall
Ridge-Classifier	0.523	**0.967**	0.521
Perceptron-Classifier	**0.663**	0.638	**0.629**
SGD-classifier	0.575	0.656	0.555
Passive-AggressiveClassifier	0.609	0.63	0.61
Decision-Tree-Classifier	0.576	0.586	0.568
Random-Forest-Classifier	0.519	0.634	0.518
AdaBoost-Classifier	0.627	0.706	0.596
Gradient Boosting-Classifier	0.564	0.642	0.547
SVM Classifier	0.587	0.674	0.556

Table 11: BOW Features based Results on Training and Validation Datasets for Bulgarian Language

Classifier	Macro F1	Macro Precision	Macro Recall
Ridge-Classifier	0.597	0.699	0.57
Perceptron-Classifier	0.584	0.671	0.56
SGD-classifier	0.642	0.654	**0.633**
Passive-Aggressive-Classifier	0.639	0.69	0.61
Decision-Tree-Classifier	0.619	0.646	0.603
Random-Forest-Classifier	0.546	0.78	0.533
AdaBoost-Classifier	0.649	0.7	0.622
Gradient Boosting-Classifier	0.607	**0.71**	0.578
SVM Classifier	**0.65**	0.676	0.632

In this section, we show the results of the task we submitted. We used the TF-IDF model setup for prediction since it generated a considerably better overall result. The F1-Score, precision, and recall macros were used to evaluate us. The confusion matrices are displayed below, and they display the classification of classes as well as classes that were mistakenly classified. It is a critical instrument for evaluating the efficacy and performance of our model. The Table 12 displays our positions in each subtask. The rankings were not obtained for the Spanish language.

Table 12: DistilROBERTa results on the test dataset

Task	Macro F1-Score	Rank
English	0.50	1
Hindi	0.52	4
Bulgarian	0.50	4

7 Conclusion

To summarise, this study looked into a variety of text classification techniques, including Bag-of-

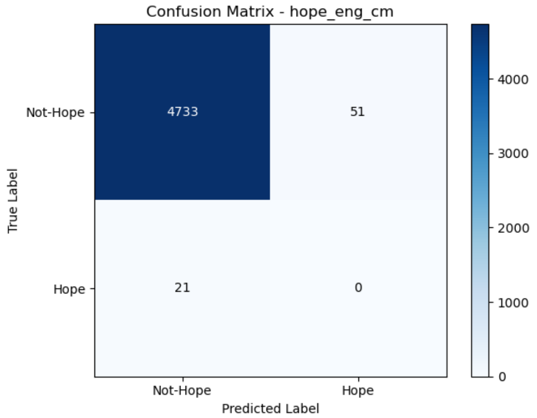

Figure 1: Confusion Matrix of English Predictions

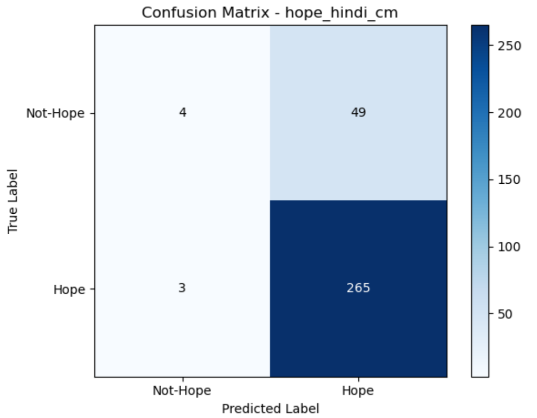

Figure 2: Confusion Matrix of Hindi Predictions

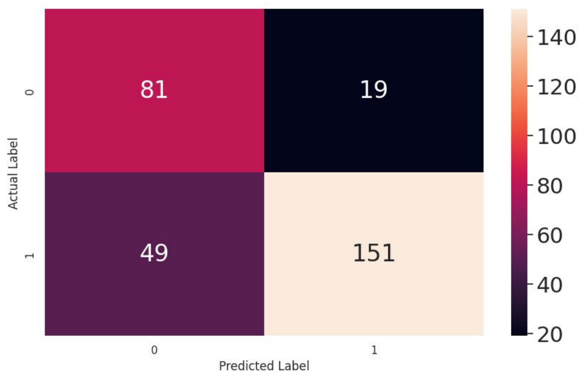

Figure 3: Confusion Matrix of Spanish Predictions

Words (BOW) features based classification, TF-IDF features based classification, and fine-tuning of the pre-trained DistilRoBERTa model. Each method has various advantages and shown its ability to effectively categorise textual data. Our model and experiments completed the task successfully. We can improve performance by fine-tuning the pre-trained model for additional similar data and through data augmentation.

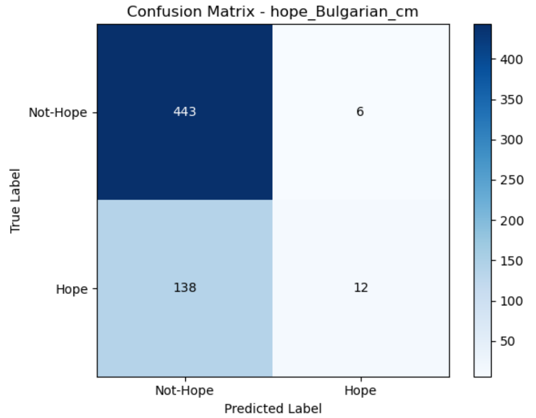

Figure 4: Confusion Matrix of Bulgarian Predictions

Acknowledgements

We are thankful to Indian Institute of Information Technology Ranchi for all the support during our research.

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