RANGANAYAKI@LT-EDI: Hope Speech Detection using Capsule Networks

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Abstract

HOPE speeches convey uplifting and motivating messages that help enhance mental health and general well-being. Hope speech detection has gained popularity in the field of natural language processing as it gives people the motivation they need to face challenges in life. The momentum behind this technology has been fueled by the demand for encouraging reinforcement online. In this paper, a deep learning approach is proposed in which four different word embedding techniques are used in combination with capsule networks, and a comparative analysis is performed to obtain results. Oversampling is used to address class imbalance problem. The dataset used in this paper is a part of the LT-EDI RANLP 2023 Hope Speech Detection shared task. The approach proposed in this paper achieved a Macro Average F1 score of 0.49 and 0.62 on English and Hindi-English code mix test data, which secured 2nd and 3rd rank respectively in the above mentioned share task.

1 Introduction

In human life, hope plays a very vital role in healing, betterment and repairing oneself inside out. Hope speech reflects the belief that one can find ways to one's desired objectives and become motivated to utilize those ways. Social media platforms like Facebook and Instagram provide users with the opportunity to establish online communities comprising individuals who share common interests, values, or goals. These communities foster a profound sense of acceptance and belonging among their members (Sundar et al., 2022). This work aims to encourage a positive way of thinking by moving away from discrimination, loneliness, or other worst things in life to building confidence, support, and good qualities based on comments by individuals. The concept of hope typically encompasses promises, potential, support, comfort, recommendations, and inspiration, all of which are offered to individuals by their peers during challenging moments of illness, stress, loneliness, and sadness (Chakravarthi, 2020). Nevertheless, conventional approaches in natural language processing such as machine learning algorithms often fall short when it comes to accurately identifying hope speeches. Hence, there exists a critical need for innovative techniques that harness the power of deep learning, incorporating the latest advancements in the field. By leveraging these advanced techniques, we can strive to enhance the precision and effectiveness of hope speech detection, ultimately contributing to the improvement of mental health and overall well-being. This progress can be achieved through the dissemination of positive content across various online platforms, aiming to uplift individuals and promote a more optimistic outlook on life (Chakravarthi, 2022). By embracing these advancements, we can foster a society where hope thrives, enabling individuals to overcome challenges and embrace a brighter future.

2 Related Works

Works on Hope Speech detection have increased in recent times. Chakravarthi (2022) proposed a novel custom deep network architecture, which uses a concatenation of embedding from T5-Sentence. Eswar et al. (2022) experimented with the CNN+BiLSTM model for deep learning, with FastText, ELMo, and Keras embeddings. Demotte et al. (2021) (2021) proposed a method to use GloVe embeddings in shallow and deep capsule networks together with static and dynamic routing for sentiment analysis of tweets. Srinivasan and Subalalitha (2021) have proposed Levenshtein distance as the preprocessing technique for Tamil-English code-mixed data and also discussed the influence of using resampling techniques such as SMOTE

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Table 1: Class Wise Distribution of Training, Validation and Test Dataset (Hindi-English Code Mix)

Class	Train	Validation	Test
Hope-Speech	343	45	53
Non Hope-speech	2219	275	268
Total	2562	320	321

Table 2: Class Wise Distribution of Training, Validation and Test Dataset (English)

Class	Train	Validation	Test
Hope-speech	1905	270	21
Non Hope-speech	20433	2534	4784
Total	22338	2804	4805

and ADASYN. Naseem et al. (2020) introduced a sentiment analysis framework known as $DICE_T$, which consists of three key components: an intelligent preprocessor, a text representation layer, and a bi-directional long- and short-term Memory (BiLSTM) integrated with attention modeling. In recent years many works are being carried out on Indian regional languages such as Hindi, and Tamil as well. Chakravarthi (2020) Chakravarthi (2022) has constructed a Hope Speech dataset that contains comments generated by YouTube users out of which 28451 comments are for English, 20198 for Tamil, and 10,705 comments for Malayalam respectively. All these comments were manually labeled as containing hope speech or not. In their study, Sundar et al. (2022) utilized a model based on stacked transformers for encoding, while also incorporating cross-lingual word embeddings.

3 Task and Dataset Overview

Dataset (Chakravarthi, 2020) used in this paper are provided by the Hope Speech Detection for Equality, Diversity, and Inclusion- LT-EDI-RANLP 2023 shared task. The objective of the shared task is to find hope in the text. The class labels are hope-speech and non-hope-speech. Each comment/post is assigned a class label. English and Hindi-English code mix data are considered in this work. A few weeks prior to the deadline for submitting the run, a testing dataset without labels was provided. The organizers later made available a labeled test dataset for verification purposes after the results were announced. Tables 1 and 2 present the sample counts for each class in the training, validation, and test sets.

4 Methodology

The overall architecture for Hope Speech Detection in English and Hindi-English code-mix is given in Figure 1.

4.1 Data cleaning and pre-processing

The English and Hindi-English code-mixed data is pre-processed before being converted into word embedding. The initial steps of pre-processing include lowercase conversion of the text, emoji-to-text conversion, user name removal and extra space removal. After the basic pre-processing is completed, spelling correction of misspelled words is performed on the English and Hindi-English code-mixed data. For spelling correction Levenshtein distance (Naseem et al., 2020) is used to find the distance between the correct and misspelled words. If the Levenshtein distance between the misspelled word and the correct word is 1 then the misspelled word is replaced with the correct word. A list of all possible English words is used to compare the words in training, validation, and testing data, to identify spelling mistakes using Levenshtein distance. Since there are no rules to govern the formation of Hinglish words, there cannot be any fixed vocabulary for Hinglish words. Hence the Vocabulary of Hindi and Hinglish words is created during training using all the Hindi and Hinglish words present in Hindi-English code-mix training data. These created vocabularies are used for checking and correcting spellings during testing, with respect to training data. The pre-processed text is fed into four different embedding models - FastText (Grave et al., 2018), ELMo (Peters et al., 2018), BERT (Devlin et al., 2019) and XLNet (Yang et al., 2019) respectively. Each vector representation has a different dimension and different ways of representing the input text. Since the data has high class imbalance, oversampling is performed in order to handle the class imbalance in the data. Over-sampling is done using ADASYN (He et al., 2008) oversampling method.

4.2 Classification model

The pre-processed and over-sampled word embedding is then fed into the capsule network (Sabour et al., 2017) to perform classification. Each of the embeddings is fed into a separate capsule network for training.

The capsule network has 5 layers, a convolution layer, a primary capsule layer, and three dense

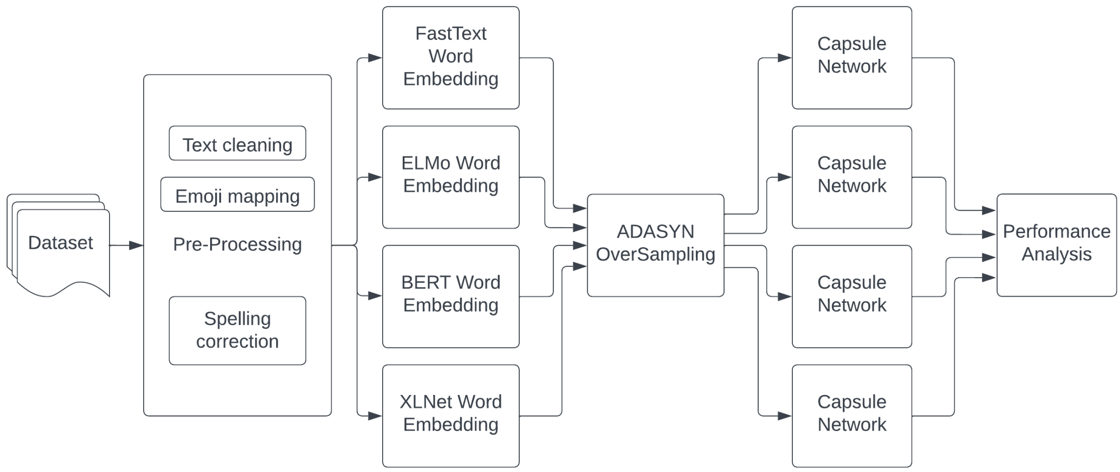

Figure 1: Hope Speech Detection Architecture

Table 3: parameters of Capsule Networks

parameter	Value
ϵ	1×10^{-7}
m_{plus}	0.9
m_{minus}	0.1
λ	0.5
α	0.0005
optimizer	Adam

layers. Dynamic routing is used to determine the optimal routing of information between primary capsules and output capsules. It involves iterative communication between capsules, where the output of one capsule is weighted and passed as input to another capsule based on agreement scores. Each of the trained capsule networks is used to perform prediction to perform a comparative analysis on the embedding based on metrics such as accuracy, precision, recall, and F1 score. The parameters used are in Table 3.

5 Result and Analysis

After the implementation of the various modules, the results obtained detect the hope texts in the comments. The evaluation metrics taken into consideration are Accuracy, Macro-precision, Macro-recall, and Macro-F1-score. FastText word embedding combined with the capsule network produced better results than the other three embedding techniques - ELMo, BERT, and XLNet. It was also observed that over-sampling has increased the performance metrics along with preprocessing and spelling correction. Tables 4 and 5 show the performance of hope speech detection with respect to various embedding techniques used in English and Hindi-English code-mix validation data. Table 6 shows the performance of the combination of FastText and Capsule Network on test data. It has been observed that the combination outperforms the other embedding techniques in both datasets.

6 Conclusion

In this paper, a hope speech detection framework has been proposed by experimenting with four different embedding techniques combined with capsule networks. The preprocessing technique used to handle class imbalance and varied spelling corrections has effectively improved the performance of the proposed model. According to the analysis performed on the four word embedding techniques FastText has outperformed the other three models in terms of accuracy, macro average precision, recall, and F1 score. This is because the combination capsule network with FastText embedding preserves spatial information. The proposed model provides an accuracy and F1-score of 0.87 and 0.70 for the Hindi-English code-mix Validation data set and 0.90 and 0.65 for the English Validation data set. An accuracy and F1-score of 0.93 and 0.49 are obtained for the Hindi-English code-mix Test data set and 0.82 and 0.82 are obtained for the English Test data set respectively. In future, the work can be extended by further experimenting with different routing techniques of capsule network and other recent word embedding models.

Table 4: Performance Metrics of Hindi-English Code-Mix Validation Dataset

Metrics	Fasttext	ELMo	BERT	XLNet
Accuracy	0.87	0.82	0.81	0.86
Precision	0.68	0.61	0.62	0.50
Recall	0.72	0.62	0.61	0.43
F1-Score	0.70	0.62	0.62	0.46

Table 5: Performance Metrics of English Validation Dataset

Metrics	Fasttext	ELMo	BERT	XLNet
Accuracy	0.90	0.81	0.81	0.24
Precision	0.65	0.76	0.58	0.51
Recall	0.66	0.62	0.55	0.51
F1-Score	0.65	0.64	0.55	0.23

Table 6: Performance Metrics of Test Datasets using Fasttext and Capsule Network

Language	Accuracy	Precision	Recall	F1-Score
English	0.93	0.50	0.56	0.49
Hindi-English Code-Mix	0.82	0.64	0.60	0.82

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