MUCIC@TamilNLP-ACL2022: Abusive Comment Detection in Tamil Language using 1D Conv-LSTM

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Abstract

Abusive language content such as hate speech, profanity, and cyberbullying etc., which is common in online platforms is creating lot of problems to the users as well as policy makers. Hence, detection of such abusive language in user-generated online content has become increasingly important over the past few years. Online platforms strive hard to moderate the abusive content to reduce societal harm, comply with laws, and create a more inclusive environment for their users. In spite of various methods to automatically detect abusive languages in online platforms, the problem still persists. To address the automatic detection of abusive languages in online platforms, this paper describes the models submitted by our team - MUCIC to the shared task on "Abusive Comment Detection in Tamil-ACL 2022". This shared task addresses the abusive comment detection in native Tamil script texts and code-mixed Tamil texts. To address this challenge, two models: i) n-gram-Multilayer Perceptron (n-gram-MLP) model utilizing MLP classifier fed with char-n gram features and ii) 1D Convolutional Long Short-Term Memory (1D Conv-LSTM) model, were submitted. The n-gram-MLP model fared well among these two models with weighted F1-scores of 0.560 and 0.430 for code-mixed Tamil and native Tamil script texts, respectively. This work may be reproduced using the code available in Github.

1 Introduction

Abusive language refers to the usage of words for any type of insult, vulgarity, profanity, sexism, or misogyny (Butt et al., 2021) that debases the target, as well as anything that causes aggravation (Spertus, 1997). The term abusive language is often reframed as offensive language (Razavi et al., 2010) and hate speech (Djuric et al., 2015; Chakravarthi et al., 2021b). In recent years, an increasing number of users have witnessed the offensive behavior on social media (Duggan, 2017) targeting individuals, group or community. In spite of many social media companies using a variety of tools such as human reviewers, user reporting procedures, etc., to censor the offensive language, the problem is growing day by day mainly because the offensive/abusive language detection algorithms fail to capture the subject and context-dependent characteristics of the text (Chatzakou et al., 2017; Priyadharshini et al., 2021; Kumaresan et al., 2021). For example, an individual message may appear harmless, but when viewed in the context of previous threads, it may appear abusive, and vice versa. It is challenging even for human beings to detect such abusive language.

Social media texts are usually written mixing regional languages such as Tamil, Kannada, Malayalam, etc., with English at sub-word, word or sentence level (Sampath et al., 2022; Ravikiran et al., 2022; Chakravarthi et al., 2022; Bharathi et al., 2022; Priyadharshini et al., 2022). Further, the usage of internet slangs, words in short forms, words of other languages, emojis etc., adds to the problem of tackling abusive language (Balouchzahi and Shashirekha, 2021; Anusha and Shashirekha, 2020). The focus of abusive comment detection algorithms on low-resources like Tamil is rarely explored due to scarcity and unavailability of annotated dataset Amjad et al. (2021b).

"Abusive Comment Detection in Tamil-ACL 2022" shared task (Priyadharshini et al., 2022) encourages researchers to develop models for detecting comments in native Tamil script texts as well as code-mixed Tamil texts. The objective of the shared task is to identify the abusive content in Tamil and categorize it into predefined abusive language categories. To address the challenges of the shared task, we - team MUCIC, submitted two models: i) n-gram-MLP model utilizing MLP classifier fed with char-n gram features and ii) 1D Conv-LSTM model utilizing MLP classifier fed with char-n gram features and i...
Conv-LSTM model, to detect abusive comments in Tamil. This paper describes the methodology of the proposed models and the results obtained.

The rest of the paper is arranged as follows: A review of related work is included in Section 2, and the methodology is discussed in Section 3. Experiments, and results are described in Section 4 followed by concluding the paper with future work in Section 5.

2 Related Work

Most of the abusive comment detection works focus on high-resource languages like English, leaving the low-resource languages such as Dravidian languages, Arabic, Persian, Urdu, etc., unexplored for the task (Amjad et al., 2021a).

A brief description of some of the recent abusive language detection works are given below:

The main problem with low-resource languages are the annotated datasets for abusive language detection. Even human annotators find it difficult to annotate some of the comments as abusive because of which building a large and reliable dataset becomes challenging. Chatzakou et al. (2017) found that datasets openly available for abusive language detection on Twitter ranged from 10K to 35K in size and are insufficient to train Deep Learning (DL) models.

Ashraf et al. (2021) explored abusive comment detection in YouTube comments using several Machine Learning (ML) and DL models as baselines and used n-grams features and pre-trained Glove embeddings to train ML and DL models respectively. Ada-boost (ML model) and 1-Dimensional Convolutional Neural Network (1D-CNN) (DL model) models obtained 87.29 and 89.24 F1-scores on comments without replies. Adding replies as conversational context enhanced the results to 91.96 and 91.68 F1-scores for Ada-boost and 1D-CNN respectively.

Lee et al. (2018) compared various learning models using Hate and Abusive SpeechTwitter dataset (Founta et al., 2018). In addition to traditional ML approaches (NB, LR, SVM, and RF), they also investigated Neural Network (NN) models (CNN, Recurrent Neural Networks (RNN) and Bidirectional Gated Recurrent Unit (BiGRU)), Term Frequency-Inverse Document Frequency (TF-IDF) of word vectors and pre-trained GloVe vectors were used to train ML and NN models. Further, Latent Topic Clustering (LTC) which extracts latent topic information from the hidden states of RNN is used as additional information in classifying the text data. BiGRU model based on word features and LTC outperformed the other models with an F1-score of 0.805.

Eshan and Hasan (2017) experimented TF-IDF of unigram, bigram, and trigram features to train ML algorithms (RF, Multinomial NB, SVM with Linear, Radial Basis Function, Polynomial, and Sigmoid kernels) and evaluated Facebook dataset of Bengali abusive text. SVM with Linear kernel and trigram feature achieved the best accuracy of 76% accuracy among all the models.

ML (Linear Support Vector Classifier (LinearSVC), LR, MNB, RF) and DL (RNN with Long Short Term Memory (LSTM)) algorithms, were used to detect multi-type abusive Bengali text by Emon et al. (2019). LinearSVC, LR, and MNB models were trained with filtered non-Bengali data transformed to vectors using a CountVectorizer, and RF classifier was trained with the TF-IDF vectors obtained after filtering punctuation, numerals, and emotions. For DL model, the raw dataset is stemmed and word embedding is utilized to encode the text. RNN with LSTM outperforms other algorithms with the highest accuracy of 82.20%.

Several code-mixed Tamil datasets are used in various shared tasks, such as Sentiment Analysis in Tamil (Chakravarthi et al., 2020), Hate Speech Detection in Dravidian Languages (Mandl et al., 2020), Hope Speech Detection (Chakravarthi, 2020), Offensive Language Identification (OLI) in Dravidian Languages, (Chakravarthi et al., 2021a), etc. Since code-mixed texts do not follow any grammar, Balouchzahi et al. (2021a) proposed a learning model using sub-words generated by char sequences to deal with code-mixed texts for the task of OLI in Dravidian languages (Chakravarthi et al., 2021a). They used word n-grams with sub-words and a majority voting classifier with eXtreme Gradient Boosting (XGB), LR, and MLP estimators and obtained a weighted average F1-score of 0.75.

In another experiment on code-mixed Tamil texts, Balouchzahi et al. (2021b) combined char sequences with syntactic bi-grams and tri-grams for Hope Speech Detection task (Chakravarthi, 2020) and fed a voting classifier with three ML estimators, namely: LR, XGB and MLP. The authors created a code-mixed BERT language model from

3https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html
scratch and obtained an average weighted F1-score of 0.54. However, in this study, the best performance was that of hard voting classifier with an average weighted F1-score of 0.59 that secured third rank in the competition.

3 Methodology

The first step in processing text data is to clean the text by removing the punctuation symbols, numerical data, frequently occurring words, and stop-words, as these features do not help in identifying the abusive content. Clean data is expected to improve the performance of the learning models. Two models: i) n-gram-MLP trained with char n-grams and ii) 1D Conv-LSTM model, were proposed to identify the abusive comment from native Tamil script and code-mixed Tamil texts. The framework of the proposed models are shown in Figure 1 and 2 and explanation of the models follows:

3.1 n-gram-MLP model

Many text processing projects utilize n-grams features since they are easy to implement and are scalable. A model with a larger ‘n’ value can store more contexts with a well-understood space-time tradeoff (Balouchzahi and Shashirekha, 2020) allowing many text processing experiments to scale up efficiently.

char n-grams in the range (1, 3) are extracted from the texts and vectorized using TfidfVectorizer. These vectors are used to train MLP classifier by setting hidden layer sizes to (150, 100, 50), maximum iterations to 300, Random state to 1, activation to Relu and solver to Adam.

3.2 1D Conv-LSTM model

Keras Tokenizer tokenizes the text and transforms it into a vector where the coefficient for each token could be binary, based on word count or TF-IDF. Further, the vocabulary size and maximum length of sequences are set to 60,000 and 50 respectively. "Pad_sequences" was utilized to keep all sequences at same length. The three parameters: "input dim", "output dim" and "input length" are set to 60,000 (vocabulary size), 1,000 (vector length of word) and 500 (maximum length of a sequence) respectively. Eventually, a 1D convolutional layer with 64 filters, two pooling layers, and a relu activation function, followed by 100 fully connected LSTM layers and a soft-max output layer are used in this model to classify the given input.

4 Experiments and Results

The datasets provided by the shared task organizers contains native Tamil script (Tamil) and code-mixed Tamil (Ta-En) texts and the task is to classify the input text into different categories as shown in Table 1. Further, the table also gives the breakup of Train and Test sets for both Tamil and Ta-En datasets. The observation of data distribution reveals that both native and code-mixed Tamil datasets are imbalanced and that makes the classification task more problematic. For example, there are only 35, 6, and 2 samples in Homophobia, Transphobic, and not-Tamil classes respectively against 446, 149 and 95 samples in Misandry, Counter-speech and Xenophobia respectively, in the Train set of Tamil dataset. Few samples of the native script and code-mixed texts in the datasets are shown in Table 2.
Table 1: Distribution of labels in the given datasets

| Label | Train | Test |
|-------|-------|------|
| Tamil | 1296  | 3720 |
| Ta-En | 346   | 919  |
| Misandry | 446 | 830 |
| Counter-speech | 149 | 348 |
| Xenophobia | 95  | 297  |
| Hope-Speech | 86  | 213  |
| Misogyny | 125 | 211  |
| Homophobia | 35  | 172  |
| Transphobic | 6   | 157  |
| Not-Tamil | 2   | -    |
| Total   | 2240 | 5791 |

Table 2: Samples of texts in the given dataset

| Language | Text | label |
|----------|------|-------|
| Tamil    | ஆட்சியும் அதிகம் வாய்ந்து மணம் தெளிவு உள்ளது இறைவனின் | Misandry |
|          | மணம் தெளிவு உள்ளது இறைவனின் மணம் தெளிவு உள்ளது இறைவனின் | Homophobia |
|          | மணம் தெளிவு உள்ளது இறைவனின் | Xenophobia |
| Ta-En    | Guru maruthi dhevudiya pulliya | Misogyny |
|          | Anna maangandu unnaitham evorada comments thappa pesara unga ellorukum samaram | Counter-speech |
|          | Sappa nose ah uddiukum alavukku | Xenophobia |

Table 3: Macro F1-score(m_F1-score) and Weighted F1-score(w_F1-score) F1-score on Development set

| Model     | Language | w_F1-score | m_F1-score |
|-----------|----------|------------|------------|
| MLP       | Ta-En    | 0.64       | 0.28       |
|           | Tamil    | 0.56       | 0.33       |
| 1D Conv-LSTM | Ta-En | 0.54       | 0.29       |
|           | Tamil    | 0.60       | 0.27       |

Table 4: Macro F1-score(m_F1-score) and Weighted F1-score(w_F1-score) F1-score on Test set

| Language | w_F1-score | m_F1-score | Rank |
|----------|------------|------------|------|
| Ta-En    | 0.560      | 0.290      | 6    |
| Tamil    | 0.430      | 0.120      | 10   |

The unlabeled Test sets shared by the organizers were used to evaluate the proposed models and the predictions were submitted to the organizers for final evaluation and ranking. As per the results in the final leaderboard of the shared task, the proposed n-gram-MLP model obtained average weighted F1-scores of 0.560 and 0.430 for Tamil and Ta-En texts respectively. Results of the proposed models on Development set and Test set are shown in Table 3 and 4 respectively. The comparison of average weighted F1-scores among the participating teams in the shared task shown in Figure 3 illustrates that the performance of the n-gram-MLP model is considerate.

5 Conclusion

This paper describes the participation of our team MUCIC in "Abusive Comment Detection in Tamil-ACL 2022" shared task. The objective of this shared task is to identify the different categories of abusive comments in native Tamil script and code-mixed Tamil texts. Among the two models, n-gram-MLP trained with n-grams and 1D Conv-LSTM model submitted for this shared task, n-gram-MLP classifier outperformed on both code-mixed Tamil and native Tamil script texts with average weighted F1-scores of 0.560 and 0.430, respectively.

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Figure 3: Comparison of average weighted F1-scores of the participating teams

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