Offence Detection in Dravidian Languages Using Code-Mixing Index-Based Focal Loss

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Abstract
Over the past decade, we have seen exponential growth in online content fueled by social media platforms. Data generation of this scale comes with the caveat of insurmountable offensive content in it. The complexity of identifying offensive content is exacerbated by the usage of multiple modalities (image, language, etc.), code mixed language and more. Moreover, even after careful sampling and annotation of offensive content, there will always exist a significant class imbalance between offensive and non-offensive content. In this paper, we introduce a novel code-mixing index (CMI) based focal loss which circumvents two challenges (1) code-mixing in languages (2) class imbalance problem for Dravidian language offence detection. We also replace the conventional dot product-based classifier with the cosine-based classifier which results in a boost in performance. Further, we use multilingual models that help transfer characteristics learnt across languages to work effectively with low-resourced languages. It is also important to note that our model handles instances of mixed script (say usage of Latin and Dravidian—Tamil script) as well. To summarize, our model can handle offensive language detection in a low-resource, class imbalanced, multilingual and code mixed setting. The code is publicly available at https://github.com/Debapriya-Tula/EACL2021-DravidianTask-Bitions.

Keywords Multilingual · Offence detection · Deep learning · Code-mixing · Loss function

Introduction
Communication has never been as sophisticated as it is today. Online communication has helped break a ton of obstructions as far as time, distance and simplicity of correspondence are concerned. As the active users of the internet filled in volumes throughout the past few years prompted an extraordinary expansion in the measure of hate speech on the open web. Online hate speech has been connected to a rise in violence against minorities around the world, including mass shootings, lynching, and ethnic genocide [23]. As more people go online, people who are prone to exhibit racism, misogyny, or homophobia have found niches that might reinforce their beliefs and provoke violence. Hate speech is frequently pointed towards a group or an individual, harming their character, convictions, identity and/or feelings. Many rogue elements use these platforms to revile and cause disharmony locally as offensive content, at many times, are inseparable from the benign posts. The absence of rigorous checking adds to the opportunity. It is thus important to solve this issue. Social media is easily accessible to a large domain of people and its scale restricts us from manually monitoring and filtering the content shared. Given the volume of data on social media, artificial intelligence (AI) must be a part of the regulatory mix and this calls for the need for (semi) automatic systems for the identification of hate or offensive speech.

The style of data on social media also plays a major role in understanding the data. The language structure is regularly absent and individuals will generally utilize words from various languages, ultimately resulting in code-switched...
data [3, 32]. The issue is exacerbated as people use words from various contents, say blending both Latin and native scripts (Devanagari, Dravidian, Mandarin, etc.) in their language. A unified model which can understand a multitude of these scripts plays a significant role in understanding the discourse in social media data and is conducive to creating a safer and healthier digital space.

The significance of the issue and the difficulties presented call for novel ideas for offensive language detection. Owing to this, multiple workshops [1, 51] and shared tasks [7, 20, 22] have been conducted to address the problem at hand.

In this paper, we extend the previous work [48], which presented a deep learning-based system for offensive language identification in Dravidian languages. Here, we introduce a novel Code-Mixing Index (CMI) based focal loss to handle the code-mixing. We further use it with Cosine Normalization to allow the classifiers to have more balanced decision boundaries i.e. more space for classes with less number of examples.

Related Works

With an increase in ease of access to social media, there is also an increase in evidence of usage of code-mixed language online. Authors in [2] found that almost 17% of the comments in a dataset of Facebook posts were multilingual. Initial attempts to analyze the sentiment in the context of Indian language tweets were made by [31] where the authors focused on the classification of the polarity of tweets in Bengali, Hindi, and Tamil languages. Vyas et. al. [50] attempted pos-tagging of code-mixed social media posts. Other studies which address various aspects related to code-mixing like language identification, language modelling, word-level language identification etc. include [3, 9, 11, 35].

Offensive language detection has been an important area of research with the growing number of internet users. This has been studied in varied formats like aggression detection, cyberbullying, offensive language, etc. Fortuna and Nunes, 2018 [14] discuss the nuances of hate speech and its potential for negative cultural effects, specifically in online communities and social media platforms. Wherein [46] investigated abusive language detection in a multilingual setting for English and German.

Research on offensive language detection is more important than ever, as demonstrated by numerous shared tasks and research works recently [4, 7, 20–22, 33]. The SemEval 2019 Task 5 [4] focused on Hate Speech detection on Immigrants and Women on Twitter. They organized two subtasks, a binary task for identification of hate speech and a fine-grained task for further identification of target group and aggression attitude. They created a new dataset with 19.6k tweets spanning two languages English and Spanish. Task 6 [52] focused on the identification and categorization of offensive language in social media. The task had a similar sub-division of tasks i.e. a binary task for classification, offensive type classification and target of the offensive content. They proposed a new dataset, OLID, which has 14k tweets annotated using a hierarchical annotation model. OffensEval 2020 [53] was a profanity identification task presented in SemEval 2020. It was conducted in 5 languages—English, Arabic, Danish, Greek, and Turkish.

There are various works on offensive language and hate speech detection using machine learning and deep learning algorithms like CNN, RNN, LSTM, etc. [29, 45]. With the advent of Transformer [49] and BERT-based models [12, 18, 44] there has been an increase in their usage in this field.

The authors in [45] used an ensemble of CNN and RNN-based models for offensive language detection in German Tweets. The authors in [39] accomplished the task of Robust Aggression Identification describing an ensemble of multiple fine-tuned BERT models based on bootstrap aggregating (Bagging). Transfer learning capabilities can be augmented using Task Adaptive pre-training on BERT models [37]. To alleviate the data imbalance and low-resource issues, [25] proposed a generative-based augmentation technique. Further, word-level recognition of code-mixed data is used in emotion classification for sentiment analysis [9]. Ma et al. [27] proposed an approach based on a weighted loss for multilingual models focusing on the complexity of code-mixing sentences, concluding that the eccentricity of word representations used has a considerable impact on the performance of a model.

There have been advances in offensive content detection in German [40], Italian [10], English-Hindi [30, 34], Bengali [42] but little progress has been made in Dravidian languages. Recent efforts include LSTM [28], Transformer [13] and BERT [43] based methods for offensive content detection in Dravidian languages. In [38], authors experiment with various inter-task and multi-task transfer learning techniques to leverage the useful resources available for offensive speech identification in the English language and enhance the multilingual models with knowledge transfer from related tasks.

Data

Three languages are considered for our work: Kannada [17], Malayalam [5], and Tamil [6]. The six class labels in Kannada and Tamil are:

- Not Offensive—(NO)
- Not Native—(NN)
- Offensive Individual—(OI)
- Offensive Group—(OG)
• Offensive Untargeted—(OU)
• Offensive Other—(OO)

All the above-mentioned classes except “Offensive Other” are present in the Malayalam dataset. The distribution of the data is described in Table 1 for all three languages. In total, there are 5936, 11695, 34898 samples for Kannada, Malayalam and Tamil, respectively. The values of Krippendorf’s alpha, which signifies the inter-annotator agreement, for Kannada, Tamil and Malayalam are 0.78, 0.66, 0.89, respectively.

There was a significant class imbalance in all 3 languages in the dataset. “Not Offensive” class, which is the majority class in all three languages, accounts for 56.97% of the samples in Kannada, 88.77% of the samples in Malayalam and 72.25% of the samples in Tamil data. To overcome this skewness, we utilize class weighting to penalize more for the under-represented classes. This is discussed in detail in the next section.

We often see the same native word written in different ways in English. The word “your” in Kannada is written as nin/ninna (singular) and nim/nimma (plural). nin/ninna (singular) and nim/nimma (plural).

On sampling and manually validating a few examples from the dataset, we noticed some instances in the Kannada data which have unlikely ground truth or could be perceived differently than how the annotators did. However, we did not make any changes to the labels. Some examples:

- Krishana shapa tatteleebeku (Krishana should curse (you)) is marked not offensive, however, the intent of this is to offend someone.
- Nana yash sudeep darshan appu cinema bittu yardu nodalla (I only watch Yash, Sudeep, Darshan and Sudeep’s movies) seems not offensive but is marked Offensive_targeted_insult_other.
- Nija Film channagidya nanu nodide nange kandita arta agle Illa (Is the film really that good? I saw it and honestly didn’t understand it), marked Not-offensive, but could be perceived as Offensive.

### Methodology

This section outlines our approach to detect (classify) offensive content in Dravidian languages. Given the presence of both Latin script and text in the native language, we tackle this problem from the multi-lingual learning space. We employ large language models that are pre-trained on multiple languages, including Dravidian languages. Further, because of the extreme class-imbalance present in the data, we use the focal loss along with class weighting to mitigate the model biases towards a particular dominant class. Owing to the code-mixed data presence, we propose a novel loss function: CMI-FL which integrates Code-Mixing Index (CMI) with focal loss. Further, we enhance our results by utilizing cosine normalization and pseudo-labelling.

### Model

We leverage the multilingual transformer-based models DistilBERT [44] and IndicBERT [18].

#### DistilBERT

DistilBERT [44] has the same general architecture as BERT [12], however, is only about 60% the size of BERT as the number of layers is reduced by a factor of 2. The model is trained with the same pre-training objective as BERT i.e. Masked Language Modelling (MLM) and Next Sentence Prediction (NSP). The DistilBERT is 60% faster than the BERT and retains almost 97% of BERT’s language understanding capabilities.

The efficacy of the DistilBERT inspired us to use a distilled version of the BERT base multilingual model (mBERT-base) called the DistilBERT-base-multilingual-model (DistilmBERT). DistilmBERT is about twice as fast as mBERT-base, according to HuggingFace. The model has 6 layers, 768 dimensions and 12 heads, totaling 134M parameters compared to 177M parameters for mBERT-base. For our work, we use the cased model as the data is code-mixed with English (the only case-sensitive language in the corpora). The model was pre-trained on the concatenation of Wikipedia data in 104 different languages including Tamil, Malayalam and Kannada.

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1. https://huggingface.co/distilbert-base-multilingual-cased#model-card.
IndicBERT

IndicBERT [18] is an ALBERT-based model trained exclusively on Indian languages. The model is pre-trained on 11 Indian languages (including Dravidian languages - Kannada, Telugu, Malayalam, Tamil), and English using the standard MLM objective. The model is pre-trained on news articles, magazines and blog posts.

CMI-FL: Code-Mixing Index Based Focal Loss

The data is code-mixed, which adds to the difficulty of the classification task. To incorporate the difficulty due to code-mixing, we propose a novel loss function called Code-Mixing Index (CMI) loss function. It is a modification of focal loss [24], like [27]. Here, the focal loss is weighed by the level of code-mixing in a sentence, which is given by the Code-Mixing Index (CMI) [15]. The loss function \( L \) is calculated as:

\[
L = \alpha \times CE \times (1 - CMI)^\gamma + \alpha \times CE \times CMI^\gamma
\]

where CMI is the Code-Mixing Index, CE is the initial cross-entropy, \( \alpha \) and \( \gamma \) are the constant positive scaling factor and the focusing parameter, respectively. The word-level annotations for the datasets required by the CMI are approximated by using the pyenchant tool, which provides language identification, spellchecking and a host of other capabilities. This CMI loss function can be used on tasks beyond the Dravidian languages.

Class Weighting

As mentioned in “Data”, the class imbalance is observed in the dataset, which can skew the model’s predictions against underrepresented classes. We use an inverse weighting strategy which helps penalize the under-represented classes more in the loss function.

Pseudo-Labelling

Pseudo-labeling is a semi-supervised learning technique where instead of manually labelling the unlabeled data, approximate labels are given on the basis of labelled data using a pretrained model. The model is first trained over the small set of labelled examples, which is then used to predict the labels for test data and this pseudo-labelled (test) data is used along with the train set for training the model further. This results in a considerable boost in performance.

Cosine Normalization

Cosine classifier has demonstrated encouraging results in vision-based applications like few/zero-shot learning and long-tail recognition. Inspired by these results we adopted a cosine similarity-based classifier [16, 26, 36] to obtain the final classification scores. We use a cosine similarity-based classifier instead of a dot product based classifier when computing the class activation scores. We normalize the final input embedding \( (e) \) viz., the embedding just before the classification layer, as well as the classifier’s weight vectors \( \{w_j\}_{j=1}^C \). Here \( C \) corresponds to the number of classes. Bias is not used for the classifier.

\[
e_{\text{norm}} = \frac{||e||^2}{1 + ||e||^2}
\]

\[
W_{\text{norm}} = \frac{W_C}{||W_C||^2}
\]

Here \( W_C \) corresponds to classifier’s weight matrix. The matrix multiplication is performed on the two matrices normalized input embedding \( (e_{\text{norm}}) \) and normalized weight matrix \( (W_{\text{norm}}) \) to obtain the final classification logits. The input embedding’s normalization is a non-linear squashing function adopted from [26, 41], which ensures that small-magnitude vectors are reduced to almost zeros, while large-magnitude vectors are normalized to a value slightly below one. Balancing the norms leads to more balanced decision boundaries, allowing the classifiers for few-shot classes to occupy more space [19]. In this work, we check the effectiveness of the cosine-based classifier using multiple loss functions, such as cross-entropy loss, CMI loss, and focal loss. The results are tabulated in Table 2.

Experiments

Here, we describe the experiments performed. The models are trained on colab. The code is publicly available at https://github.com/Debapriya-Tula/EACL2021-DravidianTask-Bitions.

DistilmBERT

The text is tokenized using the DistilmBERT tokenizer having a vocabulary size of 110k. The maximum sequence length used is 128. The long input text is truncated and

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shorter sequences are handled by padding special tokens. A batch size of 8 is used for training the model for 10 epochs. The model’s weights are optimized by using the Adam optimizer with a learning rate of 1e−8.

IndicBERT

For pre-processing, the IndicBERT tokenizer having a vocabulary size of 200k is used. A max sequence length of 200 is used and input sequences are truncated or padded depending on their length as in DistilmBERT. For our downstream task of offence detection, we add a fully connected layer with a dropout of 0.3 on top of the AlBERT model. The model is trained using the pre-trained IndicBERT weights only. A batch size of 32 is used during training, while a batch size of 16 is used for validation. The model was optimized using the Adam optimizer with a learning rate of 1e−5.

Code-Mixing Index (CMI) Loss

For labelling the languages at the word level, we use the polyglot [8] module, known to support many multilingual applications. We calculate the amount of code-mixing of the native language with English and assign a CMI for the entire batch of data at a time.

\[ \alpha = 1.7 \] (constant positive scaling factor) and \[ \gamma = 0.25 \] (focusing parameter) are fixed for all experiments.

Results and Analysis

Table 2 shows the results of all the experiments over all languages. All values mentioned are in percentage.

|                | Kannada | Malayalam | Tamil |
|----------------|---------|-----------|-------|
|                | Precision | Recall | F1 | Precision | Recall | F1 | Precision | Recall | F1 |
| Distilmbert + CE loss + PL | 66.5 | 69.1 | 67.5 | 96.8 | 96.8 | 96.8 | 74.6 | 77.0 | 75.2 |
| Distilmbert + Focal loss + PL | 65.8 | 68.4 | 66.9 | 96.1 | 96.2 | 96.1 | 75.1 | 76.8 | 75.8 |
| Distilmbert + CMI loss + PL | 67.5 | 69.1 | 67.9 | 96.4 | 96.4 | 96.3 | 74.6 | 77.3 | 75.6 |
| Distilmbert + CE loss + CN + PL | 65.9 | 68.2 | 66.7 | 96.2 | 96.3 | 96.2 | 73.7 | 76.4 | 74.8 |
| Distilmbert + Focal loss + CN + PL | 66.5 | 68.5 | 67.3 | 96.6 | 96.8 | 96.7 | 73.7 | 73.4 | 74.8 |
| Distilmbert + CMI loss + CN | 67.0 | 68.6 | 67.4 | 96.4 | 96.5 | 96.3 | 74.9 | 76.3 | 75.5 |
| Distilmbert + CMI loss + CN + PL | **68.5** | **70.3** | **69.1** | **97.0** | **97.1** | **96.9** | 74.4 | 77.1 | 75.6 |
| IndicBert + CE loss | 66.5 | 65.1 | 65.6 | 93.9 | 93.9 | 93.9 | 60.8 | 65.4 | 62.3 |
| IndicBert + CE loss + CN | 63.5 | 60.4 | 60.6 | 95.9 | 95.7 | 95.8 | 68.9 | 69.7 | 69.2 |
| IndicBert + CMI loss + CN | 67.0 | 67.4 | 65.6 | 95.4 | 95.5 | 95.4 | 69.3 | 70.0 | 69.3 |
| IndicBert + CMI loss | 61.3 | 59.6 | 60.2 | 93.7 | 94.4 | 93.9 | 70.0 | 69.9 | 69.8 |

All experiments use class weighting. Boldfaced scores are the highest score in that column.

CE cross entropy, CN cosine normalization, PL pseudo-labeling.

do not hallucinate.
further makes it easier to classify Malayalam than Tamil and Kannada. For Tamil and Kannada, the inter-annotator agreement is low (Krippendorff’s alpha = 0.66, 0.78 respectively), which means that the instances in these datasets have high subjectivity, confusion and overlapping boundaries between the classes. Hence, even the models find it more difficult to learn from the labelled data. The models perform better in Tamil than Kannada because the Tamil dataset is approximately six times larger than the Kannada dataset.

We conduct Stuart-Maxwell’s test [47] to check the statistical significance of our results. We compare our proposed solution (DistilmBERT + CMI loss + Cosine Normalization + Pseudo-labelling) with the baseline ensemble model from [48]. We achieve p-values 0.0005 for Kannada, 0.0003 for Tamil and 0.0376 for Malayalam. This

Table 3  Class-wise F1 scores of experiments with the distilmbert model for the Kannada dataset

| Support          | NO   | OTIG | OTII | OTIO | OU  | NK  |
|------------------|------|------|------|------|-----|-----|
| CE loss + PL     | 76.8 | 28.9 | 52.4 | 8.7  | 17.02 | 74.5 |
| Focal loss + PL  | 77.1 | 26.7 | 56.5 | 9.5  | 0.0 | 73.9 |
| CMI loss + PL    | 77.8 | **34.3** | 55.2 | 20.0 | 8.0 | 72.9 |
| CE loss + CN + PL| 77.0 | 21.7 | 53.3 | 10.0 | 15.3 | 72.6 |
| Focal loss + CN + PL | 77.9 | 32.0 | 53.1 | 9.0  | 9.8 | 71.4 |
| CMI loss + CN    | 77.1 | 29.9 | 55.9 | 14.8 | 6.9 | 73.7 |
| **CMI loss + CN + PL** | **78.4** | 32.5 | **58.0** | 28.5 | 12.2 | 73.9 |

All values reported are in percentage. All experiments use class weighting. Boldfaced scores are the highest score in that column.

CE cross entropy, CN cosine normalization, PL pseudo-labeling. Classes: NO Not_offensive, OTIG Offensive_Targeted_Insult_Group, OTII Offensive_Targeted_Insult_Individual, OTIO Offensive_Targeted_Insult_Other, OU Offensive_Untargeted, NK not-Kannada

| Sl. no. | Language | Input                                           | Translated input                                                                 | Actual label                                      | Predicted label                                      |
|---------|----------|-------------------------------------------------|----------------------------------------------------------------------------------|--------------------------------------------------|-----------------------------------------------------|
| 1       | Kannada  | Thu nem yogyathe ge maha vishnu hesaru ettu entha movie tegitira naghie agebeku nemge | Shame on you, you have made such a (bad) movie and named it Maha Vishnu          | Offensive Untargeted                               | Offensive Targeted Insult Individual                 |
| 2       | Kannada  | ఉత్తరం ఉత్తరం | Both of you are thieves                                                       | Offensive Targeted Insult Group                   | Not Offensive                                        |
| 3       | Kannada  | Yar Guru evlu chaina hudugi nnaa indian aa gothilla | Who is this girl guru, I don’t know if she’s Indian or Chinese              | Offensive Targeted Insult Individual              | Offensive Targeted Insult Individual                 |
| 4       | Tamil    | Comment la en da picha edukuringa… pichakara pasangala | Why are they begging in the comment section… beggars                         | Offensive Targeted Insult Group                   | Offensive Targeted Insult Other                      |
| 5       | Tamil    | தமிழ் விளக்கம் | The movie was on a diff level, congrats ravi comali (joker)               | Not Offensive                                     | Offensive Targeted Insult Individual                 |
| 6       | Tamil    | பிரிக்குந்துகள் | For haters, movies asuran, pari erum perumal, madras, kala, when he was directing/taking all these where were you? | Not Offensive                                     | Offensive Untargeted                                 |
| 7       | Tamil    | Mokka trailer thala ana padam super a irukum   | Boring trailer thala but the movie will be superb                          | Not Offensive                                     | Offensive Targeted Insult Individual                 |
shows that our results are statistically significant against an $\alpha$ of 0.05.

**Error Analysis**

We take the IndicBERT model and analyze some of the instances where the model did and did not predict the expected output. Table 4 gives such instances.

Figure 1 shows the attention weights plot for sentence 1 from Table 4. The word “vishnu” is given high importance. The reason for this (mis)prediction could be the word “vishnu” (or other nouns) being present in a lot of sentences belonging to the “Offensive Targeted Insult Individual” class.

For sentences 2 and 6, the ground truth labels seem unlikely and the predicted labels are better. This shows that the model is robust to errors in human labelling to an extent. The unlikely ground truth labels can be attributed to the low inter-annotator agreement for Tamil and Kannada.

Sentence 3 has subtle racism. Our model correctly predicts the label “Offensive Targeted Insult Individual”. Further, from its attention plot (Fig. 2), we can observe that the most importance is given to “chaina” (China) which is the word related to racism.

Sentence 4 in the table is offensive, but it’s not clear who it is offending. The model correctly predicts “Offensive Targeted Insult Other”. From Fig. 3, we see that the model does a good job in figuring out that “pichakara pasangala” (beggar people) is the part it should pay attention to.

Sentence 5 is not offensive but it is predicted as “Offensive Targeted Insult Individual”. This is because the word “comali” here refers to a movie but in a literal sense means ‘joker’ which could be used to offend someone.
Sentence 7 is a not offensive instance predicted as “Offensive Targeted Insult Individual”. From its attention weights plot (Fig. 4), we see that high importance was given to the words “a”, “padam” and “thala”. A possible reason for the misprediction could be that the word “thala” appeared in many “Offensive Targeted Insult Individual” sentences (since the word is used to describe a movie actor).

Conclusion and Future Work

In this paper, we introduce a novel CMI based focal loss that leverages the code-mixed phrases present in the data to better predict offensive language in Dravidian code-mixed sentences. We also notice that augmenting this with cosine normalization helps improve the model. To better understand our results, we compare them both quantitatively and qualitatively. Our method is language-agnostic and can therefore be extended to other low-resource languages. Our additions (CMI loss and Cosine Normalization) are simple yet effective and could be augmented to other models and approaches with minimal effort. Additionally, constructing synthetic code-mixed data and the usage of language-specific tokenizers for the multi-lingual models are potential future research directions.

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Declarations

Conflict of interest

No conflict of interest.

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