AtteSTNet - An attention and subword tokenization based approach for code-switched Hindi-English hate speech detection

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Abstract— Recent advancements in technology have led to a boost in social media usage which has ultimately led to large amounts of user-generated data which also includes hateful and offensive speech. The language used in social media is often a combination of English and the native language in the region. In India, Hindi is used predominantly and is often code-switched with English, giving rise to the Hinglish (Hindi+English) language. Various approaches have been made in the past to classify the code-mixed Hinglish hate speech using different machine learning and deep learning-based techniques. However, these techniques make use of recurrence mechanisms which are computationally expensive and have high memory requirements. Past techniques also make use of complex data processing making the existing techniques very complex and non-sustainable to change in data. Proposed work gives a much simpler approach which is not only at par with these complex networks but also exceeds performance with the use of subword tokenization algorithms like BPE and Unigram, along with multi-head attention-based techniques, giving an accuracy of 87.41% and an F1 score of 0.851 on standard datasets. Efficient use of BPE and Unigram algorithms help handle the nonconventional Hinglish vocabulary making the proposed technique simple, efficient and sustainable to use in the real world.

Keywords—Natural language processing, Text classification, Cyber abuse, Self-attention, Deep learning

1. INTRODUCTION

With easy access to technology, social media has seen a rapid increase in usage over the globe. Every individual has a smartphone and an instant access to social media sites like Facebook, Twitter. These social media networks generate massive amounts of data daily which also contains huge amounts of hate speech. The term "hate speech" can be defined in many ways and its definition changes from person to person, but to generalize the definition, it can be said that any form of speech or writing that denigrates and belittles another person’s beliefs, views, or orientation, especially based on race, sexual orientation, or religion, is hate speech. Now since social media users are around the globe the text data that’s generated also doesn’t have any limitation on language. It is largely observed that English with native languages is predominantly used on social media. Focusing on social media users in India the text content that’s generated largely has a general trend of containing some English, Hindi, and code-mixed Hindi words and sentences. Hate speech is often discouraging and can have adverse effects on people as it forms a part of cyberbullying. Detecting this type of speech can be useful for identifying users and for imposing strict actions on them. Hate speech detection in a code-mixed language is particularly a challenge due to its nature of having the essence of more than one language. Previous approaches for Hindi-English code-switched language have used various machine learning and deep learning algorithms. Advanced deep learning-based approaches have also made use of concurrence and recurrence mechanisms [1], [2]. However, the use of such mechanisms increases the complexity of the architecture. Further, encoding the HindiEnglish texts is also a challenge. Past approaches have either made use of a manually created profanity list [3] for Hinglish language or made use of translation [4], [5] to convert the Hindi words to English.
Also, the approaches make use of a manually created dictionary for translation of some Hinglish words when the automatic translation fails. However, usage of such approaches in the real world might be difficult due to such complex data processing steps. And in case the model has to be modified due to a change in the data, it would take a lot of time to modify the profanity list and the translation dictionary. Therefore, an approach that is simple, efficient, and sustainable is the need of the hour. This paper proposes the use of a simple and sustainable model architecture using an attention mechanism along with Byte Pair Encoding (BPE) and Unigram sub word tokenization algorithms. In particular, the author makes use of multi head self-attention. Individual texts are encoded using BPE as well as Unigram algorithms, and the encoded sequences are passed on to their respective positional encoding and attention layers. The outputs obtained are then concatenated and passed on to further layers of the model architecture. The proposed architecture is found to be superior in handling code-switched Hindi-English language hate speech detection and provides optimum results on the standard dataset proposed in [5] across various metrics. This paper also compares the obtained results to previous approaches used by previous researchers on the same dataset, demonstrating the superior performance of the proposed approach. Main contributions in the paper could be listed as follows:

- This paper has made effective use of BPE and Unigram algorithms to handle the non-conventional Hinglish vocabulary without requiring very complex data processing steps like manually creating a profanity list or translating the Hindi words to English in the sentence, unlike past approaches.
- This paper has achieved quality results by using attention despite eliminating the whole recurrence mechanism, which is used in most approaches.
- In this work, the authors made constructive use of positional encoding in the absence of recurrence to provide sequence-related information.
- By using the concatenation of BPE and Unigram padded sequences, the authors have been able to illustrate the effective retention of the maximum information present in a sequence.

The rest of the paper is structured as follows: Section 2 talks about related work in this area while the proposed methodology is explained in section 3. Dataset description and the results obtained are discussed in section 4. Analysis of the work conducted is presented in section 5 while the paper is concluded in section 6.

II. RELATED WORK
Hate speech detection has been an active area of research in the field of natural language processing. Multiple approaches in the past have been tried in the area of hate speech detection, especially after the rise in the use of machine learning algorithms as well as the availability of computational power and data. However, most of the studies in hate speech detection are based on monolingual content, primarily English. Dinakar et al. [6] proposed the use of various features like Tf-Idf, PoS tagging, and label-specific features to detect offensive tweets. Badjatiya et al. [7] proposed the use of multiple approaches like CNNs, LSTMs, and FastText for hate speech detection. Pitsilis et al. [8] built an ensemble model of RNN classifiers for identifying hateful posts from a large dataset of Twitter posts. Studies are also being carried out on hate speech detection in languages other than English. Ibrohim et al. [9] employed various classifiers like SVM, Random Forest Decision Tree, Naïve Bayes for multi-label Indonesian tweets classification. Vo et al. [10] employs a multi-channel CNN-LSTM network to detect hate speech in the Vietnamese language. Although the majority of the approaches are based on monolingual content, some approaches are proposed for hate speech detection of code-switched texts. One of the earlier works for code switched texts was presented by [11] demonstrating cross-lingual interaction on the semantic level. There have been various attempts to translate the HindiEnglish mixed language into pure English previously, but the major obstacle to this is that the grammatical rules of Hinglish are very uncertain and user-dependent. [1] used subword level LSTM models for Hinglish sentiment analysis. [12] proposed the use of contrastive learning with Siamese networks to map code-mixed and standard language text to a common sentiment space. Hate speech can often be complex and hence [2] has used two kinds of encoders that take note of overall sentiment and individual sentiment-bearing units. In addition to this, they have also used a featured network that uses linguistic features to augment the model. Baroi et al. [13] uses CNNs and LSTMs based ensemble models to detect hate speech. CNN-based transfer learning has also been used for the detection of Hinglish hate speech [5]. Gupta [4] has utilized bi-directional sequence models such as GRU, BiLSTM, etc with data augmentation techniques such as synonym replacement, Random Insertion, Random Swap, Random Deletion on the text to achieve scores. However, the majority of the approaches have relied on recurrence or convolution along with complex data processing steps for offensive text classification in codeswitched languages. Also, the comparatively recent attention mechanism has not yet been actively used in this domain. While Chopra et al. [3] does make use of attention, they use complex text encoding steps for bias elimination and also combine the attention layer with LSTM in the final architecture. Further, advanced transformer architecture [14], [15] have also been tried for code-switched hate speech detection but the higher complexity of these models makes them impractical to use in real-world.

III. PROPOSED METHODOLOGY
Main task is to classify a given text sample into one of the three categories of non-abusive, abusive, and hate-inducing. The authors explained their solution by describing their approach for each phase of the standard text classification pipeline: preprocessing, text encoding, and model architecture.

Data preprocessing
The tweets obtained through data sources were passed through a pre-processing pipeline. The pre-processing
pipeline can be broken down into intermediate steps as follows:

- **Lower case:** The data is transformed to lowercase throughout.
- **Replace emojis:** Emojis that appear in tweets are replaced with relevant textual information with the help of `emoji` an Emoji for python library.
- **Strip hashtags, user mentions, and HTML tags:** Hashtags, user-mentions, and HTML links that are often used in tweets are removed. User-mentions are replaced with the keyword “username”. Links are replaced with the keyword “link” and hashtags are replaced with corresponding plain text.
- **Expand Contractions:** The apostrophe is a punctuation mark that is often used to abbreviate a word or a group of words. For example, the word "don't" means "do not," while "can't" means "can not". In this phase, the abbreviated forms are extended.
- **Remove special characters:** Special characters are neither alphabets nor numbers and these induce noise hence are removed from the text data.
- **Transliterate:** This step involves transliteration of the Hinglish text data i.e. conversion of Hindi text into relevant sounding English text. This step is carried out using the in dic transliteration package's "sanscript" library.

A. **Text Encoding**

This paper makes use of subword tokenization to convert the text into model-friendly data. Subword tokenization breaks the sentence into chunks based on the word frequency. As Hindi + English code-mixed data contains non-conventional vocabulary, this approach helps to solve the issues faced by word-based tokenization (large vocabulary, large number of OOV tokens, and different meanings of very similar words) and character-based tokenization (very long sequences and less meaningful individual tokens). Subword tokenization deals with an infinite potential vocabulary through a finite list of known words. For example, the authors can make up the word "unfortunately" via "un" + "for" + "un" + "the" + "ly". Common words like "for" and "the" are tokenized as whole words, while rarer words are broken into smaller chunks. Various subword tokenization algorithms like Byte Pair Encoding (BPE), Probabilistic Subword Tokenization, and Unigram Subword Tokenization have been used by researchers in the past. For experimental use, this paper focuses on the BPE [16] and [17] subword tokenization algorithms. The authors make use of both the BPE and Unigram algorithms, as BPE might build an ambiguous tokenized sequence sometimes, and the Unigram algorithm helps to tackle this shortcoming of BPE. 1) **Byte Pair Encoding (BPE):** In BPE, frequently occurring subwords are merged finding the ideal balance between character and word level representation. This helps to manage large corpora and encoding of any rare words in the vocabulary with appropriate subword tokens without introducing any “unknown” tokens. The BPE operates as follows: • Get the word count frequency. • Get the frequency of character level counts. • Merge the most common byte pairing and add this to the list of tokens. • Recalculate the frequency count for each token. • Rinse and repeat until the defined token limit or number of iterations is reached. 2) **Unigram Subword Tokenization:** The Unigram language model is another algorithm for subword segmentation. One of the assumptions is all subword occurrences are independent and subword sequence is produced by the product of subword occurrence probabilities. Unlike BPE, unigram helps to overcome the problem that one has no way to predict which particular token is more likely to be the best one when encoding any new input text rather than choosing the best option. The Unigram operates as follows:

- Choose the seed subword token set and the most frequently occurring substrings.
- Calculate the probability for each subword token.
- Calculate a loss value of each subword. The Expectation-Maximization (EM) algorithm is used to calculate the loss.
- Drop the bottom x% of the subword tokens based on the loss. To avoid OOV words, single characters are kept.
- Rinse and repeat until the desired vocabulary size or there is no change in token numbers after successive iterations.

To improve the performance of the model, sequences are usually padded to a fixed length. This is usually performed by adding characters or truncating characters at the start (pre-padding) or at the end (post-padding). However in a task like hate speech detection, profanity is generally used by the user at the start or at the end of the sentence. Thus, if padding the sequences in only one particular way, there is a risk of losing information. To overcome this issue, the authors pass two inputs to the proposed model for every sample. One sequence is obtained by pre-padding the BPE encoded sentence and the Fig. 1. Block diagram of the proposed model architecture other by post-padding the sequence obtained by the Unigram algorithm. This approach of using pre-padded BPE and postpadded Unigram encoded sequence helps us to retain the features of the entire sequence and subsequently boost the results as shown later. It should be noted that the layers used in proposed model architecture are the same for both the sequences and parameters used for layers like positional encoding, and the multi-head attention layers are also the same.
Preprocessed text

Pre-padded BPE encoded sequence

Embedding layer

Positional Encoding

Multi-head Attention

Concatenate

128 FC (Hidden)

Dropout (0.2)

3 FC (Output)

Fig. 1. Block diagram of the proposed model architecture

B. Model Architecture

In this paper, the author proposes the use of a multi-headed self-attention mechanism [18] as the principal component of the model architecture. This paper makes use of an attention mechanism to completely skip the recurrence mechanism from the model and reduce the memory requirement and complexity. Therefore, due to a lack of a recurrence mechanism, no information regarding the order of the sequence is present. To overcome this problem, the authors use a positional encoding layer to provide information regarding the position of a word in the sequence. For each of the two inputs, the embedding layer output is passed to the positional encoding layer. Subsequently, the output from the positional encoding layer is passed to the multi-head attention layer. Further, the two representations obtained are concatenated together and then passed through a dense layer, a dropout layer, and then to the output nodes. The model architecture is as shown in fig 1. The working of each layer is as follows:

1) Positional Encoding: The positional Encoding layer provides information regarding the absolute and relative position of tokens in the sequence. The layer connects properly as it has the same dimension as that of the embedding layer. In the past, both fixed as well as learned positional encodings have been employed by researchers. The proposed approach uses fixed positional encodings derived from sinusoidal functions of different frequencies:

\[ PE_{pos,i} = \sin \left( \frac{pos}{1000 \sqrt{d_{model}}} \right) \]  

\[ PE_{pos,i+1} = \cos \left( \frac{pos}{1000 \sqrt{d_{model}}} \right) \]  

Where pos is the position, i is a particular dimension, and dmodel is the dimension of the embeddings. The advantage of these functions is that they are able to address relative positions properly. Every n + kth positional encoding could be represented as a linear function of PE_n.

2) Multi-head Attention: Attention function is the mapping of queries and key-value pairs to an output. In selfattention, different positions of a sequence are related to calculate representations of the same sequence. Based on correlation with other words present in the sequence, an attention vector is calculated to predict a new word. Particularly in our case, this paper makes use of scaled dot product variation of self-attention. The attention function calculates a dot product of query (Q) and key values (K) and the result of the dot product is passed through Softmax before obtaining final weights to be multiplied with the values (V). The formula for scaled dot product attention is as follows:

\[ \text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right)V \]  

where,

V is the value vector,
Query (Q) = EWq,
Key (K) = EWk,
Value (V) = EWv.

Wq, Wk, Wv are the respective weight matrices for queries, keys, and values. 1/√dk is used as a scaling factor, and thus it is named as scaled dot product attention. In our case, Q, K, and V are all the same representations obtained from the positional encoding layer. As this paper makes use of multi-head self-attention, attention function output for n different projections of the queries, keys, and values are calculated rather than making use of only one attention function output. Further, all the obtained output values are
where, 
\[ h_i = \text{Attention}(Q(W_i)Q^T, K(W_i)K^T, V(W_i)V^T) \]
Based on empirical studies, the authors found \( n = 8 \) to be the ideal number of parallel attention layers for our task. To obtain the final value, the values of parallel attention layers are concatenated together as shown in Fig 3. After this stage, concatenation of the outputs obtained for two input sequences takes place which is then passed to the next layers in the architecture. Fig. 2. Schematic representation of self dot product attention [18] Fig. 3. Multi head attention consisting of parallel running attention layers [18]

3) Dense and Dropout: After the concatenation of two outputs obtained from previous layers, the output is passed to a dense layer containing 128 nodes. In the dense layer, every neuron receives input from all the neurons in the previous layer i.e. they are deeply connected. The dense layer helps to change the dimension of the vector. It does so by performing a matrix-vector multiplication. The values in the matrix are parameters that are trained and updated through backpropagation. Further, to avoid overfitting, this paper uses a dropout layer next. The dropout layer ignores a certain set of neurons at random while training the model so that no intra network co-dependency is formed [19]. As per experimentation, the authors found a dropout value of 0.2 to be ideal for the architecture. The output from the dropout layer is passed through to a dense layer containing three nodes that represent the final output layer, with each node corresponding to one label. Additionally, the authors train their model by optimizing the sparse categorical cross-entropy loss.

IV. DATASET DESCRIPTION AND RESULTS
A. Dataset Description
Two datasets have been used for the study and analysis in this paper which are developed by [5] and [20]. Table 1 shows the tweet distribution in the English dataset provided by [20] and the HEOT dataset provided by [5]. The HEOT dataset consisting of 3679 tweets was developed using the Twitter Streaming API by gathering specified profane terms in Hinglish language and choosing tweets in Hindi-English code-switched language. Another corresponding labeled dataset for English tweets consists of 14509 records. This dataset was collected using the Twitter API which collected samples from 33485 users, this resulted in a collection of 85.4 million tweets from which random samples were labeled manually.

| Label             | HEOT            | Davidson     |
|-------------------|-----------------|--------------|
| Non-abusive       | 1414            | 7274         |
| Abusive           | 1942            | 4836         |
| Hate-inducing     | 323             | 2399         |
| Total             | 3679            | 14509        |

It can be observed that the size of the HEOT dataset is noticeably small as compared to the English tweets dataset. In reality, users identifying to a specific demographic division are small in comparison to the total users. Thus, this unusual distribution is advantageous as the small size of Hinglish tweet samples represents a true world scenario. Further, the tweets are classified into three categories: non-offensive, abusive, and hate-inducing. Example of each category of the HEOT dataset and their English translation are given in Table 2.

| Label        | HEOT                        | English                              |
|--------------|-----------------------------|--------------------------------------|
| Non-abusive  | RT @username HNY k time pe 15000 kamaya tha maine.. is baar payment nahi de rahe hai | RT @username I had this earned 15000 during new year.. time people are not paying |
| Abusive      | @username K*tiya! Mujhe mat sikhna/ | @username B*tch! Do not teach me |
| Hate-inducing| @username Gujarat wale Teri tarah chu*iya nhi ... | @username People from Gujarat are not |
B. Results
The results obtained on the test set are evaluated across accuracy, weighted precision, weighted recall, and weighted F1 score. This paper compares the proposed model with approaches used by researchers in the past and different combinations of padding types used in the ensemble method. The results are as shown in Table 3. It can be seen that the attention ensemble model using pre-padded BPE encoded sequence and post-padded Unigram encoded sequence outperforms individual models as well as ensemble models with different padding structures. Next, it can also be seen that the proposed ensemble model has performed better than the models employed by researchers in the past. Next, this paper shows the impact of BPE and Unigram text encoding algorithms by combining attention with 128 units of BiLSTM and using BPE and Unigram text encoded sequences in Table 4. It can be seen that with BiLSTM layers, the performance obtained is better, but it comes at the cost of increased complexity. Furthermore, the authors also carried out a complexity analysis of various layer types, as shown in Table 5. Thus, attention tends to be less complex as compared to conventional approaches. Therefore, a brief result analysis shows the benefit of using a multi-head self-attention mechanism over conventional approaches with slight variation in performance based on changes in certain factors. The use of attention and recurrent components yields slightly better performance than the proposed approach, but its complexity is substantially higher than the proposed approach.

Table III Performance metrics of various models, post and pre refers to post-padding and pre-padding.

| Model | Accuracy | F1 | Precision | Recall |
|-------|----------|----|-----------|--------|
| Attention + BPE (Post) + Unigram (Post) | 87.02 | 0.842 | 0.848 | 0.865 |
| Attention + BPE (Pre) + Unigram (Pre) | 87.04 | 0.846 | 0.851 | 0.864 |
| Attention + BPE (Pre) + Unigram (Post) | 87.41 | 0.851 | 0.862 | 0.868 |
| Attention + BPE (Post) + Unigram (Pre) | 86.17 | 0.836 | 0.842 | 0.853 |

Table IV Comparison of results for combination of attention and lstm with bpe and unigram encoding.

| Model | Accuracy | F1 |
|-------|----------|----|
| Attention + LSTM + BPE | 88.14 | 0.875 |
| Attention + LSTM + Unigram | 88.33 | 0.877 |
| Attention + LSTM + BPE + Unigram | 88.56 | 0.878 |

V. ANALYSIS
Main observations after performing out the study have been
- Recurrent models perform slightly better than the self-attention-based models, but the minimum number of sequential operations required and complexity per layer of self-attention is less in comparison to the recurrent or convolution models. Therefore, the use of self-attention is a desirable choice.
- Use of BPE and Unigram encoded sequences with attention leads to impressive results, especially in the case of Hindi-English code-switched data where the vocabulary is full of non-conventional words.
- Concatenation of pre-padded BPE and post-padded Unigram encoded sequences leads to substantial improvement in results.
- Recent development of models based on transformer architecture like XLM [21] tend to perform better than the proposed architecture, but they require huge computational power, and the training cost is also very
VI. CONCLUSION

By making use of the attention mechanism, the proposed work has been able to achieve standard results in the field of Hindi-English code-switched hate speech detection. To overcome the shortcoming of attention that it does not retain all information of a sequence, it can be coupled with features like positional encoding while cutting down the memory requirement as well as complexity. While some earlier approaches used very complex preprocessing steps to handle the non-conventional Hindi language, experimental results show that by using simpler but efficient preprocessing steps over the previous approaches, which are symptoms to the power of steps like the use of BPE and Unigram subword tokenization algorithms, the proposed work obtains better results. The improved results across metrics which the subword tokenization algorithms and attention mechanism hold. In the future, modifications in the post attention layers can be carried out for better information transfer. Also, the approach can be tried out for hate speech detection in other code-switched languages as they play a major role in the online structuring of multilingual societies. With the dominance of models based on attention like Transformer, BERT, XLMNet on traditional methods, the idea of using recurrence for sequence modeling is becoming weaker gradually. Models based on attention have proven to be a better alternative and can be used in sentiment classification effectively.

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