DeepHateExplainer: Explainable Hate Speech Detection in Under-resourced Bengali Language

Md. Rezaul Karim
Fraunhofer FIT & RWTH Aachen University, Aachen, Germany

Sumon Kanti Dey
Noakhali Science and Technology University, Bangladesh

Tanhim Islam
RWTH Aachen University, Aachen, Germany

Sagar Sarker
Begum Rokeya University, Rangpur, Bangladesh

Mehadi Hasan Menon
Begum Rokeya University, Rangpur, Bangladesh

Kabir Hossain
The University of Alabama, Tuscaloosa, USA

Bharathi Raja Chakravarthi
National University of Ireland, Galway, Ireland

Md. Azam Hossain
Islamic University of Technology, Gazipur, Bangladesh

Stefan Decker
Fraunhofer FIT & RWTH Aachen University, Aachen, Germany

ABSTRACT
The exponential growths of social media and micro-blogging sites not only provide platforms for empowering freedom of expressions and individual voices, but also enables people to express anti-social behavior like online harassment, cyberbullying, and hate speech. Numerous works have been proposed to utilize textual data for social and anti-social behavior analysis, by predicting the contexts mostly for highly-resourced languages like English. However, some languages are under-resourced, e.g., South Asian languages like Bengali, that lack computational resources for accurate natural language processing (NLP). In this paper, we propose an explainable approach for hate speech detection from the under-resourced Bengali language, which we called DeepHateExplainer. Bengali texts are first comprehensively preprocessed, before classifying them into political, personal, geopolitical, and religious hates using a neural ensemble method of transformer-based neural architectures (i.e., monolingual Bangla BERT-base, multilingual BERT-cased/uncased, and XLM-RoBERTa). Important (most and least) terms are then identified using sensitivity analysis and layer-wise relevance propagation (LRP), before providing human-interpretable explanations for the hate speech detection. Finally, we compute comprehensiveness and sufficiency scores to measure the quality of explanations w.r.t faithfulness. Evaluations against machine learning (linear and tree-based models) and neural networks (i.e., CNN, Bi-LSTM, and Conv-LSTM with word embeddings) baselines yield F1-scores of 78%, 91%, 89%, and 84%, for political, personal, geopolitical, and religious hates, respectively, outperforming both ML and DNN baselines.

KEYWORDS
Hate speech detection, Under-resourced language, Bengali, Multimodal memes, Embeddings, Transformers, Interpretability.

1 INTRODUCTION
Exponential growths of micro-blogging sites and social media not only empower freedom of expressions and individual voices, but also enables people to express anti-social behavior [1, 2], such as cyberbullying, online rumours, and spreading hatred statements [3, 4]. Abusive speech expressing prejudice towards a certain group is also very common [2], and based on race, religion, and sexual orientation is getting pervasive. United Nations Strategy and Plan of Action on Hate Speech [4] defines hate speech as any kind of communication in speech, writing or behaviour, that attacks or uses pejorative or discriminatory language regarding a person or a group based on their religion, ethnicity, colour, gender or other identity factors. Bengali is spoken by 230 million people in Bangladesh and India [5], making it one of the major languages in the world. Although Bengali is a rich language with a lot of diversity, it is severely low-resourced for natural language processing (NLP). This is mainly due to the lack of necessary computational resources such as language models, labelled datasets, and efficient machine learning (ML) methods for various NLP tasks. Similar to other major languages like English, the use of hate speech in Bengali is also getting rampant, which is due to unrestricted access and use of social media and digitalization [6].

Some examples of Bengali hate speech and their respective English translations are shown in Fig. 1 that are either directed towards a specific person or entity or generalized towards a group. These examples signify how severe Bengali hateful statements could be. Nevertheless, there is a potential chance that these could lead to serious consequences such as hate crimes [2], regardless of languages, geographic locations, or ethnicity. Automatic identification of hate speech and raising public awareness is a non-trivial task [2]. However, manually reviewing and verifying a large volume of online content is not only time-consuming but also labor-intensive [7]. Further, accurate identification requires automated and robust ML methods. Compared to traditional ML and neural networks (DNNs)-based approaches, state-of-the-art (SotA) language models are becoming increasingly effective. Nevertheless, a serious drawback of many existing approaches is that the outputs can neither be traced back to the inputs, nor it is clear why outputs are transformed in a certain way. This makes even the most efficient language models black-box methods. Therefore, how a prediction is made by an algorithm should be as transparent as possible to users to gain human trust in AI systems.
Figure 1: Example hate speech in Bengali, either directed towards a specific person or entity, or generalized towards a group

| Statement | English translation | Context |
|-----------|--------------------|---------|
| • মানুষেরের ব্যস্তাদের হাস্যরসের কোন স্থান নেই। | • Hindus have no place in Bangladesh. | Religious |
| • মুসলমানের আলো বেলায়, আলেমজ এবং আশু। | • Muslims are Al-Qaeda, Taliban, and terrorists. | Religious |
| • কৃষ্ণের মৃত্যুর হাস্যরসের কোন স্থান নেই। | • Awami League is a terrorist organization and they are conspicuous businessmen. | Political |
| • তৃণমূল রহস্য ঋণাগারের আদিকাল। | • Anti-terror war criminals should be deported from Bangladesh. | Political |
| • ঘর দেওয়া মৃত্যুরের ধর্মন কেবল হুমকী। | • Trespass each house and kill women after raping. | Personal |
| • পুলিশ বাহিনীর ত্রুটি করে না। | • You mother fucker live with drugs and whore. | Personal |
| • অবাধ শাখা শাখার ধার যেদিন যাপা দিয়ে বিক্ষোভ করা হবে। | • Illegal Bangladeshis will be immediately pushed to the neck and be deported. | Geopolitical |
| • ফুটফেটে স্ক্রিপ্টের ধারা পড়া। | • Indians are the main enemies of Bangladesh. | Geopolitical |

To mitigate the opaqueness of black-box models and inspired by recent successes of transformer language models (e.g., BERT [8], RoBERTa [9], XLNet [10], and ELECTRA [11]), we propose Deep-HateExplainer - an explainable approach for hate speech detection from under-resourced Bengali language. Our approach is based on ensemble of BERT variants, including monolingual Bangla BERT-base [12], m-BERT (cased/uncased), and XLM-RoBERTa. Further, we provide global and local explanations of the predictions in a post-hoc fashion and measures of explanations w.r.t faithfulness.

2 RELATED WORK

Numerous works have been proposed to accurately and reliably identification of hate speech from major languages like English [1, 7]. Classic methods traditionally rely on manual feature engineering, e.g., support vector machines (SVM), Naïve Bayes (NB), logistic regression (LR), decision trees (DT), random forest (RF), and gradient boosted trees (GBT). On the other hand, DNN-based approaches that learn multilayers of abstract features from raw texts, are primarily based on convolutional (CNN) or long short-term memory (LSTM) networks. In comparison with DNNs, these approaches are rather incomparable as the efficiency of linear models at dealing with billions of such texts proven less accurate and unscalable.

CNN and LSTM are two popular DNN architectures: CNN is an effective feature extractor, whereas LSTM is suitable for modelling orderly sequence learning problems. CNN extracts word or character combinations, e.g., n-grams, and LSTM learns long-range word or character dependencies in texts. While each type of network has relative advantages, several works have explored combining both architectures into a single network [13]. Conv-LSTM is a robust architecture to capture long-term dependencies between features extracted by CNN and found more effective than structures solely based on CNN or LSTM, where the class of a word sequence depends on preceding word sequences.

However, accurate identification of hate speech in Bengali is still a challenging task. Only a few restrictive approaches [14, 15, 2] have been proposed so far. Romim et al. [14] prepared a dataset of 30K comments, making it one of the largest datasets for identifying offensive and hateful statements. However, this dataset has several issues. First, it is very imbalanced as the ratio of hate speech to non-hate speech is 10K:20K. Second, the majority of hate statements are very short in terms of length and word count compared to non-hate statements. Third, their approach exhibits a moderate level of effectiveness at identifying offensive or hateful statements, giving an accuracy of 82%. Fourth, their approach is a black-box method.

In a recent approach, Karim et al. [2], provided classification benchmarks for document classification, sentiment analysis, and hate speech detection for the Bengali language. Their approach, by combining fastText embeddings with multichannel Conv-LSTM network architecture, is probably the first work among a few other studies on hate speech detection. Their Conv-LSTM architecture, by combining fastText embeddings, outperformed Word2Vec and GloVe models, since fastText works well with rare words such that even if a word was not seen during the training, it can be broken down into n-grams to get its corresponding embeddings. All these restrictive approaches are black-box methods. On the contrary, interpretable methods put more emphasis on the transparency and traceability of opaque DNN models. With layer-wise relevance propagation (LRP) [16], relevant parts of inputs that caused a result can be highlighted [17]. To mitigate opaqueness and to improve explainability in hate speech identification, Binny et al. [18] proposed 'HateXplain' - a benchmark dataset for explainable hate speech detection. They observe that high classification accuracy is not everything, but high explainability is also desired. They measure the explainability of an NLP model w.r.t plausibility and faithfulness that are based on human rationales for training [19].
3 PROPOSED APPROACH

Inspired by SotA approaches and interpretability methods such as sensitivity analysis (SA) [20] and LRP [16], we propose DeepHateExplainer - a novel approach to accurate identification of hate speech in the Bengali. Bengali texts are first comprehensively pre-processed, before classifying them into political, personal, geopolitical, and religious hates, by employing an ensemble of different transformer-based neural architectures: monolingual Bangla BERT-base, multilingual BERT (mBERT)-cased/uncased, and XLM-RoBERTa. Then, we identify important terms with SA and LRP to provide human-interpretable explanations, covering both global and local explainability. To evaluate the quality of explanations, we measure comprehensiveness and sufficiency. Further, we train several ML (i.e., LR, NB, KNN, SVM, RF, GBT) and DNN (i.e., CNN, Bi-LSTM, and Conv-LSTM with word embeddings) baseline models. To the end, DeepHateExplainer focuses on algorithmic transparency and explainability, with the following assumptions:

- A majority voting-based ensemble from a panel of independent NLP expert or linguists provides fairer and trustworthy prediction than a single expert.
- By decomposing the inner logic (e.g., what terms the model put more attention to) of a black-box model with probing and SA, the opaqueness can be reduced.
- By highlighting the most and least important terms, we can generate human-interpretable explanations.

Overall contributions of our approach are 4-folds:

1. We prepared the largest hate speech detection dataset to date for the Bengali language.
2. To the best of our knowledge, we are the first batch of researchers to employ neural transformer-based language models for hate speech detection for Bengali.
3. We prepared several computational resources, such as annotated dataset, language models, source codes, and interpretability techniques that will further advance the NLP research for under-resourced Bengali language.
4. We improved both local and global explainability and algorithmic transparency of black-box models by mitigating their opaqueness.

4 DATASETS

We extend the Bengali Hate Speech Dataset [2] with additional 5,000 labelled examples. The Bengali Hate Speech Dataset categorized observations into political, personal, geopolitical, religious, and gender abusive hates. However, based on our empirical study and linguist analysis, we observe that distinguishing personal from gender abusive hate is often not straightforward, as they often semantically overlap. To justify this, let consider example hate statements in Fig. 3. These statements (non-Bengali speakers are requested to refer to English translations) express hatred towards a person or entity or generalized towards a group, which are only considered. Texts were collected from Facebook, YouTube comments, and newspapers. We categorize the samples into political, personal, geopolitical, and religious hate. Sample distribution and definition of different types of hates are outlined in Table 1.

4.1 Data annotation

Three annotators (a linguist, a native Bengali speaker, and an NLP researcher) participated in the annotation process. To reduce possible bias, unbiased contents are supplied to the annotators and each label was assigned based on a majority voting on the annotator’s independent opinions. To evaluate the quality of the annotations and to ensure the decision based on the criteria of the objective, we measure inter-annotator agreement w.r.t Cohen’s Kappa statistic [21]. Let consider n target objects are annotated by m(≥ 2) annotators into one of k(≥ 2) mutually exclusive categories, the proportion of score \( \hat{p}_j \) and the kappa \( \hat{k}_j \) for category j are computed as follows [21]:

\[
\hat{p}_j = \frac{\sum_{i=1}^{n} x_{ij}}{nm} \quad (1)
\]

\[
\hat{k}_j = 1 - \frac{\sum_{i=1}^{n} x_{ij} (m - x_{ij})}{nm(m-1)\hat{p}_j (1 - \hat{p}_j)} \quad (2)
\]

where \( x_{ij} \) is possible scores on subject i into category j. The overall kappa \( \hat{k} \) is subsequently computed as [21]:

\[
\hat{k} = \frac{\sum_{j=1}^{k} \hat{p}_j (1 - \hat{p}_j) \hat{k}_j}{\sum_{j=1}^{k} \hat{p}_j (1 - \hat{p}_j)} . \quad (3)
\]

Taking into account the personal vs. gender abusive hate consideration, we observed a \( \hat{k} \) score of 0.87, which is 3% of improvement over the previous approach by Karim et al. [2].

5 METHODS

In this section, we discuss our proposed approach in detail, covering word embeddings, network (ML/DNN/transformers) training, explanation generation, and measuring explainability.

5.1 Data preprocessing

We remove HTML markups, links, image titles, special characters, and excessive use of spaces/tabs, before initiating the annotation process. Further, following preprocessing steps are followed before training ML and DNN baseline models:

- **Hashtags normalization**: inspired by positive effects in classification task [22], hashtags were normalized.
- **Stemming**: inflected words were reduced to their stem, base or root form.
- **Emojis and duplicates**: all emojis, emoticons, duplicate, and user mentions were removed.
- **Infrequent words**: tokens with a document frequency less than 5 were removed.

However, as research has shown that BERT-based models perform better classification accuracy on uncleaned texts, we did not perform major preprocessing tasks, except for the lightweight preprocessing discussed above.
Figure 2: Schematic representation of proposed approach: each of 4 BERT variants is finetuned by adding a fully-connected softmax layer on top and cross-validation based on ensemble optimization, followed by majority voting ensemble.

Table 1: Statistics of the hate speech detection dataset

| Hate type       | Description                        | #Examples |
|-----------------|------------------------------------|-----------|
| Political       | Directed towards a political group/party | 999       |
| Religious       | Directed towards a religion/religious group | 1,211     |
| Geopolitical    | Directed towards a country/region   | 2,364     |
| Personal        | Directed towards a person           | 3,513     |
| **Total**       |                                    | **8,087** |

Figure 3: Example hate statements directed towards a person, but may contextually be directed towards a women.

| Bengali hate statement                                                                 | English translation                                                                 |
|----------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| যান্ত্রিক ব্যবহারের মুখতারা তেরো নুয়া ছুঁড়া। বেলা ঘোড়া পালিয়ে যায়, পালিয়ে যায়। | It was wrong to execute them, the children of the prostitute should have died at the cost of their lives. |
| প্রাণাঞ্চলের সর্বনাশে যত্নী মানুষিক।                                           | You’re a fucking whore, brothel is the right place for you.                           |
| প্রাণাঞ্চলের সর্বনাশে যত্নী মানুষিক।                                           | Prova (Bangladeshi actress) is the worst slut in Bangladesh.                        |
| রিতুমনি (গুরুত্ত্বপূর্ণ অভিনেত্রী)                                               | Perimoni (Bangladeshi actress) becomes owner of houses and cars overnight by giving fuck to producers. |
| রিতুমনি (গুরুত্ত্বপূর্ণ অভিনেত্রী)                                               | Rituparna (Indian actress) is a fucking slut. The older this bitch gets, the more duty her acting becomes. |
5.2 Training of ML baseline models

We train LR, SVM, KNN, NB, RF, and GBT ML baselines models\(^3\), using character n-grams and word uni-grams with TF-IDF weighting. The best hyperparameters are produced through random and with 5-fold cross-validation tests.

5.3 Neural word embeddings

We train the fastText [23] word embedding model on Bengali articles used for the classification benchmark study by Karim et al. [2]. The preprocess reduces vocabulary size due to the colloquial nature of the texts and some degree, addresses the sparsity in the word-based feature representations. We have also tested, by keeping word inflexions, lemmatization, and lower document frequencies. We observe slightly better accuracy using the lemmatization, which is the reason we reported the result based on it. The fastText model represents each word as an n-gram of characters, which helps capture the meaning of shorter words and allows the embeddings to understand suffixes and prefixes. Each token is embedded into a 300-dimensional real-valued vector, where each element is the weight for the dimension for the token. Since the annotated hate statements are relatively short, we constrain each sequence to 100 words by truncating longer texts and pad shorter ones with zero values to avoid padding in convolutional layers with many blank vectors for the majority of articles.

5.4 Training of DNN baseline models

We train three DNN baselines: CNN, Bi-LSTM, and Conv-LSTM. Weights of embedding layer for each network is initialized with the embeddings based on the fastText embedding model. Embedding layer maps each hate statement into a sequence (for LSTM and CNN layers) and transforms into feature representation, which is then flattened and feed into a fully connected softmax layer. Further, we add Gaussian noise and dropout layers to improve model generalization. AdaGrad optimizer is used to learn the model parameters by reducing the categorial-cross-entropy loss. We train each DNN architecture 5 separate times in a 5-fold CV setting, followed by measuring the average macro F1-score on the validation set to choose the best hyperparameters\(^4\) using random search.

5.5 Training of transformer-based models

As shown in Fig. 2\(^5\), we train monolingual Bangla BERT-base, mBERT (cased and uncased), and XLM-RoBERTa large models. Bangla-BERT-base\(^6\) is a pretrained Bengali language model built with BERT-based mask language modelling. RoBERTa [9] is an improved variant of BERT, which is optimized by setting larger batch sizes, introducing dynamic masking, and training on larger datasets. XLM-RoBERTa [24] is a multilingual model trained on web crawled data. XLM-RoBERTa not only outperformed other transformer models on cross-lingual benchmarks but also performed better on various NLP tasks in a low-resourced language setting.

We shuffle training data for each epoch and apply gradient clipping. We set the initial learning rate to \(2e^{-5}\) and employ Adam optimizer with the scheduled learning rate. Pre-trained BERT variants are fine-tuned by setting the maximum input length to 256. We experimented with 2, 3, and 4 layers of multi-head attention, followed by a fully connected softmax layer. As we perform the ensemble of best models to report final predictions (as Fig. 4), several experiments with different hyperparameters combinations are carried out (Table 2), before saving the best epochs, for each model.

5.6 Generating explanations

We provide global and local explanations in a post-hoc fashion. For the former, a list of most and least relevant words for each class is identified based on linguist analysis. To provide overall global interpretability, feature importance (FI) is computed for model \(f\). For feature \(x_i\) in observation \(x \in X\) and for each repetition \(r \in 1, 2, \ldots, R\), column \(x_i\) is randomly shuffled to generate a corrupted version \(X_{r, x_i}\) for \(X\). A reference balanced score \(s_{r, x_i}\) is then computed for \(f\). The mean importance \(\sigma_{x_i}\) for feature \(x_i\) is then computed as follows [25]:

\[
\sigma_{x_i} = s - \frac{1}{R} \sum_{r=1}^{R} s_{r, x_i}.
\]

For the latter, we identify which features in a sample are important for individual prediction. Relevance score (RS) as a measure of importance is computed with SA and relevance conservation LRP [25]. For input vector \(x\), RS \(R_d\) is computed for each input dimension \(d\). This is analogous to quantify the relevance of \(x_d\) w.r.t to target class \(c\). Then the RS \(R_d\) is generated by computing squared partial derivatives as [25]:

\[
R_d = \left( \frac{\partial f_c}{\partial x_d} (x) \right)^2,
\]

where \(f_c\) is a prediction score function for class \(c\). Total relevances is then computed by summing relevances of all input space dimensions \(d\) [25]:

\[
\|\nabla f_c (x)\|_2^2.
\]

In contrast to SA, LRP is based on the layer-wise relevance conservation principle. LRP redistributes the quantity \(f_c (x)\) from output layer to the input layer. The relevance for the output layer neuron is set to \(f_c (x)\) w.r.t to the target class \(c\), by ignoring irrelevant output layer neurons. The layer-wise relevance score for each intermediate lower-layer neuron is computed based on weighted connections. Assuming \(z_j\) and \(z_i\) are an upper-layer and a lower-layer neuron, respectively, and the value of \(z_j\) is already computed in the forward pass as \(\sum_j z_i \cdot w_{ij} + b_j\), where \(w_{ij}\) and \(b_j\) are the weight and bias, the relevance score \(R_i\) for the lower-layer neurons \(z_j\) is then computed by distributing the relevances onto lower-layer. The relevance propagation \(R_{i \to j}\) from upper-layer neurons \(z_j\) to lower-layer neurons \(z_i\) is computed as a fraction of the relevance \(R_j\). Subsequently, all the incoming relevance for each lower-layer neuron is summed up as [25]:

\[
R_{i \to j} = \frac{z_i \cdot w_{ij} + e \cdot \text{sign}(z_i) + \delta \cdot b_j}{z_i + e \cdot \text{sign}(z_i)} \cdot R_j
\]

\(^3\) Supplementary materials in arXiv version: https://arxiv.org/abs/2012.14353
\(^4\) Supplementary materials in arXiv version: https://arxiv.org/abs/2012.14353
\(^5\) English translation: Porimoni becomes the owner of houses and cars overnight after giving fuck to film producers.
\(^6\) https://huggingface.co/sagorsarker/bangla-bert-base
Figure 4: A representation of cross-validation (CV) ensemble optimization process. The final ensemble weights $\alpha_1, \alpha_2, \ldots, \alpha_M$ in which $M$ is the number of CV folds used to combine model predictions and evaluate performance on test set.

where $N$ is total number of lower-layer neurons connected to $z_j$, $\epsilon$ is a stabilizer, $\text{sign}(z_j) = \{1_{z_j \geq 0} - 1_{z_j < 0}\}$ is the sign of $z_j$, and $\delta$ is a constant multiplicative factor set to 1, to conserve the total relevance of all neurons in the same layer. Finally, $R_i$ is computed as $R_i = \sum_j R_{i-j}$ [25].

5.7 Measuring explainability

System causability scale (SCS) [17] is proposed to measure the quality of explanations. SCS is based on the notion of causability and adapted from a usability scale and aims to determine whether and to what extent a user interface is explainable or which explanation process itself is suitable for the intended purpose [17]. Since SCS is based on usability feedback for an explainable interface, it is not suitable for our case. Therefore, we compute faithfulness w.r.t comprehensiveness and sufficiency to measure the quality of explanations based on ERASER [26]. To measure comprehensiveness, a contrast example $\tilde{x}_i$ is created, for each sample $x_i$, where $\tilde{x}_i$ is calculated by removing predicted rationales $r_j$ from $x_i$. Let $f(x_i)_c$ be the original prediction probability for model $f$ and $f(x_i)_{r_j}$ be the predicted probability of $\tilde{x}_i$ ($\approx x_i \setminus r_j$), it is expected that the prediction will be lower on removing the rationales [26]. The comprehensiveness metric $\epsilon$ is then calculated as follows [26]:

$$\epsilon = f(x)_c - f(x \setminus r)_c$$

(8)

The concept of rationales is proposed by Zaidan et al. [19] in NLP in which human annotators would highlight a span of text that could support their labelling decision, e.g., to justify why a review is positive, an annotator can highlight most important words and phrases that would tell someone to see the movie. To justify why a review is negative, highlight words and phrases that would tell someone not to see the movie. It is found to be useful in downstream NLP tasks like hate speech detection [18], text classification [27]. We conceptualize a similar idea w.r.t leave-one-feature-out analysis, where the rationale is computed based on the number of highlighted features divided by the number of features in a test sample. A prediction is considered a match if it overlaps with any of the ground truth rationales $r_i \geq 0.5$. A high value of comprehensiveness implies that the rationales were influential in the prediction. The sufficiency $s$, which measures the degree to which extracted rationales are adequate for the model $f$, which is measured as follows [26]:

$$s = f(x)_c f(r)_c$$

(9)

6 RESULTS

We discuss experimental results both qualitatively and qualitatively and explain the predictions globally and locally. Besides, we provide a comparative analysis with baselines.

6.1 Experiment setup

Programs were implemented using scikit-learn, Keras, and PyTorch and networks are trained on Nvidia GTX 1050 GPU. Open source implementation of fastText is used to learn embeddings. SHAP8 and ELIs9 are used to compute FI. Each model is trained on 80% of data, followed by evaluating the model on 20% held-out data. We report precision, recall, F1-score, and Matthias correlation coefficient (MCC). Finally, we perform the ensemble of top-3 models to report the final predictions. We select the best models with WeightWatcher10 [28]. Using WeightWatcher, the models giving the lowest log-norm and highest weighted-alpha are only considered. This is backed by the

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8. https://github.com/slundberg/shap
9. https://github.com/eli5-org/eli5
10. https://github.com/CalculatedContent/WeightWatcher
fact that a lower log-norm signifies better generalization of network weights for unseen examples [28].

6.2 Analysis of hate speech detection

We evaluated 4 variants of BERT models on the held-out test set and report the results\(^1\) in Table 3. XML-RoBERTa model turns out to be both best performing and best-fitted model, giving the top F1-score of 0.87, which is about 2% to 5% better than other transformer models, while Bangla BERT-base and mBERT-uncased also performed moderately well. Based on metrics and the lowest log-norm, top-3 models were picked using WeightWatcher for the ensemble prediction, followed by discarding the mBERT-based model from the voting ensemble. The highest MCC score of 0.82 is achieved with the ensemble prediction, which is slightly better than that of the XLM-RoBERTa, giving an MCC score of 0.808. Overall, MCC scores of ≥0.77 were observed for each BERT-based model w.r.t Pearson correlation coefficient. This signifies that predictions are strongly correlated with ground truths and BERT variants are more effective compared to ML or DNN baseline models.

Confusion matrices in Fig. 5 show the breakdown of correct and incorrect classifications for each class, which correspond to ground truths vs. predicted labels. Ensemble prediction boosts the accuracy by at least 1.8% across the classes w.r.t F1-score, compared to top mBERT-based and XML-RoBERTa models. Nevertheless, misclassification rates for all the classes have reduced significantly and overall 21 observations were correctly classified. This improvement signifies, to large extent, that ensemble prediction is effective at minimizing confusions. Further, as classes are imbalanced, accuracy alone gives a distorted estimation of the performance. Thus, we provide class-specific classification reports in Table 4 based on the ensemble prediction. Overall, our approach identifies personal hates more accurately compared to other types of hate w.r.t F1-score. Identifying political hate was more challenging (giving an F1-score of 0.78) as political hates contain some terms that are often used to express personal hates.

6.3 Comparison with baselines

Since efficient feature selection can have significant impacts on model performance for ML methods [2], we observe the performance with manual feature selection. Forests of trees concept\(^1\) is employed to compute impurity-based FI. Each model is then trained by discarding irrelevant features. The feature selection helped SVM, KNN, RF, and GBT models improve their accuracy. GBT model performs the best among all ML baseline models, giving an MCC score of 0.571, albeit F1-scores for both RF and GBT are equal. RF model performs reasonably well, giving an F1-score of 0.68. Contrarily, performance of SVM, LR, and NB classifiers degraded significantly. LR model is not resilient to class discriminating features that could be lost during the feature selection, perhaps the conditional independence assumption (where features are assumed to be independent when conditioned upon class labels) of NB is not hold. Overall, the performance of each ML baseline model was severely poor, making them not suitable for reliable identification of hate statements.

Each DNN baseline model is evaluated by initializing the embedding layer’s weight with fastText embeddings. As observed, each model either outperforms or gives comparable performance to ML baseline models. In particular, Conv-LSTM performs the best among DNN baselines, giving F1 and MCC scores of 0.78 and 0.694, respectively, which is about 4 to 5% better than Bi-LSTM (the second-best DNN baseline) and GBT (the best among ML baseline) models, respectively; while the F1-scores for CNN and Bi-LSTM reached to 0.73 and 0.75, respectively, making them comparable to GBT and RF models. Overall, DNN baseline models also performed poorly compared to transformer-based models (ref. Table 3), albeit the fastText embedding model could have captured the word-level semantics sufficiently.

6.4 Explaining hate speech detection

We provide both local and global explanations for hate speech identification. For the former, we highlight globally important terms. Fig. 6 shows most frequently used terms expressing hatred statements (English terms: Rajakar, war criminals, Muslim, militant, Hindu, Jihadi\(^1\), Rohingya\(^1\), Pakistanis, Indians, Bangladesh Jamaat-e-Islami\(^1\), war criminals, whore, fuck, ass, rape, execution, Kutta League\(^1\), consciousness\(^1\), Hammer League\(^1\), son of a pig, slut, bastard, son of a bitch, broker\(^1\)). These findings are further validated with the linguistic analysis, outlining the semantic meaning and relevance of these words. The most and least SA- and LRP-relevant word lists for each class are shown in Fig. 8 and Fig. 7, respectively that are used to express hatred statements.

Local explanations for individual samples are provided by highlighting the most important terms. We provide class-wise example heat maps based on SA and LRP-based relevances in Fig. 9 exposing different types of hates, where the colour intensity is normalized to the maximum relevance per hate statement. To quantitatively validate the word-level relevances for local explainability, we perform the leave-one-out experiment – we aim to improve the greedy backward elimination algorithm by preserving more interactions among terms. First, we randomly select a sample hate statement (e.g., same as Fig. 9b) in the test set. Then, we generate prediction probabilities for all the classes, followed by explaining word-level relevance for the two highest probable classes.

Let consider the example in Fig. 10: words on the right side are positive, while words on the left are negative. Words like जाति, नागर, और सिंह (race, Occup, and Hindu in English, respectively) are positive for religious class, albeit the most significant word जाति (race in English) is negative for personal hate category (where words बंगाली जनसंघ (son of a bitch) and bastard in English) are more important). Word जाति has the highest positive score of 0.27 for class religious. Our model predicts this as a religious hate statement too, with the probability

\(^{11}\) Based on hyperparameter combinations in Table 2. 12 Forests of trees concept is a meta-transformer for selecting features w.r.t importance weights.

\(^{13}\) Term to accuse Muslims to be terrorist in India, Pakistan, and Bangladesh. 14 People who flew from genocide and ethnic cleansing by the Myanmar army and got asylum in Bangladesh. 15 Islamist political party in Bangladesh. 16 Hatred term for student organization of Bangladesh Awami League, where Kutta means dogs. 17 Supporters of Bangladesh Awami League are called brokers of India, while supporters of Bangladesh Nationalist Party and Bangladesh Jamaat-e-Islami are called brokers of Pakistan.
Table 3: Performance of hate speech detection

| Method       | Classifier | Precision | Recall | F1    | MCC  |
|--------------|------------|-----------|--------|-------|------|
| ML baselines | LR         | 0.68      | 0.68   | 0.67  | 0.542|
|              | NB         | 0.65      | 0.65   | 0.64  | 0.511|
|              | SVM        | 0.67      | 0.67   | 0.66  | 0.533|
|              | KNN        | 0.67      | 0.67   | 0.66  | 0.533|
|              | RF         | 0.69      | 0.69   | 0.68  | 0.561|
|              | GBT        | **0.71**  | **0.69**| **0.68**| **0.571**|
| DNN baselines| CNN        | 0.74      | 0.73   | 0.73  | 0.651|
|              | Bi-LSTM    | 0.75      | 0.75   | 0.75  | 0.672|
|              | Conv-LSTM  | **0.79**  | **0.78**| **0.78**| **0.694**|
| BERT variants| Bangla BERT| 0.86      | 0.86   | 0.86  | 0.799|
|              | mBERT-cased| 0.85      | 0.85   | 0.85  | 0.774|
|              | XML-RoBERTa| 0.87      | 0.87   | 0.87  | **0.808**|
|              | mBERT-uncased| 0.86      | 0.86   | 0.86  | 0.795|
|              | Ensemble*  | **0.88**  | **0.88**| **0.88**| **0.820**|

(a) For standalone XLM-RoBERTa
(b) For ensemble prediction

Figure 5: Confusion matrices: standalone XLM-RoBERTa vs. ensemble prediction (color code: red, blue, and black indicate misclassification rates, correct classification rates (in %), and count, respectively)

Figure 6: Globally most important terms that are used to express hatred statements for all the hate classes

Table 4: Class-wise classification report based on majority voting ensemble of top-3 classifiers

| Hate type    | Precision | Recall | F1 |
|--------------|-----------|--------|----|
| Personal     | 0.91      | 0.90   | 0.91|
| Political    | 0.82      | 0.74   | 0.78|
| Religious    | 0.79      | 0.90   | 0.84|
| Geopolitical | 0.89      | 0.89   | 0.89|

of 32% (i.e., 59% − 27%). Word *জাতি* is negative for personal hate category, albeit words *বাচ্চা* and *হয়রানজনা* have positive scores of 0.23 and 0.17 for the class personal. These identified words not only reveals the relevance of important terms for classifier’s decision, but also signify that removing most relevant terms will impact the final decision, accordingly to their relevance value.

6.5 Measure of explainability

For measuring the explainability, only top models (ML, DNN, and BERT variants) are considered based on the results we analyzed
in Section 6.2 and Section 6.3. Results of the faithfulness in terms of comprehensiveness and sufficiency are shown in Table 5. As shown, XML-RoBERTa attained the highest comprehensiveness and sufficiency scores, outperforming other standalone models. Overall, BERT variants not only attained higher scores but also consistently outperforms other models such as GBT and Conv-LSTM baselines. Further, our study outlines two additional observations:

(1) GBT model shows both higher comprehensiveness and sufficiency compared to Conv-LSTM model, albeit the latter outperformed the former in classification task w.r.t classification metrics.

(2) As for BERT variants, Bangla BERT and mBERT-cased generate the least faithful explanations.

This signifies that a model that attains the best scores w.r.t metrics, may not perform well in terms of faithfulness explainability metrics. Based on this observation, it would not be unfair to say that a model’s performance metric alone is not enough as models with slightly lower performance, but much higher scores for faithfulness might be preferred for sensitive use cases such as hate speech detection at hand.

7 CONCLUSION
In this paper, we proposed DeepHateExplainer - an explainable approach for hate speech detection for under-resourced Bengali language. Based on ensemble prediction, DeepHateExplainer can detect different types of hates with an F1-score of 88%, outperforming several ML and DNN baselines. Our study suggests that: i) feature

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**Table 5: Measure of explainability**

| Classifier      | Comprehensiveness | Sufficiency |
|-----------------|-------------------|-------------|
| GBT             | 0.79              | 0.25        |
| Conv-LSTM       | 0.73              | 0.15        |
| Bangla BERT     | 0.78              | 0.25        |
| XML-RoBERTa     | 0.84              | 0.44        |
| mBERT-uncased   | 0.81              | 0.35        |
| mBERT-cased     | 0.76              | 0.28        |

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This table shows the measure of explainability for different classifiers with their respective comprehensiveness and sufficiency scores.
Figure 8: Global feature importance, highlighting important terms per class

(a) Political hate

(b) Religious hate

(c) Personal hate

(d) Geopolitical hate

Figure 9: Example heat maps for different types of hate, highlighting relevant terms

Figure 10: Word-level relevance test using leave-one-out

selection can have non-trivial impacts on learning capabilities of ML and DNN models, ii) even if a standalone ML and DNN baseline model does not perform well, the ensemble of several models may still outperform individual models.

Our approach has several potential limitations too. First, we had a limited amount of labelled data at hand during the training. Therefore, it would be unfair to claim that we could rule out the chance of overfitting. Secondly, we applied SA and LRP on a DNN baseline model (i.e., Conv-LSTM), albeit it would be more reasonable to do the same on the best performing standalone XLM-RoBERTa model. In future, we want to overcome these limitations by extending the datasets with a substantial amount of samples and applying SA and LRP on the XLM-RoBERTa model. Besides, we want to focus on other interesting areas such as named entity recognition, part-of-speech tagging, sense disambiguation, and question answering for the Bengali language.

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APPENDIX

Here, we provide more detail about baseline ML/DNN and transformer models. Further, to foster reproducibility, we make available the source codes, data, and interactive notebooks. This repository will be updated with more reproducible resources, e.g., models, notebooks in the coming weeks.

Training details for DNN baseline models

The architectural parameters used to train a vanilla CNN, Bi-LSTM, and Conv-LSTM models are listed in Table 6, Table 7, and Table 8, respectively. The BiLSTM model is trained for 500 epochs. The idea is to observe how learning unfolds for each model and how the learning behaviour differs with bidirectional LSTM layers. The placement of bidirectional LSTM layers will create two copies of the hidden layer, one fit in the input sequences as it is, while the second one on a reversed copy of the input sequence. This will make sure that the TimeDistributed layer receives 100 (or 300) timesteps of 32 outputs, instead of 10 timesteps of 64 (32 units + 32 units) outputs. That is, the first hidden layer will have 100 memory

20 https://github.com/rezacse/DeepHateExplainer

21 https://keras.io/api/layers/recurrent_layers/time_distributed/
units, while the output layer will be a fully connected layer that outputs one value per timestep. The softmax activation function is used on the output to predict the types of hate. In other words, the output values from both BiLSTM layers will be concatenated, be fed into a fully connected softmax layer for the classification.

### Table 6: Parameters for CNN model

| Parameter name     | Parameter value |
|--------------------|-----------------|
| Embedding dimension| 100, 200, 300    |
| Batch size         | 32, 64          |
| CNN layer 1        | 64, 128         |
| CNN layer 2        | 32, 64          |
| Pooling size       | 2, 3            |
| Dense layer 1      | 128, 256        |
| Dense layer 2      | 256, 512        |
| Dropout             | 0.2, 0.3        |
| Gaussian noise     | 0.1, 0.2, 0.3, 0.5 |
| Learning rate      | 0.001, 0.01, 0.1 |

### Table 7: Parameters for Bi-LSTM model

| Parameter name     | Parameter value |
|--------------------|-----------------|
| Embedding dimension| 100, 200, 300    |
| Batch size         | 32, 64          |
| Bidirectional LSTM layer 1 | 32, 64 |
| Bidirectional LSTM layer 2 | 32, 64 |
| Dense layer 1      | 128, 256        |
| Dense layer 2      | 256, 512        |
| Dropout             | 0.2, 0.3        |
| Gaussian noise     | 0.1, 0.2, 0.3, 0.5 |
| Learning rate      | 0.001, 0.01, 0.1 |

### Table 8: Parameters for Conv-LSTM model

| Parameter name     | Parameter value |
|--------------------|-----------------|
| Embedding dimension| 100, 200, 300    |
| Batch size         | 32, 64          |
| CNN layer 1        | 64, 128         |
| CNN layer 2        | 32, 64          |
| Pooling size       | 2, 3            |
| LSTM layer 1       | 32, 64          |
| LSTM layer 2       | 32, 64          |
| Dense layer 1      | 128, 256        |
| Dense layer 2      | 256, 512        |
| Dropout             | 0.2, 0.3        |
| Gaussian noise     | 0.1, 0.2, 0.3, 0.5 |
| Learning rate      | 0.001, 0.01, 0.1 |

During the training of Conv-LSTM, an LSTM layer treats an input feature space of $100 \times 300$ and its embedded feature vector dimension as timesteps, which generates 100 hidden units per timestep. Once the embedding layer passes an input feature space $100 \times 300$ into a convolutional layer, the input is padded such that the output has the same length as the original input. Then the output of each convolutional layer is passed to the dropout (or Gaussian noise) layer to regularize learning to avoid overfitting. This involves the input feature space into a $100 \times 100$ representation, which is then further down-sampled by three different 1D max-pooling layers, each having a pool size of 4 along with the word dimension, each producing an output of shape $25 \times 100$, where each of 25 dimensions can be considered as extracted features. Each max-pooling layer follows to flatten the output space by taking the highest value in each timestep dimension, which produces a $1 \times 100$ vector that forces words that are highly indicative of interest. These vectors are then fed into a fully connected softmax layer to predict the probability distribution over the hate classes.

### Training details for ML baseline models

We train LR, SVM, KNN, NB, RF, and GBT ML baselines models using the scikit-learn library. We apply both character n-grams and word uni-grams with TF-IDF weighting. The best hyperparameters are produced through random and with 5-fold cross-validation tests. More specifically, Fig. 11 listed the hyperparameters considered in a random search setting.

### Classification results

We enlist evaluation results of each BERT variant and ensemble of top models on the held-out test set, where the following class encoding to interpret the class-specific classification: i) personal hate: class 0, ii) political hate: class 1, iii) religious hate: class 2, and iv) geopolitical hate: class 3. We provide class-wise classification result for each BERT variant, while the same based on the ensemble prediction is shown in Table 4, covering each hate category.

### Explanations

We provide two examples that highlight important terms a DNN model puts more attention to. The example\(^{22}\) in fig. 16, shows positive feature importances represent the extent that the word was important towards the classification of the selected label, while negative feature importances represents words that encouraged the model away from the selected label. Either positive, negative or both positive and negative features can be selected, outlining their relative importance, while ?? shows an example\(^{23}\) detection of personal hate based on using SA, LRP, and integrated gradients (GI). LRP accurately highlights (deep blue) most relevant

\(^{22}\) https://github.com/rezacsedu/DeepHateExplainer/blob/main/notebooks/Example_interpret_text.ipynb

\(^{23}\) https://github.com/rezacsedu/DeepHateExplainer/blob/main/notebooks/LRP_BiLSTM_FastText_Embbeddings_4_Class.ipynb
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Figure 15: Class-wise classification results based on XLM-RoBERTa model

Figure 16: Example-1: identification of political hate, showing most relevant terms

Figure 17: Example-2: identification of personal hate, showing most relevant terms

words (Bangladeshi actress Mithila), which signify a personal hate.