In this paper, we present HS-BAN, a binary class hate speech (HS) dataset in Bangla language consisting of more than 50,000 labeled comments, including 40.17% hate and rest are non hate speech. While preparing the dataset a strict and detailed annotation guideline was followed to reduce human annotation bias. The HS dataset was also preprocessed linguistically to extract different types of slang currently people write using symbols, acronyms, or alternative spellings. These slang words were further categorized into traditional and non-traditional slang lists and included in the results of this paper. We explored traditional linguistic features and neural network-based methods to develop a benchmark system for hate speech detection for the Bangla language. Our experimental results show that existing word embedding models trained with informal texts perform better than those trained with formal text. Our benchmark shows that a Bi-LSTM model on top of the FastText informal word embedding achieved 86.78% F1-score. We will make the dataset available for public use.

1 Introduction

Hate speech (HS) has been rapidly spreading in recent years through various social media sites. HS detection in the user’s comment section remains a difficult challenge due to lack of formal language syntax, spelling mistakes, and use of various slang and non-standard acronyms. Researchers have started working in this very challenging domain, but much of their efforts concentrated on English language. There are almost 46 million Facebook and 29 million YouTube Bangladeshi users but there has been a severe lack of large, linguistically diverse Bangla HS datasets.

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1https://www.statista.com/statistics/268136/top-15-countries-based-on-number-of-facebook-users/
2https://www.statista.com/forecasts/1146236/youtube-users-in-bangladesh
Existing datasets for Bangla HS have some significant drawbacks. First, as Table A.1 of Appendix A shows, the datasets are not large enough. Most of them contain less than 10k sentences. Secondly, the majority portions of those datasets come from one or two domains, which makes them domain-dependent [3], [4] and [5]. Thirdly, annotating HS is inherently a complex and challenging task [1]. [6] showed how annotator’s bias on HS can influence the annotation process and subsequently affect classification task. To combat this, [7] created a stringent and detailed annotation guideline, providing specific points on what constitutes HS and what not. Although [8] followed a guideline to prepare a small Bangla HS dataset, it lacks inter-annotator scores, which makes it difficult to judge annotation quality. To the best of our knowledge, only [9] mentioned Cohen’s kappa score in their paper.

In this paper, we manifest HS-BAN, the largest binary class Bangla HS dataset comprised of more than 50,000 comments crawled from Facebook and YouTube. We present a few examples from the dataset in Table 1. To ensure cross-domain generalization, we collected comments from seven categories as presented in Section 2. A strict annotation guideline was followed to reduce human annotation bias for labeling the dataset achieving an inter-annotator agreement score of 0.658. In Section 3, we present the different natural language processing approaches we used to extract linguistic features by processing noisy social media text. Finally, in Section 4, we present the benchmarking outcome for hate speech classification showing that a Bi-LSTM model on top of the FastText informal word embedding achieved 86.78% F1-score. The dataset and source code will be made publicly available to foster future research.

2 Dataset

| Sentence                                | HS   | Category |
|-----------------------------------------|------|----------|
| মহিলার বিচার চাই                        | Not HS | Crime   |
| We want judgement for the woman.       |      |          |
| হুঁরেপো তোর কত বড় সাহস? Bastard, how dare you? | HS    | Sports   |
| We are with you brother                | Not HS | Entertainment |
| এই পাখার বাংলা, কি বলিদান তুই hey idiot, what are you saying? | HS    | Crime    |
| Oh Allah, give him wellness            | Not HS | Celebrity |

Table 1: Examples of the annotate HS-BAN dataset

Data Collection: We collected more than 100,000 comments from different YouTube channels and Facebook pages in seven categories: sports, entertainment, crime, politics, religion, celebrity, and miscellaneous. For each category except miscellaneous, we compiled a list of controversial events that happened recently (2017-2020) in Bangladesh that falls under those categories. Then public comments were extracted on those issues by using an open-source tool called Facepager. Furthermore, for the miscellaneous category, we searched for videos on YouTube related to Bangla TikTok, roasting, or similar videos as the comment section in these videos tend to be very toxic. We removed duplicate, highly similar comments based on Jaccard Index > 0.8 to reduce repetitiveness and ensure a diverse vocabulary.

Annotation: We prepared a detailed annotation guideline based on the community guidelines of Facebook and YouTube (Appendix B). We worked with 50 annotators who are undergraduate students within the age range from 20 to 25 years. They know about the sensitive nature of the task and they willingly volunteered in this research. Three annotators tagged each comment, and the majority vote decided the final decision. The inter-annotator agreement score of 0.658 indicates that our dataset has moderate agreement among annotators.

Dataset Statistics: Our dataset has 50,314 comments in total; among them, 20,209 of the dataset comments are HS and 30,105 are Not-HS, which implies that our dataset is moderately imbalanced. A more detailed statistics of our dataset is presented in Table 2. We can see that each category is also moderately imbalanced, especially the politics and celebrity categories, whereas crime has the highest hate speech percentage. Observing the average word count (AWC) for each category, we can find that, celebrity category has the highest AWC per sentence with the most standard deviation while miscellaneous has the lowest.

[3] https://github.com/strohne/Facepager
| Category   | Total | HS%   | AWC     | Vocabulary |
|------------|-------|-------|---------|------------|
| Sports     | 5937  | 40.02 | 13.51 ± 18.27 | 16299      |
| Entertainment | 6843  | 41.31 | 12.30 ± 13.31 | 16915      |
| Crime      | 4969  | 43.71 | 16.48 ± 21.53 | 15272      |
| Religion   | 4978  | 38.31 | 13.25 ± 21.54 | 13717      |
| Politics   | 2665  | 33.06 | 12.90 ± 17.93 | 9059       |
| Celebrity  | 2394  | 30.49 | 22.96 ± 33.59 | 14220      |
| Miscellaneous | 22,528 | 41.35 | 11.35 ± 14.16 | 33646      |
| Total      | 50314 | 40.17 | 13.07 ± 17.97 | 72660      |

Table 2: Category-wise Comment distribution

3 Experimental Setup

We removed all hashtags, numbers, and non-Bangla words. However, we kept emoji and punctuation (e&p) in order to confirm [1]'s claim whether e&p can be good indicators for HS. F1 score and Matthews correlation coefficient (MCC) were used to evaluate all models. We split the dataset into train(80%) and test(20%) datasets using stratified sampling so that each category in both dataset contains an equal ratio of hate to not-hate comments. The training dataset was further divided into train(80%) and development(20%) datasets for feature selection and hyper-parameter tuning purposes.

Machine Learning Models: We trained linear Support Vector Machine (SVM)[11] with Term Frequency Inverse Document Frequency (TF-IDF) weighted score as a feature. Regularizer C, penalty, and loss were fine-tuned to find the best hyperparameter combination. And for the deep learning model, we fine-tuned Convolutional Neural Networks (CNN) as described in [12] to get the best F1 score in the development set. We also implemented Bi-directional Long Short Term Memory (Bi-LSTM) as described in [13].

Word Embedding Models: We experimented with BengFastText(BFT)[14] pretrained on 250 million Bangla articles and FastText[15], a multilingual model pretrained on 157 languages. Note that both are pretrained on formal texts; thus denoted as formal embedding. Additionally, 1.47 million Bangla comments from Facebook and YouTube on eight different categories: education, entertainment, health, influencer, religion, politics, sports, technology were collected. Then four different word-embedding models were trained using those datasets. Two word2vec[16] models denoted as W2V(SG) (Word2Vec skip-gram) and W2V(CBOW) (Word2Vec continuous bag of words) and two FastText embeddings denoted as FT(SG) (FastText skip-gram) and FT(CBOW) (FastText continuous bag of words) were trained using informal texts, hence denoted as informal embedding.

Transformer Models: We experimented with some transformer-based models: monolingual Bangla-BERT[17], multilingual BERT-cased and uncased[18]. The hyperparameters were set according to literature [9] except for mBERT-uncased. In this case, the learning rate was changed from its original value of 5e-5 to 3e-5 as the validation loss during the initial training phase was terrible.

4 Result and Analysis

Baseline analysis: We present our experimental findings in table 3. We experimented with different combinations of char and word ngram, and only the most notable combinations were presented. It becomes apparent that in our dataset, e&p do not serve as valuable features. Word n-gram with e&p had the worst F1 score, and for char n-gram (1,6) and (2,6), when e&p are present, the F1 score drops. For this reason, in hyper-parameter tuning and neural network experiments, e&p were removed in the prepossessing step. The experimental results show that char n-gram as a feature performs better than word n-gram. Our dataset contains many spelling mistakes, which means the same words can have inconsistent and multiple spelling variations for which SVM performs poorly [2]. The performance drops with experiments combining char n-gram with word n-gram further validated the fact. Overall, char ngram (1,6) is the best performing feature with F1 score of 85.86.

Formal vs Informal Embeddings: We observed that, SVM with char (1-6) gram as feature outperformed neural networks with FastText and BFT as embedding by a good margin. [19] found similar observations for their informal sentiment analysis dataset. They proposed that pre-trained models based on formal text do not perform well on the
informal dataset. Two FastText informal embedding \textit{FT(SG)} and \textit{FT(CBOW)} outperformed SVM in three out of four instances. Only \textit{CNN+FT(CBOW)} achieved a lower F1 score. Most notably, they were trained on a small 1.47 million informal sentences compared to embeddings such as \textit{BFT} and \textit{FastText} but still managed to outperform the bigger embeddings by a large margin. From the experiments, we conclude, word embedding trained from scratch on informal corpus will perform better for the informal dataset collected from social media.

\textit{FT(SG)} and \textit{FT(CBOW)} performed comparatively better than both \textit{W2V(SG)} and \textit{W2V(CBOW)} as presented in Table 3. According to [20], \textit{FastText} is generally a better choice compared to \textit{Word2Vec} for our dataset. We can also see that \textit{W2V(SG)} and \textit{FT(SG)} outperformed \textit{W2V(CBOW)} and \textit{FT(CBOW)}, respectively. From this, we can summarize that word embedding created on the \textit{SG} method tends to perform better than the \textit{CBOW} method for our dataset. Overall, combining \textit{Bi-LSTM} with \textit{FT(SG)} or \textit{Bi-LSTM+FT(SG)} achieved the best result with an F1 score of 86.85%.

**Transformer vs Other:** All BERT variants performed significantly worse compared to other models. Possible reasons could be that mBERT is under-tuned for Bangla informal text as it was trained with Bangla Wikipedia for which we observe the lower performance. The experimental success with informal word embedding over formal embedding support the last assumption.

| Model                  | F1  | MCC |
|------------------------|-----|-----|
| Unigram (U)            | 82.89 | 72.95 |
| U+e&p                  | 82.38 | 72.17 |
| Bigram (B)             | 63.12 | 49.23 |
| Trigram (T)            | 24.85 | 23.60 |
| U+B                    | 82.11 | 71.32 |
| U+B+T                  | 81.16 | 70.38 |
| Char 1-6 gram(C(1,6))  | 85.97 | 77.15 |
| C(1,6)+e&p             | 85.86 | 77    |
| C(2,6)                 | 85.89 | 77.04 |
| C(2,6)+e&p             | 85.76 | 76.86 |
| U+B+C(1,6)             | 84.71 | 75.04 |
| U+B+C(2,6)             | 84.73 | 75.10 |
| CNN+BFT                | 71.58 | 53.06 |
| Bi-LSTM+BFT            | 76.09 | 61.51 |
| CNN+FastText           | 84    | 72.89 |
| Bi-LSTM+FastText       | 83.89 | 73.43 |
| CNN+W2V(CBOW)          | 80.03 | 68.42 |
| Bi-LSTM+W2V(CBOW)      | 80.48 | 69.46 |
| CNN+W2V(SG)            | 81.07 | 69.23 |
| Bi-LSTM+W2V(SG)        | 80.93 | 69.25 |
| CNN+FT(CBOW)           | 85.05 | 75.15 |
| Bi-LSTM+FT(CBOW)       | 86.73 | 77.76 |
| CNN+FT(SG)             | 86.58 | 77.33 |
| Bi-LSTM+FT(SG)         | 86.85 | 77.90 |
| mBERT-cased            | 81.66 | 72.81 |
| mBERT-uncased          | 82.56 | 73.33 |
| Bangla-BERT            | 83.68 | 74.63 |

Table 3: Benchmarking the hate speech classification models.

**Category-wise Result:** From Table 4 we can see that for each category, the F1 scores of 5 top-performing models: SVM, Bi-LSTM+FT(SG), CNN+FT(SG), Bi-LSTM+FT(CBOW), and CNN+FT(CBOW) were averaged and presented in the \textit{F1 avg} column. \textit{Politics} and \textit{Celebrity} categories achieved the lowest average F1 scores. Two reasons might contribute to this: both categories have the lowest training data and the lowest HS%. To check this hypothesis, we dropped some NHS in each category so that each of them has an equal number of HS and NHS. Then, the average F1 score for all five models was calculated and shown in the \textit{F1 improved} column. Note that F1 scores for \textit{Politics} and \textit{Celebrity} improved the most. On the other hand, \textit{Crime} has the best HS% and achieved the most \textit{F1 avg score}. And so, it also improved the least (only 0.5) after balancing.
Table 4: Category wise result comparison

| Category     | Total | HS%  | F1 avg | F1 improved |
|--------------|-------|------|--------|-------------|
| Sports       | 4748  | 40.01| 84.99  | 87.70       |
| Entertainment| 5468  | 41.32| 87.09  | 88.51       |
| Crime        | 3973  | 43.71| 92.27  | 92.77       |
| Religion     | 3978  | 38.31| 85.92  | 88.67       |
| Politics     | 2137  | 33.04| 80.69  | 86.39       |
| Celebrity    | 1909  | 30.49| 78.84  | 83.02       |
| Miscellaneous| 18,021| 41.35| 85.99  | 88.00       |

Table 5: Influence of traditional and non traditional slang words

| Model             | TS acc | NTS acc |
|-------------------|--------|---------|
| SVM               | 84.27  | 79.53   |
| Bi-LSTM+FT(SG)    | 84.87  | 79.40   |
| Bi-LSTM+FT(CBOW)  | 85.08  | 77.97   |
| CNN+FT(SG)        | 84.95  | 77.59   |
| CNN+FT(CBOW)      | 83.39  | 74.87   |

Influence of slang words: The dataset vocabulary was extracted, and slang words were annotated with the help of a linguistic expert. These slang words were divided into two types: traditional slang (TS) and non-traditional slang (NTS). NTS is not usually used as slang words but can be interpreted as such depending on the context. Figure C.1 in Appendix C shows some examples of both types of slang words. Then we looked at how models predicted comments that contain at least one such slang word. For simplicity, we ignored comments that contained both TS and NTS words. Our initial hypothesis was that models would face more trouble detecting sentences NTS as these words are often used as HS as well as NHS. Table 5 shows this result. TS acc shows how models predicted comments containing TS and NTS acc is for NTS. We can see that models performed better when comments contained TS words rather than NTS. NTS words are often vague in meaning, and so they pose special difficulty for the models.

5 Conclusion

In this paper, we present HS-BN, the largest Bangla HS dataset collected from social media comments. We followed various schemes to ensure linguistic diversity and reduce repetitiveness. We found that emoji and punctuation do not affect HS detection. We also found that word embedding trained on informal text outperforms available embedding trained on formal text. We also observed that traditional slangs make the detection of hate speech much easier than that of comments with non-traditional slangs. In the future, we plan to research on the interpretability and generalizability of hate speech detection model.

References

[1] Chikashi Nobata, Joel Tetreault, Achint Thomas, Yashar Mehdad, and Yi Chang. Abusive language detection in online user content. In Proceedings of the 25th international conference on world wide web, pages 145–153, 2016.

[2] Anna Schmidt and Michael Wiegand. A survey on hate speech detection using natural language processing. In Proceedings of the Fifth International workshop on natural language processing for social media, pages 1–10, 2017.

[3] Alvi Md Ishman and Sadia Sharmin. Hateful speech detection in public facebook pages for the bengali language. Proceedings - 18th IEEE International Conference on Machine Learning and Applications, ICMLA 2019, pages 555–560, 2019.

[4] Estiak Ahmed Emon, Shihab Rahman, Joti Banarjee, Amit Kumar Das, and Tanni Mittra. A Deep Learning Approach to Detect Abusive Bengali Text. 2019 7th International Conference on Smart Computing and Communications, ICSCC 2019, pages 1–5, 2019.
[5] Puja Chakraborty and Md Hanif Seddiqui. Threat and Abusive Language Detection on Social Media in Bengali Language. *1st International Conference on Advances in Science, Engineering and Robotics Technology 2019, ICASERT 2019*, 2019(Icasert):1–6, 2019.

[6] Zeerak Waseem. Are you a racist or am i seeing things? annotator influence on hate speech detection on twitter. In *Proceedings of the first workshop on NLP and computational social science*, pages 138–142, 2016.

[7] Ona de Gibert, Naiara Perez, Aitor García-Pablos, and Montse Cuadros. Hate speech dataset from a white supremacy forum. *arXiv preprint arXiv:1809.04444*, 2018.

[8] Nauros Romim, Mosahed Ahmed, Hriteshwar Talukder, and Md Saiful Islam. Hate speech detection in the bengali language: A dataset and its baseline evaluation. In *Proceedings of International Joint Conference on Advances in Computational Intelligence*, pages 457–468. Springer, 2021.

[9] Md Karim, Sumon Kanti Dey, Bharathi Raja Chakravarthi, et al. Deephateexplainer: Explainable hate speech detection in under-resourced bengali language. *arXiv preprint arXiv:2012.14353*, 2020.

[10] Joseph L Fleiss. Measuring nominal scale agreement among many raters. *Psychological bulletin*, 76(5):378, 1971.

[11] Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine learning*, 20(3):273–297, 1995.

[12] Ye Zhang and Byron Wallace. A sensitivity analysis of (and practitioners’ guide to) convolutional neural networks for sentence classification. *arXiv preprint arXiv:1510.03820*, 2015.

[13] Mohammad Sadegh Rasooli, Noura Farra, Axinia Radeva, Tao Yu, and Kathleen McKeown. Cross-lingual sentiment transfer with limited resources. *Machine Translation*, 32(1):143–165, 2018.

[14] Md. Rezaul Karim, Bharathi Raja Chakravarthi, John P. McCrae, and Michael Cochez. Classification Benchmarks for Under-resourced Bengali Language based on Multichannel Convolutional-LSTM Network. 2020.

[15] Edouard Grave, Piotr Bojanowski, Prakhar Gupta, Armand Joulin, and Tomas Mikolov. Learning word vectors for 157 languages. In *Proceedings of the International Conference on Language Resources and Evaluation (LREC 2018)*, 2018.

[16] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119, 2013.

[17] Sagor Sarker. Banglabert: Bengali mask language model for bengali language understading, 2020.

[18] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018.

[19] Khondoker Ittehadul Islam, Md Saiful Islam, and Mohammad Ruhul Kar, Sudipta Amin. Sentnob: A dataset for analysing sentiment on noisy bangla texts. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Association for Computational Linguistics, November 2021.

[20] Armand Joulin, Edouard Grave, Piotr Bojanowski, Matthijs Douze, Hervé Jégou, and Tomas Mikolov. Fasttext: zip: Compressing text classification models. *arXiv preprint arXiv:1612.03651*, 2016.

[21] Md Abdul Awal, Md Shamimur Rahman, and Jakaria Rabbi. Detecting Abusive Comments in Discussion Threads Using Naïve Bayes. *2018 International Conference on Innovations in Science, Engineering and Technology, ICISET 2018*, (October):163–167, 2018.

[22] Nayan Banik. Toxicity Detection on Bengali Social Media Comments using Supervised Models. (November), 2019.
Appendix

A: Bangla HS dataset comparison

| Dataset size | No of HS | Annotation guideline | Agreement score |
|--------------|----------|----------------------|-----------------|
| (Chakraborty and Seddiqui, 2019) | 5,644 | 2500 | No | No |
| (Emon et al., 2019) | 4,700 | 3137 | No | No |
| (Awal et al., 2018) | 2665 | 1214 | No | No |
| (Ishmam and Sharmin, 2019) | 5,126 | 3178 | No | No |
| (Banik, 2019) | 10,219 | 4255 | No | No |
| (Karim et al., 2020a) | 6115 | 6115 | No | Yes |
| (Romim et al., 2021) | 30,000 | 10,000 | Yes | No |
| **Our** | **50,314** | **20,209** | Yes | Yes |

Table A.1: Overview of binary hate speech dataset of Bangla social media

B: Annotation Guidelines

We chose three criteria for a comment to be labeled as HS. These are:

- Deliberate attack
- Directed towards a specific group of people
- Motivated by an aspect of groups identity

But bellow we also present a more nuanced guideline for annotation, based on the community standard of Facebook and YouTube.

Criteria for HS

- If a comment targets an individual or group based on age, ethnicity, nationality, religion, sexual orientation, gender, physical and mental disability, and disease. For example:
  
  রোহিঙ্গা চুরি করাতে পারবে তাদের ধারা আর কিছু হবে না
  
  Translation: "Rohingyas can only steal things. Nothing useful can come out of them."

- If a comment does not directly dehumanize a person but supports the act of HS.
  
  বোরকা পার না, ধরিয়ে তো হবেই।
  
  Translation: "It is obvious that girls who do not wear a burqa will be raped."

- If someone feels disgusted by another person.
  
  তর কাজ দেখে বমি করে দিতে ইচ্ছে করছে।
  
  Translation: "Seeing your work makes me want to puke"

- Comparing a person with an insect, object, animal, known criminal, or historically villainous person.
  
  যে একটা কুকুর।
  
  Translation: "You are a dog."

  তুই একটা মিরজাফার।
  
  Translation: "You are a Mirzafar." (The word Mirzafar here indicates a traitor.)
Criteria for not HS

- If a sentence contains a slang word but not targeted towards a human, it is not HS. In the following sentence, the slang word was targeted towards the movie, not the director or actors. So it was not considered as HS.

ফি বালের মুভি
Translation: "What an ass movie."

- Sarcasm is not HS unless it directly dehumanizes a person or community. For example:

কমেন্ট পড়তে আসলাম।
Translation: "Came here to read the comments."

- It does not matter if the stand is right or wrong. Because very few things are universally right and wrong, and it often depends on context and time. So if a sentence objectively dehumanizes a person or community, it is considered HS.

C: Traditional and non traditional slang words

![Traditional Slang WordCloud](image1)

![Non Traditional Slang WordCloud](image2)

Figure C.1: Comparison of traditional and non-traditional slang words.