BanglaBook: A Large-scale Bangla Dataset for Sentiment Analysis from Book Reviews

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Abstract

The analysis of consumer sentiment, as expressed through reviews, can provide a wealth of insight regarding the quality of a product. While the study of sentiment analysis has been widely explored in many popular languages, relatively less attention has been given to the Bangla language, mostly due to a lack of relevant data and cross-domain adaptability. To address this limitation, we present BanglaBook, a large-scale dataset of Bangla book reviews consisting of 158,065 samples classified into three broad categories: positive, negative, and neutral. We provide a detailed statistical analysis of the dataset and employ a range of machine learning models to establish baselines including SVM, LSTM, and Bangla-BERT. Our findings demonstrate a substantial performance advantage of pre-trained models over models that rely on manually crafted features, emphasizing the necessity for additional training resources in this domain. Additionally, we conduct an in-depth error analysis by examining sentiment unigrams, which may provide insight into common classification errors in under-resourced languages like Bangla. Our codes and data are publicly available at https://github.com/mohsinulkabir14/BanglaBook.

1 Introduction

The resources publicly available for scholarly investigation in the realm of Sentiment Analysis (SA) for the Bangla language are scarce and limited in quantity (Khatun and Rabeya, 2022; Sazzed, 2021; Rahman et al., 2019) despite its literary gravitas as the 6th most spoken language[1] in the world with approximately 200 million speakers. In the existing literature on Bangla Text SA, as shown in Table 5, the largest dataset consists of 20,468 samples (Islam et al., 2022) while the smallest has a mere 1,050 samples (Tabassum and Khan, 2019). Besides these, Islam et al. (2020) created a dataset consisting of 17,852 samples and Islam et al. (2021) utilized a dataset of 15,728 samples. All other datasets apart from these either have <15,000 samples or are publicly unavailable. Another limitation of the existing research works in Bangla Text SA is the deficiency of datasets having product-specific review samples. Most of the available Bangla SA datasets are focused on user-generated textual content from cyberspace. The insights derived from these may not accurately represent sentiment in the context of product reviews, thus hindering their usefulness for businesses. The tonal and linguistic analysis of reviews from product-specific datasets can aid businesses to gain valuable insights into customer attitudes, preferences, and experiences which can then be leveraged to improve products and services, design targeted marketing campaigns, and make more informed business decisions. In this paper, we introduce a large-scale dataset, BanglaBook, consisting of 158,065 samples of book reviews collected from online bookshops written in the Bangla language. This is the largest dataset for Bangla sentiment analysis to the best of our knowledge. We perform an analysis of the dataset's statistical characteristics, employ various ML techniques to establish a performance benchmark for validating the dataset, and also conduct a thorough evaluation of the classification errors.

2 Dataset Construction

In order to create this dataset, we collect a total of 204,659 book reviews from two online bookshops (Rokomari[2] and Wafilife[3]) using a web scraper developed with several Python libraries, including `BeautifulSoup`, `Selenium`, `Pandas`, `Openpyxl`,

*These authors contributed equally to this work. Author names are in alphabetic order.

[1] https://en.wikipedia.org/wiki/List_of_languages_by_total_number_of_speakers

[2] https://www.rokomari.com/

[3] https://www.wafilife.com/

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Source	Language	Annotated	Unannotated	Total
Rokomari	Bangla	84,672	24,806	109,478
	Bangla† + English	56,485	15,408	71,893
	Bangla + Bangla† + English	13,144	4,114	17,258
	Total	154,301	44,328	198,629
Wafilife	Bangla	4,699	59	4,758
	Bangla† + English	370	3	373
	Bangla + Bangla† + English	896	3	899
	Total	5,965	65	6,030
	Bangla	89,371	24,865	114,237
	Bangla† + English	56,855	15,411	72,266
	Bangla + Bangla† + English	14,040	4,117	18,157
	Total	160,266	44,393	204,659
	Untranslated Data (Removed)	2,201		
	Final Dataset Size	**158,065**		

Table 1: Summary statistics of our dataset. Bangla† denotes Romanized Bangla text.

and Webdriver, to collect and process the raw data.

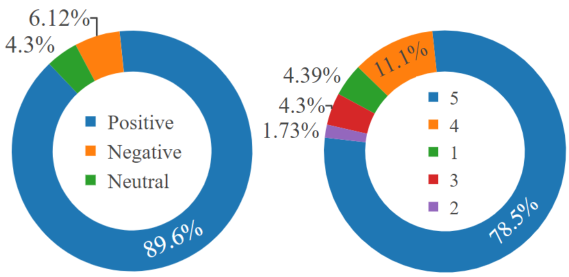
For the data collection and preparation process of the BANGLABOOK dataset, we first compile a list of URLs for authors from online bookstores. From there, we procure URLs for the books. We meticulously scrape information such as book titles, author names, book categories, review texts, reviewer names, review dates, and ratings by utilizing these book URLs.

General Properties	# of Reviews	158,065
	# of Books	30,253
	# of Reviewers	44,616
	# of Categories	1,573
	Total Review Words	44,429,201
Single Review	max. Word length	765
	min. Word length	1
	avg. Word length	281.08

Table 2: General overview of BANGLABOOK.

2.1 Labeling & Translation

If a review does not have a rating, we deem it unannotated. Reviews with a rating of 1 or 2 are classified as negative, a rating of 3 is considered neutral, and a rating of 4 or 5 is classified as positive. Two manual experiments are carried out to validate the use of ratings as a measure of sentiment in product reviews. In the first experiment, around 10% of the reviews are randomly selected and annotated manually. The annotated labels are cross-checked with the original labels, resulting in a 96.7% accuracy in the corresponding labels. In addition, we consult the work of Wang et al. (2020) that explored the issue of incongruous sentiment expressions with regard to ratings. Specifically, the study scrutinized two categories of reviews: *high ratings lacking a positive sentiment*, and *low ratings lacking a negative sentiment*. We perform an analysis to identify such inconsistencies within our dataset and discovered that only a minuscule 3.41% of the samples exhibited this pattern. This figure is relatively insignificant when considering the substantially large scale of our dataset.



(a) Sentiment Distribution (b) Rating Distribution

Figure 1: Class Distribution of BANGLABOOK.

After discarding the unannotated reviews, we curate a final dataset of 158,065 annotated reviews. Of these, 89,371 are written entirely in Bangla. The remaining 68,694 reviews were written in Romanized Bangla, English, or a mix of languages. They are translated into Bangla with Google Translator and a custom Python program using the googletrans library. The translations are subsequently subjected to manual review and scrutiny to confirm their accuracy. The majority of inaccurate translations primarily comprise spelling errors and instances where English words remain untranslated within samples containing a combination of Bangla and English text. The meticulous evaluation process of untranslated samples involves a thorough assessment by post-graduate native Bangla speakers, who critically compare the translated text against the original untranslated text to ascertain the correctness of the translation.

3 Statistical Analysis

Tables 1 and 2 provide an overview of the statistical properties of the BANGLABOOK dataset. The sentiment doughnut chart in Figure-1a illustrates the proportion of positive, neutral, and negative reviews, while the rating doughnut chart in Figure-1b displays the percentage of reviews that corre-

Method	Negative	Neutral	Positive	Weighted Avg.
Random Forest (`word 2-gram + word 3-gram`)	0.56	0.34	0.96	0.9106
SVM (`word 2-gram + word 3-gram`)	0.40	0.15	**1.00**	0.9053
Random Forest (`word 1-gram`)	0.48	0.35	0.96	0.9043
Logistic Regression (`char 2-gram + char 3-gram`)	0.55	0.13	0.96	0.8978
Bangla-BERT (`base-uncased`)	0.60	0.22	0.96	0.9064
Logistic Regression (`word 2-gram + word 3-gram`)	0.53	0.13	0.96	0.8964
Bangla-BERT (`large`)	**0.72**	**0.40**	0.97	**0.9331**
XGBoost (`char 2-gram + char 3-gram`)	0.31	0.02	0.95	0.8723
Multinomial NB (`word 2-gram + word 3-gram`)	0.23	0.03	0.95	0.8663
LSTM (`GloVe`)	0.11	0.00	0.10	0.0991
XGBoost (`word 2-gram + word 3-gram`)	0.23	0.01	0.95	0.8651
Multinomial NB (`BoW`)	0.18	0.05	0.94	0.8564
SVM (`word 1-gram`)	0.08	0.04	0.94	0.8519

Table 3: Catergory-wise Binary Task F1-score and Weighted Average F1-score of each method on BANGLABOOK.

spond to each rating on a scale of 1 to 5.

Upon analyzing the sentiment chart, it appears that the majority of the reviews (124,084 + 17,503 = 141,587 samples) are positive, with a significant portion also being negative (2,728 + 6,946 = 9,674 samples). A relatively small fraction of the reviews are neutral (6,804 samples). This suggests that overall, the books have been well received by the readers, with the majority expressing favorable opinions. The distribution of the dataset is representative of real-world scenarios and it tessellates well with previous content analysis works on book reviews (Lin et al., 2005; Sorensen and Rasmussen, 2004). In Figure-2, we can visualize an illustration of the sentiment distribution among the 5 most frequently reviewed categories of books. We can gain some salient insights from the popularity of these genres. Contemporary novels are bestsellers as they reflect current events, social issues, and trends, making them relatable and thought-provoking for the readers while self-help and religious books provide guidance, inspiration, and a sense of purpose, catering to individuals' quest for personal growth and spiritual fulfillment.

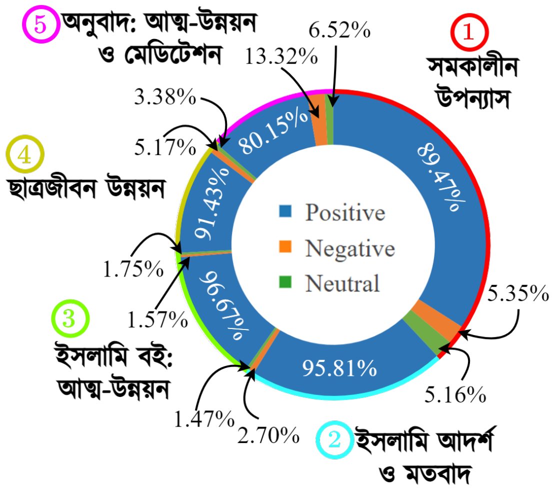


Figure 2: Sentiment Distribution of top 5 most popular genres. In clockwise order, সমকালীন উপন্যাস (Contemporary Novel), ইসলামি আদর্শ ও মতবাদ (Islamic Ideals and Doctrines), ইসলামি বই: আত্ম উন্নয়ন (Islamic Books: Self-Development), ছাত্রজীবন উন্নয়ন (Student Life Development), অনুবাদ: আত্ম-উন্নয়ন ও মেডিটেশন (Translated Books: Self-Development and Meditation).

4 Developing Benchmark for BANGLABOOK

A series of baseline models with combinations of different lexical and semantic features are chosen to evaluate the BANGLABOOK dataset. An overview of the models, evaluation metrics, results, and analysis of the experimental results are provided in this section.

4.1 Baseline Models & Features

For the lexical features, we extract bag-of-words (BoW), char n-grams (1-3), and word n-grams (1-3) from the reviews as these representations have performed well in different classification tasks (Islam et al., 2022). After extracting the features, they are vectorized using TF-IDF and count vectorizer and trained on a series of ML models such as Random Forest (Breiman, 2001), XGBoost (Chen and Guestrin, 2016), linear SVM (Cortes and Vapnik, 1995), Logistic Regression (le Cessie and van Houwelingen, 1992) and Multinomial Naive Bayes (John and Langley, 1995). We choose LSTM (Hochreiter and Schmidhuber, 1997) with GloVe (Pennington et al., 2014) embedding for its ability to understand context along with recent dependency. We also fine-tuned two available transformer-based models in Bangla: Bangla-BERT (`base-uncased`) (110M parameters) (Sarker, 2020) and Bangla-BERT (`large`) (2.5B parameters) (Bhattacharjee et al., 2022), due to the recent success of BERT (Devlin et al., 2019) in various downstream NLP tasks. We select F1-score and weighted average F1-score to evaluate the models because the dataset has an un-

Class	10 Most Frequent Words
Positive	ভালো (good) , সুন্দর (nice) , অসাধারণ (extraordinary) , দুর্দান্ত (splendid) , সেরা (best) , সহজ (facile), চমৎকার (beautiful) , আশা (hope) , ধন্যবাদ (gratefulness), আলহামদুলিল্লাহ (gratitude)
Neutral	ভালো (good) , সুন্দর (nice) , খারাপ (bad) , মোটামুটি (average) , ভুল (fault) , আশা (hope) , সহজ (facile), অসাধারণ (extraordinary) , কম (low) , দুর্দান্ত (splendid)
Negative	ভালো (good) , বাজে (trash) , খারাপ (bad) , ভুল (fault) , সুন্দর (nice) , আশা (hope) , নষ্ট (waste) , ফালতু (useless) , হতাশা (disappointment) , কম (low)

Table 4: Most frequent word unigrams conveying the strongest sentiments of each class with English translation. The colors respectively denote Positive , Neutral and Negative sentiments.

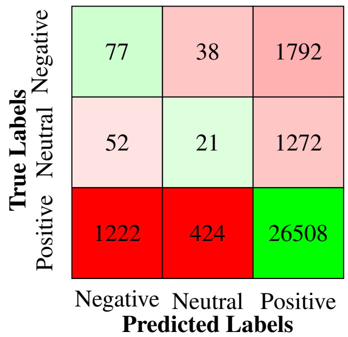


Figure 3: Confusion Matrix for Bangla-BERT

even class distribution. F1-score is the harmonic mean of precision and recall and it helps balance the metric across the imbalanced positive/negative samples (Sokolova et al., 2006). All our experiments are done using `scikit-learn`, `pytorch`, and `transformers` (Vaswani et al., 2017) and run on Google Colaboratory. The training, testing, and validation split of the entire dataset was 70-20-10 with previously unseen samples in the test and validation set.

4.2 Results & Findings

Table 3 summarizes the experimental results for BANGLABOOK. Results show that Bangla-BERT`(large)` outperforms all other models by a clear margin. Also, the combination of word/char 2-gram and word/char 3-gram perform exceptionally well with respective classifiers. Our hypothesis is that these two features result in a large number of unique word and character combinations, aiding the models' ability to generalize effectively across categories. Islam et al. (2022, 2021); Taher et al. (2018) concur on the same verdict by implying that the task predominantly relies on word units, with minimal dependence on subword level information and the nature of the Bangla language itself. Furthermore, Majumder et al. (2002) outlined the suitability of n-gram approaches in generating language profiles for Indo-European languages in their work. The bag-of-words (BoW) feature is inept at classifying the corresponding categories because of its inability to capture critical contextual information and nuance (Zheng and Casari, 2018). Although word 1-gram does not outperform word 2-gram and word 3-gram, it does predict the 'Neutral' class well. Both the pre-trained Bangla-BERT models perform fairly consistently across all categories on the BANGLABOOK dataset, demonstrating the usefulness of contextual understanding and transfer learning in classification tasks even in low-resource languages like Bangla. The LSTM model with GloVe embedding recognizes the 'Negative' and 'Positive' classes very marginally and fails completely to identify the 'Neutral' category. It is also notable that, SVM with bigram and trigram achieves perfect scores in the 'Positive' class.

To summarize, the utilization of pre-trained models (i.e. Bangla-BERT) that undergo training on extensive corpora, leading to exposure to extensive general language knowledge, has significantly contributed to their superior classification performance compared to other models and word embeddings. Additionally, models trained on handcrafted features also perform significantly well. It should be noted that Bangla pre-trained models are currently undergoing development, and further training on expansive corpora has the potential to enhance their ability to generalize and achieve even more impressive results.

4.3 Error Analysis

In the 'Positive' class, all the models produce excellent classification results. While some models perform reasonably well on the 'Negative' class, nearly all of the models perform poorly on the 'Neutral' class. The class imbalance of the dataset, as shown in Figure 1, is one obvious cause of this fluctuation in results. The confusion matrix for

Bangla-BERT on our dataset, presented in Figure-3, reveals that most of the 'Negative' and 'Neutral' samples are misclassified as 'Positive' samples by our classifiers. To further analyze the misclassifications, we examine the W1 (word unigrams) of these three classes. We find 124,796 unique W1 for the 'Positive' class, 20,714 unique W1 for the 'Negative' class, and 19,096 unique W1 for the 'Neutral' class. 77.57% of the W1 from the 'Neutral' class and 79.83% of the W1 from the 'Negative' class are found in the 'Positive' class. Table 4 depicts the most frequent W1 conveying the strongest sentiments for each class. With only one distinct 'Neutral' W1 and even the 'Negative' class having multiple positive W1, the dominance of 'Positive' sentiment W1 over the other two classes is evident. This may have contributed to the lack of distinctive words in the 'Negative' and 'Neutral' classes, which inevitably prevented the feature-based models from generalizing.

5 Morphology and Negation Patterns of Bangla

Understanding the morphology and negation patterns of a language holds paramount importance in the realm of sentiment analysis because negation can alter the meaning of words and phrases, thereby affecting the overall sentiment conveyed by a text. We provide a concise yet insightful recapitulation of the topic in the case of Bangla accompanied by review samples from our dataset BANGLABOOK as the respective examples. From the linguistic typological standpoint, Bangla is categorized as a *subject-object-verb* (SOV) language because the subject, object, and verb generally adhere to said order in its sentential structure (Ramchand, 2004). The most common juxtaposition of polarity from positive to negative is the use of *ni* (নি) as a tensed negative. For example,

আমি তাঁর অনুরাগী হওয়ায় আমি এই বইটি কেনা
থেকে নিজেকে প্রতিরোধ করতে পারিনি !!!!
Translation: As I am a fan of his I couldn't resist myself from buying this book!!!!

Another negational feature is expressed by placing *na* (না) prior to the non-finite verb and after the finite verb in a sentence (although there are some exceptions). For example,

অবশ্য হুমায়ুন আহমেদ লিখেছেন এই বইটার
উপরে তিনি নিজেও সন্তুষ্ট না ।
Translation: Of course, Humayun Ahmed wrote that he himself is not satisfied with this book.

The Bangla language consists of no negative adverbs or pronouns (Thompson, 2006). This is why the negative element responsible for the reversal of polarity transcends from the word-level to the sentence-level rendering the occurrences of almost all negations in Bangla manifest on the syntactic level (Thompson, 2006).

In the cases of double negatives, we see the involvement of lexical negation, a morphological feature that works with negative affixes (prefixes and suffixes) attached to a root word. The prefixes in Bangla have two different phonetic variations or allophones depending on whether the prefix precedes a vowel or a consonant. The same is true for prefixes that imbue a negative connotation to a root word, e.g. *o* (অ) and *on* (অন্). For example,

কিন্তু এই বইটি এই অপূর্ণতা ঢেকে ফেলেছে।
Translation: But this book has covered up this incompleteness.

ওমর খৈয়ামের ভাষায় কিছু বই অনন্ত যৌবনের বই,
যাদের কোন ক্ষয় নেই।
Translation: In the words of Omar Khayyam, some books are books of never-ending youth, which have no decay.

Another negative prefix that precedes a root word to invert its polarity is *nir* (নির্). For example,

লেখকের নিরলস শ্রম লেখায় ফুটে উঠেছে।
Translation: The relentless effort of the author is reflected in the writing.

On the contrary, the suffix *hin* (হীন) succeeds a root word to convert it to the corresponding negative form. For example,

এরকম ভিত্তিহীন কাল্পনিক গল্প শিশুদের না পড়াই ভালো।
Translation: It is better for children not to read such baseless fictional stories.

The expression of negative sentiment is, therefore, very nuanced in the Bangla language as every occurrence of negative is intertwined with features like the tense, hierarchy of syntax, verb status, case-specific issues, and sequential arrangement of words (Thompson, 2006).

6 Conclusion

This paper introduces BANGLABOOK, the largest Bangla book review dataset with 158,065 samples, each labeled with 1 of 3 user sentiments. We provide extensive statistical analysis and strong baselines facilitating the utility of the dataset. Given its massive size and fine-grained sentiment distribution, BANGLABOOK has the potential to alleviate the resource scarcity in Bangla language research.

7 Limitations

Many of the reviews that were gathered for constructing BANGLABOOK are discarded because they lack a corresponding rating. A manual annotation process would have yielded a much larger dataset, which was not feasible due to resource constraints. Moreover, one of the challenges for validating the dataset is the lack of statistical models and word-embeddings pre-trained on the Bangla language. Some pre-trained Bangla-BERT models, yet to be trained on extensive corpora, have only recently been proposed. Improving transformer-based models for Bangla can enhance sub-word level contextual understanding which will consequently help in more accurate identification of the sentiments in BANGLABOOK (Islam et al., 2022).

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A Appendix

Dataset	Sentiment Classification	Sentiment Distribution	Total # of Samples	Availability	Type of Content	Source(s)	Baseline Models
(Tabassum and Khan, 2019)	Positive Negative	- -	1,050	Closed	Posts, comments	Facebook, Twitter	RF
(Chowdhury and Chowdhury, 2014)	Positive Negative	- -	1,300	Closed	Posts, comments	Twitter	-
(Nabi et al., 2016)	Positive Negative	- -	1,500	Closed	Posts, comments	Social Media	-
(Mahtab et al., 2018)	Praise Criticism Sadness	513 604 484	1,601	Closed	Comments	Prothom Alo Online News Portal	SVM, DT, NB
(Akter and Aziz, 2016)	Positive Negative Neutral	- - -	3,600	Closed	Posts, comments	Facebook	NB
(Rahman and Kumar Dey, 2018)	Positive Negative Neutral	- - -	4,700	**Open**	Comments	Facebook pages: BBC Bangla, Prothom Alo	SVM, LR, KNN, DT, LSTM NB, CNN
(Dey and Sarker, 2019)	Positive Negative	2,600 2,600	5,200	Closed	Comments, reviews	Facebook, Twitter, YouTube, News Portals	DT, NB, SVM
(Khatun and Rabeya, 2022)	Positive Negative	- -	5,500	Closed	Comments, reviews	Social Media	-
BEmoC (Iqbal et al., 2022)	Anger Fear Surprise Sadness Joy Disgust	- - - - - -	7,000	**Open**	Posts, comments	Facebook, YouTube, Online blogs, Bangla story books, novels, newspapers, discourse	-
(Tuhin et al., 2019)	Happy Tender Excited Sad Angry Scared	- - - - - -	7,500	Closed	-	-	NB, Tropical Method
(Akter et al., 2021)	Positive Negative Neutral	- - -	7,905	Closed	Product reviews	Daraz	RF, LR, SVM, KNN, XGB
(Hassan et al., 2016)	Positive Negative Ambiguous	- - -	9,337	Closed	Comments, reviews	Facebook, Twitter, YouTube, News Portals	LSTM
(Rahib et al., 2022)	Insightful Curious Gratitude	3,800 3,549 3,232	10,581	Closed	Comments	Social Media	SVM, RF, CNN, LSTM
(Al Kaiser et al., 2021)	Positive: Wishful Thinking, Appreciation Negative: Gender-based hate, Religious hate, Political hate, Personal hate, Sarcasm Neutral: -	Positive 1,909: 967, 942 Negative 5,237: 525, 731, 572, 1,995, 1,414 Neutral 3,860: 3,860	11,006	Closed	Comments	Facebook	LR, DT, RF, MNB, KNN, Linear SVM, RBF SVM, XGB
(Sazzed, 2020a)	Positive Negative	8,500 3,307	11,807	**Open**	Comments	YouTube	SVM, ET, RF, LR, VADER, TextBlob
(Sazzed, 2020b)	Positive Negative	- -	12,000	Closed	Comments	YouTube	-
SentNoB (Islam et al., 2021)	Positive Negative Neutral	6,410 5,709 3,609	15,728	**Open**	Comments	Prothom Alo Online Newspaper, YouTube	RNN
(Islam et al., 2020)	Positive Negative Neutral	4,769 8,351 4,732	17,852	**Open**	Comments	Prothom Alo Online Newspaper	CNN, LSTM, BERT, GRU, fastText
EmoNoBa (Islam et al., 2022)	Love Joy Surprise Anger Sadness Fear	4,202 9,249 939 3,905 5,109 307	20,468	**Open**	Comments	YouTube, Facebook, Twitter, Prothom Alo	Bi-LSTM, fastText, Bangla-BERT-base
BanglaBook (ours)	Positive Negative Neutral	141,587 9,674 6,804	**158,065**	**Open**†	Book reviews	Rokomari, Wafilife	RF, LSTM, LR, GRU MNB, SVM, XGB Bangla-BERT

Table 5: Comparison of notable Bangla Sentiment Analysis datasets sorted in ascending order of size. The abbreviations respectively denote, Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes (NB), Logistic Regression (LR), K-Nearest Neighbors (KNN), Long Short-term Memory (LSTM), Convolutional Neural Network (CNN), Extreme Gradient Boost (XGB), Multinomial Naive Bayes (MNB), Radial Basis Function (RBF), Extreme Random Tree (ET), Recurrent Neural Network (RNN), Bidirectional Encoder Representations from Transformers (BERT), Gated Recurrent Unit (GRU), Bi-LSTM (Bidirectional LSTM). All the publicly available datasets are hyperlinked. Open† denotes the redaction of the link for anonymity.

ACL 2023 Responsible NLP Checklist

A For every submission:

☑ A1. Did you describe the limitations of your work?
Left blank.

☐ A2. Did you discuss any potential risks of your work?
Not applicable. Left blank.

☑ A3. Do the abstract and introduction summarize the paper's main claims?
Left blank.

☒ A4. Have you used AI writing assistants when working on this paper?
Left blank.

B ☒ Did you use or create scientific artifacts?

Left blank.

☐ B1. Did you cite the creators of artifacts you used?
Not applicable. Left blank.

☐ B2. Did you discuss the license or terms for use and / or distribution of any artifacts?
Not applicable. Left blank.

☐ B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?
Not applicable. Left blank.

☐ B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?
Not applicable. Left blank.

☐ B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?
Not applicable. Left blank.

☑ B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.
Left blank.

C ☑ Did you run computational experiments?

Left blank.

☒ C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?
Left blank.

The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.

☒ C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
Left blank.

☒ C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
Left blank.

☑ C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
Left blank.

D ☒ Did you use human annotators (e.g., crowdworkers) or research with human participants?

Left blank.

☐ D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?
Not applicable. Left blank.

☐ D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants' demographic (e.g., country of residence)?
Not applicable. Left blank.

☐ D3. Did you discuss whether and how consent was obtained from people whose data you're using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
Not applicable. Left blank.

☐ D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
Not applicable. Left blank.

☐ D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
Not applicable. Left blank.