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 pretrained 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 language¹ in the world with approximately 200 million speakers. In the existing literature on Bangla Text SA, as shown in Table 6, 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 usergenerated 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 (Rokomari² and Wafilife³) using a web scraper developed with several Python libraries, including BeautifulSoup, Selenium, Pandas, Openpyxl,

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¹https://en.wikipedia.org/wiki/List_of_ languages_by_total_number_of_speakers

²https://www.rokomari.com/

³https://www.wafilife.com/

Source	Language	Annotaated	Unannotated	Total
-	Bangla	84,672	24,806	109,478
Rokomari	Bangla [†] + English	56,485	15,408	71,893
	Bangla + Bangla [†] + English	13,144	4,114	17,258
	Total	154,301	44,328	198,629
	Bangla	4,699	59	4,758
Wafilife	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.

	# of Reviews	1,58,065
eral rtie	# of Books	30,253
ene	# of Reviewers	44,616
.g.	# of Categories	1,573
_ 	Total Review Words	44,429,201
le le	max. Word length	765
ng.	min. Word length	1
ž Š	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 considerable scale of our dataset.

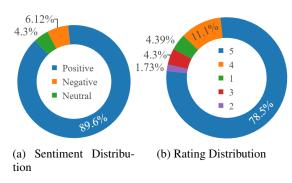


Figure 1: Class Distribution of BANGLABOOK.

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 of 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 in order to determine the accurate translation.

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.

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 correspond 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. We believe that the distribution of the dataset is representative of real-world scenarios. 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 thoughtprovoking 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.

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, re-

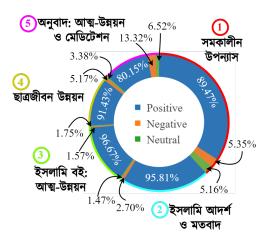


Figure 2: Sentiment Distribution of top 5 most popular genres. In clockwise order, সমকালীন উপন্যাস (Contemporary Novel), ইসলামি আদর্শ ও মতবাদ (Islamic Ideals and Doctrines), ইসলামি বই: আত্ম উন্নয়ন (Islamic Books: Self-Development), ছাত্রজীবন উন্নয়ন (Student Life Development), অনুবাদ: আত্ম-উন্নয়ন ও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

sults, 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), XG-Boost (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).

Class	25 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) , <mark>মোটামুটি (average)</mark> , ভুল (fault) , আশা (hope) , সহজ							
	(facile), <mark>অসাধারণ (extraordinary)</mark> , কম (low) , দুর্দান্ত (splendid)							
Negative	ভালো (good), বাজে (trash), খারাপ (bad), ভুল (fault), সুন্দর (nice), আশা (hope), নষ্ট (waste),							
	ফালতু (useless), হতা শা (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.

Labels	Neutral Positive	52 1,222	21 424	1,272 26,508			
ne		Negative	Neutral	Positive			
Ė	Predicted Labels						

Table 5: Confusion Matrix for Bangla-BERT

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 uneven 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 com-

binations, aiding the models' ability to generalize effectively across categories. The bag-of-words (BoW) feature is not very useful in classifying the corresponding category. Though word 1-gram does not outperform word 2-gram and word 3gram, it does predict the 'Neutral' class well. Both the pre-trained Bangla-BERT models performs 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 tigram achieves perfect score 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 Table 5, 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 124796, 20714, and 19096 unique W1 for the 'Positive', 'Negative', and 'Neutral' classes respectively. 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 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).

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.

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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		51 60 48)4	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)	N N	Positive legative Neutral		-	4,700	Open	Comments	Facebook pages: BBC Bangla, Prothom Alo	SVM, LR, KNN DT, LSTM NB, CNN
(Dey and Sarker, 2019)	F	Positive legative	2,6	500 500	5,200	Closed	Comments, reviews	Facebook, Twitter, YouTube, News Portals	DT, NB, SVM
(Khatun and Rabeya, 2022)	F	Positive legative		-	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		-	- - - -	7,500	Closed	-	-	NB, Tropical Method
(Akter et al., 2021)	Scared Positive Negative Neutral		-	- - -	7,905	Closed	Product reviews	Daraz	RF, LR, SVM, KNN, XGB
(Hassan et al., 2016)	N	Positive legative nbiguous			9,337	Closed	Comments, reviews	Facebook, Twitter, YouTube, News Portals	LSTM
(Rahib et al., 2022)	Insightful Curious Gratitude		3,5	800 549 232	10,581	Closed	Comments	Social Media	SVM, RF, CNN, LSTM
(Al Kaiser et al., 2021)	Positive Negative Neutral	Wishful Thinking Appreciation Gender-based hate Religious hate Political hate Personal hate Sarcasm	967 942 525 731 572 1,995 1,414 3,860	1,909 5,237 3,860	11,006	Closed	Comments	Facebook	LR, DT, RF, MNB, KNN, Linear SVM, RBF SVM, XGB
(Sazzed, 2020a)	Positive Negative		8,5 3,3	500 807	11,807	Open	Comments	YouTube	SVM, ET, RF, LR VADER, TextBlo
(Sazzed, 2020b)	Positive Negative				12,000	Closed	Comments	YouTube	-
SENTNOB (Islam et al., 2021)	Positive Negative Negative Neutral		6,4 5,7 3,6	709	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-bas
Positive BANGLABOOK (ours) Negative Neutral		141 9,6 6,8	574	158,065	Open [†]	Book reviews	Rokomari, Wafilife	RF, LSTM, LR, GI MNB, SVM, XG Bangla-BERT	

Table 6: 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.