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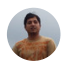
Nayan Banik
Comilla University

Shima Chakraborty
University of Chittagong


Hanif Seddiqui
University of Chittagong


Md. Hasan Hafizur Rahman
Comilla University

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Survey on Text-Based Sentiment Analysis of Bengali Language

Nayan Banik*, Md. Hasan Hafizur Rahman*, Shima Chakraborty†, Hanif Seddiqui†, Muhammad Anwarul Azim†
*Department of Computer Science & Engineering
Comilla University, Comilla - 3506, Bangladesh
Email: cse.nayan@gmail.com, hhr@cou.ac.bd
†Department of Computer Science & Engineering
University of Chittagong, Chittagong - 4331, Bangladesh
Email: shimactg@gmail.com, hanif@cu.ac.bd, azim@cu.ac.bd

***Abstract*—Digital contents in Bengali text are increasing with the advancements of World Wide Web (WWW) to express the sentiment of content originators from mixed perspectives. These high voluminous unstructured web contents can be utilized to build smarter tools to assist people through Natural Language Processing (NLP). Though Bengali NLP tools are still inadequate due to its inherent complexities, research on Sentiment Analysis in Bengali is flourishing as a challenging area and is getting researcher's attention at a rapid pace. To do research in this area, researchers spend a lot of their time to investigate previously published works to understand the advancements for further enhancement; one of the most stressful and challenging parts of research. In this regard, we are going to demonstrate domain specific available pre-processing steps along with existing research methodologies, respective datasets and evaluation metrics of notable works related to sentiment analysis of Bengali language as our research finding. Moreover, we also incorporate a series of directions for future researchers to augment their research in this exciting domain.**

Keywords: *Sentiment Analysis*, *Opinion Mining*, *Machine Learning*, *Information Extraction*

I. Introduction

Textual documents in Bengali are continuously increasing together with web contents of other languages on the World Wide Web (WWW) consisting of our regular activities like enhancing Banglapedia, producing social media posts, publishing documents of financial and economic markets, spreading political views, sharing reviews of online products along with published online news and so on. These available web information express originators sentiments and emotions toward various topics in daily life and they are important to make human decisions as well as for making automatic decisions through machines. Though, human being can extract sentiment in a limited extent by utilizing their intuitive learning, machines are incapable of doing so. In this regard, researchers performed their research in the last few decades all over the world to develop smarter methods by experimenting with classical machine learning and statistical tools to detect major properties of the text including subjectivity detection and emotion or polarity detection. The subjectivity detection determines the text is either subjective or objective, while the polarity detection asserts that the text is either positive, negative or neutral[1].

Furthermore, textual documents of a language are analyzed from document level, sentence level, phrase level or lexical level perspectives. The analysis in these perspectives are performed using supervised, unsupervised, semi-supervised or case based reasoning techniques[2]. In the supervised approach, researchers applied classical machine learning models, such as Naïve Bayes (NB), Maximum Entropy (ME), Artificial Neural Network (ANN), Support Vector Machines (SVM), whereas Latent Dirichlet Allocation (LDA) and theme based clustering are used as unsupervised techniques[3][4]. Moreover, graph based and deep learning approaches[5] are also applied as modern trend for Sentiment Analysis (SA) research now-a-days.

Additionally, domain-specific data plays an important role in SA research; however, the lack of annotated and standard benchmarking datasets make the research much harder in this area[6]. Research in these multi-domain areas is considered as a part of Natural Language Processing (NLP) tasks which attract research community to perform their research[7]. As a result, researchers have developed a series of language-specific NLP tools to extract text properties of many languages like *Arabic, Hindi, Chinese, Czech, French, German, Italian, Japanese, Russian, Thai* to enrich their linguistic area for knowledge extraction[8]. In spite of having some research works in SA on the Bengali language, this area is still underdeveloped and therefore, research in this area would provide extensive opportunities to develop linguistic NLP tools for analyzing Bengali texts in the next few decades. In this connection, it is important for researchers to understand the chronological improvement in this area because imminent research constantly relies on the advancement of outcomes of previous works.

The rest of the paper is organized as follows. **Section II** introduces general terminologies together with related processing activities. Overview of a system related to SA is articulated in **section III**, while **section IV** focuses on the review of SA research along with our judgment in Bengali language text.

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Concluded remarks in addition to some directions for future research are described in **Section V**

II. General Terminologies and Related Processing Activities

In this section, we introduce some definitions of general terminologies along with various processing activities of SA research those are found in our investigation. This will help researchers to understand the essence of our review on textual documents of Bengali language.

A. Sentiment Analysis and Emoticons

Sentiment Analysis (SA), also known as Opinion Mining (OM) refers to extract the subjective impressions or attitudes of content originators from published texts in terms of topics or contextual polarity through the use of NLP, statistics or classical machine learning techniques. On the other hand, emoticons are graphical facial expressions that represent the meaning of verbal communications without observing the change of body language. These pictorial presentations express a range of tone or feeling which plays an important role in social media as well as messaging in cyber-world[9][10]. The Fig.1 represents a snippet of Bengali text document that includes emoticon, hash tags, punctuation, and URLs.

'আয়নাবাজি' দেখে এলাম; যেমন ভেবেছিলাম, তার চেয়েও হাজার গুন ভালো লেগেছে :) ছবির এই দৃশ্য অসাধারণ ছিল http://images.myreviewsite.com/aynabaji.jpg। সময় করে দেখে নিন। #আয়নাবাজি #Aynabaji

Fig. 1. A snippet of document written in Bengali language

B. Stop Words, Punctuation, Hash Tags and URL Removal

Single letter words or less influential extremely high frequent words known as stop-words should be filtered out before processing the text. Since stop words and punctuation characters have no association with sentiment polarity, they are also removed by using their Unicode representations. Uniform Resource Locators (URL) are used to identify resources in the WWW but have no significance in SA. Moreover, hashtags in social networks are also marked with a number sign (#) in front of a word or unspaced phrase in a document[11][12]. The Fig. 2 shows the output of Fig. 1 after removing stop-words, punctuations, hash tags and URLs to understand the significance of this process in SA.

আয়নাবাজি দেখে এলাম ভেবেছিলাম হাজার গুন ভালো লেগেছে ছবির দৃশ্য অসাধারণ সময় দেখে নিন

Fig. 2. Stop-Words, Punctuation, Hash Tags and URL remove from Fig. 1

C. Tokenization and Normalization

Tokenization or text segmentation is a process of dividing the written text into meaningful units or tokens, such as words, sentences, or topics delimited by whitespace, tab, new line and so on. In bag-of-words approach, each input sentence is tokenized into words which act as the primary features of SA. Normalization is the process of converting each token into unified scale for further processing. The Fig. 3 demonstrates the process of tokenization of texts after removing stop-words, punctuations, hashtags, URLs of Fig. 1 to close look the process of recognized individual words in a system.

'আয়নাবাজি', 'দেখে', 'এলাম', 'ভেবেছিলাম', 'হাজার', 'গুন', 'ভালো', 'লেগেছে', 'ছবির', 'দৃশ্য', 'অসাধারণ', 'সময়', 'দেখে', 'নিন'

Fig. 3. Tokenization of words from Fig. 2.

D. Vectorization

Vectorization is a process to reconstruct a collection of texts in a document into numerical feature vectors. A document is considered as a collection of words with or without considering the information of their relative position. High frequent words having very little meaning must be excluded to prioritize rarer yet more interesting terms in the corpus. In order to re-weight these count features into floating point values, Term-Frequency and Inverse Document-Frequency ($TF-IDF$) transformation or word embeddings are used. Fig. 4 illustrates the vectors of words of Fig. 1 after removing less important words and performing tokenization operation.

(আয়নাবাজি, 9), (দেখে, 34), (এলাম, 69), (ভেবেছিলাম , 54), (হাজার, 21), (গুন, 60), (ভালো, 45), (লেগেছে, 11), (ছবির, 76), (দৃশ্য, 51), (অসাধারণ, 75), (সময়, 23), (দেখে, 34), (নিন, 97)

Fig. 4. Vectorization of text from Fig. 3

E. Stemming and Lemmatization

Stemming is used to reduce inflectional forms of a language by splitting a word into its constituent root part and affix without doing the complete morphological analysis. As Bengali is a highly inflected language with pragmatically free word order i.e., Bengali (verb, noun, adjective) words are inflected forms of roots stemming is performed on the tokenized words[13] to reduce the dictionary size. In Fig. 5, we portrayed stemmed words of sentences that are given in Fig. 1 to comprehend the essence of a stemmer in SA. On

'আয়না', 'দেখ', 'এল', 'ভাব', 'হাজার', 'গুন', 'ভালো', 'লাগ', 'ছবি', 'দৃশ্য', 'অসাধারণ', 'সময়', 'দেখ', 'নে'

Fig. 5. Stemmed words from sentences of Fig. 1

the other hand, *lemmatization* is the process of grouping different inflected words so that these words analyzed as a single item. Though the stemmer operates on a single word without contextual knowledge, lemmatization process understands the context of a word in a sentence. To familiar with the lemmatized words as output Fig. 6 is given to demonstrates the importance of lemmatization process.

'আয়নাবাজি', 'দেখে', 'এলাম', 'ভেবেছিলাম', 'হাজার', 'গুন', 'ভালো', 'লেগেছে', 'ছবির', 'দৃশ্য', 'অসাধারণ', 'সময়', 'দেখে', 'নিন'

$\Downarrow$

'আয়না', 'দেখ', 'এল', 'ভাব', 'হাজার', 'গুন', 'ভালো', 'লাগ', 'ছবি', 'দৃশ্য', ,অসাধারণ', 'সময়', 'দেখ', 'নে'

Fig. 6. Lemmatization after tokenization of contents of Fig. 1

F. Parts-of-Speech (POS) Tagger

Automated POS tagger is used as a NLP tool to detect each word with a corresponding POS in a sentence. It helps to verify and validate textual data, annotate named entities in the large corpus, translate one language to another language, correct the grammatical errors, and so on. As a result, Bengali POS tagger is an essential tool to enrich Bengali language, especially in the area of NLP. To comprehend the influential effect of a POS tagger, the Fig. 7 recognize respective POS of texts those are given in the Fig. 1.

'আয়না_NN', 'দেখ_VRB', 'এল_VRB', 'ভাব_VRB', 'হাজার_NN', 'গুন_NN', 'ভালো_ADJ', 'লাগ_VRB', 'ছবি_NN', 'দৃশ্য_NN', 'অসাধারণ_ADJ', 'সময়_NN', 'দেখ_VRB', 'নে_VRB'

Fig. 7. Parts-of-Speech Tag of words of contents in Fig. 1

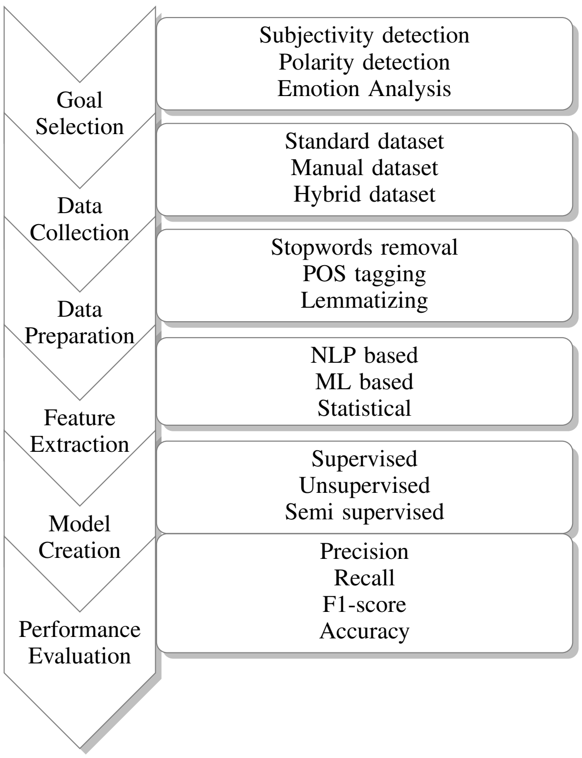

Fig. 8. Steps in a Sentiment Analysis System

G. WordNet and SentiWordNet

$WordNet$ is a lexical database of English language having nouns, adjectives, verbs and adverbs grouped into sets of cognitive synonyms called $synsets$. This database is used for word-sense disambiguation, information retrieval, automatic text classification, text summarization, machine translation and so on. On the other hand, $SentiWordNet$ is a lexical resource for SA which assigns three numerical sentiment scores (positivity, negativity or objectivity) to each synset of WordNet for the quantitative analysis of associated synsets and the use of vectorial term representations for semi-supervised synset classification[14].

III. Overview of a Sentiment Analysis System

Sentiment Analysis (SA) is a complex system that follows step-by-step logical phases to execute specific operations to achieve particular goals of the research. These phases of SA system are demonstrated in Fig. 8 to figure out the significance of SA research.

a) Goal Selection: Considering the application areas and associated text properties, the system goal is defined in the first phase which determines whether the given text is subjective or not. If the text is identified as subjective then the polarity is extracted and emotional level is investigated by quantifying sentiment scores.

b) Data Collection: Domain-specific datasets play an important role to achieve the desired goal where they can be either standardized or manually developed for benchmarking. Though standard benchmark datasets are available for some rich languages, most of the low resource languages use manual dataset either created by the expert system or crawling diverse online sources by custom crawlers.

c) Data Preparation: Raw data consisting extraneous noise like emoticons, stop words, punctuations, hashtags, $URLs$ must be removed. In this phase, stemming or lemmatization is used for highly inflected languages to convert words to its base form while POS tagger is used to detect each word with a corresponding POS in a sentence.

d) Feature Extraction: Influential features having a positive impact on the performance of the system can be examined from various perspectives such as NLP, Machine Learning (ML) or Statistical. For NLP based feature extraction, the system implements linguistic knowledge where ML approaches use training on corpus data and the statistical techniques consider the weighted importance of features in the system.

e) Model Creation: Selected features from the feature extraction phase are fed to a model that can be either lexicon based, supervised, unsupervised or semi-supervised. As a supervised model, NB, ME, SVM, ANN can be considered where clustering approaches and bootstrapping are considered as unsupervised and semi-supervised models respectively.

f) Performance Evaluation: The performance of SA system is evaluated by several metrics including expert analysis, precision, recall, F-score, accuracy to justify the acceptance of the system under considerations. Therefore, remarks on limitations and future directions are given by discussing the performance of a system.

IV. Sentiment Analysis in Bengali Language

Numerous amount of textual electronic documents in the Bengali language from diverse domains such as online news portals, social media text, online product reviews and so on are published on the WWW and it is continuously increasing where subjective information plays a great role from both the user and organizational perspectives. Due to this twofold importance and the exponential growth of Bengali text on the web, researchers are attracted to perform their research in this area. Although Bengali is an highly inflected language suffering from major challenges such as lack of labeled dataset or absence of rich NLP tools[15], researchers performed their individual research in the document level, sentence level, phrase level or lexicon level.

Document level SA represented in [16] use Mutual Information (MI) as a feature extractor for NB classifier. The researchers used Amazon Watch Reviews and their word by word translation in Bengali as datasets. After performing standard preprocessing, the experiment results show that the system works well for Bengali considering negation. But the drawback is word by word translation of the English dataset. Another similar works in [17] utilizes translated Bengali dataset from Amazon watches for polarity detection. But these texts are cross-checked using dictionary word mapping to avoid meaningless sentences. The system recognize positive and negative polarity where each polarity is subdivided into weak, steady and strong. Though the work presents 85% accuracy for Bengali, it requires double translation for negation handling. In [18], the authors use NB classifier to extract sentiment from Facebook user comments (3000 statuses from 70 users) where negations are handled by antonym substitution. Standard preprocessing steps are performed before stemming operation extract bigram as features. The system demonstrates 77% precision but the small size to dataset is a limiting factor in this work. Relating to that, researchers in [19] claims NB model is incapable to detect complex multi-line sentences of a document for SA. The system results 83.20% accuracy for NB with bigram, stemmer, and normalizer. It also shows that WE performs better when the the dataset size is increased. Moreover in [20], the authors claim that NB classifier is ineffective for social media texts as these texts are not well written by maintaining a standard format. Using Facebook user comments on food reviews as dataset, the work represents lexicon-based approach for SA. Though they claim that dictionary-based approach exhibits better accuracy; however, they do not perform any sort of experiments to evaluate performance metrics regarding their statement.

Sentence level polarity detection on twitter posts is presented in [21] where the authors us SVM and ME text classifiers. This work demonstrates semi-supervised bootstrapping method where a small labeled dataset is used to label other unlabeled texts and generate sentiment lexicon. Investigators consider several features in this scholary work and show that SVM (accuracy 93%) outperformed ME (accuracy 85%). Relating to that, polarity detector for Bengali online news texts is presented in [22] where the authors utilize several features in SVM classifier. Separating subjective texts from the acquired dataset, authors use sentiment lexicons from SentiWordNet(Bengali)[23] in order to score the sentences. The system considers many features like POS tags, chunk level information, functional words, stemming cluster, negative words, and dependency tree features. The experimental result by considering all of these features demonstrate precision of 70.04% where the baselines are 63.02%. Moreover in [24], the authors investigate linear and non-linear SVM using N-gram based modeling on diverse social media documents. The system preprocess manually collected data and shows that N-gram vectorization approach results in highest accuracy 91.581% and 89.271% for linear and non-linear SVM respectively. Another traditional SVM based SA system having accuracy of 64% on Bengali cricket review is done in [25].

Furthermore, word level experiment is performed in [37] by demonstrating data standardization techniques where the automatic translation process is accomplished to organize positive and negative words of SentiWordNet. But this elementary research without dataset is less efficient for complex systems and it does not consider Bengali inflected word terms, spelling errors, colloquial terms for sophisticated analysis. Therefore, different researchers perform experiment in [38] to exhibit shared SA task of Bengali tweets along with Hindi and Tamil. Since the datset is very small, this work in not compatible with modern deep learning techniques. On the other hand, one more research in [26] presents a theme cluster-based approach in a corpus developed from news and blog domains to recognize the subjectivity of texts. As a subjectivity classifier researchers deal with various features in their experiment and they examine the results by using Samsad English-Bangla Dictionary, Multi-Perspective Question Answering ($MPQA$) corpus and International Movie Database ($IMDB$). In addition, document-level SA in [27] propose Contextual Valence Analysis (CVA) for polarity detection in Bengali language texts using WordNet and SentiWordNet. To evaluate the proposed system, authors use expert analysis to justify the approach to a satisfactory level. The deficiency of this work is the earlier translation process from Bengali to English to perform their analysis. One more research on horoscope data is observed in [29] where the data are annotated by two native speakers and when disagreement appears between them, a third annotator finally annotate these sentences. After the dataset preparation, five classifiers are trained (NB, SVM, $K - Nearest\ Neighbours$ (KNN), Decision Tree (DT) and Random Forest (RF)) with their different parameters. Among these five classifiers, SVM with unigram features produce an accuracy rate of 98.7% as the best sentiment classification model. Relating to that in [33], the authors demonstrate SVM outperforms NB when applied to a manually developed Bengali movie review dataset. The system also provides a comparative analysis on different features having precision of 0.86 while considering stemmed unigram in SVM classifier. In the same fashion, sentence level research introduces deep learning methods for both plain Bengali and Romanized Bengali texts to extract the sentiment in the context of either positive or negative polarity [28]. In this research, they use binary cross entropy and categorical cross-entropy as loss functions with Recurrent Neural Network (RNN) specially Long Short Term Memory ($LSTM$) model. The major challenge of this research is lack of standard and large dataset since deep learning models require a huge dataset compared to other machine learning models. The successive research in [31] shows the Word Embedding (WE) with Hellinger PCA can be useful for detecting sentiment from Bengali text. In this stage, WE extracts the syntactic context of the

TABLE I
SUMMARY OF INVESTIGATION OF SENTIMENT ANALYSIS ON BENGALI LANGUAGE

Paper	Analysis	Context	Dataset	Preprocessing	Methods	Result
[26]	Subjectivity Detection	Reviews, news, blog sites	Manual, Standard	POS tagging, clustering	CRF	Precision - 72.16% and 74.6%
[27]	Document Level		Manual	Word translation, sense values from SentiWordNet	CVA	
[16]	Document Level	Product reviews	Manual	Review rating selection, stop-words removal, negation handling	NB	Accuracy - 85%
[28]	Sentence Level	Social media, news, product reviews	Manual	Emoticons, proper noun removal	RNN (LSTM)	Accuracy - 70%
[29]	Sentence Level	Horoscope	Manual	Punctuations, stopwords removal, IG index	NB, SVM, KNN, DT, RF	Accuracy - 98.7% (SVM)
[17]	Sentence Level	Product reviews	Standard	Translation, negation handling	NB	Accuracy - 85%
[18]	Sentence Level	Social media	Manual	Hashtag, url removal, stemming	NB	Precision - 77%, Recall - 68%, F-score - 72%
[21]	Sentence Level	Social media	Manual	Tokenization, normalization, POS tagging	SVM,ME	Accuracy - 93%
[30]	Sentence Level	Social media	Manual	Removal of punctuation marks, extra spaces, unrecognized characters	word2vec, WE	Accuracy - 75.5%
[31]	Sentence Level	Microblogging sites	Manual	Removal of punctuation marks, extra spaces, unrecognized characters	WE	Accuracy - 70.0%
[22]	Phrase Level	News	Manual	POS tagging, clustering	SVM	Precision - 70.04%, Recall - 63.02%
[32]	Sentence Level	Social media	Standard	Special characters removal, irrelevant features removal, word level sentiment polarity tagging	CNN	Accuracy - 46.80%
[24]	Sentence Level	Social media	Manual	POS tagging, emoticons and punctuation removal, stemming, negativity separation	SVM	Accuracy - 91.684% and 89.271%
[33]	Sentence Level	Social media	Manual	URL, emoticon, punctuation, stop words removal	NB, SVM	Precision - 0.86%
[25]	Sentence Level	Reviews, Social Media	Manual, Standard	Tokenization, stop words removal, punctuation and number removal	SVM	Accuracy - 64%
[34]	Sentence Level	Social Media	Manual, Standard	Emojis, symbols, numbers, stickers, English letters removal	RNN	Accuracy - 85.67%
[35]	Sentence Level	Reviews, Social Media	Manual	Non Bengali character and symbol removal	Word2Vec	Accuracy - 83.79%
[36]	Sentence Level	Social Media	Manual	Tokenization, URL, punctuation, user tags, mentions and stop words removal	LSTM, CNN, NB, SVM	Accuracy - 65.97% and 54.24%

words rather than the sentiment words. The authors implement Sentiment Specific Word Embeddings ($SSWE$) to recognize their respective sentiment in this research. The results depict that the performance can be increased with large corpus. In addition, the research in [30] depicts words2vec model for Bengali SA in the sentence level; where researchers claim that WE of sentences determine the characteristics of words and their respective context. In this research, investigators remove all noise from the data source through some general preprocessing steps. Then positive and negative scores are calculated using both syntactic score and mutual score among these data. Although the performance is low, the authors use WE to capture the sentiment properties of words in a sentence. Researchers also neutralize the effects of valence shifting words by using threshold value for highly positive and highly negative in their corpus. With the recent improvements in deep learning techniques, authors in [32] develop a SA system based on deep Convolutional Neural Network (CNN) for twitter dataset[38]. The proposed method includes preprocessing for removing special characters, irrelevant features and lexical level sentiment polarity from Sentiwordnet[23]. In order to compare the performance, the authors have implemented a traditional Deep Belief Network (DBN). More related deep learning based systems in [34] and [35] shows that the scarcity of benchmark dataset in Bengali poses a challenge for deep learning techniques in SA task. Table I provides a summary of discussed notable research works in Bengali SA task.

V. Conclusion

This review article demonstrates existing procedures, achievements, and limitations of available works of Sentiment Analysis (SA) on Bengali texts. In our findings, we represent preprocessing steps regarding the domains, context of research, comparisons of different experimental methods as well as performance evaluation of a system which will help the new researchers to do their research in this field. In our judgment, a small number of evaluation metrics are satisfactory regarding problem domains on Bengali texts; however, there are a large number of domains available that are not explored till now and hence it can be an exciting field to contribute. Moreover, Bangla Natural Language Processing ($BNLP$) tools, standardized datasets for benchmarking are not up to date for Bengali language to develop SA system effectively which must be kept in mind during the future experiments.

References

[1] B. Liu, "Sentiment analysis and opinion mining," *Synthesis lectures on human language technologies*, vol. 5, no. 1, pp. 1–167, 2012.

[2] K. M. Rahman and A. Khamparia, "Techniques, applications and challenges of opinion mining."

[3] S. Sun, C. Luo, and J. Chen, "A review of natural language processing techniques for opinion mining systems," *Information Fusion*, vol. 36, pp. 10–25, 2017.

[4] K. D. Varathan, A. Giachanou, and F. Crestani, "Comparative opinion mining: a review," *Journal of the Association for Information Science and Technology*, vol. 68, no. 4, pp. 811–829, 2017.

[5] R. Feldman, "Techniques and applications for sentiment analysis," *Communications of the ACM*, vol. 56, no. 4, pp. 82–89, 2013.

[6] T. Al-Moslmi, N. Omar, S. Abdullah, and M. Albared, "Approaches to cross-domain sentiment analysis: A systematic literature review," *IEEE Access*, 2017.

[7] R. Piryani, D. Madhavi, and V. Singh, "Analytical mapping of opinion mining and sentiment analysis research during 2000–2015," *Information Processing & Management*, vol. 53, no. 1, pp. 122–150, 2017.

[8] D. Vilares, M. A. Alonso, and C. Gómez-Rodr íguez, "Supervised sentiment analysis in multilingual environments," *Information Processing & Management*, vol. 53, no. 3, pp. 595–607, 2017.

[9] B. Pang, L. Lee *et al.*, "Opinion mining and sentiment analysis," *Foundations and Trends® in Information Retrieval*, vol. 2, no. 1–2, pp. 1–135, 2008.

[10] S.-M. Τζιωρτζής, "Sentiment analysis by emoticons and unsupervised comment summarization in greek e-government data," 2013.

[11] I. Hemalatha, G. S. Varma, and A. Govardhan, "Sentiment analysis tool using machine learning algorithms," *International Journal of Emerging Trends & Technology in Computer Science (IJETTCS)*, vol. 2, no. 2, pp. 105–109, 2013.

[12] S. Rosenthal, A. Ritter, P. Nakov, and V. Stoyanov, "Semeval-2014 task 9: Sentiment analysis in twitter." in *SemEval@ COLING*, 2014, pp. 73–80.

[13] M. H. Seddiqui, M. N. Hoque, and M. H. H. Rahman, "Semantic annotation of bangla news stream to record history," in *Computer and Information Technology (ICCIT), 2015 18th International Conference on*. IEEE, 2015, pp. 566–572.

[14] S. Baccianella, A. Esuli, and F. Sebastiani, "Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining." in *LREC*, vol. 10, 2010, pp. 2200–2204.

[15] M. Karim, *Technical challenges and design issues in bangla language processing*. IGI Global, 2013.

[16] A. K. Paul and P. C. Shill, "Sentiment mining from bangla data using mutual information," in *Electrical, Computer & Telecommunication Engineering (ICECTE), International Conference on*. IEEE, 2016, pp. 1–4.

[17] K. A. Hasan, M. S. Sabuj, and Z. Afrin, "Opinion mining using naïve bayes," in *Electrical and Computer Engineering (WIECON-ECE), 2015 IEEE International WIE Conference on*. IEEE, 2015, pp. 511–514.

[18] M. S. Islam, M. A. Islam, M. A. Hossain, and J. J. Dey, "Supervised approach of sentimentality extraction from bengali facebook status," in *Computer and Information Technology (ICCIT), 2016 19th International Conference on*. IEEE, 2016, pp. 383–387.

[19] M. Al-Amin, M. S. Islam, and S. D. Uzzal, "A comprehensive study on sentiment of bengali text," in *Electrical, Computer and Communication Engineering (ECCE), International Conference on*. IEEE, 2017, pp. 267–272.

[20] S. Akter and M. T. Aziz, "Sentiment analysis on facebook group using lexicon based approach," in *Electrical Engineering and Information Communication Technology (ICEEICT), 2016 3rd International Conference on*. IEEE, 2016, pp. 1–4.

[21] S. Chowdhury and W. Chowdhury, "Performing sentiment analysis in bangla microblog posts," in *Informatics, Electronics & Vision (ICIEV), 2014 International Conference on*. IEEE, 2014, pp. 1–6.

[22] A. Das and S. Bandyopadhyay, "Opinion-polarity identification in bengali," in *International Conference on Computer Processing of Oriental Languages*, 2010, pp. 169–182.

[23] ——, "Sentiwordnet for bangla," *Knowledge Sharing Event-4: Task*, vol. 2, 2010.

[24] S. A. Taher, K. A. Akhter, and K. A. Hasan, "N-gram based sentiment mining for bangla text using support vector machine," in *2018 International Conference on Bangla Speech and Language Processing (ICBSLP)*. IEEE, 2018, pp. 1–5.

[25] S. A. Mahtab, N. Islam, and M. M. Rahaman, "Sentiment analysis on bangladesh cricket with support vector machine," in *2018 International Conference on Bangla Speech and Language Processing (ICBSLP)*. IEEE, 2018, pp. 1–4.

[26] A. Das and S. Bandyopadhyay, "Subjectivity detection in english and bengali: A crf-based approach," 2009.

[27] K. A. Hasan, M. Rahman *et al.*, "Sentiment detection from bangla text using contextual valency analysis," in *Computer and Information Technology (ICCIT), 2014 17th International Conference on*. IEEE, 2014, pp. 292–295.

[28] A. Hassan, M. R. Amin, A. K. Al Azad, and N. Mohammed, "Sentiment analysis on bangla and romanized bangla text using deep recurrent models," in *Computational Intelligence (IWCI), International Workshop on*. IEEE, 2016, pp. 51–56.

[29] T. Ghosal, S. K. Das, and S. Bhattacharjee, "Sentiment analysis on (bengali horoscope) corpus," in *India Conference (INDICON), 2015 Annual IEEE*. IEEE, 2015, pp. 1–6.

[30] M. Al-Amin, M. S. Islam, and S. D. Uzzal, "Sentiment analysis of bengali comments with word2vec and sentiment information of words," in *Electrical, Computer and Communication Engineering (ECCE), International Conference on*. IEEE, 2017, pp. 186–190.

[31] M. S. Islam, M. Al-Amin, and S. D. Uzzal, "Word embedding with hellinger pca to detect the sentiment of bengali text," in *Computer and Information Technology (ICCIT), 2016 19th International Conference on*. IEEE, 2016, pp. 363–366.

[32] K. Sarkar, "Sentiment polarity detection in bengali tweets using deep convolutional neural networks," *Journal of Intelligent Systems*.

[33] N. Banik and M. H. H. Rahman, "Evaluation of naïve bayes and support vector machines on bangla textual movie reviews," in *2018 International Conference on Bangla Speech and Language Processing (ICBSLP)*. IEEE, 2018, pp. 1–6.

[34] A. A. Sharfuddin, M. N. Tihami, and M. S. Islam, "A deep recurrent neural network with bilstm model for sentiment classification," in *2018 International Conference on Bangla Speech and Language Processing (ICBSLP)*. IEEE, 2018, pp. 1–4.

[35] S. H. Sumit, M. Z. Hossan, T. Al Muntasir, and T. Sourov, "Exploring word embedding for bangla sentiment analysis," in *2018 International Conference on Bangla Speech and Language Processing (ICBSLP)*. IEEE, 2018, pp. 1–5.

[36] N. I. Trinto and M. E. Ali, "Detecting multilabel sentiment and emotions from bangla youtube comments," in *2018 International Conference on Bangla Speech and Language Processing (ICBSLP)*. IEEE, 2018, pp. 1–6.

[37] D. Das and S. Bandyopadhyay, "Developing bengali wordnet affect for analyzing emotion," in *International Conference on the Computer Processing of Oriental Languages*, 2010, pp. 35–40.

[38] B. G. Patra, D. Das, A. Das, and R. Prasath, "Shared task on sentiment analysis in indian languages (sail) tweets-an overview," in *International Conference on Mining Intelligence and Knowledge Exploration*. Springer, 2015, pp. 650–655.