Sentiment Classification in Bangla Textual Content: A Comparative Study

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Abstract—Sentiment analysis has been widely used to understand our views on social and political agendas or user experiences over a product. It is one of the cores and well-researched areas in NLP. However, for low-resource languages, like Bangla, one of the prominent challenges is the lack of resources. Another important limitation, in the current literature for Bangla, is the absence of comparable results due to the lack of a well-defined train/test split. In this study, we explore several publicly available sentiment labeled datasets and designed classifiers using both classical and deep learning algorithms. In our study, the classical algorithms include SVM and Random Forest, and deep learning algorithms include CNN, FastText, and transformer-based models. We compare these models in terms of model performance and time-resource complexity. Our finding suggests transformer-based models, which have not been explored earlier for Bangla, outperform all other models. Furthermore, we created a weighted list of lexicon content based on the valence score per class. We then analyzed the content for high significance entries per class, in the datasets. For reproducibility, we make publicly available data splits and the ranked lexicon list. The presented results can be used for future studies as a benchmark.

Index Terms—Sentiment Analysis, SVM, Random Forest, FastText, CNN, Transformers models

I. Introduction

The wide use of social media sites and other digital technologies are now integrated with our daily life. Every day we share information, voice our opinions and concerns through these platforms. Access to such enormous and opinionated digital content gives the research community an opportunity to analyze and summarize the content in order to help in a decision making process, understand the sentiment of a product, or views on cultural, social, international, and political agendas [1]. It is one of the well studied and active research areas in NLP. The research mostly focused on classifying sentiment in either one of two labels (i.e., positive or negative) or five labels (i.e., very positive to very negative) from textual information such as movie-reviews [2], newspaper articles and comments [3], and emotion from spoken conversations [4].

The majority of the existing research is limited to English and other resource-rich languages, due to the availability of large public resources and benchmarks. Earlier, one of the commonly used approaches is to use sentiment lexicon (e.g., SentiWordNet, Sentiment Treebank, and Psycholinguistic features) [5], [6] as features for designing the sentiment classifier. Considering it as a text classification problem, it has been widely addressed using machine learning – from classical to deep learning algorithms. Unlike these resource-rich languages, studies and resources for Bangla are still very limited. This limitation is the results of (i) having a very few publicly available datasets and (ii) inconsistent benchmarks due to incompatible train/dev/test splits (except in 1-2 datasets). From the modeling perspective, the current literature explored both classical (e.g., SVM, Random Forest, Naive Bayes) and deep learning algorithms (e.g., Convolution Neural Network (CNN), Long Short-Term Memory (LSTM)). The literature lacks the use of the recent successful algorithms such as Transformer models [7].

To address such limitations in this study we conduct comparative experiments by utilizing publicly available Bangla sentiment datasets, and our in house developed dataset. We experimented with both classical and deep learning algorithms in order to understand the performance difference – in terms of training complexity, model performance, and implication in real deployment (e.g., deep learning algorithms requires GPU to train and for inference). The motivation is to understand the trade-off between computational demand and performance. While doing so, our contributions of this study are as follows:

- We curated publicly available datasets, carefully cleaned and split into the train, dev, and test set. We make them available for reproducibility.1
- We analyze the datasets to better understand the lexicons that significantly reflect the positive and negative sentiment.
- We experiment with both classical, and deep learning algorithms, that are widely used – Random Forest, SVM, CNNs, Transformer models among others; and report our findings for future reference.

II. Related Work

The rise of social media has increased the interest among the researchers to analyze the sentiment using social media data. The rapid advancement of sentiment analysis started

1https://github.com/banglanlp/bangla-sentiment-classification
back in the early 2000s. Earlier studies include document [8], [9], sentence and aspect level [10] classification tasks.

The initial study of sentiment analysis for Bangla language started back in the 2010s [11]. In [11], authors developed a corpus-based WordNet for sentiment analysis named “SentiWordNet”, in which authors claimed that uses of SentiWordNet are reliable. In another study [12], authors reported an SVM-based polarity classification task on news data, in which authors achieved a precision 70.04% and a recall 63.02%. However, the authors also used Part-of-Speech (PoS) tagging, SentiWordNet, stemming, and negative word list. The study in [13] proposed a semi-supervised technique for Bangla sentiment analysis using Twitter posts and achieve an accuracy of 93% using unigrams with emoticons. The authors also used preprocessing steps such as tokenization, normalization, and PoS tagging before classifying the data. For classifying, the authors used NLTK toolkit for designing the SVM and the MaxEnt model. However, the dataset is not publicly available and the results are not reproducible.

In the study of [14], authors report SVM models in combination with N-gram for sentiment analysis on Bangla news comments, in which authors achieved a maximum accuracy of 91.7 with the use of non-linear SVM. The study also translates all the emoticons into text and removed unnecessary punctuation marks. In another study [15], authors used a single layer LSTM model for sentiment analysis with the use of word embeddings and achieve an accuracy of 83.9%, in which word embeddings were developed using Skip-gram and CBOW approaches. In [16], authors used LSTM and CNN models on comments data and achieve an accuracy of 65.97% and 54.24% in three and five class labels, respectively. Additionally, the authors used both Skip-gram and CBOW word embeddings.

The study of [17] reports an overview of a shared task on sentiment analysis in Indian languages (SAIL), in which all the participants developed a dataset for sentiment analysis using tweets. In the SAIL 2015, authors in [18] used the Naive Bayes model to classify the SAIL dataset and achieved an accuracy of 33.6%. In another study [19], the authors used an SVM-based approach and using the SAIL dataset it reports an accuracy of 42.20%. One of the recent studies using the SAIL dataset has been done by Kumar et al. [20], where the authors proposed dynamic model-based features with a random mapping approach for sentiment analysis, in which authors achieved an accuracy of 95.36%.

Most recent works on sentiment analysis are using deep learning techniques. Among them, notable research work includes Long Short-Term Memory (LSTM) [21]–[23], CNN [22], and variational auto-encoder [24]. In [21], authors used SVM, Naive Bayes, and LSTM methods in order to classify the movie reviews.

Our work differs from previous works in a way that we provide a comparative analysis with multiple datasets and diverse classical and deep learning algorithms including transformer models - such as BERT.

In this section, we first discuss the available datasets we used in the study. Following, we analyzed the data to understand how distinctive these lexical content are with respect to the positive and negative sentiment classes.

A. Data Description

The datasets that we used in our study are:

- **Sentiment Analysis in Indian Languages (SAIL) Dataset [17]**: This dataset, consists of tweet posts, has developed in the Shared task on Sentiment Analysis in Indian Languages (SAIL) 2015. The training, development, and test set of this dataset has 1000, 500, and 500 tweets, respectively. In our study, we only use the training set and split it into train, development, and test set.

- **ABSA Dataset [25]**: This dataset has developed to perform aspect-based sentiment analysis task in Bangla. The dataset contains two categories of data which are cricket and restaurant. In the cricket category, authors collected data from Facebook, BBC Bangla, and Prothom Alo and manually annotated them, and in the restaurant category, authors directly translated the English benchmark’s Restaurant dataset [26].

- **BengFastText Dataset [27]**: This data was collected from several newspapers, TV news, books, blogs, and social media. The original dataset reports 320,000 data for sentiment analysis, however, a fraction of it is publicly available. The public version includes 8,420 posts including a test set. We combined the training and test set first, then we split the data into train, development, and test sets.

- **YouTube Comments Dataset [16]**: This dataset was developed by extracting comments from various YouTube videos. The dataset were labeled using three class, five class, and emotion labels. In our study, we only took the data of three class label and converted five class into three class label. As a result, we got total 2,796 comments which we split into train, development, and test sets.

- **Social Media Posts (CogniSenti Dataset)**: This is our in-house developed dataset consists of posts from Twitter and Facebook. We manually annotated the collected posts by native Bangla speakers in three class labels. We have annotated total 6,570 posts in which 942 posts are Facebook statuses and 5,628 are tweets. We split this data into train, development, and test set, which contains 4599, 985, and 986 posts, respectively.

In Table I, we report the distribution of the datasets we curated and used in our experiments. For this study, we removed romanized Bangla annotated posts² to have a clear view about Bangla content. Hence, the prepared datasets are purely on Bangla.

B. Data Analysis

One of the major focus of this study was to understand the characteristics of the datasets. For this, we first discussed basic
The computed distribution of tokens is reported in Figure 1. Across different datasets, the number of tokens is less than 90. The average number of token in the combined dataset is 16 and the median is 13. Only in a very few cases, it is above this range (e.g., Youtube comments, BanglaFastText, and CogniSenti dataset). This analysis helps us in understanding what is the typical maximum number of tokens in social media data that could be used as sequence length – an important hyperparameter for deep learning algorithms.

**Table 1: Data splits and distributions of different datasets**

| Class label | Train | Dev | Test | Total |
|-------------|-------|-----|------|-------|
| **ABSA: Cricket Dataset** |       |     |      |       |
| Positive    | 376   | 71  | 73   | 520   |
| Neutral     | 194   | 27  | 34   | 255   |
| Negative    | 1515  | 274 | 273  | 2062  |
| Total       | 2085  | 372 | 380  | 2837  |
| **ABSA: Restaurant Dataset** |       |     |      |       |
| Positive    | 872   | 143 | 116  | 1131  |
| Neutral     | 167   | 35  | 46   | 248   |
| Negative    | 326   | 46  | 57   | 429   |
| Total       | 1465  | 224 | 219  | 1808  |
| **BengFastText Dataset** |       |     |      |       |
| Positive    | 2403  | 595 | 788  | 3786  |
| Negative    | 3107  | 783 | 744  | 4634  |
| Total       | 5510  | 1378| 1532 | 8420  |
| **SAIL** |       |     |      |       |
| Positive    | 331   | 69  | 71   | 471   |
| Neutral     | 194   | 39  | 44   | 277   |
| Negative    | 174   | 41  | 35   | 250   |
| Total       | 699   | 149 | 150  | 998   |
| **Youtube Comments Dataset** |       |     |      |       |
| Positive    | 553   | 103 | 96   | 752   |
| Neutral     | 539   | 106 | 116  | 761   |
| Negative    | 865   | 210 | 208  | 1283  |
| Total       | 1577  | 419 | 316  | 2302  |
| **Social Media Posts (CogniSenti Dataset)** |       |     |      |       |
| Positive    | 1047  | 285 | 236  | 1488  |
| Neutral     | 2633  | 553 | 563  | 3749  |
| Negative    | 919   | 227 | 187  | 1333  |
| Total       | 4599  | 985 | 986  | 6570  |

Figure 2: Word-cloud for **highly positive tokens (selected from positive class)**, in the combined datasets with valence score, \( \vartheta(.) = 1 \). – is used to indicate space between the bi-grams

Figure 3: Word-cloud for **highly negative tokens (selected from negative class)**, in the combined datasets with valence score, \( \vartheta(.) = 1 \). – is used to indicate space between the bi-grams

**a) Token Length Distribution:** The computed distribution of tokens is reported in Figure 1. Across different datasets, the number of tokens is less than 90. The average number of token in the combined dataset is 16 and the median is 13. Only in a very few cases, it is above this range (e.g., Youtube comments, BanglaFastText, and CogniSenti dataset). This analysis helps us in understanding what is the typical maximum number of tokens in social media data that could be used as sequence length – an important hyperparameter for deep learning algorithms.

**b) Class-wise Lexical n-gram Discrimination:** For a better understanding of all sentiment datasets used in this paper and their discrimination power with respect to the categories – positive vs negative, we analyzed the lexical content of each
We choose the weighted metric, which takes care of the class imbalance problem. For all models, we used the multilinguial version of the base model. We computed weighted average precision (P), recall (R), F1-measure (F1) to measure the performance of each classifier. We choose the weighted metric, which takes care of the class imbalance problem.

### IV. Experimental Setup

In this section, we describe the details of our classification experiments and results. To run the experiments, we split data into training, development, and test sets with a proportion of 70%, 15%, and 15%, respectively.

#### A. Preprocessing

Social media content is always noisy, which consists of many symbols, emoticons, URLs, username, and invisible characters. Previous studies show that filtering and cleaning the data before training a classifier helps significantly. Hence, we preprocess the data before classification experiments. The preprocessing steps include removal of stop words, invisible characters, punctuations, URLs, and hashtags. Note that most of the datasets contain romanized text and we removed them for this study.

#### B. Models and Architectures

We have conducted classification experiments using both classical and deep learning algorithms. As the classical algorithms, we used the two most popular algorithms (i) Random Forest (RF) [30], and (ii) Support Vector Machines (SVM) [31].

As deep learning algorithms, we used CNN [32], FastText [33] and transformers based models such as BERT [7], DistilBERT [34] and XLM-RoBERTa [35]. The choice of algorithms is motivated by several factors. CNN has been widely used with static embedding (i.e., word2vec) for many NLP tasks in the past years where FastText extends static embedding to use n-grams (i.e., context). Static embedding based approaches generate a single embedding for each word where transformers based models take contextual information into account and generates contextual embedding. It uses WordPiece tokenization [36], that is a data-driven approach, which addresses out-of-vocabulary problem. Among the transformer models BERT and XLM-RoBERTa are larger in parameter size (168 million parameters in BERTbase_multilingual and 550 million in XLM-RoBERTalarge) whereas DistilBERT consists of 134 million parameters. Network size and the number of parameters also reflect the performance and computation time, which we wanted to understand.

For all models, we used the multilingual version of the models. We follow the fine-tuning procedure using a task-specific layer on top of the transformers network.

#### C. Evaluation

We computed weighted average precision (P), recall (R), F1-measure (F1) to measure the performance of each classifier.
Table III: Classification results using RF, SVM, CNN, FastText, BERT, DistilBERT and RoBERTa. Best results are highlighted with bold form.

| Dataset            | RF   | SVM  | CNN-W2V | CNN-Glove | FastText | BERT   | DistilBERT | XLM-RoBERTa |
|--------------------|------|------|---------|-----------|----------|--------|------------|-------------|
| ABSA cricket       | 0.662| 0.636| 0.679   | 0.696     | 0.688    | 0.682  | 0.699      | 0.682       |
| ABSA restaurant    | 0.407| 0.498| 0.391   | 0.491     | 0.519    | 0.531  | 0.581      | 0.579       |
| SAIL               | 0.546| 0.552| 0.557   | 0.595     | 0.532    | 0.566  | 0.570      | 0.566       |
| BengFastText       | 0.612| 0.613| 0.663   | 0.657     | 0.661    | 0.674  | 0.669      | 0.674       |
| Youtube comments   | 0.586| 0.605| 0.669   | 0.663     | 0.658    | 0.729  | 0.701      | 0.729       |
| CogniSenti         | 0.545| 0.584| 0.604   | 0.587     | 0.614    | 0.686  | 0.589      | 0.686       |

Avg. 0.560 0.581 0.594 0.615 0.612 0.653 0.635 0.671

D. Experiments

a) Classical Algorithms: To train the classifiers using the classical algorithms mentioned above, we first converted the preprocessed data into bag-of-n-gram vectors weighted with tf-idf. We used n-grams (i.e., unigram, bigram, and tri-gram) to utilize contextual information. For both SVM and RF we use grid search to optimize the parameters.

b) CNN: To train the model with CNN we used a filter size of 300 filters with a window size of 2, 3, and 4 with the same pooling length. We used Adam optimizer [37] and the maximum number of epochs was set to 3,000. To reduce the computation without impacting the performance we used early stopping based on the accuracy on the development set. The patience size in early stopping was set to 200. These parameter settings varied in different experiments. To train the CNN, we experiment with two different in-house developed pre-trained static embedding models i) word2vec skip-gram [38], ii) glove [39]. For training the pre-trained word embedding models we used the dataset reported in [40] along with the latest Bangla Wikipedia dump.

c) FastText: For the FastText, we use pre-trained embeddings, which is released by FastText for Bangla. To tune the hyperparameter we use the built-in hyperparameter setups from the FastText.

d) Transformers models: For transformer-based models, we used the Transformer Toolkit [41]. We fine-tune each model using a learning rate of $1e^{-5}$ for ten epochs [7]. The training of the pre-trained models has some instability as reported in [7], therefore, we run each experiment 10 times using different random seeds and select the model that performs the best on the development set. With transformer models, we used model specific tokenizer available with Transformer Toolkit.

V. Results and Discussion

A. Results

In Table III, we report the classification results for each dataset. It summarizes the results obtained by different classification algorithms described above. Though we computed several metrics for the performance measure, because of the limited space, we only report F1-score. We reported other results in a public repository along with the data split. From the table, we observe that among the classical algorithms the performance of SVM is better than RF except for ABSA cricket dataset where RF is 2.6% higher. As expected we have consistent improvement with deep learning models. Both skip-gram (word2vec) and glove embedding with CNN are performing comparatively. The performance of FastText is higher in three datasets and low on other datasets though overall FastText is better than CNN. Across different results transformer models consistently perform better than others, which highlights the capability of the pretrained transformer models. Among transformer based models, BERT is performing better on three datasets and XLM-RoBERTa is performing well on two datasets.

B. Discussion and Future Works

Our findings on data analysis suggest that computing the valence scores, $\vartheta$, can help to develop a sentiment lexicon in an automated fashion, with a meaningful representation per class. In terms of performance difference between classical vs deep learning algorithms, there is a significant gap. Hence a compromise has to make between computational cost vs accuracy to use them in real-time applications. For example, we used the 4 NVIDIA Tesla V100-SXM2-32GB GPU machine consists of 56 cores and 256GB CPU memory for the experiments. To perform a fine-tuning experiment on a single GPU machine, on average it took 40 minutes using a BERT base model. Whereas, the training an SVM model took less than 5 minutes. Note that running/execution time varies depending on the dataset size as well.

From the perspective of performance comparison across datasets, an end to end comparison might not possible because of the different test set, however, from the results, we conclude that we obtain higher weighted F1 on the Youtube comments dataset. Among the datasets SAIL is the smallest in size, this could be a reason that we have a low performance on this dataset.

As future work, we will investigate cross model performance, and consolidate the datasets to see if it enhance the performance of the models. Another future study could be aspect-based sentiment while understanding the diversity of the dataset.

VI. Conclusions

In this study, we have conducted comparative experiments using different annotated sentiment datasets consisting of Bangla content from social media for multiple domains. We curated, cleaned, and split the dataset for the classification experiments. We analyzed the datasets to understand the
discerning aspects of lexical content for positive and negative sentiment. Our analysis, using the valence score, show a reasonable, meaningful, and clearly visible distinction between the classes. We investigated diverse machine learning algorithms ranging from classical (e.g., SVM) to deep learning algorithms (e.g., CNN, transformer models). The performance of deep learning algorithms is comparatively higher compared to classical algorithms. This improvement comes with the cost of increased resource and time complexity. Given that the official splits in most of the datasets are not available, hence, we are not able to compare our results with previous results. With that in mind we release the data split used in this study, for the purpose of reproducibility and using the obtained results as benchmarks.

References

[1] B. Liu, Sentiment analysis: Mining opinions, sentiments, and emotions. Cambridge University Press, 2015.
[2] B. Pang, L. Lee, and S. Vaithyanathan, “Thumbs up?: sentiment classification using machine learning techniques,” in Proc. of EMNLP. Association for Computational Linguistics, 2002, pp. 79–86.
[3] F. Celli, A. Ghosh, F. Alam, and G. Riccardi, “In the mood for sharing contents: Emotions, personality and interaction styles in the diffusion of news,” Information Processing & Management, vol. 52, no. 1, pp. 93–98, 2016.
[4] M. Danieli, G. Riccardi, and F. Alam, “Emotion unfolding and affective scenes: A case study in spoken conversations,” in Proceedings of the International Workshop on Emotion Representations and Modelling for Companion Technologies, 2015, pp. 5–11.
[5] E. Cambria, S. Poria, R. Bajpai, and B. Schuller, “Senticnet 4: A semantic resource for sentiment analysis based on conceptual primitives,” in Proc. of COLING, 2016.
[6] F. Alam, M. Danieli, and G. Riccardi, “Annotating and modeling empathy in spoken conversations,” CSL, vol. 50, pp. 40 – 61, 2018.
[7] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: pre-training of deep bidirectional transformers for language understanding,” arXiv preprint arXiv:1810.04805, 2018.
[8] P. D. Turney, “Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews,” in Proc. of the 40th ACL. ACL, 2002, pp. 417–424.
[9] B. Pang and L. Lee, “A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts,” in Proc. of the 42nd ACL. ACL, 2004, pp. 271.
[10] M. Hu and B. Liu, “Mining and summarizing customer reviews,” in Proc. of the 13th ACM SIGKDD. ACM, 2004, pp. 168–177.
[11] A. Das and S. Bandyopadhyay, “Sentiwordnet for bangla,” Knowledge Sharing Event-4: Task, vol. 2, pp. 1–8, 2010.
[12] D. Amitava and S. Bandyopadhyay, “Phrase-level polarity identification for bangla,” Int. J. Comput. Linguist. Appl.(IJCLA), vol. 1, no. 1-2, pp. 169–182, 2010.
[13] S. Chowdhury and W. Chowdhury, “Performing sentiment analysis in bangla microblog posts,” in Proc. of ICIEL. IEEE, 2014, pp. 1–6.
[14] S. A. Taher, K. A. Akhter, and K. A. Hasan, “N-gram based sentiment mining for bangla text using support vector machine,” in Proc. of ICBSLP. IEEE, 2018, pp. 1–5.
[15] S. H. Sumit, M. Z. Hossan, T. Al Muntasir, and T. Sourouf, “Exploring word embedding for bangla sentiment analysis,” in Proc. of ICBSLP. IEEE, 2018, pp. 1–5.
[16] N. I. Tripto and M. E. Ali, “Detecting multilabel sentiment and emotions from bangla youtube comments,” in Proc. of ICBSLP. IEEE, 2018, pp. 1–6.
[17] B. G. Patra, D. Das, A. Das, and R. Prasath, “Shared task on sentiment analysis in indian languages (sail) 2015: sentiment analysis in indian languages,” in Proc. of MIKE. Springer, 2015, pp. 650–655.
[18] S. Se, R. Vinayakumar, M. A. Kumar, and K. Soman, “Amrita-cen@ sail2015: sentiment analysis in indian languages,” in Proc. of MIKE. Springer, 2015, pp. 703–710.
[19] A. Kumar, S. Kohail, A. Ekbal, and C. Biemman, “Iit-tuda: System for sentiment analysis in indian languages using lexical acquisition,” in Proc. of MIKE. Springer, 2015, pp. 684–693.
[20] S. S. Kumar, M. A. Kumar, K. Soman, and P. Poomnachandran, “Dynamic mode-based feature with random mapping for sentiment analysis,” in Intelligent Systems, Technologies and Applications. Springer, 2020, pp. 1–15.
[21] R. R. Chowdhury, M. Shahadat Hossain, S. Hossain, and K. Andersson, “Analyzing sentiment of movie reviews in bangla by applying machine learning techniques,” in Proc. of ICBSLP. IEEE, 2019.
[22] M. A.-u.-z. Ashik, S. Shovon, and S. Haque, “Data set for sentiment analysis on Bengali news comments and its baseline evaluation,” in Proc. of ICBSLP. IEEE, 2019.
[23] M. F. Wahid, M. J. Hasan, and M. S. Alom, “Cricket Sentiment Analysis from Bangla Text Using Recurrent Neural Network with Long Short Term Memory Model,” in Proc. of ICBSLP. IEEE, 2019.
[24] S. Palash, Mehedi Hasan and Das, Partha Protim and Haque, “Sentimental style transfer in text with,” in Proc. of ICBSLP. IEEE, 2019.
[25] M. Rahman, E. Kumar Dey et al., “Datasets for aspect-based sentiment analysis in bangla and its baseline evaluation,” Data, vol. 3, no. 2, p. 15, 2018.
[26] M. Pontiki, D. Galanis, J. Pavlopoulos, H. Papageorgiou, I. Androu­sopoulos, and S. Manandhar, “SemEval-2014 task 4: Aspect based sentiment analysis,” in Proc. of SemEval 2014. Dublin, Ireland: ACL, Aug. 2014, pp. 27–35.
[27] M. Rezaul Karim, B. Raja Chakravarthi, M. Arcan, J. P. McCrae, and M. Cochez, “Classification benchmarks for under-resourced Bengali language based on multichannel convolutional-lstm network,” arXiv, pp. arXiv-2004, 2020.
[28] M. D. Conover, J. Ratkiewicz, M. Francisco, B. Goncalves, F. Menczer, and A. Flammini, “Political polarization on twitter,” in Proc. of 5th ICWSM, 2011.
[29] S. A. Chowdhury, H. Mutubarak, A. Abdelali, S.-g. Jung, B. J. Jansen, and J. Salminen, “A multi-platform arabic news comment dataset for offensive language detection,” in Proc. of 12th LREC, 2020, pp. 6203–6212.
[30] A. Liaw, M. Wiener et al., “Classification and regression by random forest,” R news, vol. 2, no. 3, pp. 18–22, 2002.
[31] J. Platt, “Sequential minimal optimization: A fast algorithm for training support vector machines,” Microsoft, Redmond, USA., Tech. Rep., 1998.
[32] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in neural information processing systems, 2012, pp. 1097–1105.
[33] A. Joulin, E. Grave, P. Bojanowski, and T. Mikolov, “Bag of tricks for efficient text classification,” in Proc. of EACL. Association for Computational Linguistics, April 2017, pp. 427–431.
[34] V. Sanh, L. Debut, J. Chaumond, and T. Wolf, “DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter,” arXiv:1910.01108, 2019.
[35] A. Conneau, K. Khandelwal, N. Goyal, V. Chaudhary, G. Wenzek, F. Guzmán, E. Grave, M. Ott, L. Zettlemoyer, and V. Stoyanov, “Unsupervised cross-lingual representation learning at scale,” arXiv preprint arXiv:1911.02116, 2019.
[36] Y. Wu, M. Schuster, Z. Chen, Q. V. Le, M. Norouzi, W. Macherey, M. Krikun, Y. Cao, Q. Gao, K. Macherey et al., “Google’s neural machine translation system: Bridging the gap between human and machine translation,” arXiv preprint arXiv:1609.08144, 2016.
[37] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.
[38] T. Mikolov, K. Chen, G. Corrado, and J. Dean, “Efficient estimation of word representations in vector space,” arXiv:1301.3781, 2013.
[39] J. Pennington, R. Socher, and C. D. Manning, “Glove: Global vectors for word representation,” in Proc. of EMNLP. 2014, pp. 1532–1543.
[40] F. Alam, S. A. Chowdhury, and S. R. H. Noori, “Bidirectional LSTMs—CRFs networks for bangla pos tagging,” in Proc. of IJCCIT. IEEE, 2016, pp. 377–382.
[41] T. Wolf, L. Debut, V. Sanh, J. Chaumond, C. Delangue, A. Moi, P. Cistac, T. Rault, R. Louf, M. Funtowicz, and J. Brew, “Huggingface’s transformers: State-of-the-art natural language processing,” ArXiv, vol. abs/1910.03771, 2019.