

Emotion Classification in a Resource Constrained Language Using Transformer-based Approach

Avishek Das, Omar Sharif, Mohammed Moshiul Hoque and Iqbal H. Sarker

Department of Computer Science and Engineering

Chittagong University of Engineering & Technology

Chittagong-4349, Bangladesh

u1504018@student.cuet.ac.bd, {omar.sharif, moshiul_240, iqbal}@cuet.ac.bd

Abstract

Although research on emotion classification has significantly progressed in high-resource languages, it is still infancy for resource-constrained languages like Bengali. However, unavailability of necessary language processing tools and deficiency of benchmark corpora makes the emotion classification task in Bengali more challenging and complicated. This work proposes a transformer-based technique to classify the Bengali text into one of the six basic emotions: anger, fear, disgust, sadness, joy, and surprise. A Bengali emotion corpus consists of 6243 texts is developed for the classification task. Experimentation carried out using various machine learning (LR, RF, MNB, SVM), deep neural networks (CNN, BiLSTM, CNN+BiLSTM) and transformer (Bangla-BERT, m-BERT, XLM-R) based approaches. Experimental outcomes indicate that XLM-R outdoes all other techniques by achieving the highest weighted f_1 -score of 69.73% on the test data. The dataset is publicly available at <https://github.com/omar-sharif03/NAACL-SRW-2021>.

1 Introduction

Classification of emotion in the text signifies the task of automatically attributing an emotion category to a textual document selected from a set of predetermined categories. With the growing number of users in virtual platforms generating online contents steadily as a fast-paced, interpreting emotion or sentiment in online content is vital for consumers, enterprises, business leaders, and other parties concerned. Ekman (Ekman, 1993) defined six basic emotions: happiness, fear, anger, sadness, surprise, and disgust based on facial features. These primary type of emotions can also be extracted from the text expression (Alswaidan and Menai, 2020).

The availability of vast amounts of on-line data and the advancement of computational processes have accelerated the development of emotion classification research in high-resource languages such as English, Arabic, Chinese, and French (Plaza del Arco et al., 2020). However, there is no notable progress in low resource languages such as Bengali, Tamil and Turkey. The proliferation of the Internet and digital technology usage produces enormous textual data in the Bengali language. The analysis of these massive amounts of data to extract underlying emotions is a challenging research issue in the realm of Bengali language processing (BLP). The complexity arises due to various limitations, such as the lack of BLP tools, scarcity of benchmark corpus, complicated language structure, and limited resources. By considering the constraints of emotion classification in the Bengali language, this work aims to contribute to the following:

- Develop a Bengali emotion corpus consisting of 6243 text documents with manual annotation to classify each text into one of six emotion classes: anger, disgust, fear, joy, sadness, surprise.
- Investigate the performance of various ML, DNN and transformer-based approaches on the corpus.
- Proposed a benchmark system to classify emotion in Bengali text with the experimental validation on the corpus.

2 Related Work

Substantial research activities have been carried out on emotion analysis in high-resource languages like English, Arabic, and Chinese (Alswaidan and Menai, 2020). A multi-label

with multi-target emotion detection of Arabic tweets accomplished using decision trees, random forest, and KNN, where random forest provided the highest f_1 -score of 82.6% (Alzu'bi et al., 2019). Lai et al. (2020) proposed a graph convolution network architecture for emotion classification from Chinese microblogs and their proposed system achieved an F-measure of 82.32%. Recently, few works employed transformer-based model (i.e., BERT) analyse emotion in texts. (Huang et al., 2019; Al-Omari et al., 2020) used a pre-trained BERT for embedding purpose on top of LSTM/BiLSTM to get an improved f_1 -score of 76.66% and 74.78% respectively.

Although emotion analysis on limited resource languages like Bengali is in the preliminary stage, few studies have already been conducted on emotion analysis using ML and DNN methods. Irtiza Tripto and Eunus Ali (2018) proposed an LSTM based approach to classify multi-label emotions from Bengali, and English sentences. This system considered only YouTube comments and achieved 59.23% accuracy. Another work on emotion classification in Bengali text carried out by Azmin and Dhar (2019) concerning three emotional labels (i.e., happy, sadness and anger). They used Multinomial Naïve Bayes, which outperformed other algorithms with an accuracy of 78.6%. Pal and Karn (2020) developed a logistic regression-based technique to classify four emotions (joy, anger, sorrow, suspense) in Bengali text and achieved 73% accuracy. Das and Bandyopadhyay (2009) conducted a study to identify emotions in Bengali blog texts. Their scheme attained 56.45% accuracy using the conditional random field. Recent work used SVM to classify six raw emotions on 1200 Bengali texts which obtained 73% accuracy (Ruposh and Hoque, 2019).

3 BEmoC: Bengali Emotion Corpus

Due to the standard corpus unavailability, we developed a corpus (hereafter called 'BEmoC') to classify emotion in Bengali text. The development procedure is adopted from the guidelines stated in (Dash and Ramamoorthy, 2019).

3.1 Data Collection and Preprocessing

Five human crawlers were assigned to accumulate data from various online/offline sources. They manually collected 6700 text documents over three months (September 10, 2020 to December 11, 2020). The crawler accumulated data selectively, i.e., when a crawler finds a text that supports the definition of any of the six emotion classes according to Ekman (1993), the content is collected, otherwise ignored. Raw accumulated data needs following pre-processing before the annotation:

- Removal of non-Bengali words, punctuation, emoticons and duplicate data.
- Discarding data less than three words to get an unerring emotional context.

After pre-processing the corpus holds 6523 text data. The processed texts are eligible for manual annotation. The details of the preprocessing modules found in the link¹.

3.2 Data Annotation and Quality

Five postgraduate students working on BLP were assigned for initial annotation. To choose the initial label majority voting technique is applied (Magatti et al., 2009). Initial labels were scrutinized by an expert who has several years of research expertise in BLP. The expert corrected the labelling if any initial annotation is done inappropriately. The expert discarded 163 texts with neutral emotion and 117 texts with mixed emotions for the intelligibility of this research. To minimize bias during annotation, the expert finalized the labels through discussions and deliberations with the annotators (Sharif and Hoque, 2021). We evaluated the inter-annotator agreement to ensure the quality of the annotation using the coding reliability (Krippendorff, 2011) and Cohen's kappa (Cohen, 1960) scores. An inter-coder reliability of 93.1% with Cohen's Kappa score of 0.91 reflects the quality of the corpus.

3.3 Data Statistics

The BEmoC contains a total of 6243 text documents after the preprocessing and annotation process. Amount of data inclusion in BEmoC

¹<https://github.com/omar-sharif03/NAACL-SRW-2021/tree/main/Code%20Snippets>

varies with the sources. For example, among online sources, Facebook contributed the highest amount (2796 texts) whereas YouTube (610 texts), blogs (483 texts), and news portals (270 texts) contributed a small amount. Offline sources contributed a total of 2084 texts, including storybooks (680 texts), novels (668 texts), and conversations (736 texts). Data partitioned into train set (4994 texts), validation set (624 texts) and test set (625 texts) to evaluate the models. Table 1 represents the amount of data in each class according to the train-validation-test set.

Class	Train	Validation	Test
Anger	621	67	71
Disgust	1233	155	165
Fear	700	89	83
Joy	908	120	114
Sadness	942	129	119
Surprise	590	64	73

Table 1: Number of instances in the train, validation, and test sets

Since the classifier models learn from the training set instances to obtain more insights, we further analyzed this set. Table 2 shows several statistics of the training set.

Class	Total words	Unique words	Avg. words per text
Anger	14914	5852	24.02
Disgust	27192	7212	22.35
Fear	14766	5072	21.09
Joy	20885	7346	23.40
Sadness	22727	7398	24.13
Surprise	13833	5675	23.45
Total	114317	38555	-

Table 2: Statistics of the train set of BEmoC

The *sadness* class contains the most unique words(7398), whereas the *fear* class contains the least(5072). In average all the classes have more than 20 words in each text document. However, a text document in *sadness* class contained the maximum number of words (107) whereas *fear* class consisting of a minimum number of words (4). Figure 1 represents the number of texts vs the length of texts distribution for each class of the corpus. Investigating this figure revealed that most of the data varied a length between 15 to 35 words. Interestingly, most of the texts of *Disgust* class have a length less than 30. The *Joy* & *Sadness*

classes seem to have almost similar number of texts in all length distributions.

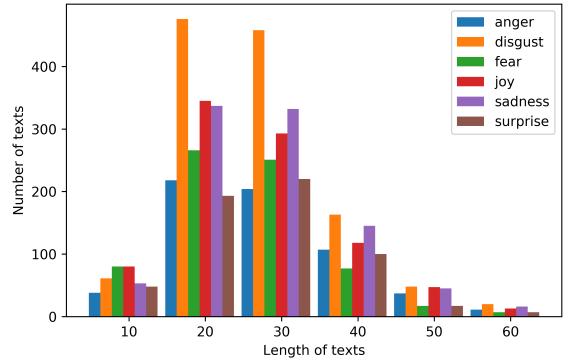


Figure 1: Corpus distribution concerning number of texts vs length

For quantitative analysis, the *Jaccard* similarity among the classes has been computed. We used 200 most frequent words from each emotion class, and the similarity values are reported in table 3. The *Anger-Disgust* and *Joy-Surprise* pairs hold the highest similarity of 0.58 and 0.51, respectively. These scores indicate that more than 50% frequent words are common in these pair of classes. On the other hand, the *Joy-Fear* pair has the least similarity index, which clarifies that this pair’s frequent words are more distinct than other classes. These similarity issues can substantially affect the emotion classification task. Some sample instances of BEmoC are shown in Table 9 (Appendix B).

	C1	C2	C3	C4	C5	C6
C1	1.00	0.58	0.40	0.43	0.45	0.47
C2	-	1.00	0.41	0.45	0.47	0.44
C3	-	-	1.00	0.37	0.45	0.46
C4	-	-	-	1.00	0.47	0.51
C5	-	-	-	-	1.00	0.48

Table 3: *Jaccard* similarity between the emotion class pairs. Anger (c1), disgust (c2), fear (c3), joy (c4), sadness (c5), surprise (c6).

4 Methodology

Figure 2 shows an abstract view of the used strategies. Various feature extraction techniques such as TF-IDF, Word2Vec, and Fast-Text are used to train ML and DNN models. Moreover, we also investigate the Bengali text’s emotion classification performance using

transformer-based models. All the models are trained and tuned on the identical dataset.

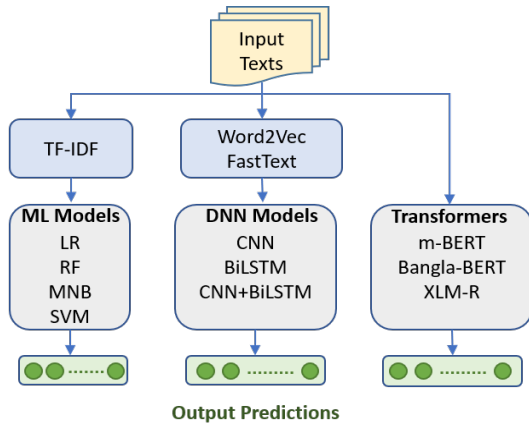


Figure 2: Abstract process of emotion classification

4.1 Feature Extraction

ML and DNN algorithms are unable to learn from raw texts. Therefore, feature extraction is required to train the classifier models.

TF-IDF: Term frequency-inverse document frequency (TF-IDF) is a statistical measure that determines the importance of a word to a document in a collection of documents. Uni-gram and bi-gram features are extracted from the most frequent 20000 words of the corpus.

Word2Vec: It utilizes neural networks to find semantic similarity of the context of the words in a corpus (Mikolov et al., 2013). We trained Word2Vec on Skip-Gram with the window size of 7, minimum word count to 4, and the embedding dimension of 100.

FastText: This technique uses subword information to find the semantic relationships (Bojanowski et al., 2017). We trained FastText on Skip-Gram with character n-grams of length 5, windows size of 5, and embedding dimension of 100.

For both Word2Vec and FastText, there are pre-trained vectors available for the Bengali language trained on generalized Bengali wiki dump data (Sarker, 2021). We observed that the deep learning models perform well on vectors trained with our developed BEmoC rather than the pre-trained vectors.

4.2 ML Approaches

We started an investigation on emotion detection system with ML models. Logistic Regres-

sion (LR), Support Vector Machine (SVM), Random Forest (RF) and Multinomial Naive Bayes (MNB) techniques are employed using TF-IDF text vectorizer. For LR *lbfgs* solver and *l1* penalty is chosen and *C* value is set to 1. The same *C* value with *linear* kernel is used for SVM. Meanwhile, for RF *n_estimators* is set to 100 and *alpha=1.0* is chosen for MNB. A summary of the parameters chosen for ML models are provided in Table 6 (Appendix A).

4.3 DNN Approaches

Variation of deep neural networks (DNN) such as CNN, BiLSTM and a combination of CNN and BiLSTM (CNN+BiLSTM) will investigate the performance of emotion classification task in Bengali. To train all the DNN models, ‘adam’ optimizer with a learning rate of 0.001 and a batch size of 16 is used for 35 epochs. The ‘sparse_categorical_crossentropy’ is selected as the loss function.

CNN: Convolutional Neural Network (CNN) (LeCun et al., 2015) is tuned over the emotion corpus. The trained weights from the Word2Vec/FastText embeddings are fed to the embedding layer to generate a sequence matrix. The sequence matrix is then passed to the convolution layer having 64 filters of size 7. The convolution layer’s output is max-pooled over time and then transferred to a fully connected layer with 64 neurons. ‘ReLU’ activation is used in the corresponding layers. Finally, an output layer with softmax activation is used to compute the probability distribution of the classes.

BiLSTM: Bidirectional Long-Short Term Memory (BiLSTM) (Hochreiter and Schmidhuber, 1997) is a variation of recurrent neural network (RNN). The developed BiLSTM network consists of an Embedding layer similar to CNN, a BiLSTM layer with 32 hidden units, and a fully connected layer having 16 neurons with ‘ReLU’ activation. An output layer with ‘softmax’ activation is used.

CNN+BiLSTM: An embedding layer followed by a 1D convolutional layer with 64 filters of size three and a 1D max-pool layer is employed on top of two BiLSTM layers with 64 and 32 units. Outputs of BiLSTM layer fed to an output layer with ‘softmax’ activation.

Table 7 (Appendix A) illustrates the details

of the hyperparameters used in the DNN models.

4.4 Transformer Models

We used three transformer models: m-BERT, Bangla-BERT, and XLM-R on BEmoC. In recent years transformer is being used extensively for classification tasks to achieve state-of-the-art results (Chen et al., 2021). The models are culled from the Huggingface² transformers library and fine-tuned on the emotion corpus by using Ktrain(Maiya, 2020) package.

m-BERT: m-BERT (Devlin et al., 2019) is a transformer model pre-trained over 104 languages with more than 110M parameters. We employed ‘bert-base-multilingual-cased’ model and fine-tuned it on BEmoC with a batch size of 12.

Bangla BERT: Bangla BERT (Sarker, 2020) is a pre-trained BERT mask language modelling, trained on a sizeable Bengali corpus. We used the ‘sagorsarker/Bangla-bert-base’ model and fine-tuned to update the pre-trained model fitted for BEmoC. A batch size of 16 is used to provide better results.

XLM-R: XLM-R (Liu et al., 2019) is a sizeable multilingual language model trained on 100 different languages. We implemented the ‘xlm-Roberta-base’ model on BEmoC with a batch size of 12.

All the transformer models have been trained with 20 epochs with a learning rate of $2e^{-5}$. By using the checkpoint best intermediate model is stored to predict on the test data. Table 8 (Appendix A) shows a list of

parameters used for transformer models.

5 Results and Analysis

This section presents a comprehensive performance analysis of various ML, DNN, and transformer-based models to classify Bengali texts emotion. The superiority of the models is determined based on the weighted f_1 -score. However, the precision (Pr), recall (Re) and accuracy (Acc) metrics also considered. Table 4 reports the evaluation results of all models.

Among ML approaches, LR achieved the highest (60.75%) f_1 -score than RF (52.78%), MNB (48.67%) and SVM (59.54%). LR also performed well in Pr , Re and Acc than other ML models. In DNN, BiLSTM with FastText outperformed other approaches concerning all the evaluation parameters. It achieved f_1 -score of 56.94%. However, BiLSTM (FastText) achieved about 4% lower f_1 -score than the best ML method (i.e., LR).

After employing transformer-based models, it observed a significant increase in all scores. Among transformer-based models, Bangla-BERT achieved the lowest of 61.91% f_1 -score. However, this model outperformed the best ML and DNN approaches (56.94% for BiLSTM (FastText) and 60.75% for LR). Meanwhile, m-BERT shows almost 3% improved f_1 -score (64.39%) than Bangla-BERT (61.91%). XLM-R model shows an immense improvement of about 6% compared to Bangla-BERT and 5% compared to m-BERT, respectively. It achieved a f_1 -score of 69.73% that is the highest among all models.

²<https://huggingface.co/transformers/>

Method	Classifier	Pr(%)	Re(%)	F1(%)	Acc(%)
ML models	LR	61.07	60.64	60.75	60.64
	RF	55.91	54.72	52.78	54.72
	MNB	60.23	54.08	48.67	54.08
	SVM	61.12	60.10	59.54	60.00
DNN models	CNN (Word2Vec)	53.20	52.12	51.84	52.12
	CNN (FastText)	54.54	53.45	52.52	53.48
	BiLSTM (Word2Vec)	56.81	55.78	53.45	57.12
	BiLSTM (FastText)	57.30	58.08	56.94	58.08
	CNN + BiLSTM (Word2Vec)	56.48	56.64	56.39	56.64
	CNN + BiLSTM (FastText)	55.74	55.68	55.41	55.68
Transformers	Bangla-BERT	62.08	62.24	61.91	62.24
	m-BERT	64.62	64.64	64.39	64.63
	XLM-R	70.11	69.61	69.73	69.61

Table 4: Comparison of various approaches on test set. Here Acc, Pr, Re, F1 denotes accuracy, weighted precision, recall, and f_1 -score

5.1 Error Analysis

It is evident from Table 4 that XLM-R is the best performing model to classify emotion from Bengali texts. A detailed error analysis is performed using the confusion matrix. Figure 3 illustrates a class-wise proportion of the number of predicted labels. It is observed from the

True label	anger	45 63.38%	8 11.27%	4 5.63%	4 5.63%	5 7.04%	5 7.04%
	disgust	18 10.91%	124 75.15%	4 2.42%	4 2.42%	12 7.27%	3 1.82%
	fear	3 3.61%	3 3.61%	64 77.11%	3 3.61%	6 7.23%	4 4.82%
	joy	5 4.39%	6 5.26%	2 1.75%	79 69.30%	7 6.14%	15 13.16%
	sadness	5 4.20%	18 15.13%	9 7.56%	3 2.52%	78 65.55%	6 5.04%
	surprise	2 2.74%	7 9.59%	6 8.22%	4 5.48%	9 12.33%	45 61.64%
		Predicted label					

Figure 3: Confusion matrix of XLM-R model

matrix that few data classified wrongly. For example, 8 instances among 71 of the *anger* class predicted as *disgust*. In *fear* class, 6 data out of 83 mistakenly classified as *sadness*. In the *sadness* class, misclassification ratio is the highest (15.13%). That means, 18 data out of 119 in *sadness* class misclassified as *disgust*. Moreover, among 73 data in *surprise* class 9 are predicted as *sadness*. The error analysis reveals that *fear* class achieved the highest rate of correct classification (77.15%) while *surprise* gained the lowest (61.64%).

The possible reason for incorrect predictions might be the class imbalance nature of the corpus. However, the high value of *Jaccard similarity* (Table 3) also reveals some interesting points. Few words are used multi-purposely in multiple classes. For instance, hate words can be used to express both *anger* and *disgust* feelings. Moreover, emotion classification is highly subjective, depends on the individual’s perception, and people may contemplate a sentence in many ways (LeDoux and Hofmann, 2018). Thus, by developing a balanced dataset with diverse data, incorrect predictions might be reduced to some extent.

5.2 Comparison with Recent Works

The analysis of results revealed that XLM-R is the best model to classify emotion in Bengali texts. Thus, we compare the performance of

XLM-R with the existing techniques to assess the effectiveness. We implemented previous methods (Irtiza Tripto and Eunus Ali, 2018; Azmin and Dhar, 2019; Pal and Karn, 2020; Ruposh and Hoque, 2019) on BEmoC and reported outcomes in f_1 -score. Table 5 shows a summary of the comparison. The results show

Methods	F1(%)
Word2Vec + LSTM (Irtiza Tripto and Eunus Ali, 2018)	53.54
TF-IDF + MNB (Azmin and Dhar, 2019)	48.67
TF-IDF + LR (Pal and Karn, 2020)	60.75
BOW + SVM (Ruposh and Hoque, 2019)	59.17
XLM-R (Proposed)	69.73

Table 5: Performance comparison. Here F1 denotes weighted f_1 -score.

that XLM-R outperformed the past techniques with achieving the highest f_1 -score (69.73%).

6 Conclusion

This paper investigated various ML, DNN and transformer-based techniques to classify the emotion in Bengali texts. Due to the scarcity of benchmark corpus, we developed a corpus (i.e., BEmoC) containing 6243 Bengali texts labelled with six basic classes. Co-hen’s Kappa score of 0.91 reflects the quality of the corpus. Performance analysis on BEmoC illustrated that XLM-R, a transformer model provided a superior result among all the methods. Specifically, XLM-R achieved the highest f_1 -score of 69.61% which indicates the improvement of 8.97% (than ML) and 11.53% (than DNN). Although XLM-R exhibited the most elevated scores, other technique (such as the ensemble of the transformer models) can also investigate enhancing performance. Additional categories (such as love, hate, and stress) can also include generalization. Moreover, transformer-based models can also investigate extending the corpus, including text with sarcasm or irony, text with comparison and mixed-emotion.

Acknowledgements

We sincerely acknowledge the anonymous reviewers and pre-submission mentor for their insightful suggestions, which help improve the work. This work was supported by the Directorate of Research & Extension, CUET.

References

- H. Al-Omari, M. A. Abdullah, and S. Shaikh. 2020. [Emodet2: Emotion detection in english textual dialogue using bert and bilstm models](#). In *2020 11th International Conference on Information and Communication Systems (ICICS)*, pages 226–232.
- Nourah Alswaidan and Mohamed El Bachir Menai. 2020. [A survey of state-of-the-art approaches for emotion recognition in text](#). *Knowledge and Information Systems*, pages 1–51.
- S. Alzu’bi, O. Badarneh, B. Hawashin, M. Al-Ayyoub, N. Alhindawi, and Y. Jararweh. 2019. [Multi-label emotion classification for arabic tweets](#). In *2019 Sixth International Conference on Social Networks Analysis, Management and Security (SNAMS)*, pages 499–504.
- S. Azmin and K. Dhar. 2019. [Emotion detection from bangla text corpus using naïve bayes classifier](#). In *2019 4th International Conference on Electrical Information and Communication Technology (EICT)*, pages 1–5.
- Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. [Enriching Word Vectors with Subword Information](#). *Transactions of the Association for Computational Linguistics*, 5:135–146.
- Ben Chen, Bin Chen, Dehong Gao, Qijin Chen, Chengfu Huo, Xiaonan Meng, Weijun Ren, and Yang Zhou. 2021. Transformer-based language model fine-tuning methods for covid-19 fake news detection. *arXiv preprint arXiv:2101.05509*.
- Jacob Cohen. 1960. [A coefficient of agreement for nominal scales](#). *Educational and Psychological Measurement*, 20(1):37–46.
- Dipankar Das and Sivaji Bandyopadhyay. 2009. Word to sentence level emotion tagging for bengali blogs. In *Proceedings of the ACL-IJCNLP 2009 Conference Short Papers*, pages 149–152.
- Niladri Sekhar Dash and L Ramamoorthy. 2019. [Utility and application of language corpora](#). Springer.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. [Bert: Pre-training of deep bidirectional transformers for language understanding](#).
- Paul Ekman. 1993. Facial expression and emotion. *American psychologist*, 48(4):384.
- Sepp Hochreiter and Jürgen Schmidhuber. 1997. [Long Short-Term Memory](#). *Neural Computation*, 9(8):1735–1780.
- Chenyang Huang, Amine Trabelsi, and Osmar R. Zaiane. 2019. [ANA at semeval-2019 task 3: Contextual emotion detection in conversations through hierarchical lstms and BERT](#). *CoRR*, abs/1904.00132.
- N. Irtiza Tripto and M. Eunus Ali. 2018. [Detecting multilabel sentiment and emotions from bangla youtube comments](#). In *2018 International Conference on Bangla Speech and Language Processing (ICBSLP)*, pages 1–6.
- Klaus Krippendorff. 2011. [Agreement and information in the reliability of coding](#). *Communication Methods and Measures*, 5(2):93–112.
- Yuni Lai, Linfeng Zhang, Donghong Han, Rui Zhou, and Guoren Wang. 2020. [Fine-grained emotion classification of chinese microblogs based on graph convolution networks](#). *World Wide Web*, 23(5):2771–2787.
- Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. 2015. Deep learning. *nature*, 521(7553):436–444.
- Joseph E LeDoux and Stefan G Hofmann. 2018. [The subjective experience of emotion: a fearful view](#). *Current Opinion in Behavioral Sciences*, 19:67–72. Emotion-cognition interactions.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. [Roberta: A robustly optimized BERT pre-training approach](#). *CoRR*, abs/1907.11692.
- D. Magatti, S. Calegari, D. Ciucci, and F. Stella. 2009. [Automatic labeling of topics](#). In *2009 Ninth International Conference on Intelligent Systems Design and Applications*, pages 1227–1232.
- Arun S Maiya. 2020. ktrain: A low-code library for augmented machine learning. *arXiv preprint arXiv:2004.10703*.
- Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.
- Aditya Pal and Bhaskar Karn. 2020. Anubhuti—an annotated dataset for emotional analysis of bengali short stories. *arXiv preprint arXiv:2010.03065*.
- Flor Miriam Plaza del Arco, Carlo Strapparava, L. Alfonso Urena Lopez, and Maite Martin. 2020. [EmoEvent: A multilingual emotion corpus based on different events](#). In *Proceedings of the 12th Language Resources and Evaluation Conference*, pages 1492–1498, Marseille, France. European Language Resources Association.

H. A. Ruposh and M. M. Hoque. 2019. [A computational approach of recognizing emotion from bengali texts](#). In *2019 5th International Conference on Advances in Electrical Engineering (ICAEE)*, pages 570–574.

Sagor Sarker. 2020. [Banglabert: Bengali mask language model for bengali language understading](#).

Sagor Sarker. 2021. Bulp: Natural language processing toolkit for bengali language. *arXiv preprint arXiv:2102.00405*.

Omar Sharif and Mohammed Moshiul Hoque. 2021. [Identification and classification of textual aggression in social media: Resource creation and evaluation](#). In *Combating Online Hostile Posts in Regional Languages during Emergency Situation*, pages 9–20, Cham. Springer International Publishing.

Appendices

A Model Hyperparameters

Classifier	Parameters
LR	optimizer = ‘lbfgs’, max_iter = 400, penalty = ‘l1’, C=1
SVM	kernel=‘linear’, random_state = 0, γ =‘scale’, tol=‘0.001’
RF	criterion=‘gini’, n_estimators = 100
MNB	α = 1.0, fit_prior = true, class_prior = none,

Table 6: Optimized parameters for ML models

Hyperparameter	Value
Fit method	‘auto_fit’
Learning rate	2e-5
Epochs	20
Batch size	12,16
Max sequence length	70

Table 8: Optimized hyperparameters for transformers models

Hyperparameters	Hyperparameter Space	CNN	BiLSTM	CNN + BiLSTM
Filter Size	3,5,7,9	7	-	3
Pooling type	‘max’, ‘average’	‘max’	-	‘max’
Embedding Dimension	30, 35, 50, 70, 90, 100, 150, 200, 250, 300	100	100	100
Number of Units	16, 32, 64, 128, 256	64	32	64,64,32
Neurons in Dense Layer	16, 32, 64, 128, 256	64	16	-
Batch Size	16, 32, 64, 128, 256	16	16	16
Activation Function	‘relu’, ‘tanh’, ‘softplus’, ‘sigmoid’	‘relu’	‘relu’	‘relu’
Optimizer	‘RMSprop’, ‘Adam’, ‘SGD’, ‘Adamax’	‘Adam’	‘Adam’	‘Adam’
Learning Rate	0.5, 0.1, 0.05, 0.01, 0.005, 0.001, 0.0005, 0.0001	0.001	0.001	0.001

Table 7: Hyperparameters for DNN methods

B Data Examples

Data	Class
যা শুনলাম সত্যিই অসাধারণ ছিল। কিছু মানুষের জীবনে জমা স্বপ্ন গুলো সত্যি হয়। তোমায় না দেখলে তা বুঝতে পারতাম না। (What I heard was really awesome. Some people's dreams come true. I couldn't understand it without seeing you.)	Joy
রিয়াকে আমি কয়েক বছর আগে দেখেছিলাম। অনেক হাসিখুশি, মিষ্টি একটা মেয়ে ছিল। কিন্তু আজকে সেই উচ্ছলতা কোথায় যেন বিলীন হয়েছে। (I saw Riya a few years ago. She was a very happy, sweet girl. But today, that fun seems to have disappeared.)	Sadness
ফালতু নিউজ, পত্রিকা বিক্রি বন্ধ হয়ে যাচ্ছে তাই এরকম মিথ্যা তথ্য দিচ্ছে আর মানুষকে মৃত্যুর মুখে ঠেলে দিতে চাচ্ছে এই পুজিবাদী শালারা। (False news, magazines are being stopped selling so they are giving such false information and these capitalist bastards are trying to push people to the brink of death.)	Anger
লাশের মিছিল হবে এবার। চোখের সামনে লাশ পড়ে থাকবে, দাফন করতে আসবেনা কেউ। সেই দিন আসতেসে, বেশি দেরী নাই ভাই। There will be a procession of corpses this time. The dead bodies will be lying in front of the eyes, no one will come to bury it. That day is coming soon brother.)	Fear
বলতে লজ্জা হয় কিন্তু সত্য হচ্ছে জাতি হিসাবেই আমরা ধর্ষণকারী এবং বর্বর প্রকৃতির। নাহলে কিভাবে সম্ভব, অন্যের মোবাইল নম্বর সোশ্যাল মিডিয়াতে পোস্ট করা! (It is a shame to say but the truth is that as a nation we are rapist and barbaric in nature.) Otherwise, how is it possible to post someone else's mobile number on social media !)	Disgust
আমি সিগারেটের ধোঁয়া ছাড়তে গিয়ে বিষম খেয়ে গেলাম! ছোট্ট একটা মেসেজ। "আমি আসছি!" নিজের চোখকে বিশ্বাস করতে পারছিলামনা যে সে আসলেই আসছে। (I was smoking and got shocked! A short message. "I'm coming!" I couldn't believe my eyes that he was really coming.)	Surprise
পাত্রী দেখতে এসে পাত্রীর মুখে এমন অদ্ভুত প্রশ্ন শুনে আমার সামনে বসে থাকা ভদ্রলোক যে বেশ অবাক হয়েছেন তা আমি বুঝতে পারছি। (I understand that the gentleman sitting in front of me was quite surprised to hear such a strange question on the face of the bride when she came to see him)	Surprise
মহিলার চেহারায কোন অভিব্যক্তি নেই তিনি হাউমাউ কান্নায় ভেঙ্গে পড়লেন। (There was no expression on the woman's face and she broke down in tears.)	sadness
সেই তিনি মাঝ না পরার জন্য তিনজন বয়স্ক লোককে কানে ধরাচ্ছে খুবই দুঃখজনক। (It is very sad that he is holding the ears of three old men for not wearing a mask.)	sadness
অনেকেই তাদের ব্যস্ততার মাঝে সময় করে উইশ করছেন, অনেকে উইশ করেন নাই, কিন্তু মন থেকে দোয়া করছেন। সকলের নিকট আমি কৃতজ্ঞ। (Many are wishing in their busy time, many are not wishing but praying from the heart. I am grateful to everyone.)	joy
শত চেষ্টা থাকার সত্ত্বেও এই আতংকিত পরিস্থিতির মধ্যে বাসা থেকে যেতে না দেওয়ায় উপস্থিত হতে পারলাম নাহ। (Despite hundreds of attempts, I could not attend because I was not allowed to leave the house in this panic situation.)	fear
বাংলাদেশের মানুষদের মধ্যে একটা আইডেন্টিটি ক্রাইসিসে ভুগার মেন্টালিটি আছে, যে যে পেশায় না ঠিক অন্য পেশার মানুষকে গালি দিতে এক সেকেন্ডও সময় নেয়না। (There is an identity crisis mentality among the people of Bangladesh that they don't take even a second to abuse people of other professions.)	disgust
পাপন মাদারচোদ একে একে সব ক্রিকেটারের ক্যারিয়ারে এভাবে ধ্বংস করে ছাড়বে যেমন সাকিবকে করছে। (Papon Motherchod will destroy the careers of all cricketers one by one as done to Shakib.)	anger

Table 9: Sample instances in BEmoC.