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BANGLA ASPECT-BASED SENTIMENT ANALYSIS BASED ON CORRESPONDING TERM EXTRACTION

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***Abstract*— Aspect-based sentiment analysis is a text analysis technique that extracts and separates each aspect term and identifies the sentiment polarity associated with each aspect term. Bangla is the seventh most spoken language in the world. Sentiment analysis in the Bangla language is considered a crucial and well-timed research topic. Aspect-based sentiment analysis of the Bangla language is treated as a complicated task because of the scarcity of resources like annotated datasets, corpora, etc. In this research, we have proposed a new technique named PSPWA (Priority Sentence Part Weight Assignment) to perform aspect category or term extraction on publicly available datasets named Cricket and Restaurant. We have used conventional supervised learning algorithms and Convolutional Neural Network (CNN) to demonstrate results. Dataset preparation, feature engineering, description of PSPWA, CNN architecture, experimental results along with a state-of-art comparison has been shown in this paper. The public dataset was imbalanced. CNN has performed better among other learning algorithms. CNN has achieved an f1-score of 0.59 and 0.67 for the cricket and the restaurant dataset respectively.**

Keywords*— *Sentiment Analysis, Aspect Based Sentiment Analysis (ABSA), Aspect Terms Extraction, Bangla ABSA

I. INTRODUCTION

The number of social media users is increasing enormously. At least 3.96 billion people across the world are using social media today, equating to 51% of the total global population. On average, they are spending 2 hours and 22 minutes using social media each day [1]. Alike, online shopping is popularizing day by day. An estimation of 1.79 billion people buys digital goods worldwide in 2019. The forecast says the number of online buyers will increase by over 2.14 billion in 2021 [2]. People on the internet are from different regions, casts, cultures, and languages. As a result, a large number of online contents are generated every day in various aspects. According to Forbes, 2.5 quintillion bytes of data are created each day at the current pace [3].

In 2020, the world has met an unexpected situation due to the Covid-19 pandemic. People have to stay at home to stay safe. But necessity has no bound. They have to buy daily essentials. In this situation, people have bought their food from the restaurant, grocery from the super shop, medicine from the medicine shop through e-Commerce. A survey found people are spending on an average of 10-30% more online and e-commerce sales increased significantly (grocery 250%, restaurants food 18.88%, hygienic good 300%) [4]. A significant number of documents, reviews, comments generated daily through the web, mobile apps, social media, etc. around the world in various languages. It is hard to read all the content and extract the people's sentiment from those contents. So, sentiment analysis (SA) will be the right option to extract the hidden sentiment of the contents.

Before buying goods or settling any decision on the internet, people are very much aware of checking or verifying reviews, comments, any related documents, social posts, etc. Traditional SA predicts the overall sentiment of reviews or texts and provides a narrow insight. Unlike, ABSA performs a fine-grained analysis that identifies each aspect of the given documents or reviews and calculates the polarity score associated with each aspect term. This level of analysis is capable of discovering complex opinions from reviews [5]. In this paper, we have introduced a new technique named PSPWA in data pre-processing step for achieving improved performance on the dataset than previous ABSA studies.

II. LITERATURE REVIEW

Liu, B. had first introduced ABSA in his research paper as a chapter. He had described the ABSA, its methods, and sub-problems [6]. Pontiki et al. divided the ABSA task into four sub-tasks to identify the aspects of given target entities and the sentiments expressed for each aspect in SemiVal-2014 [7]. Shindu et al. conducted ABSA research based on Amazon products using feature-level sentiment analysis in 2018 [8]. The same year, Cahyadi et al. built an ABSA model using bi-directional LSTM for opinion target expression extraction and Convolutional Neural Network (CNN) for sentiment polarity [9]. Pandey et al. had divided the ABSA task into five subtasks in 2019 [10]. Khin et al. used multi-attentive LSTM (MA-LSTM) using SenticNet as an external knowledge to improve accuracy [11]. Nandal et al. showed that Lexicon-Based presents less performance than the Machine Learning and Hybrid technique provides highly accurate results [12]. Nazir et al. conducted a study to find out the issues and challenges of ABSA in 2020 [13].

Rahman and Dey first introduced ABSA in the Bangla language in 2018. They provided two publicly available datasets for further analysis and built the baseline ABSA model [5]. The same year, they also developed the ABSA model based on the CNN. The study claimed CNN performs better than supervised learning algorithms [14]. Boidini, M. developed an ABSA model based on stacked auto-encoders in Bangla text and claimed a better f1-score than Rahman and Dey's research result in 2019 [15]. Wahid et al. conducted Sentiment Analysis using the ABSA dataset based on Recurrent Neural Network (RNN) with LSTM [16]. Haque et al. developed the ABSA model in Bangla based on Rahman and Dey's dataset and claimed a better f1-score result [17]. To the best of our knowledge, all authors had performed ABSA on Bangla dataset without applying any additional performance improvement technique in data pre-processing step.

III. Proposed Method

A. Dataset Collection

The dataset that has been used in this research was publicly available datasets which is the first time implemented ABSA model in Bengali by Rahman and Dey [5]. Two datasets named Cricket and Restaurant. Bengali people have an inclined about cricket and food. Generally, peoples would like to put their feedbacks on social sites, blogs, etc. about cricket and restaurant. This factor encouraged us to build for analyzing sentiments of Bengali people about Cricket and Restaurant. Table 1 represents the overall summary of both datasets. The dataset can be found at this link (https://github.com/AtikRahman/Bangla_ABSA_Datasets).

Table 1: Overall summary of datasets

	Cricket	Restaurant
No. of Sentence	2979	2059
Aspect Category	Batting, Bowling, Team Management, Team, Other	Food, Service Price, Ambiance Miscellaneous
Aspect Polarity	Positive (19%) Negative (72%) Neutral (9%)	Positive (59%) Negative (23%) Neutral (6%) Conflict (12%)

B. Pre Processing

We have preprocessed the dataset to make it useful for experiments. First of all, we have removed punctuation words, numerical words such as Dari('। '), Comma(','), Colon(';'), etc. from the dataset because those would not provide any values during the experiment.

C. Feature Engineering

The performance of machine learning models depends on perfect feature engineering. We have used Term Frequency and Inverse Document Frequency (TF-IDF) to tokenize the dataset into a number matrix to feed the machine learning model. TF-IDF identifies the most important and insignificant words from the dataset. The shape of the numbered matrix was (2980,3240) for cricket and (2112, 2449) for the restaurant dataset after applying TF-IDF.

Constant features and correlated features are a major concern in natural language processing. Constant features are those values that do not affect the target outputs. Thus, it can be ignored because it is only the unnecessary data of the dataset that increases the model complexity. We have removed constant features from the number matrix by a threshold value of 0.005. Correlated features are those values that are influenced by some common mechanism in linear space. We have removed correlated features from the numbered matrix by a threshold value of 0.75. The filtered matrix shape was (2980, 2949) for cricket and (2112, 2202) for restaurant dataset. The filter matrix represents in the form of $Matrix_{i,j}$.

D. Priority Sentence Part Weight Assignment (PSPWA)

In the ABSA model, the aspect terms rely on the NOUNS present in the sentence [18]. To extract aspect categories, we have only considered NOUNS because a NOUN is a word that functions as the name of some specific object or set of objects. We have concluded that NOUNS are the priority word and part of the sentence holding NOUNS are the priority sentence part. We have improved our research on the PWWA algorithm to build a new technique PSPWA [19]. Figure 1 shows the complete process of the proposed model.

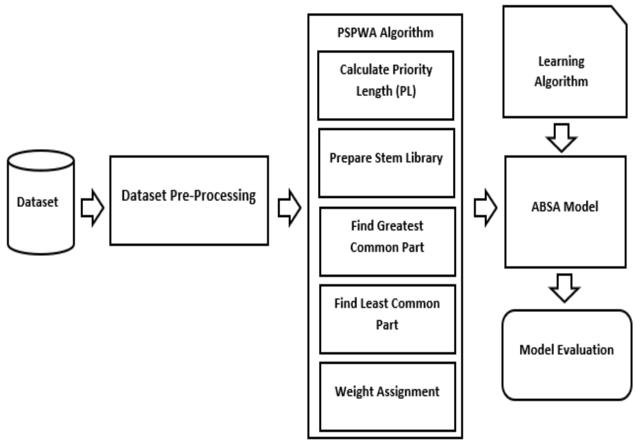

Figure 1: Process chart of the proposed model

a) Priority Length (PL):

After analyzing the dataset manually, we have proposed an equation to find out the priority part based on the length of a sentence. The proposed equation returned an integer value as a priority length. We have only considered the words between the first and the priority length position in a sentence for the PSPWA technique. The equation of priority length, PL is below. Table 2 represents an example of a splitting sentence based on PL.

$$PL = MIN(LEN\ (SENTENCE), 3) + \frac{LEN\ (SENTENCE)}{3} - 1 \qquad (1)$$

Table 2: Example of splitting sentence based on PL

Sentence	PL	Priority Part	Other	Aspect Category
বাংলাদেশের জাতীয় দলের সবাই ভালো খেলে	4	বাংলাদেশের জাতীয় দলের সবাই	ভালো খেলে	Team
বাংলাদেশের ব্যাটিং বিপর্যয়	3	বাংলাদেশের ব্যাটিং বিপর্যয়		batting
খাদ্য হিসেবে খুব সাশ্রয়ী	3	খাদ্য হিসেবে খুব	সাশ্রয়ী	Food

b) Stem / Root Form of Verb

Root words/stems are base forms of words to which affixes (suffix, prefix, etc.) can be attached but expressed the same context. Consider the following group of words বাংলাদেশ, বাংলাদেশী, বাংলাদেশের. The stem for these words is বাংলাদেশ.

c) Greatest Common Part & Least Common Part

১. বাংলাদেশ আজকে জিতবে ২. আমি বাংলাদেশ সাপোর্ট করি
৩. বাংলাদেশী হিসেবে আমি গর্বিত ৪. বাংলাদেশের প্রান সাকিব হাসান

Greatest Common Part (GCP) is the greatest occurrence sentence part in the dataset of any stem. Least Common Part (LCP) is the least occurrence sentence part in the dataset of any stem. In above four sentences, all stems of "বাংলাদেশ" presents in the priority part. Here, GCP is the Priority Part. Here, LCP is Other Part.

d) Weight Assignment

The most crucial part to develop the PSPWA technique is weight assignment for each word in the dataset. So, we have assigned an initial weight of zero (0) for each word and increased weight depending on some criteria. Below we have described each criterion gradually. An example sentence ("বাংলাদেশের জাতীয় দলের সবাই ভালো খেলে") illustrates this.

The PL of the above sentence is four. We have converted the words of the sentences to its stem because words from the same stem are identical in terms of context [20]. If any word presents in the priority part then we have increased the weight by one. The word "বাংলাদেশের" presents in the priority part. So, $W_{\text{বাংলাদেশের}} = W_{\text{বাংলাদেশের}} + 1$. If the sentence part of the word ("বাংলাদেশের") matched with the GCP of the stem then we have increased the weight of that word by one. The sentence's part of the word ("বাংলাদেশের") is the priority part and the GCP is also priority part. So, $W_{\text{বাংলাদেশের}} = W_{\text{বাংলাদেশের}} + 1$. If the sentence part of the word ("বাংলাদেশের") did not match with the LCP of the stem then we have increased the weight of that word by one. The sentence's part of the word ("বাংলাদেশের") is the priority part but the LCP is the other. So, $W_{\text{বাংলাদেশের}} = W_{\text{বাংলাদেশের}} + 1$. After that, if the weight of the word is greater than zero then we have multiplied the weight of each word with the corresponding value of that word of the TF-IDF matrix and replaced the corresponding word value of the TF-IDF matrix with the weight. We have applied the process for all items of the dataset.

$$Matrix_{i,j} = Matrix_{i,j} \times W_{i,j} \;\; ; \text{if } W_{i,j} > 0 \qquad (2)$$

E. Normalization

We have applied normalization because deep learning algorithms converge faster on [0...1]. We have applied a Min-Max classifier to transform all features into the range [0, 1] [21]. That means, the minimum value of any feature could be 0 and the maximum value of any feature could be 1. The equation of the Min-Max classifier is shown below.

$$Matrix_{i,j_{Scaled}} = \frac{Matrix_{i,j} - MIN\,(Matrix_{i,j})}{MAX\,(Matrix_{i,j}) - MIN\,(Matrix_{i,j})} \qquad (3)$$

F. Methodology

We have used several conventional supervised learning algorithms such as KNN, SVM, LR, RF and NB along with CNN to evaluate the proposed method. Various hyperparameters have been tried to maximize model performance. Table 3 shows the final value of the parameters that have been used in the experiment. Table 4 represents the proposed CNN architecture.

Table 3: Parameter list of CNN and supervised learning algorithms

Classifier	Parameter
KNN	No of neighbors = 3, Metric = Euclidean
SVM	Max iterations =1000, Multi class = 'ovr'
LR	Solver = 'sag', Max iterations = 150,
RF	Criterion = 'gini', No of estimators=150
CNN	Optimizer = 'adam', Learning rate = 0.0005, Batch Size = 100, Epochs = 20, Convolution Activation = 'relu', Dense Activation = 'softmax', Loss Function = 'crossentorpy'

Table 4: Proposed CNN architecture

CNN Architecture

1. Embedding (Input: Matrix Size, Output: 32×32)
2. CONV 1D (Filter = 3, Kernel = (32× 32), Stride = (1×1), Padding = "same", Activation = relu)
3. Max Pooling 1D (Pool = (2×2))
4. Dropout (25%)
5. Flatten
6. Dense 1 (Units = 512, Activation = relu)
7. Dense 2(Units =5, Activation = softmax)
8. End For

CNN is divided into two steps. The steps are feature extraction and classification. Feature extraction is a combination of a series of the convolutional and pooling layers. The first CONV layer identifies low-level features and adding more CONV layers makes the network adapt high-level features. The classification step is the fully connected layer and classifies the output based on CONV layers information. ADAM has been used as an optimizer with a learning rate of 0.0005 because ADAM converges faster than gradient descent [22]. Cross-entropy has been used as a loss function because it performs better than mean squared error [23]. RELU has been used as a convolutional activation function as it converts all negatives to zero; the other remains the same and tends to show better convergence performance than sigmoid. Overfitting is a major problem in deep learning and dropout is a solution to addressing this issue [24]. The proposed CNN had seven (7) layers. In the embedding layer, the TF-IDF numbered matrix is used as input and output as a 32×32 matrix which will be used as input in the CONV layer. In the CONV layer, where kernel size is (32×32), padding is "same" because of the output matrix of the CONV layer needs to be the same as input (32×32), the stride is (1×1) with filter size is 3. In the pooling payer, max poling used with pool size is 3×3. 25% of dropout has been applied after the CONV layer. After that, flatten the layer and use a Dense layer with 512 units. Five (5) units Dense with SOFTMAX activation has used in the output.

IV. Experimental Results and Analysis

A. Experimental Environment

Conventionally deep learning requires a strong CPU and GPU. We have used a core i5 processor, 16 GB ram, and 1 GB graphics card as an experimental environment. We have used python as a programming language with KERAS running on TensorFlow background.

B. Training and Test Dataset

We have split the dataset into two parts as a training dataset and a test dataset. We have used 80% of the dataset as a training dataset and 20% of the dataset as a test dataset. In the training dataset, we have used 20% of the training data as validation data.

C. Result Analysis

We have presented evaluation matrices such as f1-score, precision, and recall to evaluate the model performance using supervised learning algorithms and CNN. The True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are four parameters to measure the terms f1-score, precision, and recall. Table 5 represents the experimental results for both datasets. The formulas are, Precision (P) $= \frac{TP}{TP+FP}$ (4), Recall (R) $= \frac{TP}{TP+FN}$ (5) and F1 Score (F) $= 2 \times \frac{R \times P}{R+P}$ (6)

Table 5: Experimental results of the proposed method for datasets

Dataset	Classifier	Precision	Recall	F1-Score
Cricket	SVM	0.47	0.51	0.48
	KNN	0.33	0.38	0.31
	RF	0.41	0.57	0.41
	LR	0.45	0.53	0.48
	NB	0.36	0.48	0.39
	CNN	0.58	0.61	0.59
Restaurant	SVM	0.51	0.54	0.52
	KNN	0.39	0.46	0.39
	RF	0.35	0.50	0.35
	LR	0.44	0.55	0.44
	NB	0.37	0.47	0.34
	CNN	0.71	0.63	0.67

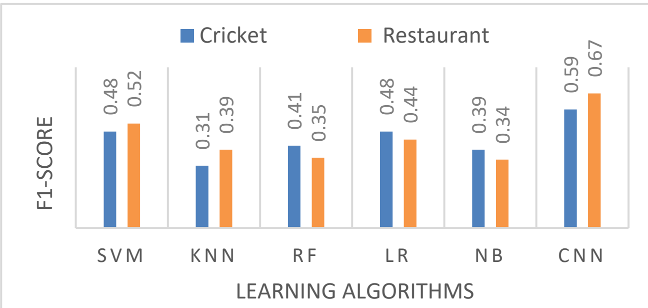

Figure 2: Representation of f1-score of both datasets

The results demonstrate, for both Cricket and Restaurant dataset, CNN has achieved the highest precision score as 0.58, 0.71 and recall score as 0.61, 0.63 for both datasets respectively. F1-score is more useful than other machine learning evaluation matrices when the dataset is imbalanced. As our dataset was imbalanced, we have used F1-score to measure the performance of the proposed model. CNN has achieved the highest F1-score, which was 0.59 and 0.67 for cricket and restaurant dataset respectively. Figure 2 shows the f1-score of both datasets.

D. Result Comparison

A state-of-art comparison has been shown in this paper in terms of methodology, F1-score. Only a few pieces of research have been done on the Bangla language because the baseline evolved in the middle of 2018. Table 6 shows a comparison between previous works and the proposed method. Figure 3 shows a comparison graph of the best f1-score between the proposed method and previous works.

Table 6: Result comparison of previous works

Works	Rahman and Dey 2018 [5, 14]	Haque et. al., 2020 [17]	Proposed Method
Dataset	Cricket (C), Restaurant (R)		
Methodology	KNN, SVM, RF, CNN	KNN, SVM, RF, LR, NB	KNN,SVM,RF, LR, NB, CNN
Evaluation Matrices	Recall, Precision, F1-Score		
F1-SCORE	**SVM**(C=0.35, R=0.38) **KNN**(C=0.25, R=0.42) **RF**(C=0.37, R=0.33) **CNN**(C=0.51, R=0.64)	**SVM**(C=0.35, R=0.39) **KNN**(C=0.27, R=0.38) **RF**(C=0.37, R=0.35) **LR**(C=0.37, R=0.43) **NB**(C=0.37, R=0.17)	**SVM**(C=0.48, R=0.52) **KNN**(C=0.31, R=0.39) **RF**(C=0.41, R=0.35) **LR**(C=0.48, R=0.44) **NB**(C=0.39, R=0.34) **CNN**(C=0.59, R=0.67)

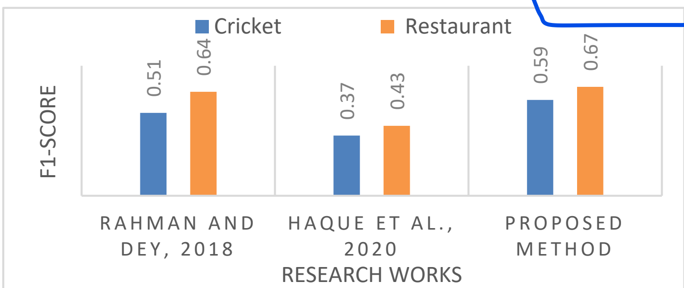

Figure 3: Comparison of best f1-score of research works

E. Discussion

a) The feature engineering has reduced the dataset shape by excluding the constant and correlated features which results in low processing and an efficient learning model.

b) The PSPWA technique replaced the TD-IDF score of the numbered matrix by assigning a new weight provided by the PSPWA technique for all words of the dataset.

c) During training CNN, we have seen that for both datasets the model was overfitting. 25% of dropout has been applied to reduce overfitting after the CONV layer. But it reduced the overfitting slightly but the model was still overfitting. Overfitting can be reduced by adding more training samples or reducing features. Feature engineering step already reduced the number of features but since datasets were public datasets adding more samples were ignored. Figure 4 and 5 show the training & validation accuracy and loss curves of both datasets.

d) The CNN performed better than conventional supervised learning and achieved f1-score of 0.59 and 0.67 for cricket and restaurant dataset respectively.

e) Applying PSPWA in data pre-processing step has helped to improve the F1-Score than previous studies.

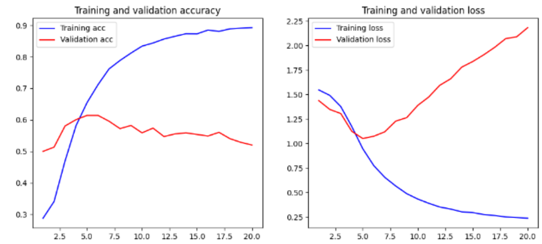

Figure 4: CNN accuracy and loss curves of cricket dataset

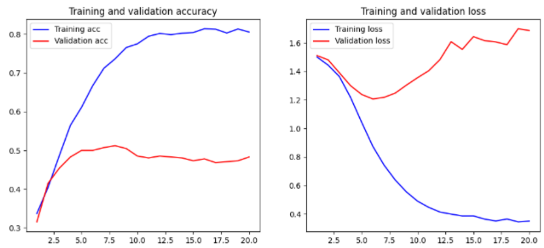

Figure 5: CNN accuracy and loss curves of restaurant dataset

V. Conclusion

In this research, we have presented a new technique named PSPWA for extracting aspect terms from the given dataset that improved the F1-score when applied to the dataset. Because of our limitation, we have researched public datasets but in the future, we will build our dataset for advanced research. The ABSA model divides into two parts as aspect terms extraction and aspect polarity determination. In this research, we have done the first part. In the future, we will work on identifying sentiment associated with each aspect.

VI. References

[1] "GLOBAL SOCIAL MEDIA STATS," [Online]. Available: https://datareportal.com/social-media-users/, [Accessed: 5 October 2020].

[2] "Number of digital buyers worldwide from 2014 to 2021," [Online]. Available: https://www.statista.com/statistics/251666/number-of-digital-buyers-worldwide/, [Accessed: 5 October 2020].

[3] "How Much Data Do We Create Every Day," [Online]. Available: https://www.forbes.com/sites/bernardmarr/2018/05/21/, [Accessed: 6 October 2020].

[4] "Product categories shifting during covid 19," [Online]. Available: https://www.bigcommerce.com/blog/covid-19ecommerce/, [Accessed: 6 October 2020].

[5] M. A. Rahman and E. K. Dey, "Datasets for aspect-based sentiment analysis in bangla dataset". MDPI Journals, 2018, doi: 10.3390/data3020015.

[6] B. Liu, "Sentiment Analysis and Opinion Mining". Synthesis Lectures on Human Language Technologies, Morgan & Claypool Publishers, 2012.

[7] M. Pontiki, D. Galanis, J. Pavlopoulos, H. Papageorgiou, I. Androutsopoulos, and S. Manandhar, et al, "SemEval-2014 Task 4: Aspect Based Sentiment Analysis". Association for Computational Linguistics, pp 27-35, 2014.

[8] C. Sindhu, S. N. Deo, Y. Mukati, G. Sravanthi and S. Malhotra, "Aspect Based Sentiment Analysis Of Amazon Product Reviews". International Journal of Pure and Applied Mathematics, vol. 118, pp. 151-157, 2018.

[9] A. Cahyadi and M. L. Khodra, "Aspect-Based Sentiment Analysis Using Convolutional Neural Network and Bidirectional Long Short-Term Memory". 5th International Conference on Advanced Informatics: Concept Theory and Applications, 2018, doi: 10.1109/ICAICTA.2018.8541300.

[10] S. V. Pandey and A. V. Deorankar, "A Study of Sentiment Analysis Task and It's Challenges". IEEE International Conference on Electrical, Computer and Communication Technologies, 2019, doi : 10.1109/ICECCT.2019.8869160.

[11] W. L. K. Khin and N. T. Aung, "Applying Deep Learning Approach to Targeted Aspect-based Sentiment Analysis for Restaurant Domain". International Conference on Advanced Information Technologies, 2019, doi : 10.1109/AITC.2019.8920880.

[12] N. Nandal, J. Pruthi and A. Choudhary, "Aspect Based Sentiment Analysis Approaches with Mining of Reviews: A Comparative Study". International Journal of Recent Technology and Engineering, issn. 2277-3878, vol. 7, 2019.

[13] A. Nazir, Y. Rao, L. Wu and L. Sun, "Issues and Challenges of Aspect-based Sentiment Analysis". IEEE Transactions on Affective Computing, issn. 1949-3045, pp. 1-1, 2010.

[14] M. A. Rahman and E. K. Dey, "Aspect Extraction from Bangla Reviews using Convolutional Neural Network". 7th International Conference on Informatics, Electronics & Vision and 2nd International Conference on Imaging, Vision & Pattern Recognition, 2018, doi: 10.1109/ICIEV.2018.8641050.

[15] M. Bodini, "Aspect Extraction from Bangla Reviews Through Stacked Auto-Encoders". MDPI Journals, 2019, doi:10.3390/data4030121.

[16] 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". International Conference on Bangla Speech and Language Processing, 2019, doi: 10.1109/ICBSLP47725.2019.201500.

[17] S. Haque, T. Rahman, A. K. Shakir, M. S. Arman, K. B. B. Biplob, F. A. Himu, D. Das, et al, "Aspect Based Sentiment Analysis In Bangla Dataset Based On Aspect Term Extraction". 2nd International Conference on Cyber Security and Computer Science, 2020.

[18] S. Chowdhury and W. Chowdhury, "Sentiment Analysis for Bangla Microblog Posts", unpublished.

[19] M. S. J. Jamil, F. A. Naim, B. Ahamed and M. N. Huda, "Customer Review Analysis by Hybrid Unsupervised Learning Applying Weight on Priority Data". International Joint Conference on Advances in Computational Intelligence, 2020.

[20] T. Tabassum, J. J. Jammy and S. Ismail, "A corpus based unsupervised Bangla word stemming using N-gram language model". International Conference on Informatics, Electronics and Vision, 2016, doi: 10.1109/ICIEV.2016.7760117.

[21] A. S. A. Rabby, S. Abujar, S. Haque and S. A. Hossain, "Bangla Handwritten Digit Recognition Using Convolutional Neural Network". Advances in Intelligent Systems and Computing, Springer, vol.755, pp. 111-122, 2018.

[22] M. Hamed and A. A. E. Desouky, "Effect of Learning Rate on the Recognition of Images", Active and Passive Electronic Components 19(1), 1996, doi: 10.1155/1996/45086.

[23] J. Czarnecki and W. M. Czarnecki, "On Loss Functions for Deep Neural Networks in Classification". arXivLabs, 2017, arXiv:1702.05659.

[24] S. M. A. Hakim and Asaduzzaman, "Handwritten Bangla Numeral and Basic Character Recognition Using Deep Convolutional Neural Network". International Conference on Electrical, Computer and Communication Engineering, 2019, doi: 10.1109/ECACE.2019.8679243.