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Sentiment Analysis on Bangla Food Reviews Using Machine Learning and Explainable NLP

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***Abstract*—Sentiment analysis (SA) is a sub-field of natural language processing (NLP) which can extract valuable insights from textual data of a language. Food review analysis is a trending domain of SA which become very useful as internet dependency has rapidly shifted people's food ordering preferences from restaurants to online platforms. This work focuses on examining various machine learning (ML) and deep learning (DL) algorithms for Bangla sentimental analysis on food reviews using a new dataset of 44,491 reviews collected from various restaurant Facebook pages and groups. Furthermore, in this study, we utilized the explainable NLP to interpret why a model is performing well or poor. Random Forest (RF) and Convolutional Neural Network-Bidirectional Gated Recurrent Unit (CNN-BiGRU) models outperformed other models and achieved the highest accuracy of 88.73% and 90.96% from ML and DL domains respectively. Friedman statistical test was performed on the obtained results and the test results are significant at $p<0.05$. "দর" is the best feature that is responsible for the hybrid DL (CNN-BiGRU) model to classify reviews more accurately.**

Keywords*— *Sentiment Analysis, Food Review Analysis, CNN, Bi-GRU, Explainable NLP

I. INTRODUCTION

Sentiment analysis (SA) is the process of predicting the sentiments or emotions of a set of text data [1]. SA is a subfield of natural language processing (NLP), has emerged as a critical tool for extracting valuable insights from textual data by discerning the emotional tone and underlying sentiment conveyed by the language used [2]. Sentiment Analysis basically focuses on assessing people's opinions, feelings, and emotions [3].

Nearly 250 million people speak Bangla as their first language, and 160 million of them are Bangladeshis [4]. While Bangla is still in the developing stage, the majority of research studies and publicly accessible datasets on sentiment analysis are restricted to English and other resource-rich languages like Arabic, Turkish, Hindi and Urdu [5]. Bangla is a language with a rich morphology that has developed over thousands of years with its longstanding customs, including numerous dialects. Bangla presents both challenges and opportunities for developing effective sentiment analysis techniques that can accurately capture the sentiment conveyed in Bangla texts across various domains [6]. In this work, we mainly focus on the food review domain of SA. The participation of Bangladeshi residents in internet activities is also rapidly increasing. Reviews of food and food distribution systems are fascinating sections. In our country, there are a rising number of online food delivery services [7]. The majority of Bangladeshis provide insightful feedback in Bangla on social media [2]. In addition to English, users also post comments in Bangla as well examining several blogs and social media [6]. There are many application areas of food review sentimental analysis such as the analysis of food delivery services [8], food quality analysis [9], financial market analysis [10] and customer satisfaction tracking [11] etc.

The majority of research on multi-class SA has been done using machine learning (ML) or deep learning (DL) algorithms to predict positive, negative or neutral sentiments. This work focuses on detecting the correct sentiments on Bangla food reviews accurately using learning models as well as explains the reason for performing with better or worse results using explainable NLP. The followings are the contributions of the proposed work:

1) Created a new specialized SA dataset on food reviews consisting of 44,491 reviews from several Facebook pages and groups.
2) Examining various ML and DL algorithms and make a comparative study among them.
3) The introduction of the proposed novel hybrid DL (CNN-BiGRU) method which outperforms all other algorithms.
4) Applying explainable NLP to explain why a model is producing good or bad results using LIME and SHAP modules.

The organization of this article: Section 2 demonstrates the related works, Section 3 is for the proposed methodology for Bangla SA on food reviews, Section 4 describes the experimental results analysis and discussions and Section 5 concludes the works with some future remarks.

II. RELATED WORKS

Some of the recent studies of Bangla SA on food reviews are discussed and summarized here.

In 2023, M. I. H. Junaid et al. [2] proposed a method based on machine learning for sentimental analysis of food reviews in Bangla by creating a dataset of only 1040 reviews from Foodpanda and Hungrynaki and showed that Long-Term Short-Term Memory (LSTM) deep learning model outperformed others with an accuracy of 90.89%. M. Hasan et al. [6] studied a method concerned on the Bangla SA topic based on "Russia-Ukraine war". A total of 10,861 Bangla comments were collected and labeled with three polarity sentiments, namely Neutral, Pro-Ukraine (Positive), and Pro-Russia (Negative). They used several transformer language models including BanglaBERT, XLM-RoBERTa-base, XLMRoBERTa-large, Distil-mBERT and mBERT and showed by experiments that BanglaBERT outperformed baseline and all the other transformer-based classifiers. Another method from 2023 proposed by E. R. Rhythm et al. [7] studied delved into SA on restaurant reviews sourced from Bangladeshi food delivery apps. They created a dataset named "Bangladeshi Restaurant Reviews" covering 15,018 instances by collecting customer feedback from popular apps like Foodpanda and Hungrynaki. They employed Robustly Optimized BERT Pretraining Approach (RoBERTa), AFINN, and DistilBERT models and obtained accuracy of 74%, 73% and 77% respectively. In 2023, another new study was performed by Bitto et al. [12] for the user reviews collected from food delivery startups. They collected 1400 reviews from 4 food delivery Facebook pages and applied bipolar SA. Applying ML and DL algorithms, they obtained highest accuracy 89.64% using XGB and 91.07% from LSTM classifier. A supervised deep learning classifier based on CNN and LSTM to conduct multi-class SA on Bengali social media comments was proposed by R. Haque et al. [13] in 2023. The performance of their proposed CLSTM (Convolutional Long Short-Term Memory) architecture greatly improved the performance of SA with 85.8% accuracy and 0.86 f1-score on a labeled dataset of 42,036 Facebook comments. The recent studies [1-13] on Bangla food reviews prove that DL and hybrid methods are more promising than traditional ML approaches.

The studies performed on [9], [14] and [15] utilized datasets of 8435, 1000 and 2053 restaurant reviews respectively. Compared to the literature being studied [1-15] for Bangla SA on food reviews, it is observed that a rich dataset is always a crisis in Bangla language. To the best of our knowledge, we have developed one of the largest Bangla SA dataset on food reviews consisting of 44,491 reviews from several Facebook pages and groups. Explainable NLP is not utilized yet in the domain of Bangla food reviews analysis. In our proposed method, we will utilize these findings and try to cover up the knowledge gap in this domain of research.

III. PROPOSED METHODOLOGY FOR BANGLA SA ON FOOD REVIEWS

Our main goal of this study is to develop different ML and DL models that can differentiate among positive, negative and neutral Bangla food reviews. The overall functioning procedure of the proposed method is depicted in a nutshell in Fig. 1.

A. Dataset Preparation

In this study, we have gathered Bengali food reviews from several Facebook food blogs and groups, such as *Street Food Hunting, Dhaka Food Review, Food Review Jashore, Food Bloggers Barishal and Rafsan the Chotobhai*.

TABLE I. SUMMARY OF THE DATASET

Sentiment	No. of Reviews	Total Reviews
Positive	14,424	44,491
Negative	12,371	
Neutral	17,696	

Six Bangla native graduate students were involved in data collection process (4 males and 2 females) and 5 were involved in data annotation process (3 males and 2 females).The proposed dataset contains a total of 44,491 Bangla food reviews and we have shown the distribution of the dataset in Table I. We have split the proposed dataset into training and test sets as 90% and 10% respectively using holdout method. A total of 40,041 reviews were used for training models and 4,450 reviews were used for testing. Since the class distribution of the reviews are unequal, the dataset got an imbalanced distribution which may produce biased results [5]. So we have used the synthetic minority oversampling technique (SMOTE) to balance the proposed dataset.

B. Data Preprocessing

Data preprocessing is a prerequisite for any classification model to perform well [2]. The reviews we collected from Facebook contain spelling mistakes, punctuation marks, emojis, special characters and numerical values and so on. Depending on Bangla language, different preprocessing processes were applied such as tokenization, non-Bangla words removal, emoji removal, URL removal, cleaning, stop words removal and stemming etc.

1) Non-Bangla Words, Punctuation, URLs and Emoticon Removal: The dataset consists of many redundant or irrelevant elements that should be removed from the dataset to eliminate ambiguity. This includes removing non-Bangla words, punctuation, URLs, special characters, emoticon etc and so on. Data cleaning is performed on the dataset to get a reduced fresh version of dataset to work with.

2) Stop Words Removal: The words those are most frequently used in a language but do not carry any domain based information are referred to as stop words [4]. In Bangla "ও"(and), "এই"(this), "এবং"(and) etc are such examples of stop words. We have used the stop words list in this work, and removed them from the dataset.We have used the Bangla stop words[1] list and removed the stop words from our developed dataset. The review "এই রেস্তোরাতে খাবারগুলি অত্যন্ত মজাদার ও দারুণ ছিল", (the food at this restaurant was very tasty and great) become "রেস্তোরাতে খাবারগুলি অত্যন্ত মজাদার দারুণ" after the elimination of stop words.

3) Stemming: Stemming reduces words to their basic roots by removing suffixes while preserving the original meaning of the word [4]. In this work we have used "Bangla-Stemmer" library from the python's package for BNLP. Matching of unknown words having the same roots can be easily performed through stemming. The food review "এই রেস্তোরাতে খাবারগুলি অত্যন্ত মজাদার ও দারুণ ছিল" (the food at this restaurant was very tasty and great) after stemming become "রেস্তোরা খাবার অত্যন্ত মজা দারুণ'. The dataset becomes more precise after stemming is carried out.

C. Feature Extraction

Learning models always require numeric representation of data to work with, and the way of doing such task from texts is termed as feature extraction [7]. We have used the Term Frequency - Inverse Document Frequency (TF-IDF) which is the most widely used feature extraction method [12]. For TF-IDF, we have considered 50,000 features with an n-gram range from 1 to 3, which works according to equation (3).

[1]https://www.ranks.nl/stopwords/bengali

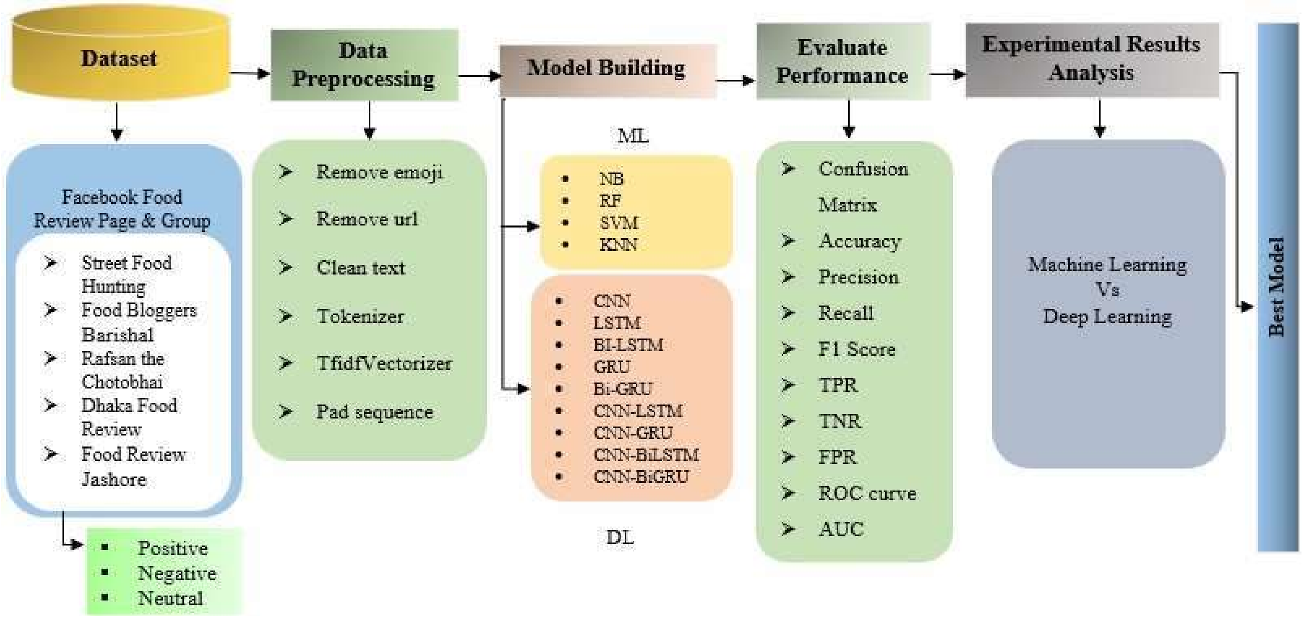

Fig. 1. Workflow of the Proposed Bangla Sentiment Analysis Method on Food Reviews

In equation (1) and (2) the terms *X*, *Y*, *P* and *Q* are the frequency of a word in a review, total number of words in the review, total number of review classes and number of review from the text classes contain the word respectively.

$$TF = \frac{X}{Y} \tag{1}$$

$$IDF = log_e \frac{P}{Q} \tag{2}$$

$$TF - IDF = TF \times IDF \tag{3}$$

D. SA Method for Bangla Food Reviews

The machine learning models we used for Bangla food review sentimental analysis are MNB, SVM, KNN, LR and RF and from deep learning we used CNN, LSTM, GRU, BiLSTM and BiGRU. Random Forest works by combining multiple decision trees to make predictions. It uses randomness in creating these trees and then combines their outputs through voting. This approach increases accuracy and prevents overfitting [4]. MNB is a probabilistic classifier works on the basis of Bayes theorem which is very time effective [10]. SVM finds the best linear separator (hyperplane) between classes in data space. It prioritizes the hyperplane that maximizes the distance from data points [11]. KNN is a lazy learner which often underperforms for text classification due to some issues [12]. DL models generally consist of embedding layer, hidden layers, fully connected layer and output layer. The experimental results of all the implemented algorithms are briefly described in section IV.

IV. Experimental Results Analysis and Discussion

The proposed work mainly focuses on detecting the correct sentiments on Bangla food reviews accurately using learning models as well as explains the reason for performing with better or worse results using explainable NLP. We consequently describe the performance metrics, obtained results analysis, Friedman test statistics, explainable NLP etc.

A. Performance Metric

The recent studies from [1-15] show that several evaluation metrics such as accuracy, f1-score, precision and recall etc are used to analyze a model's performance. Precision (equation 4) is the ratio of true positives (TP) to the true positives (TP) and false positives (FP) prediction. Recall (equation 5) is defined as the ratio of true positives (TP) to the true positives (TP) and false negatives (FN). F1-Score (equation 6) is defined as the harmonic mean of precision and recall and accuracy (equation 7) is calculated as the ratio of total true classified instances compared to all the instances.

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{7}$$

B. Obtained Results Analysis

For getting the best results, parameter tuning is a must in every classification task. From the ML and DL domain the best performed models are RF and CNN-BiGRU respectively. We have tuned the initial parameters for RF model as *n_estimators = 1.5* and *random state = 0*. Again, for the CNN-BiGRU model, the parameters are set to *max features = 50000*, *embedding dimension = 64*, *sequence length = 40*, *no. of filters = 128*, *kernel size = 3* and *dropout = 0.5* etc.

We have summarized the obtained results with and without SMOTE of the implemented ML algorithms in Table II. RF algorithm maintains its status as the best performer. We have summarized the obtained results with and without SMOTE of the implemented ML algorithms in Table II. RF algorithm maintains its status as the best performer.

TABLE II. OBTAINED RESULTS OF APPLIED MACHINE LEARNING ALGORITHMS; FRIEDMAN TEST: CHI-SQUARE = 10.04, P-VALUE = 0.03976, DEGREES OF FREEDOM = 5, SIGNIFICANCE LEVEL = 0.05 AND RESULT IS SIGNIFICANT AT P<0.05

Algorithm	Results Without SMOTE						Results With SMOTE					
	Precision	Recall	F1-Score	Accuracy (%)	AUC value	MSE value	Precision	Recall	F1-Score	Accuracy (%)	AUC value	MSE value
MNB	0.76	0.76	0.76	76.42	0.83	0.31	0.78	0.78	0.78	78.04	0.90	0.16
SVM	0.82	0.81	0.81	81.35	0.86	0.27	0.83	0.84	0.84	84.31	0.90	0.14
KNN	0.78	0.76	0.75	76.67	0.81	0.35	0.80	0.79	0.79	79.90	0.85	0.31
LR	0.81	0.82	0.81	81.77	0.87	0.24	**0.88**	0.80	0.83	83.65	0.89	0.17
RF	**0.85**	**0.85**	**0.85**	**85.46**	**0.90**	**0.15**	0.86	**0.90**	**0.87**	**88.73**	**0.95**	**0.12**

TABLE III. OBTAINED RESULTS OF APPLIED DEEP LEARNING ALGORITHMS; FRIEDMAN TEST: CHI-SQUARE = 15.9333, P-VALUE = 0.00311, DEGREES OF FREEDOM =5, SIGNIFICANCE LEVEL = 0.05 AND RESULT IS SIGNIFICANT AT P < 0.05

Algorithm	Results Without SMOTE						Results With SMOTE					
	Precision	Recall	F1-Score	Accuracy (%)	AUC value	MSE value	Precision	Recall	F1-Score	Accuracy (%)	AUC value	MSE value
CNN	**0.78**	**0.78**	**0.78**	**78.34**	0.87	0.29	0.87	0.82	0.84	83.24	0.91	0.24
LSTM	0.76	0.76	0.76	76.88	0.86	0.32	0.85	0.84	0.84	84.12	0.89	0.25
GRU	0.76	0.76	0.76	76.81	0.86	0.31	0.81	0.88	0.84	84.31	0.89	0.25
Bi-LSTM	0.77	0.76	0.76	76.91	0.86	0.31	0.84	0.83	0.83	83.29	0.89	0.25
Bi-GRU	0.77	0.76	0.76	76.89	0.86	0.32	0.85	0.82	0.83	83.88	0.89	0.26
CNN-LSTM	0.77	0.77	0.77	77.83	0.88	0.28	0.85	0.85	0.85	85.33	0.91	0.25
CNN-BiLSTM	0.76	0.76	0.76	76.95	0.89	0.28	0.86	0.90	0.87	88.21	0.90	0.23
CNN-GRU	0.77	0.77	0.77	77.93	0.89	0.29	**0.92**	0.85	0.88	87.38	0.90	0.22
CNN-BiGRU	0.76	0.76	0.76	76.98	**0.88**	**0.27**	0.89	**0.93**	**0.90**	**90.96**	**0.96**	**0.11**

It obtained the highest scores for f1-score and accuracy (88.73%). Additionally, it stands out with an area under curve (AUC) value of 0.95, which means it is really good at telling apart different classes. It is also worth noting that RF got the smallest mean squared error (MSE) value of 0.12, which is a good sign that its predictions are consistently close to the actual values. The 2nd best ML model is SVM producing an accuracy of 84.31%. The obtained results of the implemented DL algorithms with and without SMOTE are given in Table III. Among the models evaluated, the CNN-BiGRU and CNN-BiLSTM models acquired best performance across multiple metrics. The hybrid model CNN-BiGRU achieved f1-score of 0.90 and an accuracy of 90.96%. It also produced an AUC and MSE values of 0.96 and 0.11 respectively those indicate strong discriminatory power. The CNN-BiLSTM hybrid model also performed well with an accuracy of 88.21%. But the CNN model produced only 83.24% accuracy. So, hybrid models performed better than base DL models.

TABLE IV. COMPARISON BETWEEN ML AND DL ALGORITHMS

Domain	Algorithm	F1-Score	Accuracy (%)	AUC value	MSE value
ML	RF	0.87	88.73	0.95	0.12
DL	CNN-BiGRU	**0.90**	**90.96**	**0.96**	**0.11**

The comparison between ML and DL algorithms is illustrated in Table IV, and from the table it is clear that DL models outperform ML models. SMOTE was used to balance the dataset and its effect over ML and DL algorithms were depicted in Fig. 2. SMOTE significantly improves the performance of all the implemented models. The average improvement after SMOTE for ML and DL models are 3.22% and 10.81% respectively. A statistical test (Friedman test) was performed on the obtained results to observe the statistical significance with 0.05 level of significance and both the test results were significant. The comparison among existing works and our proposed work is presented in Table V. The proposed model operates on a substantial dataset of 44,491 food reviews which is comparable to or larger than many of the other studies that can positively impact the model's ability to learn patterns and generalize well. The proposed hybrid model CNN-BiGRU achieves the highest accuracy of 90.96% and an f1-score of 0.90. This performance level puts it in line with or even surpasses some of the existing works in the sentiment analysis domain.

C. *Explainable NLP*

In the previous section we have analyzed different model performance but we can not explain the reason why a model is classifying perfectly or not. The very fundamental problem of AI and learning related tasks is the lacking of interpretability of a model being performing well or poor, which features are responsible to classify a document to a category, which are the top most important features and so on. We have used the local interpretable model-agnostic explanations (LIME) and Shapley additive explanations (SHAP) module of python for this purpose. LIME can explain which features are making significant contribution for categorizing a document, and it can also interpret which category is more likely to be chosen with their prediction probabilities. A sample LIME explanation for prediction of a review is shown in Fig. 3 where the responsible text features are highlighted. SHAP provides a comprehensive view by quantifying the importance of each dimension to the selection of a model in a broader context. Fig. 4 demonstrates the average impact on the CNN-BiGRU model output magnitude using Shapley value. There is total 50,000 features for the model, but we have shown only the top 20 features for predicting 3 target classes.

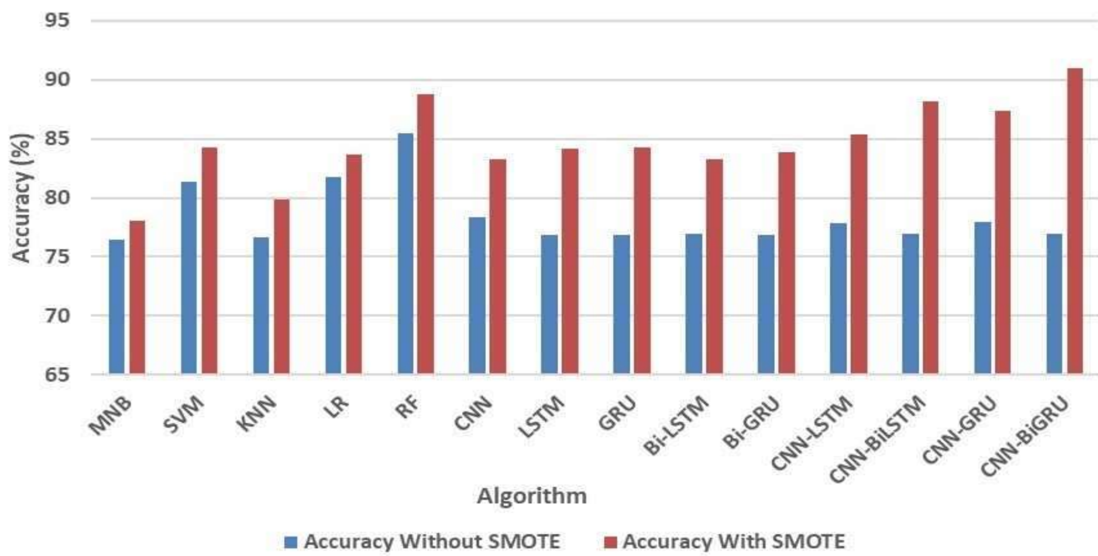

Fig. 2. Effect of Different Model Performance After Balancing the Dataset

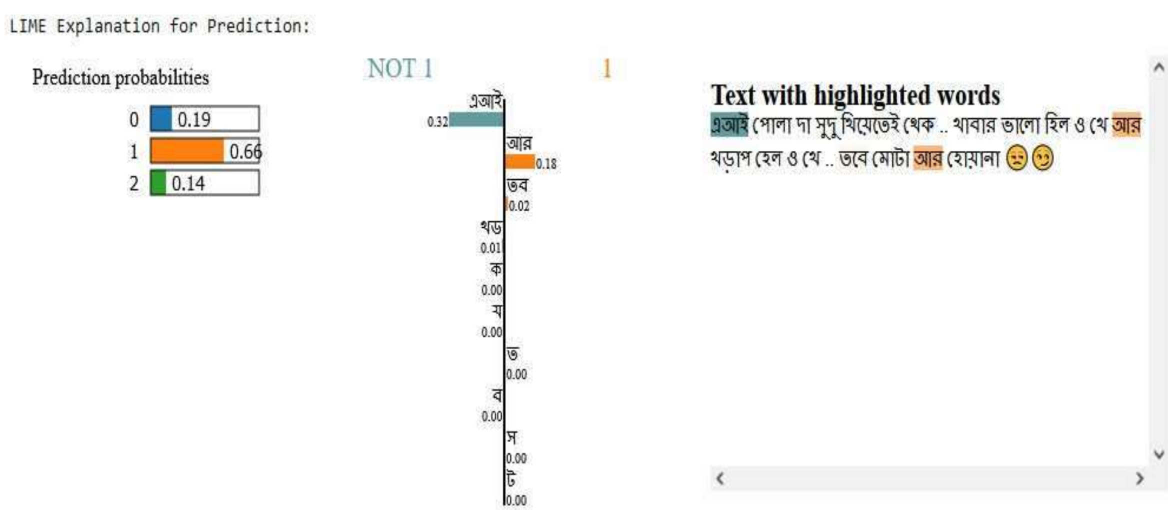

Fig. 3. Sample LIME Explanation for Prediction

TABLE V. COMPARISON AMONG EXISTING RECENT WORKS AND OUR PROPOSED WORK

Name	Year	Dataset Used	No. of Classes	Best Model	F1-Score	Accuracy (%)
M. I. H. Junaid et al. [2]	2023	1040	2	LSTM	N/A	90.89
M. Hasan et al. [6]	2023	10,861	3	Bangla-BERT	0.82	86.00
E. R. Rhythm et al. [7]	2023	15,018	N/A	DistilBERT	N/A	77.00
Our Proposed	**2023**	**44,491**	**3**	**CNN-BiGRU**	**0.90**	**90.96**

V. CONCLUSIONS AND FUTURE WORKS

Sentiment analysis on food review is a topic of great importance in every language due to its versatile applications. But the unfortunate thing is that there is still no benchmark datasets and researches to refer to for food reviews in Bengali language. In this work we have developed a dataset of 44,491 Bangla food reviews from various food review Facebook pages and groups and annotated them manually. We mainly keep focus on detecting the correct sentiments of Bangla food reviews properly using learning models as well as explains the reason for performing with better or worse results using explainable NLP. SMOTE significantly improves the performance of all the implemented models, the average improvement after SMOTE for ML and DL models are 3.22% and 10.81% respectively. RF and CNN-BiGRU models outperformed other models and achieved the highest accuracy

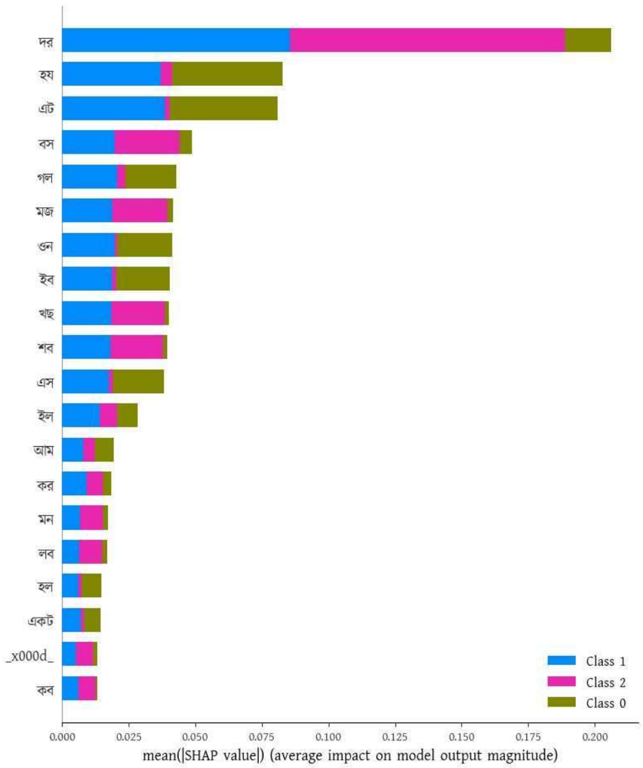

Fig. 4. Average Impact on CNN-BiGRU Model Output Magnitude Using Shapley Value

of 88.73% and 90.96% from ML and DL domains respectively. The hybrid deep learning methods outperforms the base deep learning methods. Friedman statistical test was performed on the obtained results and the test results are significant at $p<0.05$. Additionally LIME and SHAP from explainable NLP are used to observe the reason for a model being performing well or poor from local and global point of views. "দর" is the best feature that is responsible for the prediction of Bangla food reviews. In the future, we want to enrich and balance our dataset more and explore different hybrid feature extraction techniques for the SA on Bangla food reviews, implement transformer based learning and different hybrid methods.

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