Interpretable Bangla Sarcasm Detection using BERT and Explainable AI

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Abstract—A positive phrase or a sentence with an underlying negative motive is usually defined as sarcasm that is widely used in today's social media platforms such as Facebook, Twitter, Reddit, etc. In recent times active users in social media platforms are increasing dramatically which raises the need for an automated NLP-based system that can be utilized in various tasks such as determining market demand, sentiment analysis, threat detection, etc. However, since sarcasm usually implies the opposite meaning and its detection is frequently a challenging issue, data meaning extraction through an NLP-based model becomes more complicated. As a result, there has been a lot of study on sarcasm detection in English over the past several vears, and there's been a noticeable improvement and vet sarcasm detection in the Bangla language's state remains the same. In this article, we present a BERT-based system that can achieve 99.60% while the utilized traditional machine learning algorithms are only capable of achieving 89.93%. Additionally, we have employed Local Interpretable Model-Agnostic Explanations that introduce explainability to our system. Moreover, we have utilized a newly collected bangla sarcasm dataset, BanglaSarc that was constructed specifically for the evaluation of this study. This dataset consists of fresh records of sarcastic and non-sarcastic comments, the majority of which are acquired from Facebook and YouTube comment sections.

Index Terms—Machine Learning, Natural Language Processing, Sarcasm Detection, BERT.

I. INTRODUCTION

Sarcasm is the use of words that mean the complete opposite of what we are attempting to convey and most of the time it is used in order to mock, criticize, or express discontent. Sarcasm is ingrained in today's online culture all around the world and is used often in verbal exchanges in person as well as in chat rooms and comment sections of social networking sites. Automated sarcasm detection algorithms can be beneficial for various NLP applications, including marketing analysis, opinion mining, and information classification.

Sarcasm often alters the polarity of a remark, making its detection and processing crucial in an automated NLP system. In recent times, a great deal of effort has been put towards

automating the sarcasm detection process since it allows for more accurate analytics in online comments and reviews. Sentiment and emotion analysis approaches are being used to study predicting and removing phrases that suggest sarcasm with the growth of artificial intelligence (AI) tools, notably NLP and as a result sarcasm detection in the English language has improved a lot in the past few years. However, for the Bangla language, it still remains a challenging task, and a very limited effort has been made to address this fundamental problem. The primary objectives of our investigation are as follows: (i) Introduce an Automated sarcasm detection system in the Bangla language that can aid in various NLPbased systems such as sentiment analysis, opinion mining, and marketing tools. (ii) Increase the efficiency of the entire process by performing a thorough study in order to find out the optimal framework. While conducting we encountered some challenges. The availability of Bangla sarcasm data was the most notable along with the limitations of previous studies.

The contributions of this article are as follows:

- A Bidirectional Encoder Representations from Transformers(BERT) based model with Stratified K-fold Cross Validation has been proposed for detecting sarcasm. A comprehensive study of various traditional machine learning models with the proposed system is presented as well.
- Local Interpretable Model-Agnostic Explanations is utilized in order to explore the interpretability of the proposed model.
- To assess the effectiveness of this study's proposed model, we have utilized the BanglaSarc dataset, a fresh dataset on sarcasm. This dataset is collected from Facebook, YouTube, and various online resources for the validation of the proposed model specifically.

In our article, section II briefly covers recent work in the field of sarcasm detection. The dataset has been used to train our model as described in section III. Section IV demonstrates the process of the model. The results and analysis have been illustrated in Section V. Finally, section VI concludes with a hope for improved performance of our model and future work in the same sector.

II. RELATED WORK

Sarcasm analysis has caught the curiosity of the academic community for a long time. Many studies on sarcasm detection have lately been published, with the majority of them focusing on English and other Indo-European languages [3]. The majority of sarcasm detection research has been done on textual data by evaluating lexical features. As NLP is a field that primarily focuses on evaluating textual documents, it is vastly useful in terms of sarcasm detection.

For instance, Razali et al. used a Convolution Neural Network (CNN) to extract deep features from sarcastic tweets, with an Artificial Neural Network (ANN) as their training approach [4]. Their research centered on the detection of sarcasm in tweets by combining deep learning-derived features with contextual handcrafted information. 780,000 English tweets (130,000 sarcastic and 650,000 non-sarcastic) were distributed unevenly across their produced dataset. The dataset used for their research was divided into training and testing portions, respectively, of 80% and 20%. With all of the feature sets combined, they performed an experiment using Logistic Regression as a classification technique along with other techniques. They discovered that it was the most effective method for the task. However, it does not perform as well as a stand-alone function.

A context-based feature strategy based on a deep learning model and standard machine learning was proposed by Eke et al. [5]. To make the model training process more efficient, they combined the Internet Argument Corpus, version two (IAC-v2) benchmark dataset with two Twitter datasets: the Riloff dataset (1956 tweets) and the Ghosh and Veale dataset (54929 tweets). For learning context and word embedding, the author combined Bi-LSTM, a type of RNN, and the BERT model with Global Vector Representation (GloVe). When compared to the current approaches, their third model's(Proposed Feature Fusion model) average detection precision ranged from 3.7 to 10.2 percent and was based on feature fusion using the BERT feature, sentiment-related, syntactic, and GloVe embedding features.

Jamil et al. combined CNN and LSTM networks to recognize sarcasm in input by looking at it as a sequence of embedded words [6]. Its foundation is based on a deep neural network (DNN), which can mimic biological neurons and conduct complex computational modeling. They have used multiple datasets in this study including the Tweet dataset(39,267 tweets) and News Headlines dataset(26,709) for training and testing purposes also the Reddit dataset(15,000) and Sarcasm Corpus V2(6,520) for validation. With an accuracy of 91.60 %, the experimental findings showed that the suggested model outperformed the capabilities of the standard machine learning algorithms.

TABLE I
COMPARISON OF VARIOUS STUDIES ON SARCASM DETECTION

Model	Dataset	Accuracy	Ref
Logistic Regression	English Tweets	94%	[4]
Proposed Feature Fusion	English Tweets	76.3%	[5]
CNN + LSTM	News Headlines	73%	[6]
XGBoost	MUStARD	93.1%	[7]
LSTM	MUStARD	98.5%	[8]

Kumar et al. proposed one of the most widely used algorithms for detecting sarcasm in conversations, with the primary goal of anticipating sarcasm in each speaker's statement [7]. They used the MUStARD dataset, which contains 690 lines of conversation from four well-known sitcoms. There are an equal amount of sarcastic and non-sarcastic exchanges among the data. They used the Python framework sci-kit-learn to create the XGBoost learning model. Accuracy, F1 score, precision, and recall were used as metrics to assess XGBoost's classification performance.

Another ensemble model developed by the authors Das et al. proposed a sarcasm detection model with four Parallel Long Short Term Memory (pLSTM) networks and softmax activation function and got the best overall validation accuracy of 98.31 percent [8]. They chose the MUStARD or Multimodal Sarcasm Detection Dataset's final textual corpus, which consists of 690 lines of individually indexed dialogues, to train their model on. The dataset included the initial token average for the sentences as well as the instances of sarcastic word utterances that are part of the relevant sentences.

Additionally, LIME has been employed so that users may understand how predictions are created [12]. LIME is broadly used in interpreting various deep learning-based frameworks that are used in both image and text-based tools [14] [13] [15].

Unlike the studies mentioned above, we generated a Bangla Dataset specifically for this research and utilized a traditional machine-learning model along with BERT in order to classify sarcasm.

III. METHODOLOGY

In this section, we get an overview of our proposed sarcasm detection model, which is separated into three subsections. Sub-section III-A of this paper discusses our proposed model. However, Sub-section III-B is divided into two sub-subsections. In the initial sub-subsection we discuss about our data acquisition techniques and description and in the later sub-subsection we discuss data pre-processing. Finally, III-C exposes our model's framework.

A. Proposed Model

Initially, we started by gathering data from various social media platforms namely Facebook, YouTube, etc. Since collected data from social platforms tend to be very noisy, we had to consider a series of pre-processing techniques in order to clean the data. However, before doing so, we manually examined and labeled each of the data to confirm that there are no discrepancies between the data. After performing manual

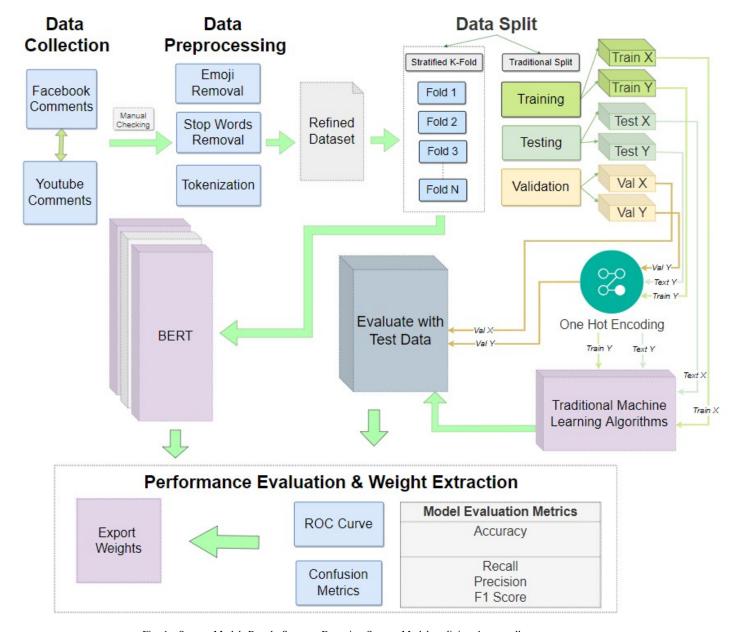


Fig. 1. System Model: Bangla Sarcasm Detection System Model outlining the overall process.

checking and pre-processing techniques over our gathered dataset, it proved to be advantageous. Finally, before feeding our data to our preferred model, we have split the data into two parts which are stratified K-Fold and traditional split where stratified K-Fold is used with BERT. Furthermore, the traditional split is divided into three sections which are train, test, and validation whereas the train set contains 60% of the data and the other two sets have 20% each. In addition, we have also performed one hot encoding on the labels for all three of the split sets. Later, we fed the train and test set into various traditional machine learning models namely, Logistic Regression, Decision Tree, Random Forest, Naive Bayes, K-Nearest Neighbor(KNN), Support Vector Machine(SVM),

SGD, TFIDF along with K-Fold as Cross-Validation with a BERT. After training our model, with the validation set, we evaluate our trained model's performance. We have as well employed various performance metrics along with ROC Curve and confusion metrics. Here, we have performed a comprehensive comparison between the trained models from BERT and evaluated them with a test dataset in order to find out which model tends to be more efficient in terms of accuracy, memory, speed, etc finally we export the best-fitted model according to our analysis. With the exported model we have employed LIME (Local Interpretable Modelagnostic Explanations) that introduces explainability to our study. This explainability helps us understand how our model

comprehends and classifies a prediction.

B. Data: BanglaSarc:

- 1) Data Acquisition & Description: In this work, we utilized the BanglaSarc Dataset in order to evaluate our proposed model [1]. BanglaSarc Dataset is gathered with Bangla comments from Facebook, YouTube, and other online resources. Afterward, these data were manually reviewed and assigned labels for each of the collected records. The authors then excluded noisy data throughout the screening process. Authors further labeled the data with '0' and '1' where '0' implies a non-sarcastic statement and '1' denotes a sarcastic statement in this situation. However, these gathered datasets turned out to be rather noisy after all, which necessitated us to manually clean the data. Initially, BanglaSarc Dataset is consisted of 7800 comments however, after manually filtering authors had to discard almost 2700 records. As a result, the final dataset consisted of 5112 comments whereas it contains about 3159 non-sarcastic data and 1951 sarcastic data. Even though the BanglaSarc dataset is not entirely balanced, we may nevertheless draw the conclusion that its quality is moderate.
- 2) Data Pre-processing: We begin by removing all of the emojis as managing emojis and emoticons is essential when doing text pre-processing tasks in NLP. The stopwords are then removed since stopwords do not add much sense to a phrase. Generally, they are excluded from the dataset to improve model performance. We tokenized the text and then removed all the punctuation. Tokenization is the process of breaking down a piece of text into smaller chunks or units known as tokens. Data pre-processing is an important step in the development of a machine learning model. Figure 2 represents an example input and output using our pre-processing methods.

before : বোকামির বিরুদ্ধে সার্কাসম হল দেহের প্রাকৃতিক প্রতিরক্ষা after : বোকামির সার্কাসম হল দেহের প্রাকৃতিক প্রতিরক্ষা

Fig. 2. Data Pre-processing: Sample Input.

C. Model Specification

Initially, We have employed Random Forest, Decision Tree, K-Nearest Neighbor(KNN), Support Vector Machine(SVM), Multinomial Naive Bayes, Logistic Regression, Stochastic Gradient Descent(SGD). and later we further employed BERT with Stratified K Fold to evaluate our system. BERT is an artificial intelligence (AI) method for comprehending natural language and is also known as Bidirectional Encoder Representations from Transformers. In Transformers, each output element is connected to each input element, and the weightings between them are dynamically determined based on their connection. It only requires the encoder component because its goal is to build a language representation model. The BERT encoder receives a sequence of tokens, which are then translated into vectors and processed by the neural network. The

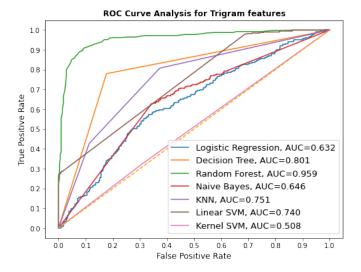


Fig. 3. Traditional Machine Learning Algorithms: ROC Curve

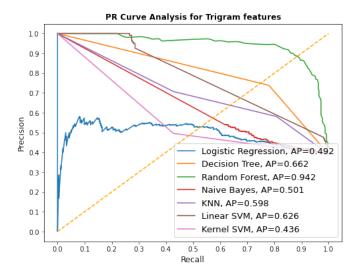
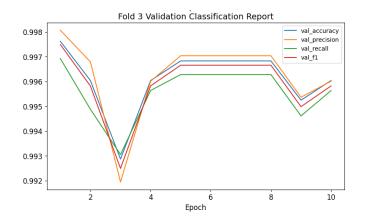


Fig. 4. Traditional Machine Learning Algorithms: Precision-Recall Curve

Transformer works by stacking a layer that maps sequences to sequences, resulting in an output that is also a set of vectors with a 1:1 correlation between input and output tokens at the same index. In a number of tasks relevant to general language understanding, such as natural language inference and linguistic acceptability, BERT outperformed the present state-of-the-art. To fine-tune the model, we must first transform the data into the particular format used for pre-training the core BERT models, which includes adding special tokens to label the beginning and end of sentences, as well as segment IDs to differentiate different sentences, and then transform the data into the features used by BERT. Moreover, K-fold is a cross-validation approach used to measure a machine learning model's skill using unknown data. It is often used to validate a model since it is simple to understand and execute, and the findings are more useful than traditional validation methods.

TABLE II
PERFORMANCE EVALUATION: TRADITIONAL MACHINE LEARNING MODELS

Model	Accuracy	Precision	Recall	F-1 Score
Random Forest	89.93	89.93	89.93	89.93
Decision Tree	83.58	83.58	83.58	83.58
K-Nearest Neighbor	74.78	74.78	74.78	74.78
Support-Vector Machines	71.55	71.55	71.55	71.55
Multinomial Naive Bayes	65.10	65.10	65.10	65.10
Logistic Regression	62.46	62.46	62.46	62.46
Stochastic Gradient Descent	53.86	53.86	53.86	53.86
BERT	99.60	99.60	99.56	99.58



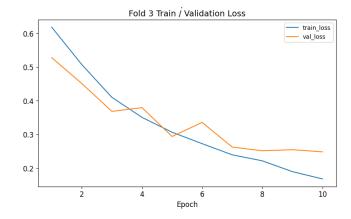


Fig. 5. BERT using Stratified K-Fold 4: Left Image depicts the curve of validation Accuracy, Precision, Recall, and F-1 Score. The right image represents the loss curve during the training.

IV. PERFORMANCE EVALUATION AND ANALYSIS

We have evaluated our dataset using our proposed system. We have divided our system training into two parts. In the initial part, we have employed various machine learning algorithms which is discussed in part IV-A, and in the later part we have utilized BERT using Stratified K-Fold which is discussed in part IV-B.

A. Traditional Machine Learning Algorithms

Table II depicts our findings employing traditional machine learning algorithms. We have employed Random Forest, Decision Tree, K-Nearest Neighbor(KNN), Support Vector Machine(SVM), Multinomial Naive Bayes, Logistic Regression, and Stochastic Gradient Descent(SGD). Among these algorithms, Random Forest managed to acquire an accuracy of 91.10% with a precision, recall, and F-1 score of 89.82%, 87.09%, and 88.43% respectively. Decision Tree however managed to reach 80.61% with precision, recall, and F-1 score between 73.86% to 77.97%. The rest of the algorithms performed poorly with an accuracy ranging from 71% - 60%. Figure 3 represents the corresponding ROC curve for all 7 of the mentioned machine learning framework. Here, we can visualize the superiority of Random forest among the other frameworks. In addition, Figure 4 depicts the precision-recall curve for the mentioned models.

B. BERT

Table II's last row represents our findings of our training using BERT with Stratified K-fold. At the initial fold, our model already managed to reach a validation accuracy of 90.58% with a validation precision, recall, and F-1 score of 90.06%, 90.09%, and 90.07% respectively. This proves the stability of the model's training. In the next fold, it's accuracy improved to 95.88% which is already superior to traditional machine learning algorithms. In terms of its validation precision, recall, and F-1 score it again scored around 95% in each section. In Fold 3, it was still able to maintain its increasing accuracy. Finally, in Fold 4 which is presented in the table, we get a validation accuracy of 99.60% with precision, recall, and F-1 score ranging from 99.56% to 99.60%. Figure 5 depicts the accuracy, validation, recall, and F1-score curve along with its train loss and validation loss curve.

C. Local Interpretable Model-Agnostic Explanations

We have employed LIME which introduces explainability to our system. Figure 6 shows 4 inputs and their prediction along with LIME prediction. Here, Input (a) is confidently identified as sarcasm, and LIME highlights the main elements so that the users may see how LIME arrived at its conclusion. However, Input (b) is predicted as non-sarcasm with 100% accuracy and the reason behind its prediction is highlighted as well. While Interpreting Input (c), our proposed system furthermore made a confident prediction with 98% accuracy. It was predicted

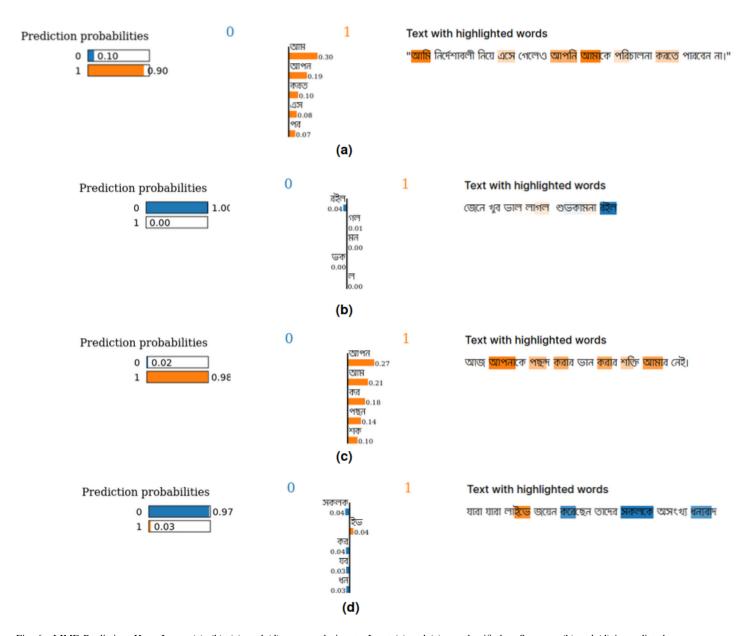


Fig. 6. LIME Prediction: Here, Image (a), (b), (c), and (d) are sample inputs. Input (a) and (c) are classified as Sarcasm. (b) and (d) is predicted as non-sarcasm. Orange highlighted regions represent the negative or sarcasm level of a single word whereas Blue highlighted regions are represented as positive or non-sarcasm.

as sarcasm. Finally, Input (d) was firmly identified as a nonsarcasm, and LIME has emphasized both the positive and negative qualities.

V. CONCLUSION

In this article, we have proposed a BERT-based model for detecting Bangla sarcasm that is capable of achieving 99.60% whereas utilizing the traditional machine learning models reached only up to 89.93% accuracy. Another novel contribution of this study is the utilization of a new Bangla sarcasm dataset, BanglaSarc that was collected specifically for the evaluation of this study's proposed system. Furthermore, we have utilized LIME which introduces explainability to our system. BERT's pre-trained layer along with the Fully

connected layer is utilized in this study to grasp deep features and classify sarcasm. Additionally, we have employed various machine learning algorithms and conducted a thorough comparison in order to find the best-fitted model. NLP-based technologies are gaining popularity recently and need cutting-edge accuracy to function properly. However, sarcasm becomes a significant issue since it is often difficult to detect and thus reduces the overall system's performance. Although, numerous work has been conducted in detecting sarcasm from the English language, very low effort has been put into detecting sarcasm from the Bangla language. Our proposed approach would address this issue and bridge the gap between these two languages in terms of sarcasm identification. In

the future, we hope to increase the quantity along with the quality of the dataset. Moreover, we aim to improve memory efficiency along with inference time by proposing a lighter framework.

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