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A fusion approach to detect sarcasm using NLTK models BERT and XG Boost

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Abstract

The context-dependence of sarcasm recognition in textual data makes it a challenging problem. This article describes a fusion technique that combines the XGBoost gradient boosting algorithm with BERT embeddings for sarcasm detection. Using this method, textual input is transformed into rich contextual embeddings that are then used to train an XGBoost classifier. The resulting hybrid model is evaluated and trained across multiple datasets, demonstrating its ability to distinguish between text that is sarcastic and non-sarcastic. The results of the experiment indicate that the accuracy matrix performs better than individual models. A comprehensive word cloud analysis that identifies important

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phrases and language patterns associated with sarcasm is also included in this paper. This study combines the benefits of BERT and XGBoost to advance sarcasm detection techniques.

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Keywords: *Sarcasm detection, BERT embeddings, XGBoost, Hybrid model, Contextual embeddings.*

1. Introduction

Since sarcasm relies heavily on contextual cues and is sophisticated, recognizing it in textual data presents a challenge for natural language processing. Sentiment analysis, social media monitoring, and customer feedback interpretation are among the applications where accurate detection is essential since it requires an understanding of the various language levels. The XGBoost gradient boosting algorithm and BERT embeddings are combined in this paper to propose a fusion solution for sarcasm detection. Contemporary language representation model BERT is an ideal candidate for capturing sarcastic attitudes since it is adept at capturing contextual subtleties and complex verbal patterns. The method transforms text into contextual embeddings using pre-trained BERT models, providing a complete representation of the input text. After training an XGBoost classifier on these embeddings, a robust hybrid model for sarcasm detection is produced. Numerous datasets are analyzed to validate the model's the fusion technique's potential is demonstrated by its ability to discern sarcasm more precisely than standalone models [1]. In this study, key phrases and language patterns associated with sarcasm are identified using a qualitative analysis of word clouds. This provides valuable insights into the linguistic nuances that characterize sardonic utterances. The work improves sarcasm detection by integrating strong machine learning methods with sophisticated language representation models. This method increases the accuracy and depth of sarcasm detection in textual data.

2. Literature Review

Support Vector Machine (SVM) is the most popular ML algorithm, with high accuracy attained by lexical, pragmatic, and part-of-speech tagging, according to a systematic review of many studies on sarcastic tweet detection on social media. The study tackled the difficulties in anticipating satirical tweets and offered insightful information for further investigation and machine learning advancement.an unbalanced corpus of manually annotated Twitter conversations was created for a recent study [2] on sarcasm detection to address shortcomings in classification methods. The study demonstrated how labelling practices and class imbalance affect performance, emphasizing the necessity for an innovative labelling approach.

Researchers are focusing on sarcasm detection in opinion mining [3], using Recurrent Neural Network (RNN) models and Long Short-Term Memory (LSTM) cells to extract crucial features. This study proposes a context-based [3] feature technique integrating BERTand conventional machine learning for sarcasm detection on e-commerce and social media platforms. The technique shows superior precision, reaching 98.5% on Twitter datasets, highlighting advancements over baseline approaches.

The study discusses the use of advanced algorithms [4] and deep learning models for sarcasm detection on social media. It introduces a Multi-Head Attention-based Bidirectional LSTM network, which outperforms feature-rich SVM models in identifying sarcastic comments. Research study of [5] tackles Twitter sarcasm analysis using four approaches: parsing-based lexical generation, likes and dislikes contradiction, tweet contradicting universal facts, and tweet contradicting temporary facts. They use machine learning classifiers to extract text features, achieving significant accuracy improvement over existing techniques.

A proposed hyperbolic [5] feature-based sarcasm detector uses intensifiers and interjections for Twitter data analysis. It has shown promising accuracy with SVM leading at 80.67%. However, limitations and challenges persist, emphasizing the ongoing complexity in achieving comprehensive sarcasm detection. Paper [6] presents a novel approach to detecting sarcasm using LSTM and RNN models. Recent literature [6] highlights diverse approaches to automatic sarcasm detection, leveraging natural language processing techniques. Recent studies on sarcasm detection [7] have used hyperbole features in negative sentiment tweets, using algorithms like Support Vector Machine, Random Forest, and Random Forest with Bagging. The research found that elongated words significantly improve accuracy (78.74%) and F-score (71%). However, limitations in the research highlight the need for further exploration and refinement in hyperbole-based sarcasm detection models.

The article introduces a hybrid approach for sarcasm detection [7], combining text and audio features. It shows superior performance, with individual models outperforming existing ones. The hybrid model achieves the highest F1- score of 70.35%, capturing nuances that individual models miss. A challenge in studying sarcasm detection in natural language processing (NLP) is comprehending subtle contextual information contained in utterances. This investigation is aided by machine learning classifiers that have been developed on pragmatic features. The study emphasizes the value of contextual cues, a variety of datasets, algorithmic developments, and the continuous difficulty of obtaining the best possible accuracy when identifying sarcastic expressions. Researchers have achieved accuracy rates of 74.59 percent to 83.53 percent by using algorithms such as Support Vector Machine (SVM) [8] for sarcasm detection on social media sites like Facebook and Twitter. Top tf-idf characteristics improve identification, while sentiment and punctuation features are used in dataset extraction.

3. Proposed Methodology

Sarcasm detection in text is a difficult NLP (natural language processing) problem. To improve the accuracy and efficacy of sarcasm detection, proposed work uses the strengths of XGBoost for classification of text as a sarcastic and non-sarcastic text and for feature extraction BERT (Bidirectional Encoder Represent from Transformers) model is used. Figure 1 represent the block diagram of Sarcasm detection using BERT and XGBoost models.

3.1 *BERT (Bidirectional Encoder Representations from Transformers)*

Natural language processing (NLP) has been transformed by Google's cutting- edge transformer-based approach, BERT. It is particularly good at gathering contextual information in both directions, which enables it to interpret word meaning within the context of the full sentence. Some of BERT's primary components are:

- Environmental Embedded components: BERT creates embeddings that consider the components of text that surround every single phrase to capture subtle contextual information.
- Initial training: BERT can learn generic language patterns and semantic connections since it has been pre-trained on a large volume of textual material. The beforehand greatly improves its results on activities that come after.
- Fine-tuning: By fine-tuning, the model is made to fit the features of the intended dataset.

- Transformer layout: BERT processes data in batches effectively because it uses a transformer design. It can assess the relative relevance of various words inside a phrase because to the its own attention mechanism.

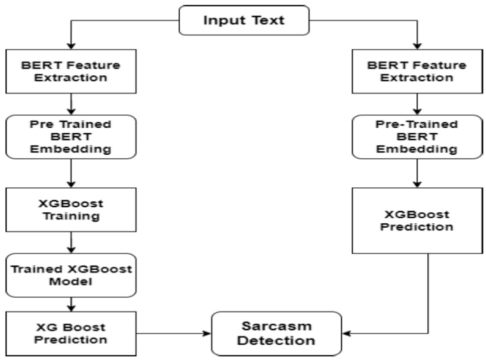

Figure 1

Block Diagram of Sarcasm Detection Model

3.2 *XGBoost (eXtreme Gradient Boosting)*

XGBoost is a robust and effective gradient boosting technique intended for problems involving regression as well as classification. Components of XGBoost consist of:

- Gradient Boosting: the XGBoost is a method of collaborative learning that creates a strong learner by combining the predictions of several beginners (decision trees). By learning from past errors, it reduces errors in an iterative manner.
- The Regularization Process: To avoid overfitting, which XGBoost uses regularization strategies. This is important because the model in detecting sarcasm must be able to generalize successfully to new, unobserved occurrences.
- Tree Pruning: To eliminate branches that don't substantially improve prediction accuracy, XGBoost uses tree pruning. This improves the efficacy and accessibility of the model.
- Managing Missing Information: A prevalent issue in real-world datasets, missing data may be handled with XGBoost in an efficient manner. Additionally, qualitative characteristics are handled immediately, negating the need for laborious processing.

We employ a fusion of two methods for sarcasm detection: we combine XG- Boost for classification with BERT for feature extraction. The "bert-base-uncased" pre- trained model serves as the initialization point for BERT, which is essential for capturing contextual reference. The BERT tokenizer splits each input text into tokens and encrypts it, with a maximum token size of 128. The mean pooling algorithm across tokens is used to extract the embeddings, creating a fixed size embedding for every sentence.

$$\text{Embeddings} = \frac{1}{N}\sum_{i=1}^{N} Token\ i \tag{1}$$

The total number of tokens in the input text is denoted by N in this case. The process of mean pooling guarantees that the final embeddings fully capture the contextual knowledge of the complete text. This process is repeated for every text in the dataset, producing a matrix of BERT embed- codes that has the semantic richness necessary for sarcasm recognition. The next step is to feed these BERT embeddings [9] into the XGBoost classifier to achieve efficient classification. The logistic regression technique, a key component of XGBoost, is utilized to predict the likelihood of sarcasm. The logistic regression [10] approach computes log- odds, which are then converted into probability using the sigmoid function, which yields a reliable classification result.

$$Log - Odds = \beta_0 + \beta_1 \cdot feature_1 + \beta_2 \cdot feature_2 + \cdots + \beta_n \cdot feature_n \tag{2}$$

$$\text{Probability} = \frac{1}{1+e^{-\log - Odds}} \tag{3}$$

By combining the contextual knowledge of BERT with the classification abilities of XGBoost, this method aims to provide a

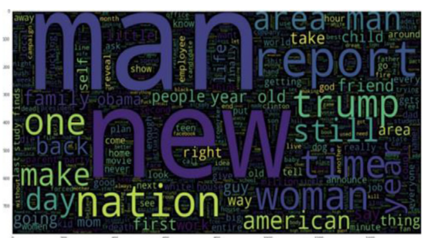

Figure 2

Word Cloud for Sarcastic Text

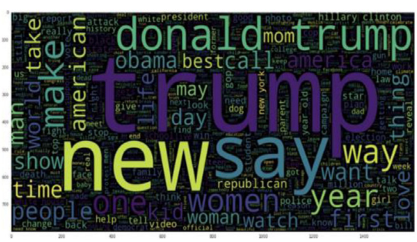

Figure 3

Word Cloud for Non-Sarcastic Text

dependable solution for sarcasm detection in textual data. It is guaranteed that characteristics that reflect linguistic features and the efficiency required for effective categorization are extracted by employing these techniques. Testing and refinement will be done to better optimization and confirm the model's performance in various sarcasm detection scenarios.

3.3 *Description of Dataset*

We are using X Dataset which consists of 2 features and 81408 samples, Represented as "tweets" and a "class". Figures 2 and 3 represent the word cloud for sarcastic and non-sarcastic text respectively.

4. Analysis of Proposed Model

We evaluated our proposed fusion based XGBoost and BERT embedding sarcasm detection model on datasets through extensive experiments. Large numbers of texts, both sarcastic and non-sarcastic, are included in the dataset to allow for a comprehensive evaluation of the model's effectiveness across a variety of linguistic contexts. Figure 4 represent the character counts in the sarcastic and non-sarcastic text in the dataset and Figure 5 represents the average word length in each text category sarcastic and non-sarcastic in the dataset. we tokenized and cleaned the dataset's text before to the experiment's first phase to guarantee uniformity in the input format. After applying the BERT-based feature extraction process, embeddings that preserved the semantic nuances necessary for sarcasm recognition were obtained. The XGBoost classifier, which is well known for its ability to handle a wide range of datasets, was trained using these BERT embeddings. The model can benefit from both BERT's contextual knowledge and XGBoost's speed. we evaluated the performance of our hybrid model using standard evaluation metrics, such as accuracy, precision, recall, and F1-score [11]. The numbers that represent the number of successfully predicted positive instances, correctly predicted negative instances, false positive instances, and accurately predicted negative instances of text are TP, FP, FN, and TN, respectively.

$$Accuracy = \frac{Number\ of\ correctly\ classified\ text}{Total\ number\ of\ text} \tag{4}$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{5}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{6}$$

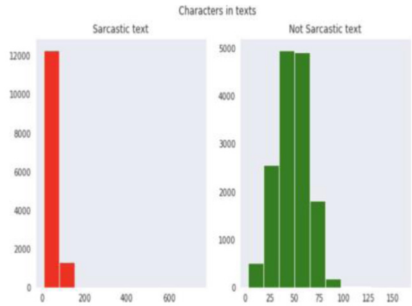

Figure 4

Characters in Dataset

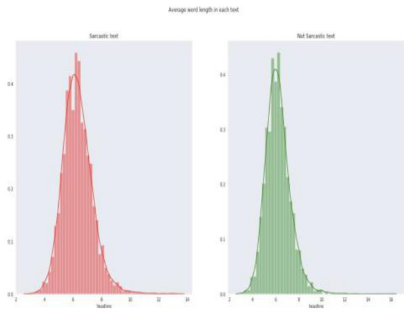

Figure 5

Average Word Length in Dataset

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

In addition, we studied the impact of adjusting hyperparameters on overall performance and fine-tuned the XGBoost classifier to yield optimal results. Proposed models generate the accuracy of 88%, precision of 89%, recall of 82% and F1 score of 85%. We carried out a thorough performance analysis to assess the efficacy of various- classifier models [11] for sarcasm detection on social media tweets. Figure 6 shows the training and testing efficacy of the BERT model throughout epochs, which is approximately 85%, and Table 1 shows the efficiency of the classifier model (SVM, NB, Random Forest, LR and proposed model) on dataset, which contains approximately 81 thousand tweets.

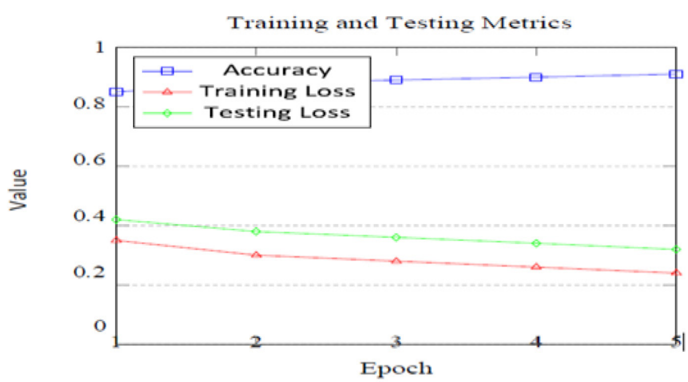

Figure 6

Training and Testing Metrices over Epochs for BERT Model

Table 1

Comparative Study of Different ML model's performance

Algorithm	F1-Score	Recall	Accuracy	Precision
XGBoost + BERT	0.85	0.82	0.88	0.89
Random Forest	0.78	0.75	0.81	0.80
Support Vector Machine	0.79	0.77	0.83	0.82
Logistic Regression	0.82	0.80	0.86	0.85
Naive Bayes	0.75	0.72	0.79	0.78

5. Discussion and Conclusion

Our preliminary findings demonstrate the promising accuracy rates of the hybrid model of XGBoost and BERT for sarcasm detection. This integrated model is a useful tool for deciphering complex expressions in text because it can identify minute language indicators that suggest sarcasm. Like any model, this one need to be continuously optimized and refined to handle changing language trends and boost overall performance. Further investigation and testing will investigate the sarcasm of different types and explore other optimization strategies to enhance the model's performance in a variety of linguistic contexts.

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