Detecting Sarcasm Across Headlines and Text

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***Abstract*—In this era with the rapid growth in social media usage among the current generation, a huge amount of content and comments, most of them sarcastic, is seen. Sarcasm has turned out to be an important part of daily life, especially in news and social media, where sarcastic comments are often used for better attention. However, detecting sarcasm is always challenging because it deals with understanding the difference between what has been said and what is meant. The current paper focuses on the detection of sarcasm in news headlines with the help of deep learning. Previous works were based on a wide range of datasets; however, these had limitations regarding either size or quality. In this respect, the authors propose creating a new dataset of headlines from sarcastic news sites and real news sites that is large and of high quality, hence appropriate for machine learning model training. The authors have also used the CNN-BILSTM architecture for text analysis, identifying sarcasm expression and deciding whether it is sarcastic or not-sarcastic which gained an accuracy of 97%. This dataset is made publicly available to enable further research in this direction.**

***Index Terms*—Sarcasm detection, News headlines dataset, Text, Deep learning, NLP, Convolutional Neural Network(CNN), BI-LSTM.**

I. Introduction

These days, the phone and technology are slowly and gradually becoming an inseparable part of our existence. We cannot even imagine a single day without social media browsing, video watching, or messaging. In turn, because of this, social media has become congested, and people express themselves more than ever. But with the rise of social media comes an increase in sarcastic comments and humorous postings. It would seem like each one of them had now become some kind of stand-up comedian online. Some use sarcasm to be funny or make a point, others to cover their feelings or even cruelly. Whichever way it goes, sarcastic comments are taking over in social media, and this presumably changes how we interact online. Sarcasm is a subtle way of expressing things where the words mean quite the opposite of their literal sense [2,3,4]. It is often employed to mock or to show contempt. It is widely used while speaking and in writing with the intention of drawing attention and stating one's opinion. The detection of sarcasm remains a challenging task, as it is by nature ambiguous in nature and depends on context and common sense knowledge [14]. Hence, even humans and machines find it difficult to correctly detect the presence of sarcasm.

The need for sarcasm detection in NLP is immense in the present digital age, since a huge amount of content is being produced on online platforms such as social media and news websites. Most of the informal languages with contextual references end up in noisy datasets, which in turn makes the process of detection tough. Also, the labeling of sarcasm in datasets manually is a time-consuming process and may lead to inconsistencies in many cases due to different levels of interpretation of sarcasm as seen in [2,16]. Research in sarcasm detection has applied several different techniques: rule-based approaches, machine learning, and deep learning. The collection of social media datasets is typically performed through tag-based supervision, which is both error-prone and limited with regard to vocabulary as mentioned in [7,8]. At the same time, high-quality, manually labeled datasets are rather small in size and too costly to produce, which results in under-powered models. More overwhelming is the fact that models have to comprehend the subtlety and contextual dependency of sarcastic language. While NLP has come a long way, most of the models lack this subtlety in sarcasm and instead depend on lexical cues rather than actual comprehension. While sarcasm detection keeps improving, new challenges have opened up for researchers in multi-modal analysis that is, considering both the visual and audio cues that would give a better understanding of the nuances of sarcastic expression. The recent trend towards voice assistants and podcasts has raised the requirement for sarcasm detection in spoken language[6], which introduces new challenges when dealing with audio data and prosody. The cultural and linguistic diversity of online platforms further require the models to be apt for different styles of sarcasm and idioms [11]. In order for better algorithms that are robust and generalizable, there is a definite need for future models to develop stronger cognitive and psychological insights in designing better models that enhance capturing context-dependent inferences and implicit meaning underlying human use of sarcasm. This will open up new applications in sentiment analysis, opinion mining, and human-computer interaction by really pushing the limits of sarcasm detection and further enriching our understanding of language and communication.

Hybrid neural networks were also experimentally proved to perform better in sarcasm detection[10]. They focused on the relevant parts of the text. The paper "Sarcasm detection using news headlines dataset". These models can process sequential data effectively and are thus suitable to analyze news headlines, wherein sarcasm is often employed. The aim of this study is to conduct the task of news headline sarcasm detection using deep learning techniques that are advanced. It would leverage high-quality datasets and new neural network architectures to present an improved performance and interpretability of sarcasm detection models for an overall improved performance in sentiment analysis [7]and natural language understanding. Here, the prime focus of our project is to make the model detect sarcasm in both headlines and general sarcastic text taking information from the above-mentioned pa-per, to enhance the detecting capability of sarcasm by our model.

The rest of the paper is organized as follows: Section 2 - describes about the related work, Section 3 - Outline the proposed work, which was used for preprocessing, models and techniques applied , Section 4 - it illustrates about the datasets we have used in order to remove the limitations of the preceding bench mark datasets, training environment, evaluation-metrics, Section 5 - specifies about the results and discussions, Section 6 - shall summarise the conclusion of the work.

II. Related Work

The authors , M. S. R.Chy, M. R. H.Mahin, M.Rahman, M.Hossain, S.Rasel in , "Sarcasm Detection in News Headlines Using Evidential Deep Learning-Based LSTM and GRU,"[1] reviews the related work for various approaches to detect sarcasm. Few important works include the STSM algorithm, which fuses pragmatic and lexicon-based features and ensemble models using many word-embedding techniques. The transformer-based approaches are CNN-RoBERTa. Further, analysis of historical data using lexicon-based techniques has also been attempted. Emphasize that the integration of reliability and uncertainty measures plays an important role in sarcasm detection, addressed by Evidential deep learning.

R.Misra, P.Arora, entitled "Sarcasm detection using news headlines dataset"[2]. The base paper reviews the related works regarding prior research in sarcasm detection, citing limitations of the existing datasets and models. The authors have emphasized the need for high-quality datasets and more sophisticated models in order to capture the subtlety of sarcasm by referring to seminal works like Amir et al. (2016), Sarcasm Detection in Twitter: A Deep Learning Approach, and Joshi et al. (2015)-A Survey of Sarcasm Detection Techniques. They instead propose a new large-scale News Headlines Dataset, tailored for the purpose of sarcasm detection, arguing outperforming previous datasets. They have further used the Hybrid Neural Network architecture comprising CNN and LSTM components along with the attention mechanism, which they have proved effective using different analysis.

"Sarcasm Detection in News Headlines using Supervised Learning" gives an overview of several methods for sarcasm detection and brings out the importance of context[4]. Deep neural networks and user embeddings have also been employed by researchers to give better results. For example, Amir et al. used the combination of user and word embeddings, while Hazarika et al. designed a contextual detection system by using both user and content embeddings. Kolchinski et al. used a Bayesian approach by using dense embeddings to classify in social media.

The discussion of the paper "Deep Learning for Sarcasm Identification in News Head-lines" is done[5]. Discussed revisits sarcasm detection by presenting a number of datasets and machine learning techniques. Therefore, this research used high-quality datasets such as sarcastic headlines from The Onion, The Sarcasm Corpus V2, etc., while earlier studies had solely relied on noisy data from Twitter. This will also be discussed in-depth, since advanced techniques-LSTM networks as mentioned in the paper[6] as performing abstract summarization and CNN-are efficient and seemingly brought more improvements in the accuracy of enhancements in sarcasm detection of NLP.

Sarcasm detection is a relatively new challenge in text analysis. Various methods have been used in an attempt to address it, as reflected in the paper [7]. Some of these approaches, such as LSTM and various neural networks, focus on different aspects: some work with text, others with sentences, and some with words. Some methods, like CASCADE, use mixed con-tent and context-based approaches, while SCUBA places special emphasis on emotional differences and user behavior. Other approaches are attention-based models, BERT embedding-based methods, and some approaches based on BiLSTM and affective graph representation. Most of them incorporate context, user behavior, or emotional knowledge to present more accuracy in sarcasm detection and report remarkable results in the field.

The problem of detecting sarcasm is deliberated in the paper "Detecting Sarcasm in News Headlines" by Onyinye ChudiIwueze and Haithem Afli, [8]focusing on news headlines and social media content. Sarcasm detection has become one of the challenging tasks in NLP due to subtlety and resting so much on context. Different methods are debated in the paper as in [13] and [14] from different angles but with a strong support for feature extraction techniques as an indispensable block in improving model performance. It provides a framework to improve the systems on the detection of sarcasm by analyzing the different approaches that exist and giving a proposal for future directions to reach the solution. Decoding Sarcasm: Unveiling Nuances in Newspaper Headlines"[9] - a paper on challenges for sarcasm detection in NLP based on newspaper headlines - very effectively situates this challenge. It is the subtle contextual cues flipping the literal meaning of words that make headline sarcasm hard to detect. This paper elaborates on the different feature extraction and modeling techniques the authors tried, setting up context to a few nuances of sarcastic speech as same in [12]. Work acts like an eye-opener in improving the models for sarcasm detection. It opens the doors to much more accurate and advanced systems. O.Chudi-Iwueze, H.Afli, of "Sarcasm Detection with a New CNN+BiLSTM Hybrid Neural Network and BERT Classification Model" addresses the challenge of detecting sarcasms in social media-a place where sarcastic expressions occur quite often and have mostly been misinterpreted in NLP[10]. They also propose a hybrid model that includes CNN, BiLSTM, and BERT to enhance the efficiency of sarcasm detection as similar to [11]and[15]. It handles the intricateness of sarcastic language through a model that provides informal, contextual communication online to reduce misunderstandings and improve the capabilities of NLP systems in social media interaction analysis.

III. Proposed Work

A. Preprocessing

Among all, the preprocessing of textual data is one of the most important steps in getting the data prepared for effective analysis and model training in natural language processing that involves processing of raw text data into a form appropriate for model training and evaluation. Some of the techniques that find their employment here include special character handling, lowercasing, stopword removal, expanded shortened tokens, tokenization, and lemmatization. All these preprocessing techniques work in concert to transform raw text into a cleaner and more consistent format, which greatly enhances the performance of NLP models by better grasping the underlying semantic information contained within.

1) Data Cleaning: Objective: This removes the noise and irrelevant information so that the model focuses on what is meaningful from the text. • Handling special characters: Special character handling in deep learning refers to the process of removing or replacing non-alphanumeric characters in text to clean and standardize input data for improvement in performance of models. • Lowercasing: In deep learning, lowercasing represents a pre-processing strategy in text where all characters are converted to lowercase in order to reduce variability and thereby improve model performance. • Stopword removal: In deep learning, stopword removal refers to the removal of common words such as "the," "and," and "is" from text in order to reduce the noise and have the model focus on other, more meaningful words while training. • expanding shortend tokens: The shortening-end token expansion is a preprocessing NLP technique in which the tokens of small size, which could be words or sub-words, get transformed into more informative and helpful tokens for later tasks such as text classification or language modeling. • Tokenization: Have a look at how you tokenized the text; for example, into words or subwords. • Lemmatization: Lemmatization in deep learning refers to the reduction of inflectional forms by converting words into their base form or root and improvise consistency for model training. The Table:1 is representative of text before and after performing all the preprocessing techniques mentioned above , where the "Text-before preprocessed" column presents the text in raw form-that is, noisy, punctuation, special character-containing form-whereas the "Text-after preprocessed" column contains the text after different techniques of preprocessing have been applied to remove or correct such issues.

TABLE I
HEADLINES BEFORE AND AFTER PREPROCESSING

Text-before preprocessed	**Text-after preprocessed**
1.mother ferries 4 more shirt options back to son in gap dressing room	1. mother ferry 4 shirt option back son gap dressing room
2. zoo animals roam free after flooding in Tbilisi	2. zoo animal roam free flooding tbilisi
3. leave no person with disabilities behind	3. leave person disability behind
4. my disastrous search for the perfect swim-suit	4. disastrous search perfect swim-suit
5. my white inheritance	5. white inheritance

The Fig:I represents word-clouds of given text or headlines, indicating a clear difference in the language used in each type of headline to visually represent the tone and sentiment differences in text. Words are set out in a cloud-like pattern, with the most frequently used words appearing in larger font sizes. These word-clouds highlight the variation in the usage of words appearing in sarcastic versus non-sarcastic headlines and visually understand the tone and sentiment in text. The words are set out in a cloud-like pattern; the more frequently used words are in bigger font sizes.

Fig. 1. Word clouds for sarcastic versus non-sarcastic headlines

B. Algorithm

Model Architecture: Sarcasm detection in the news headline is a complicated task; hence, CNN-BiLSTM forms one of the promising deep learning approaches. It captures both local and global features using two techniques, converts headlines into numerical code, extracts features, analyzes context, and relationships. This model will get the probability of sarcasm and is trained on labeled headlines. Though effective, the biggest drawback it faces is related to the need for data and computational expense. This can further be improved by ensembling, transfer learning, and data augmentation. This technology could assist readers in tone and intent to make a much more aware public and hopefully decrease misinformation on social media and online forums. The CNN-BiLSTM model shows very good results in the detection of sarcasm from news headlines. First, it represents headlines as word embeddings that capture semantic relationships and then extracts local features such as n-grams and sentiment-bearing expressions using CNNs. The BiLSTM network will pick up the contextual dependencies and subtle patterns within this word sequence. Further, this will allow the model to extract even complex sarcasm cues, such as ironies and understatement which is also shown in the reference[3]. It is fed into a fully connected layer to yield a probability score on sarcasm detection. Therefore, the model will arrive at robust and highly accurate sarcasm detection, considering that CNNs are integrated along with the BiLSTMs, where the workflow is represented in a flowchart i.e, Fig.3.

IV. Experiment Setup

The main goal of the experiment is to identify sarcasm in the given headlines with the effective detection of sarcasm on general text. Here, the models are trained using publicly available datasets from the Kaggle website by the author RahulMisra. The models are trained and tested on Google Colab, a cloud-based environment that provides free access to GPUs, hence suitable for deep learning tasks. These cleaned and preprocessed text data were free of noisy data and prepared the ground for model training.

A. Dataset

In our study, we employed two datasets for sarcasm detection. First, the headlines dataset was very carefully selected in order to avoid issues such as wrong labeling and other language problems. Besides that, the fact that such headlines are written by professional journalists adds another level of reliability in the dataset. Some common problems of many user-generated datasets-such as slang, misspellings, and informal language-introduce noise, generally making the task of a model harder. But in this case, the formal structure of the language served for the model to pay attention just to the nuances of sarcasm itself and not to be distracted by irrelevant text variations. It contains sarcastic news headlines from the satirical website ”The Onion”(https://www.theonion.com/), which tends to publish humoristic or ironical materials. As a counterpoint, nonsarcastic real news headlines were collected from ”The HuffPost” (https://www.huffpost.com/), a popular news website famous for its high professional standards in regard to publications. Since both sets of headlines are in formal language, written by professional writers, the possibility of spelling errors or using informal language is very low. By using only sarcastic content from ”The Onion,” we ensure that the quality of our data is going to be high since the labels for being sarcastic will, in fact, be accurate. This reduces the chances of wrongly labeled headlines, which is a very important feature in detecting sarcasm since correct labeling will make the model work effectively. For the sarcasm detection task, we made use of a dataset from Kaggle named News Headlines Dataset for Sarcasm Detection https://www.kaggle.com/datasets/rmisra/news-headlines-dataset-for-sarcasm-detection. There used to be two versions: Version 1 and Version 2. Version 1 comprises headlines numbering about 26,709, with 11,724 labeled as sarcastic and 14,985 labeled as non-sarcastic. Version 2 comprises 28,619 head-lines of which 13,634 are sarcastic whereas the remaining 14,985 are not sarcastic. Every version consists of three columns, ”headline” for the text of the news headline, ”article-link” as an optional column, can be used for reference, and ”is-sarcastic” is a binary label. 1 means the headline is sarcastic, while 0 otherwise, which are shown in Table:II. To this end, we created a count-plot showing the number of both sarcastic and non-sarcastic headlines. In the plot below, Fig:2, 0 represents non-sarcastic headlines and 1 represents sarcastic head-lines. This chart gives us insight on the balance between the two types of head-lines in both versions of the dataset.

TABLE II
COLUMNS IN THE NEWS HEADLINES DATASET AND THEIR DESCRIPTION

Column	**Description**
headline	It has the headline text which we use later for sarcasm detection.
article_link	It has the link for the article from which the headline was taken. It was given as a reference
is_sarcastic	It has binary values as 0,1 where 1-represents the text as sarcastic and 0-represents the text as non-sarcastic

Also taken into account are the sarcasm dataset and both the version1 and version2 datasets, which are general texts consisting of 8576 general texts. These contain both sarcastic and non-sarcastic texts. The sarcasm dataset, i.e., general text, contains columns as ”text”-which has sarcastic and non-sarcastic texts-and ”Y”-output label has 0, 1 as values, which are shown in Table:III. In this case also, sarcastic news headlines are taken from the ”The Onion” website, and non-sarcastic news headlines will be collected from ”The HuffPost” website. The main reason for considering the sarcasm dataset with version1 and version2 is that while training the model with only headlines datasets, the model would be able to find out the sarcasm only on the headlines that are seen data, not the general text, which will be the unseen data. This is because, for better performance and for making correct predictions, the model has to be trained with both headlines and general sarcastic text. To do so, the sarcasm dataset is taken into consideration, which would be used for training the model to make it perform effectively on the headlines and general text. Therefore, in total, 63904 lines of texts from headlines and general texts are combined, i.e., the entire dataset.

TABLE III
COLUMNS IN THE SARCASM DATASET AND THEIR DESCRIPTION

Column	Description
text	It has the general sarcastic and non-sarcastic texts.
Y	It has values of 0 (non-sarcastic) and 1 (sarcastic).

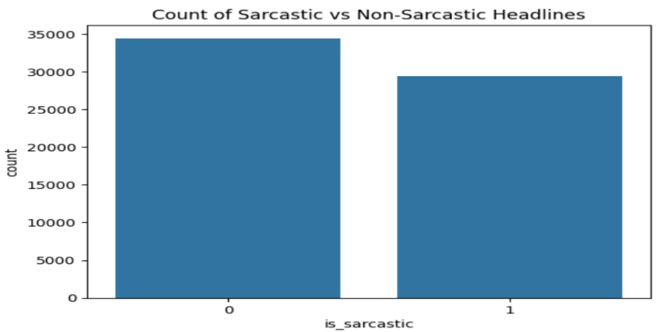

Fig. 2. Count-plot of Sarcastic vs Non-sarcastic headlines.

The Fig:2 indicates that among 63904 texts there are total of 34000 non-sarcastic texts and 29,904 sarcastic texts are present.

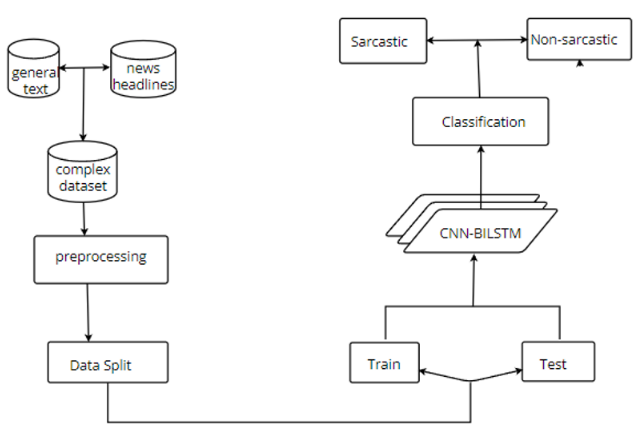

Fig. 3. Flowchart to represent the entire working of the model.

B. Training Environment

All the models have been executed on Google Colab since it provides a suitable environment to run such a computationally expensive task. In Colab, support for GPU has heavily accelerated the training processes of the models; thus, this allowed us to try out different models and hyperparameters in an efficient way.

C. Evaluation measures

For the performance of these models, we measured the performances based on accuracy. In this experiment, we evaluated the model's performance by using accuracy and the F1-score from the classification report, together with the confusion matrix to get the effectiveness of the model.

V. RESULT

Here, we analyze the performance of our proposed models using different performance metrics. Five variants of different models were tested to find out which one performed the best for text sarcasm detection. These models include: 1. Hybrid neural network: CNN and LSTM with the attention mechanism 2. Support vector machine 3. Long short-term memory 4. Gated Recurrent Unit 5. Bidirectional-LSTM + Convolutional Neural Network It is also evident that out of these five, BILSTM+CNN gave the best performance among all these models. It predicted the sarcastic news and general text rather well. On the other hand, other models were not quite working effectively well on both headlines and general text. The other models fail to predict sarcasm in general text with accuracy. This model BILSTM+CNN reached an overall accuracy of 97 percent. The integration of Bidirectional LSTM and CNN works together in capturing the essence of language contextualization. The model turns much more efficient for grasping sarcasm.

The comparison of all the other models and their accuracies are mentioned in the table:IV below.

TABLE IV
RESULTS AND COMPARISON OF ALL MODELS WITH THEIR ACCURACY

MODELS	DATASETS	ACCURACY
Hybrid neural network [2]	News Headline	79%
SVM	News Headline	77%
GRU	News Headline	85%
LSTM	News Headline	85%
CNN+BILSTM	News Headline	93%
CNN+BILSTM	News Headline + general text	97%

This trends promisingly for the proposed model, BILSTM+CNN was reveals both from loss and accuracy graphs during training in Fig:4. While the loss decreased consistently through epochs, it shows that the model gradually improves in predicting sarcastic text more correctly; simultaneously, accuracy increased linearly to touch an impressive 97% accuracy. Firstly, the similar trend in the validation loss and accuracy curves suggests that the model generalizes well on new, unseen data. As the model trains, the training-versus-validation gap in accuracy gets narrower, hence the model is not overfitting. Overall, the trends cut both ways to undergird the effectiveness of BILSTM+CNN in text sarcasm detection. The confusion matrix is telling us that the model correctly identifies sarcastic text 97% of the time and non-sarcastic text 95% of the time. It does not make many mistakes: only 3% of sarcastic text is classified as non-sarcastic and 5% of non-sarcastic text are misclassified as sarcastic as shown in Fig:5. The overall

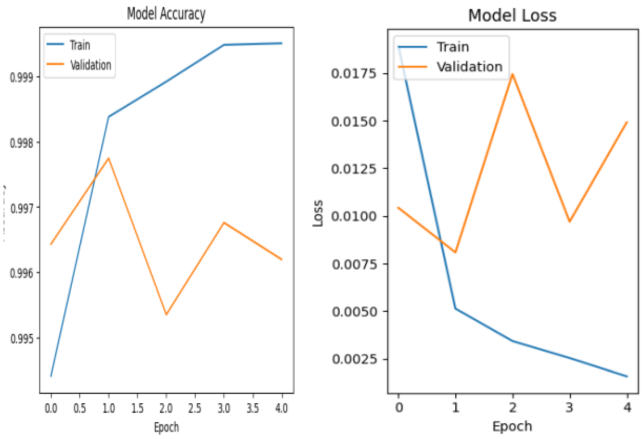

Fig. 4. Trend of loss and accuracy for the proposed method

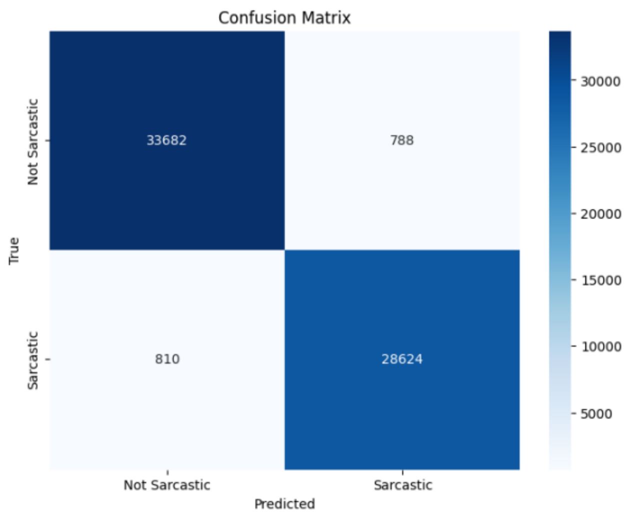

Fig. 5. confusion matrix of BI-LSTM + CNN model

confusion matrix is indicative of the high precision and recall, both from BILSTM+CNN, as proof of detection of sarcasm within text quite effectively.

VI. Conclusion

To summarize, the proposed BILSTM+CNN has shown exceptional performance in text sarcasm detection. It attained an overall accuracy of 97%, outperforming other models such as LSTM, GRU, Hybrid neural network, and SVM. The major reasons for the efficacy of this model over others are its sensitivity to the context and subtleties of language that define what text is sarcastic. The confusion matrix shows high precision and recall values of both classes, indicating that very few errors have occurred. Loss and accuracy trends are indicative of the model's learning and generalization. The word cloud speaks to the variation in the usage of language in sarcastic and non-sarcastic text. The performance of the BILSTM+CNN model is consistent over a number of datasets; hence, the approach taken to detect sarcasm is reliable. Here, the combined use of Headlines and Sarcasm datasets with 63904 texts, including headlines and sarcasm texts, may help the model get effectively trained to perform well in both seen and unseen data to detect sarcasm. This research encourages the development of more accurate natural language processing systems. These results have consequences in applications like sentiment analysis, text classification, and social media monitoring. Overall, the BILSTM+CNN model constitutes a significant leap in the detection of sarcasm and opens new avenues to future research in this area.

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