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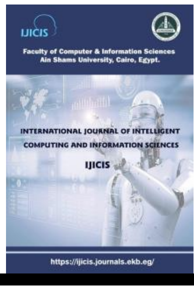

A MEMORY-EFFICIENT APPROACH FOR SARCASM DETECTION IN SOCIAL NETWORKS

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Abstract: *Sarcasm detection in social media has become a crucial task in natural language processing (NLP), where social media has become a fundamental aspect of communication, enabling billions of users to interact, share information, and express opinions. Platforms like Facebook, Instagram, and Twitter have transformed how news and entertainment are consumed, often replacing traditional media outlets. Unlike traditional sentiment analysis, sarcasm detection requires understanding the deeper context behind a statement, as the literal meaning often contrasts with the intended sentiment. This complexity is compounded by the lack of facial expressions or vocal cues, which typically aid in detecting sarcasm in face-to-face conversations. As a result, accurately identifying sarcastic content on social media demands sophisticated models that can account for both contextual and emotional subtleties within conversations. In this work, we propose an enhanced approach for sarcasm detection that combines both conversational context and emotional cues. Our method extracts emotions from the main post and each comment surrounding a response tweet, summarizes the conversation to reduce the context size while preserving key information, and incorporates both the response and the summarized, emotion-rich context into a RoBERTa-based model for classification. We evaluate our approach on a Twitter dataset. Experimental results demonstrate that our approach, which combines summarized context and emotional cues, achieves an F1-score of 83.74%, outperforming models that use only the response or rely solely on summarized context. Furthermore, our approach significantly reduces the*

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data size by 41%, leading to less memory usage, addressing computational challenges posed by large conversational contexts.

Keywords: *Sarcasm Detection, Social Media, Emotion, Conversation Summary, Context.*

1. Introduction

Social networks have seen unprecedented growth over the last decade, becoming essential tools for communication, entertainment, and information sharing. Platforms such as Facebook, Instagram, and TikTok now have billions of active users, while Twitter has millions of active users, all generating massive amounts of content every day [1]. These platforms have not only revolutionized personal communication but also have had a profound impact on various sectors, including politics, business, education, and media. Social media's unique ability to foster real-time communication and global engagement has led to its pervasive use across all age groups and demographics.

The rapid expansion of social networks has also brought about a significant shift in how information is disseminated and consumed. Many users now turn to social media for news and entertainment, bypassing traditional news outlets. The interactive nature of these platforms allows users to engage with content, discuss issues, and form online communities that can influence public opinion and trends.
In this context, sentiment analysis plays a vital role in understanding public opinion by analyzing the emotions and attitudes expressed in social media posts [2]. It helps businesses, governments, and researchers gauge user sentiment towards products, policies, or events, making it an essential tool for decision-making in a rapidly evolving digital landscape. The ability to accurately capture the emotions behind user-generated content enhances the engagement analysis and improves the user experience.
As a result, sarcasm detection has emerged as a critical research area within natural language processing (NLP) [3]. Sarcasm is a type of verbal irony where the intended meaning contrasts with the literal words spoken, which poses distinctive difficulties in analyzing text. Detecting sarcasm is crucial for improving sentiment analysis, especially in domains like social media, where people often express opinions and emotions in complex, non-literal ways.

Sarcasm detection in social media presents significant challenges, particularly due to context dependency and the high volume of context needed for accurate classification. Sarcasm is often context-dependent, requiring an understanding of the broader conversation in which a statement occurs. This complexity increases the difficulty of detection. Additionally, managing and processing vast amounts of contextual data in sarcasm detection presents several challenges. First, the need to track entire conversations or large sets of preceding interactions for accurate interpretation increases computational complexity. This requires models to not only capture the immediate text but also the nuances of how prior messages influence meaning, making the context crucial for understanding sarcasm. Moreover, long conversational histories or multiple threads can lead to memory issues, especially when using transformer-based models that have a fixed input length.

The main contribution of this paper is to address these challenges by managing the vast amount of contextual data through methods that decrease its size and focus on the most important and effective context clues. By concentrating on these key elements, we aim to enhance the accuracy and efficiency of sarcasm detection in complex conversational contexts. Our approach is evaluated using a Twitter dataset that contains responses along with their corresponding post, which may include comments or just the original post. Performance is measured using key evaluation metrics, including F1-score and accuracy, to ensure a thorough assessment of the model's effectiveness.

This paper is organized into five sections. The related work section reviews previous studies. The proposed approach outlines the workflow of our method. Experiments and evaluation describe the experimental setup and evaluation process. The experimental results present the outcomes. Finally, the conclusion summarizes the findings and suggests future directions.

2. Related Work

In this section, we examine models designed to detect sarcasm in the English language. It encompasses a range of innovative approaches, which we review and categorize into several key categories: machine learning techniques, deep learning methods, and transformer-based models. Additionally, we highlight studies that integrate contextual information to enhance sarcasm detection, emphasizing the techniques employed in these approaches.

2.1. Machine Learning Approaches

In [4], authors explore innovative methodologies for irony detection within sentiment analysis, addressing the complexities of recognizing irony in text. It highlights the importance of data preprocessing techniques, such as lemmatization, tokenization, and stemming, as foundational steps for effective irony detection. Additionally, they evaluate various machine learning classifiers including Support Vector Machine (SVM), linear regression, Naïve Bayes, and Random Forest comparing their performance based on metrics such as accuracy, precision, recall, and F-score.

In [5], authors introduce an Intelligent Machine Learning-based Sarcasm Detection and Classification (IMLB-SDC) model tailored for social media applications. Recognizing the complexities and ambiguities inherent in sarcasm, the authors develop a comprehensive framework that includes preprocessing, feature engineering, feature selection, classification, and parameter tuning. The classification task is performed using a Support Vector Machine (SVM), with optimal parameter tuning achieved through a Particle Swarm Optimization (PSO) algorithm.

In [6], authors present a Random Forest-based classifier designed for automatic sarcasm detection on Twitter data, addressing the challenges posed by nonliteral language in social media communications. The authors utilize a diverse set of textual features, including neural language fusion and natural language features, which encompass sentiment-related attributes, semantic and syntactic elements, punctuation-related features, and GloVe embeddings. These features are extracted separately from the target tweet and then fused to create a comprehensive feature set for classification.

2.2. Deep Learning Approaches

In [7], authors investigate sarcasm detection using an ensemble learning approach that combines various deep learning techniques, including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Baseline Convolutional Neural Networks (CNN). They prepare a dataset utilizing different pre-trained word embedding models, such as fastText, Word2Vec, and GloVe, comparing their respective accuracies.

In [8], authors explore the detection of sarcasm using a Bi-Directional Recurrent Neural Network (RNN)-based deep learning model, specifically designed to identify implicit sarcasm in text. Acknowledging the complexities of recognizing sarcasm. The proposed model, termed Proposed LSTM (P-LSTM), enhances sarcasm detection by capturing context-based incongruities in sentences through its bi-directional scanning capabilities, effectively considering both prefixes and suffixes of words. The classification process is organized into two levels emotional and semantic allowing for a comprehensive evaluation of tweets based on their sarcastic nature.

In [9], authors present a hybrid convolutional neural network (CNN-H) model designed for sarcasm detection in multilingual social media posts, addressing the significant challenge of sentiment extraction in informal and often noisy datasets. Recognizing that sarcasm can invert the perceived sentiment of phrases, they propose a model that integrates both character and word embeddings, enhancing its ability to capture the complexities inherent in multilingual content.

2.3. Transformer-Based Approaches

In [10], authors investigate the effectiveness of various pre-trained models (PTMs) in detecting sarcasm, a common challenge in NLP across social media platforms. The authors focus on evaluating the performance of prominent PTMs such as RoBERTa, DistilBERT, and XLNet on four established sarcasm detection datasets. The study reveals that RoBERTa consistently outperforms other models, excelling across three datasets, while DistilBERT proves to be a viable option for scenarios with limited computational resources. Notably, the research highlights the significance of hyperparameter tuning, identifying the learning rate as the most impactful factor in model performance.

In [11], authors present a novel approach to sarcasm detection that utilizes BERT and an attention mechanism to enhance the analysis of complex semantic structures in sentiment expressions, and to focus on phrase fragments, facilitating higher-level semantic feature extraction.

In [12], authors introduce an approach to sarcasm detection by developing a bilingual transformer model that effectively integrates text and emoji data from social media. The Gated Temporal Bidirectional Convolution Network (GT-BiCNet) is used to model text, while an Emoji-to-Vector Model (E-VM) captures emoji features, resulting in a deep feature fusion. The proposed Attention LSTM model, enhanced with the Amended Bidirectional Encoder Representation from Transformers (ALABerT) and optimized through the Enhanced Pelican Optimization Algorithm (EpoA).

2.4. Context-Aware Approaches

In [13], authors investigate the impact of context on sarcasm detection in social media conversations, focusing on techniques and models based on transformer architectures. The authors extend state-of-the-art pre-trained transformers, including BERT, RoBERTa, and spanBERT, to various task objectives, such as single sentence classification and sentence pair classification. By applying these models to twitter conversations and Reddit discussion threads, the research highlights the crucial role of conversational context in enhancing sarcasm detection accuracy. Additionally, the authors propose their own architecture that combines Long Short-Term Memory (LSTM) networks with transformers, further emphasizing the potential of hybrid approaches in this domain. This work contributes valuable insights into how contextual elements can improve sarcasm detection in online interactions.

In [14], authors explore the effectiveness of transformer-based models, particularly Bidirectional Encoder Representations from Transformers (BERT), in analyzing conversational contexts. They highlight the limitations of traditional models, such as Long Short-Term Memory (LSTM) variants, in detecting sarcasm that arises from multiple sentences. Additionally, the study provides insights regarding the influence of the number of sentences in a conversation on sarcasm detection, advancing the understanding of contextual nuances in sarcastic expressions.

In [15], authors investigate the efficacy of OpenAI's Generative Pretrained Transformer (GPT) models, including GPT-3, InstructGPT, GPT-3.5, and GPT-4, in the context of sarcasm detection within natural language processing. The study addresses the inherent challenges posed by sarcasm rooted in social complexity and contextual interpretation by employing both fine-tuned and zero-shot approaches. Notably, the research utilizes the Self-Annotated Reddit Corpus (SARC 2.0) dataset, focusing on its political and balanced segments, to rigorously assess model performance.

Table 1 provides a comparative overview of various research works on sarcasm detection, highlighting the scope, techniques, and datasets used in each study.

3. Proposed Approach

The primary objective of this paper is to improve sarcasm detection by addressing the challenges posed by large volumes of conversational data and the complexity of sarcasm. The proposed approach aligns with context-aware approaches by using conversational context and emotional cues to enhance detection accuracy. It allows the model to focus on relevant sarcastic cues in the conversation while maintaining computational efficiency. It takes a response (Tweet) and its surrounding comments, extracts emotions from each comment, and summarizes the conversation to reduce the context size while retaining key information. The proposed sarcasm detection approach architecture is shown in Figure. 1.

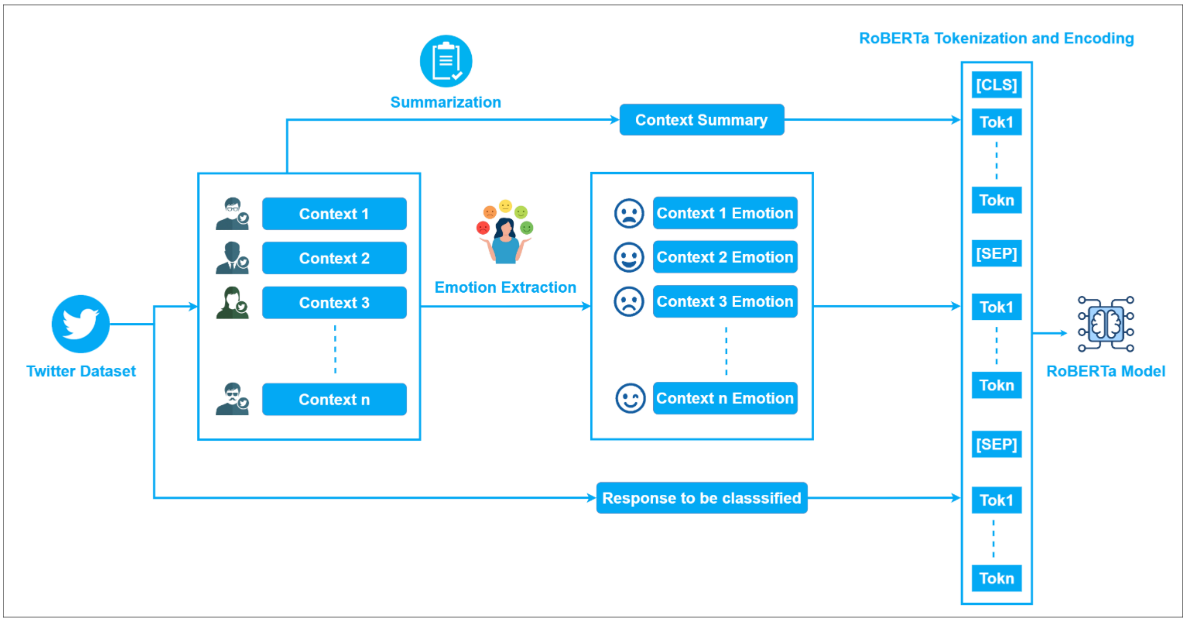

Figure 1: Proposed Sarcasm Detection Approach Architecture

Table 1 Research Works on Sarcasm Detection Across Techniques and Datasets

Research Work	Year	Scope	Technique	Dataset	Advantage
[4]	2021	Machine Learning Approaches	SVM, Naïve Bayes, Decision Tree, Random Forest	SemEval2018-T3-train-taskA	Provides a comparative analysis of multiple classifiers for sarcasm detection.
[5]	2022		Support Vector Machine (SVM) with parameter tuning via Particle Swarm Optimization (PSO).	Social Network	Comprehensive approach that integrates preprocessing, feature engineering, selection, and parameter optimization.
[6]	2022		Random Forest classifier with GloVe embeddings	Twitter	Utilizes a diverse range of textual features, including neural language fusion, sentiment-related features, and GloVe embeddings.
[7]	2022	Deep Learning Approaches	Ensemble Model (LSTM, GRU, CNN) with Word Embeddings (fastText, Word2Vec, GloVe)	News Headlines and Reddit	Combining LSTM, GRU, and CNN with word embeddings like LSTM and GloVe.
[8]	2023		Bi-Directional RNN (P-LSTM)	Automatically and manually annotated datasets	P-LSTM enhances sarcasm detection by capturing dependencies in both directions.
[9]	2024		Hybrid Convolutional Neural Network (CNN-H)	News headlines, Ghosh Tweet, Riloff Tweet)	The CNN-H model effectively integrates both character and word embeddings, allowing it to process and classify sarcastic statements in various languages.
[10]	2021	Transformer -Based Approaches	RoBERTa, DistilBERT and XLNet	SemEval, iSarcasm, Ptacek, Ghosh	RoBERTa shows superior performance in sarcasm detection across multiple datasets. DistilBERT is efficient for resource-limited environments.
[11]	2024		BERT with attention mechanism	Mishra, Ghosh, IAC-V1 and IAC-V2	Captures semantic features and phrase fragments through attention mechanisms.
[12]	2024		Gated Temporal Bidirectional Convolution Network, Emoji-to -Vector Model and Attention LSTM based on Amended Bidirectional Encoder Representation from Transformers	English twitter dataset and Semeval 18 dataset	The model effectively analyzes both textual and emoji data, enhancing the ability to capture sarcasm nuances that may be missed when using text alone.
[13]	2020	Context-Aware Approaches	BERT, RoBERTa and spanBERT	Twitter, Reddit	High performance with context-aware models, demonstrating effective sarcasm detection.
[14]	2020		BERT, LSTM and XLNet	Twitter	The use of BERT allows for better capture of syntactic and semantic information across multiple sentences, improving the detection of sarcasm in conversations.
[15]	2023		GPT-3, GPT-3.5 and GPT-4 models	Self-Annotated Reddit Corpus (SARC 2.0)	Uses powerful GPT models improve sarcasm detection.

3.1. Methodology

3.1.1. Context Summarization

Conversation contexts are summarized using the knkarthick/MEETING_SUMMARY model [16], a fine-tuned version of facebook/bart-large-xsum. To improve the effectiveness of the summarization model, we added speaker labels and numbered each conversational turn. Specifically, for every context entry (whether a post or comment), we prefixed the text with a label like "Speaker 1:" followed by the corresponding content. Speaker numbers were assigned sequentially within the same record, resetting to "Speaker 1" for each new conversation. This modification allowed the model to better differentiate between conversational turns and provided a clearer structure, leading to more accurate summaries.

3.1.2. Emotion Extraction

The pre-trained michellejieli/emotion_text_classifier model [17] from Hugging Face is used to extract emotions for each comment or post. This model, based on DistilRoBERTa-base and fine-tuned on transcripts from the Friends show, classifies text into 6 emotions (anger, disgust, fear, joy, sadness, surprise) plus a neutral class. Neutral emotions were removed as they were found to distract from the main task of sarcasm detection. This refinement helped focus the model on more relevant emotional cues. Additionally, for each speaker in the context, we appended the extracted emotion with its corresponding speaker label, such as "Speaker 1 felt Emotion." This enhancement provided clearer emotional context and improved the model's ability to identify sarcasm based on emotional cues. Figure. 2 shows an example of summarization and emotion extraction processes.

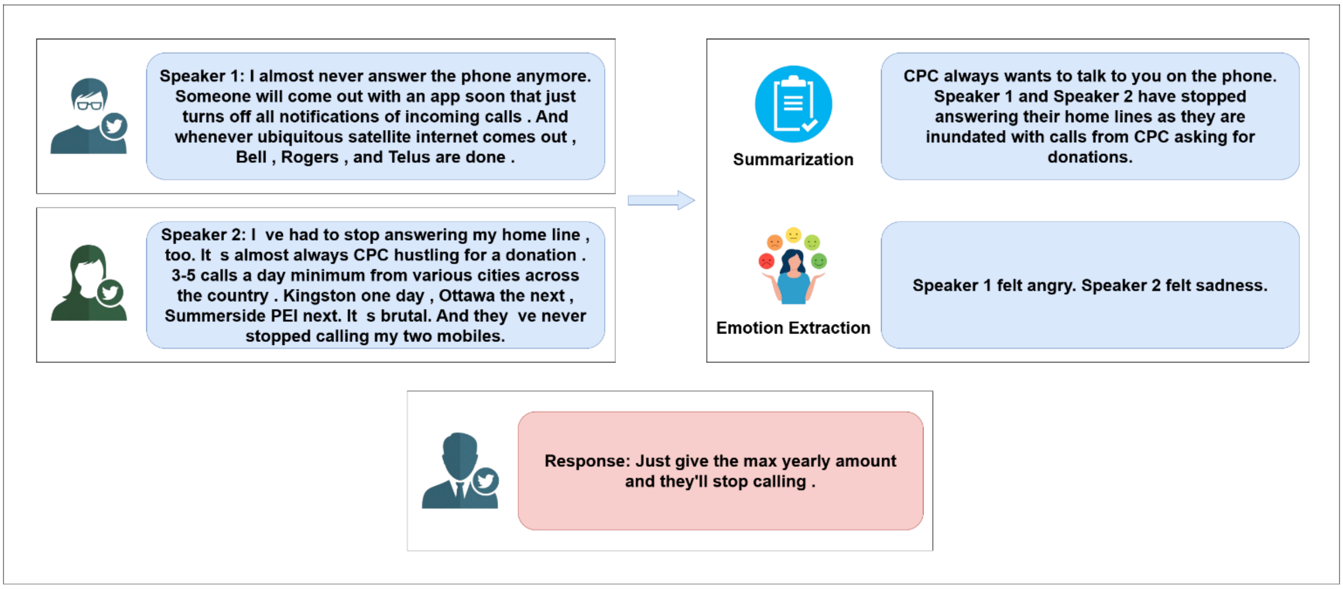

Figure 2: Example of Summarization and Emotion Extraction

3.1.3. Tokenization and Training

The RoBERTa tokenizer [18] from Hugging Face was used to tokenize both the context and response for each sample, while Roberta-base model [18] was fine-tuned for sarcasm detection using Hugging Face’s Transformers library.

4. Experiments and Evaluation

In this section, we describe the experiments conducted to assess the effectiveness of our proposed approach.

4.1. Dataset

The dataset used in this research is derived from a study [19] focused on sarcasm detection in Twitter data. The dataset contains 5000 samples, with 80% allocated for training and 20% for testing. Each sample includes:

- Context: The dataset consists of conversation histories with multiple columns representing a post and its associated comments. In our experiments, the data included context ranging from Context 1 to Context 20, where Context 1 represents the original post and Context 2 to Context 20 represent the comments (if present). The number of comments can vary, with some posts having only a few comments, while others can have up to the maximum of 19 comments. The number of context columns (n) is therefore dynamic, depending on the specific conversation.
- Response: The tweet to be classified, which is either a reply to the last comment in the conversation or, if there are no comments, a response to the original post.
- Label: the actual classification indicating whether the response is sarcastic or non-sarcastic.

4.2. Preprocessing

The dataset was preprocessed to ensure that it was suitable for training. The following steps were taken:

- Text Cleaning: The dataset was cleaned by removing emojis and non-English characters to standardize the input data.
- Context Grouping: To simplify the representation of the conversation history, all context information for each record was consolidated into a single cell.
- Data Shuffling: One important characteristic of the data is that it was originally ordered by class labels, with sarcastic responses (1s) followed by non-sarcastic responses (0s). To prevent bias during training, the data was shuffled before further processing.

4.3. Experiments Implementation

The experiments were conducted using Google Colab, using a T4 GPU for computations. To evaluate the impact of context summarization and emotion extraction on sarcasm detection, we conducted a series of experiments using the RoBERTa-base model. The training configuration included 5 epochs, a batch size of 32 for training and 64 for evaluation, and a weight decay of 0.01. The RoBERTa tokenizer processed these inputs with truncation and padding to ensure uniform input lengths. Four distinct experiments were conducted, varying the input to the model:

- Response only: The first experiment focused solely on using the response as input, without incorporating any surrounding context.

- Response combined with original context: We tested the model's performance when using the original, unmodified context in addition to the response.
- Response combined with summarized context: In the second setup, the response was combined with a summarized version of the conversational context. This allowed the model to capture some additional contextual information while maintaining computational efficiency.
- Response combined with summarized context and emotions: The fourth experiment extended the previous setup by appending emotions extracted from the context. This approach was designed to evaluate the influence of emotional content on sarcasm detection.

These experiments aimed to explore whether using the full context would enhance performance, though it presented challenges in terms of computational resource constraints. Each experiment aimed to provide insights into how different types of input ranging from isolated responses to full conversational contexts with emotional information affect the model's ability to detect sarcasm.

5. Experimental Results and Discussion

Throughout our experiments, we explored various approaches to sarcasm detection, aiming to balance computational efficiency and model performance. One of the significant challenges we faced was handling the large original context, which included up to 20 preceding comments along with the response. As shown in Table 2, the best performance was achieved when both context summaries and emotion extraction were incorporated, yielding an F1-score of 0.8374, an accuracy of 0.83 and a loss of 0.4429. Starting with the response only as the input, the model achieved an F1-score of 0.738392, accuracy of 0.769, and a loss of 0.629363. By adding summarized context, the F1-score increased by (7.3%) to 0.8114, accuracy improved by (4.7%) to 0.816, and the loss decreased by (13.3%) to 0.4962. The data size for this trial was 1766 kb, representing a reduction of approximately (48%) compared to the original data size of 3396 kb. Incorporating both summarized context and emotions further enhanced performance, with the F1-score rising by (9.9%) to 0.8374, accuracy increasing by (6.1%) to 0.83, and the loss dropping by (18.64%) to 0.4429. The data size for this experiment was 1995 kb, representing a reduction of about (41%) compared to the original data size. When testing with the original context, the model encountered CUDA out-of-memory errors due to the large input size, highlighting the practical advantage of using summarized context and emotions.

Table 2 Performance of Roberta-base Model with Different Context Inputs

Context Input	**Model**	**Loss**	**Accuracy**	**F1-score**	**Data Size (KB)**
Response Only	Roberta-base	0.6293	0.7690	0.7383	618 kb
Response + Original Context		CUDA out of memory	CUDA out of memory	CUDA out of memory	3396 kb
Response + Summarized Context		0.4962	0.8160	0.8114	1766 kb
Response + Summarized Context + Emotions		0.4429	0.8300	0.8374	1995 kb

In comparison to our work, similar results were demonstrated using the baseline (Transformer+BiLSTM+Maxpooling) [19] when incorporating context into the sarcasm detection process. Their model using the "ensemble with maximum context," achieved an F1-score of 0.8366, which is comparable to our highest F1-score of 0.8374 when using both summarized context and emotion extraction. However, while they utilized the entire context data in their model, we effectively reduced memory usage by summarizing the context and reducing the data size, making our approach more efficient without compromising performance. Additionally, our method focuses on key sarcastic clues from both context and emotions, allowing the model to detect sarcasm with high accuracy even with reduced input size.

By summarizing the context, we were able to avoid the memory issues associated with using the full context, which included up to 20 previous comments. This demonstrates the efficiency of the proposed approach, which reduces computational overhead while still improving model performance significantly.

6. Conclusion

In this research, we aimed to enhance sarcasm detection by exploring different ways to incorporate context and emotional content into the detection process. The experiments were conducted using Twitter dataset and involved evaluating the impact of various input configurations on the performance of the RoBERTa-base model. Our approach focused on the integration of context summaries and emotion extraction to improve sarcasm detection. We observed that using a combination of summarized context and extracted emotions yielded the most significant performance improvements. This approach not only enhanced the model's ability to accurately detect sarcasm but also effectively managed computational resources, addressing the challenges associated with handling large context sizes.

Future research should focus on enhancing contextual representation through advanced summarization techniques and exploring multilingual and cross-cultural applications to improve sarcasm detection across diverse languages and cultures.

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