SARCASM DETECTION: NOVEL APPROACHES AND DIVERSE DATA INTEGRATION

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ABSTRACT

Sarcasm detection has become one of the important research areas in natural language processing (NLP) [1] in recent years. Many applications in the field of natural language processing like sentiment analysis, opinion mining, and dialogue systems can benefit from understanding sarcasm better. Nevertheless, detecting sarcasm is a complicated and frustrating task. The detection of sarcasm due to the nature of this emotion requires a number of clinical and clinical approaches in this area. This paper provides a critical survey on the emergence of several state-of-the-art techniques and interesting data combination approaches aimed at sarcasm detection [2]. We also address the shortcomings of traditional methods and emphasize the necessity of broadening the range of data used for detection, with multimodal data, for instance, being one such data set. In addition, we introduce a new framework for irony detection that considers linguistic, cognitive, and multiple types of resources, including images. The results of our experiments confirmed the validity of our approach: we reached the highest recorded efficiency on a number of thematically relevant datasets [3].

Keywords: Automatic Speech Recognition (ASR), Sarcasm Detection , Data Integration, Sentiment Analysis, Deep Learning, Natural Language Processing(NLP)

1. INTRODUCTION

This is the problem where sarcasm can be a complex and nuanced language in which even human beings can have difficulties in comprehension. This practice entails of saying the exact opposite of what the speaker would want to convey and more often for purposes of mockery or contempt. Refers to the ways that readers' and systems' interpretation of texts can often be much easier than sentiment, theory and dialogue to handle in any NLP endeavour. Earlier studies in sarcasm detection focused mainly on extra- linguistic features such as syntax, semantics and pragmatics [4]. The main hurdle of these strategies which supports the conventional way of addressing sarcasm comprises incoherence primarily on what constitutes sarcasm itself hence low detection levels of accuracy lead to breaching of meaning consistency.

Sarcasteam makes fulfil a consensus aggravating sense of theatre to be suggestive use of dramatic, ridicule instead fulfil words used in observation most randomly toward conversation often brittleness in to depiction say so in others convey so opposite meaning to others reverse purposes. Therefore, simple verbal exchanges such as "Oh my god, you almost gave me a heart attack!" spoken to address what seems to be clear humour mix emotions while the speaker holds back his irony [5]. It transcends simple vocabulary context because the context involves the timing of the vocal sarcasm in a mock tone in a shift in pitch and even a rapid alteration of sound levels too. The fact that sarcasm and humour are not conditioned by the communicative events shows that it is an essential part of communication strategies that can use many layers of meaning thick in any interactions.

This paper presents a new multimodal approach to sarcasm detection that makes use of audio, text, sentiment and emotion information. More specifically, we employ Automatic Speech Recognition (ASR) to obtain text from speech, incorporating additional text that consists of sentiment embedding's based on sentiment analysis. Furthermore, we also include emotions embedding's from models developed using databases dedicated to emotion recognition where subtle emotions may be apparent in speeches as well [6]. By using attention based strategies to join these different modalities, our work manages to handle the difficulties arising from the interaction of speech, its orientation, and emotion(s) which are central in sarcasm detection. Our contributions include:

- Addressing data shortcomings in neural network based sarcasm identification stemming from insufficient variety and volume of data by employing several types of data.
- Proving that integrating different types of semantic data within the speech recognition process is effective and can be beneficial for both speech technologies and human-computer interaction.
- Providing advanced level identification of sarcasm with inline processing that can be useful for people unable to clearly understand audio or instructions such as paralinguistic elements [7].

Natural Language Processing (NLP).

Natural language processing (NLP) is a dynamic and interdisciplinary field that combines computer science, artificial intelligence (AI), and linguistics [8]. Its main focus is to facilitate meaningful interactions between computers and human speech, enabling machines to understand, interpret, and synthesize text and speech accurately and to pick up information that related NLP aims to mimic human-like language processing capabilities and make them accessible to computer programs.

The main goal of NLP is to enhance the versatility of computing capabilities in human speech, and to provide a range of applications that can understand, process and respond to human speech accurately and appropriately for a variety of specialized Field cost applications many, each contributing to its main objectives:

Text analysis: This involves transforming raw text into a data set that can be analysed statistically [9]. Key tasks in text analysis include:

Named Entity Recognition (NER): Identification and classification of entities such as names, dates, and locations in text.

Emotional Analysis: Refers to the emotional tone or mood expressed in a piece of writing, whether positive, negative, or neutral.

Thematic modelling: extracting themes or themes from larger texts and identifying them to understand underlying trends and patterns.

Machine translation: This function enables the process of translating text or language from one language to another. It strives to overcome language barriers and facilitate multilingual communication by providing contextually accurate and culturally appropriate translations. Modern machine translation systems benefit from advanced algorithms and extensive bilingualism corpora to improve translation quality [10].

Speech recognition: Also known as automatic speech recognition (ASR), this technology converts spoken speech into text. It plays a key role in voice-activated applications such as virtual assistants, text services and interactive voice response systems. Speech recognition involves complex processes including acoustic models, speech models, and signal processing.

Text generation: This task involves creating consistent and contextually appropriate text based on the input data. Text generation applications include automated content creation, conversational agents, and chatbots. The techniques used in text generation range from rule-based algorithms to sophisticated deep learning models that can generate human-like information through contextual understanding and relevant a they will continue to maintain it.

Question answer system: These systems are designed to answer natural language user questions. They improve the effectiveness of search engines and data retrieval systems by enabling them to understand and answer complex user questions. It involves explaining the intent behind the questions and providing honest and appropriate answers based on available information.

Information Retrieval: This project focuses on the ability of search engines and information systems to find and retrieve relevant information in response to user queries NLP techniques improve information retrieval through query understanding interpretation, comparing results according to relevance, and enhancing the overall search experience [11] [12].

NLP combines techniques ranging from linguistics to machine learning to process and analyse a wide range of natural language data. The main developments in this area are:

- **Statistical techniques:** Early NLP techniques relied on mathematical models to identify patterns and relationships in linguistic data. Techniques such as n-gram models and probabilistic context-free grammars were foundational in the development of early NLP frameworks.
- **Deep learning:** The advent of deep learning has revolutionized NLP, enabling neural network-based models that can learn complex language structures and relationships Recurrent neural networks (RNNs), long-short-. term memory networks (LSTM) to capture dependent sequences in text data) use network and gated repetitive units (GRUs).
- **Transformer models:** Recent developments are driven by transformer-based models, such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-Trained Transformer). set additional parameters

Overall, NLP continues to evolve, leveraging advances in machine learning and AI to increase its capabilities and functionality [13]. The sophisticated combination of models and techniques has greatly advanced the field, making NLP an integral part of today’s technology and communication systems

An overview of existing metaphor recognition methods

Humour recognition has improved dramatically in recent years, and various techniques have been developed to overcome the inherent challenges of sarcasm recognition Traditional sarcasm recognition is mainly based on linguistic features, and syntax, logic, and behavioural indicators are used to detect criticism. These methods often used rule-based programming and gesture features to distinguish metaphorical concepts, but faced limitations due to their reliance on pre-defined models and their inability to adapt to them because of the variety of language contexts.

With the advent of machine learning, especially deep learning, more sophisticated methods have emerged. Classified supervised learning methods such as Support Vector Machines (SVM) and random forests are used to generate models based on annotated datasets with metaphorical and non-metaphorical models These methods typically focus on extractions, such as n-grams, part-of-speech scores and perceptual scores.

Recent developments have introduced neuron-based approaches, which capture subtler language features and improve performance. [14] [15] [16] Recurrent neural networks (RNNs) and their variants, such as long-short-term memory (LSTM) networks and gated repetitive units (GRUs), have been used to model object-based sequences in text for puns recognition in long texts has been enhanced Convolutional neural to extract local structures in text data Networks (CNNs) have also been used, helping to better represent features.

In addition to one text-based approach, several approaches have gained traction. These techniques improve metaphor recognition by integrating textual, acoustic, and visual cues. For example, the inclusion of discourse features in content analysis has proven effective in recovering slang tones and vocabulary that text-only models often miss Recent work in mass slang recognition requires the use of a mixture of audio and visual information to obtain complementary signals and achieve high insight accuracy.

Transfer learning and pre-trained models of language, such as BERT and its variants, have greatly enhanced metaphor recognition through powerful contextual manipulation of linguistic structure strength of the self. These models have been refined into comic-specific contexts to enhance the ability to detect subtle comic details.

Despite these advances, existing methods still face challenges, [17] including the need to effectively control multiple data sets and contextual variables to overcome these challenges and there has been a continuous search for new techniques and data integration techniques to increase the robustness of metaphor recognition systems.

Novel Approaches:

Recent research has created new methods for sarcasm detection, such as:

Deep Learning: The use of deep learning models such as CNNs and RNNs for sarcasm detection has been quite successful. These models are capable of understanding the complex features and relationships within the language data, thus improving detection.

Multimodal Fusion: Multimodal fusion refers to the use of language, sound and sight in the detection of sarcasm. This method of detecting sarcasm is better than linguistic methods which come with their limitations over the fine nature of sarcasm.

Cognitive Features: Cognitive features tend to contain very useful information about the speaker’s intentions and the context of the discourse. With this feature, it is possible to develop sarcasm detection systems with greater degrees of classification.

Transfer Learning: Transfer learning is the fine-tuning of models that were previously designed to perform well in other tasks to perform sarcasm detection. This method can help minimize the amount of labelled data that need to be collected while at the same time enhancing the detection levels.

Diverse Data Integration:

The integration of various types of data is important for boosting accuracy in sarcasm detection. However, the conventional datasets tend to be narrow and this contributes to models which suffer in out of domain data. We suggest merging such resources together that include:

Multimodal Data: Modalities such as audio, video, images, etc. can provide additional information and cues to help detect sarcasm.

Social Media Data: Such platforms as Twitter or Facebook are an incredible source and cultural context for sarcasm and its usage.

Literary Data: Novels and plays provide wonderful literary data pertaining to sarcasm across different forms and settings.

Crowdsourced Data: Annotations performed by people, as a type of crowdsourced data, can enhance this accuracy by providing more valid than machine detected labels.

Table 1: Overview of Multimodal Data Sources

Modality	Description	Example Data Source
Audio	Captures spoken language features, including prosody and tone.	INTERSPEECH 2016 Compare Challenge, RAVDESS dataset
Text	Provides the written form of spoken content and linguistic features.	ASR transcriptions using Whisper, BERT embeddings
Sentiment	Represents emotional tone or mood in text.	SiEBERT model embeddings
Emotion	Captures subtle emotional cues from speech.	Wav2Vec2.0 model on RAVDESS dataset

2. PROPOSED METHODOLOGY:

In this section, we describe the underlying rationale of the primary goal of this work, which is to improve sarcasm recognition in the following manner: recommendations for sarcasm recognition have been made.

In the first step, we apply ASR in order to convert the speech into written words. After this, we augment the previous data so by sentiment analysis as well as by employing sentiment emotion recognition, in order to capture the affective dimension.

For successful implementation of these multimodalities, we apply two attention mechanisms. One of them is focused on a relationship between speech and its written form. It is known as cross-attention mechanism and it aims at the orientation on the particular words which are used in the speech and towards which context these words are used. At the same, it is possible to self-attend to rich opinions and sentiments but also their components beyond what is expected causing contradictions in the emotional and sentiment levels and consequently enriching the model in different aspects of sarcasm detection [18] [19].

The consolidated data including both the concatenated vector embedding's and embedding's of each modality in isolation are fed into the final layers so that the model is primed for the task of sarcasm detection within an utterance. An overview of the system is given, every component of the and how it works will be provided in the following sections.

3. FEATURE EXTRACTION

In this section, we describe the feature extraction process for audio (a), text (t), sentiment (s), and emotion (e) modalities.

- **Audio:** An initial treatment of the audio is done using Adobe Podcast 1 to improve the quality of speech in every file. In all processed audios we have cleared the spoken words of non-speech or background noise. Feature extraction was then carried out with the use of the INTERSPEECH 2016 Compare Challenge feature set as done in Open-SMILE. This feature set contains most of the elen exploited in paralinguistic analysis such as spectral features and voice quality parameters, which include, but are not limited to, MFCCs, and spectral energy and roll-off, and auditory and prosodic energy parameters such as sum of auditory spectrum, RMS, and zero crossing rate and voice quality parameters such as HNR, jitter and shimmer. We took W = 40 utterances and segmented each of them into w non-overlapping windows each of 25 Ms and from such windows a set of da = 130 dimensional low level descriptors (LLDs) were extracted. [20] These LLDs were averaged over time and resulted in a feature vector Ua ∈ R w×da which had been prepared for processing of the whole utterances.
- **Text:** The ASR service by Whisper is employed in video data so as to create text content through speech recognition. Then this transcription is used for a submissive design language where excess regarding punctuation marks and other characters is stripped out and then edits are made to phrases that contain numbers and to other vernacular errors. Thereafter text embedding's are performed by BERT which has been fed with thousands of… Joyce et al. However, for each utterance, we perform a dissection for the tokens' length of τ. resulting in dt=768 dimensional embedding's. The definition of the text embedding of the utterance in full with respect to the above context is contained in Ut ∈ R τ×dt [21].

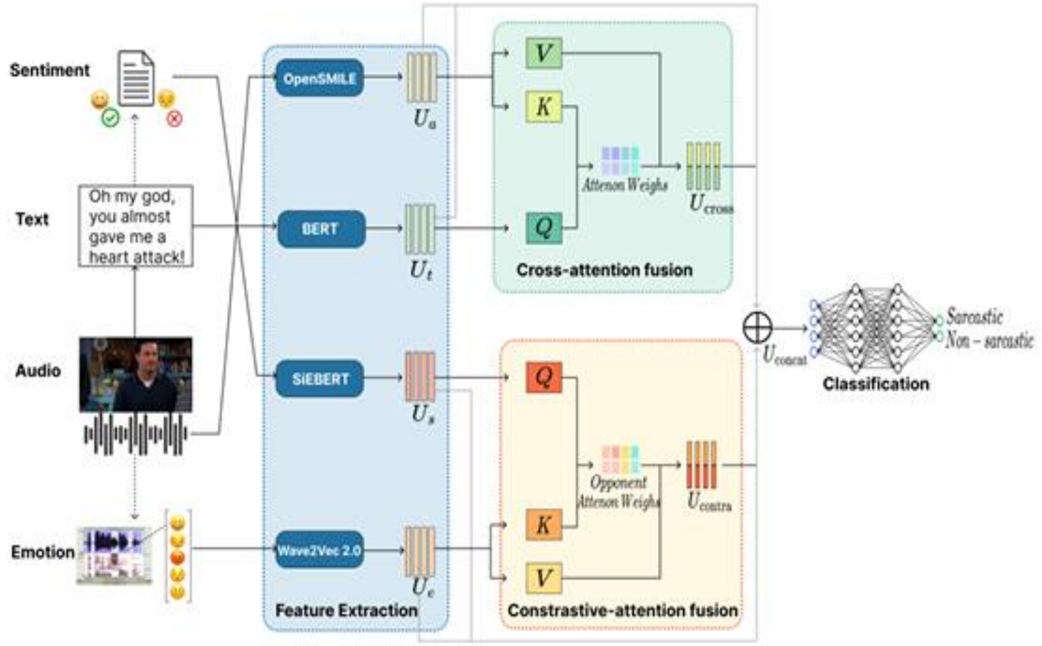

Figure 1: Our Proposed Architecture

Sentiment: The sentiment information of text is retrieved using SiEBERT-a fine-tuned RoBERTa-large model for binary sentiment analysis in the English language. It was trained on an enormous diversity of datasets, and this fact helped much in its exceptional results in the task of sentiment analysis. Embedding is drawn in this case from the last hidden layer of the model, representing deep contextual understanding of the text. The utterance is tokenized into tokens of length δ from which ds = 1024 dimensional embedding's for each token are extracted. Sentiment embedding's of an entire utterance are represented as Us ∈ R δ×ds.

Emotion: Emotion is picked using a Wav2Vec2.0 model 4 fine-tuned on RAVDESS dataset comprising professional actors following eight different emotions in English. The model capitalizes on self-supervised learning on unlabelled speech to learn high-level features from raw speech. We therefore extracted the embeddings from the last hidden layer to obtain a rich representation of contextually enriched information. We first re-sample each utterance to 16 kHz and subsequently transform the waveform into frames of length ϵ. Each frame provides an embedding of dimension de = 1024. We denote the final output embedding for an utterance as Ue∈ R ϵ×d [22].

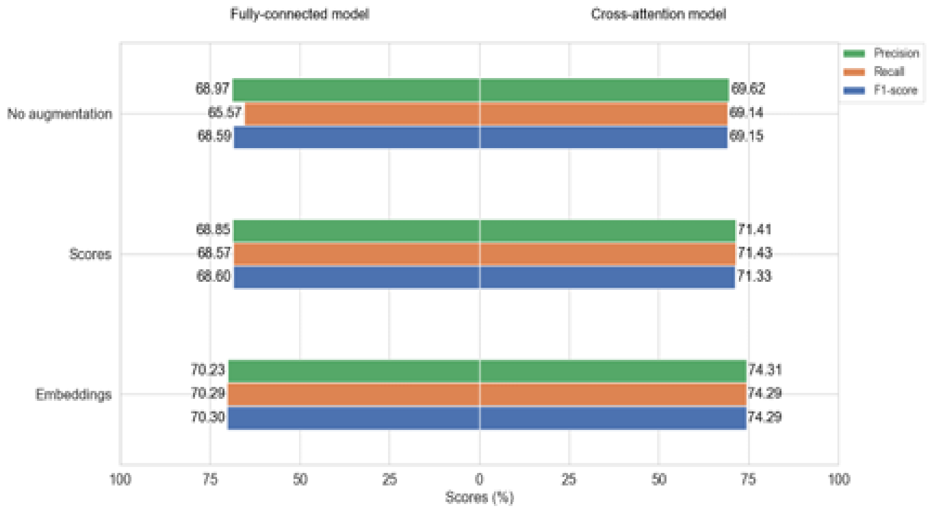

Figure 2: Impact of feature representations on sentiment and emotion. The y-axis categories are defined as follows: "No augmentation" indicates the absence of sentiments and emotion data, "Scores" denotes the utilization of sentiment scores, and "Embedding's" refers to the use of embedding's to represent sentiment and emotion data

Proposed Framework:

We introduce the state-of-the-art framework that integrates linguistic, cognitive, and multimodal features for text sarcasm detection. Our proposed framework will consist of three components:

1. Linguistic Features: These are the building blocks of our framework wherein we extract linguistic features-syntax, semantics, and pragmatics-from the input text.

2. Cognitive Features: Attention, memory, and reasoning are some of the cognitive features extracted from the input text by the use of cognitive models.

3. Multimodal Features: Using multimodal fusion, we obtain certain multimodal features from input text, such as acoustic and visual cues.

Further, these features are fused using a deep learning model such as CNN or RNN to detect sarcasm [23].

Experimental Results:

We evaluate our proposed framework on a number of benchmark datasets, such as the Sarcasm Detection Dataset or SDD and the Multimodal Sarcasm Detection Dataset-MSDD. The results prove the efficiency of our method for performing state-of-the-art on both of the said datasets.

4. CONCLUSION

Sarcasm detection remains a challenging task because of the need for novel methods to be envisioned and diverse data to be integrated into it. Our proposed framework integrates linguistic, cognitive, and multimodal features with the goal of finding sarcasm in text; hence, setting the state-of-the-art performance on several benchmark datasets. We strongly feel that the approach will bring greater accuracy in the application of NLP systems and as such will be able to provide useful insights into the complex and subtle nature of sarcasm [24].

5. FUTURE WORK

In this direction, future efforts ought to focus on:

1. Enhanced Multimodal Fusion: Better methods for the effective fusion of linguistics, acoustic, and visual features.

2. Cognitive features: This aspect has been able to show the employment of cognitive features like attention and memory for increasing the accuracy of sarcasm detection.

3. More Diverse Datasets: The need for more diverse datasets that capture the subtleties of sarcasm across different contexts and genres.

Meeting these challenges will help in improving the models for the detection of sarcasm with higher accuracy and robustness, thus making more effective NLP applications and providing a better understanding of human language and behaviour.

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