ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VIII, August 2025

# Advancing Sarcasm Detection: The Case for Naturalistic Conversational Datasets

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DOI: https://doi.org/10.51583/IJLTEMAS.2025.1408000073

**Abstract-**Sarcasm detection is a critical research area in Natural Language Sarcasm detection plays a pivotal role in advancing Natural Language Processing (NLP), influencing sentiment analysis, emotion recognition, and conversational AI. Effective models rely on diverse, well-annotated datasets that capture subtle linguistic and contextual cues. This review analyzes 46 research papers and categorizes sarcasm detection datasets into three types: text-based, visual-textual, and audio-visual. The findings highlight the growing importance of multimodal datasets for improving recognition in domains such as social media, news, and dialogues. However, current resources—particularly in audio sarcasm—often overlook critical aspects like prosody, emotional tone, and speaker variability. To address these gaps, the review emphasizes the need for naturalistic conversational data that integrates varied accents, emotional nuances, and dynamic contexts. By advancing dataset design toward real-world dialogue, sarcasm detection models can achieve greater accuracy and robustness, enhancing practical applications including healthcare chatbots, e-commerce reviews, and virtual assistants.

**Keywords:** Sarcasm Detection, Multimodal NLP, Sentiment Analysis

## I. Introduction

Sarcasm is a complex linguistic phenomenon often used to convey implicit meanings that contrast with the literal interpretation of the words. Detecting sarcasm in text, speech, and multimodal communication is an essential challenge in natural language processing (NLP) and multimodal machine learning. Sarcasm detection plays a vital role in improving sentiment analysis, opinion mining, and human-computer interactions by enabling models to accurately interpret speaker intentions. Given the widespread use of sarcasm on social media platforms, online discussions, and digital content, researchers have dedicated significant efforts to developing robust sarcasm detection models. These models require diverse and well-annotated datasets to ensure effectiveness across different contexts, languages, and modalities. Various datasets have been curated from sources such as Twitter, Reddit, news headlines, and multimodal sources like TV shows and memes, enabling the exploration of sarcasm detection in text-based, visuo-textual, and audio-visual formats.

The datasets in sarcasm detection research can be broadly classified into three main categories:

**Text-Based Datasets**: These datasets focus on detecting sarcasm in textual content such as social media posts, news headlines, and online forums. They help train NLP models that use deep learning architectures like transformers, BERT, and RoBERTa for sarcasm classification.

***Visuo-Textual Datasets****:* These datasets incorporate images along with text, allowing researchers to analyze sarcasm detection in memes, social media images, and multimedia posts. They are particularly useful in understanding the interplay between visual cues and textual context.

**Audio-Visual & Textual Datasets**: These datasets include spoken dialogue, facial expressions, and tone of voice, enabling multimodal sarcasm detection. They help improve sentiment analysis and emotion recognition in conversational AI systems, chatbots, and virtual assistants.

This review provides a comprehensive analysis of key sarcasm detection datasets, their sources, annotation methods, and research applications. By examining the methodologies and findings associated with these datasets, this review highlights their significance in advancing sarcasm detection models and their practical applications in AI-driven communication systems. Additionally, it highlights the growing need for more natural, human-like datasets, particularly for audio sarcasm detection, to improve the real-world applicability of sarcasm classification models.

## II. Research Methodology

This review adopted a structured literature selection process. An initial search across IEEE Xplore, ACM Digital Library, and Google Scholar identified 60 papers published between 2016–2024. Search terms included *'sarcasm detection dataset'*, *'multimodal sarcasm detection'*, and *'prosody sarcasm dataset'*. After removing duplicates and papers without empirical dataset analysis, 46 were selected. Criteria for inclusion were: (1) dataset-focused contributions, (2) empirical evaluation of sarcasm detection models, and (3) availability of annotation details.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VIII, August 2025

## III. Literature Review

Sarcasm detection is a significant research area in Natural Language Processing (NLP) and plays a crucial role in enhancing sentiment analysis, emotion recognition, and automated dialogue systems. Various studies have contributed to the development of sarcasm detection methodologies, including machine learning, deep learning, and hybrid approaches that integrate multimodal information. This literature review examines prior research in sarcasm detection, emphasizing dataset diversity, annotation techniques, and methodologies used for classification.

The effectiveness of sarcasm detection models heavily depends on the availability and quality of datasets. Kumar and Sarin (2022) introduced the WELMSD model, which leverages word embeddings and language modeling for sarcasm detection. This model demonstrated the importance of dataset quality and contextual understanding in improving detection accuracy (Kumar & Sarin, 2022). Similarly, Šandor and BagićBabac (2024) applied machine learning techniques to online comments, revealing challenges in detecting sarcasm due to implicit meanings and linguistic variations (Šandor&BagićBabac, 2024).Multiple research works have explored different methodologies for sarcasm detection. Lee, Chakraborty, and Banerjee (2023) discussed artificial intelligence applications in customer feedback research, highlighting the use of NLP in identifying implicit sarcasm in consumer reviews (Lee et al., 2023). Hartmann and Netzer (2023) explored NLP applications in marketing and emphasized deep learning approaches, such as transformer-based models, which have shown significant improvements in sarcasm classification (Hartmann &Netzer, 2023).

Hybrid models integrating different NLP techniques have been explored for sarcasm detection. Ayo et al. (2020) introduced a hybrid embedding technique combining word representations and deep neural networks to enhance sarcasm detection in Twitter data (Ayo et al., 2020). This approach demonstrated improved performance over traditional machine learning models. Recent research has expanded sarcasm detection beyond text-based approaches to include multimodal cues. AlRowais and Alsaeed (2024) highlighted the role of multimodal analysis in stance detection and discussed the potential of combining textual and visual information for sarcasm recognition (AlRowais&Alsaeed, 2024). Nguyen et al. (2024) introduced machine learning-based models for customer emotion detection, illustrating the benefits of integrating visual and textual information for improved sentiment classification (Nguyen et al., 2024).

Sarcasm detection is closely linked to sentiment analysis and opinion mining. Ignatow, Evangelopoulos, and Zougris (2016) explored sentiment analysis techniques applied to polarizing topics in social media, emphasizing the need for context-aware models (Ignatow et al., 2016). Similarly, Qazi et al. (2017) conducted a systematic literature review on sentiment analysis techniques, highlighting challenges in detecting sarcasm due to its implicit nature (Qazi et al., 2017).Despite advancements in sarcasm detection, several challenges persist. Fraiwan (2022) discussed artificial intelligence-based classification techniques and highlighted the limitations of current sarcasm detection models in recognizing complex linguistic nuances (Fraiwan, 2022). Lindgren et al. (2023) emphasized the role of sentiment analysis in organizational research, suggesting the need for improved contextual models to address sarcasm misclassification (Lindgren et al., 2023). Future research should focus on developing more diverse datasets, improving multimodal fusion techniques, and integrating contextual cues for enhanced sarcasm recognition.

This literature review underscores the critical role of datasets, deep learning, and multimodal techniques in sarcasm detection. By analyzing various methodologies and dataset applications, this study highlights the importance of dataset quality, contextual modeling, and hybrid approaches in advancing sarcasm detection research. Future efforts should address the challenges of implicit meaning, multimodal integration, and dataset diversity to improve sarcasm recognition in NLP applications.

| Category | Dataset Name | Source | Size (Sarcastic / Non-Sarcastic) | Annotation Method | Research Applications | Reference |
|---|---|---|---|---|---|---|
| **Text-Based** | Reddit | Reddit Posts | 232,965 posts | Self-annotated (\s token) | Large-scale sarcasm detection | (Lindgren et al., 2023) |
| **Text-Based** | BIG-bench | Multiple sources | 200+ tasks | Human-annotated | Benchmarks multiple NLP tasks, including sarcasm | (Fraiwan, 2022) |
| **Text-Based** | SARC (Khodak et al., 2018) | Reddit | 533M / 1.3M | Self-labeled via sarcasm tags | Large-scale supervised learning for sarcasm classification | Khodak et al. (2018) |
| **Text-Based** | iSarcasmEval | Twitter | 15,548 tweets | Self-labeled | Sarcasm detection | (Nguyen et al., 2024) |

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| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | evaluation dataset | |
| **Text-Based** | iSarcasm (Oprea&Magdy, 2020) | Twitter | 777 / 3,707 | Human-labeled | Transformer-based sarcasm detection models | Oprea&Magdy (2020) |
| **Text-Based** | ArSarcasm-v2 | Arabic Tweets | 15,548 tweets | Human-annotated | Arabic sarcasm dataset | (Hartmann &Netzer, 2023) |
| **Text-Based** | ArSarcasm | Arabic Tweets | 10,547 tweets | Human-annotated | Arabic dialect-based sarcasm detection | (Šandor&BagićBabac, 2024) |
| **Text-Based** | Headlines Dataset | News Websites | Not specified | Human-annotated | Sarcasm in journalism and news reporting | (Kumar & Sarin, 2022) |
| **Text-Based** | Sarcasm Corpus V2 (Bouazizi et al., 2023) | Various Sources | Not specified | Balanced dataset | Hybrid rule-based and deep learning sarcasm detection | Bouazizi et al. (2023) |
| **Text-Based** | SPIRS | Twitter | Not specified | Human-annotated | Context-aware sarcasm detection | (Kumar & Sarin, 2022) |
| **Text-Based** | Cards Against Humanity | Game Text | Not specified | Human-annotated | Sarcasm dataset derived from humor-based card game | Cai et al. (2019) |
| **Visuo-Textual** | MMSD (Cai et al., 2019) | Twitter | 10,560 / 14,075 | Hashtag-based | Deep learning-based sarcasm detection in images and text | Cai et al. (2019) |
| **Visuo-Textual** | MMSD2.0 (Qin et al., 2023) | Twitter | 11,651 / 12,980 | Manual correction | Enhanced multimodal sarcasm detection | Qin et al. (2023) |
| **Visuo-Textual** | Schifanella et al. (2016) | Instagram, Twitter, Tumblr | 22,025 / 20,025 | Hashtag-based, subset human-annotated | Multimodal sarcasm dataset | Schifanella et al. (2016) |
| **Visuo-Textual** | Silver-Standard (Sangwan et al., 2020) | Instagram | 10,000 / 10,000 | Hashtag-based | Visuo-textual sarcasm classification | Sangwan et al. (2020) |
| **Visuo-Textual** | Gold-Standard (Sangwan et al., 2020) | Instagram | 1,600 / 10,000 | Human-annotated | Benchmark dataset for multimodal sarcasm | Sangwan et al. (2020) |
| **Visuo-Textual** | MORE (Desai et al., 2022) | Instagram, Tumblr | 3,510 sarcastic utterances | Natural language explanations | Sarcasm explanation generation | Desai et al. (2022) |
| **Audio-Visual** | **MUStARD (Castro et al., 2019)** | TV Shows (Friends, The | 345 / 345 | Human-annotated | Multimodal sarcasm detection (text | Castro et al. (2019) |

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VIII, August 2025

| | | | | | | |
|---|---|---|---|---|---|---|
| | | Big Bang Theory, etc.) | | | + audio + video) | |
| **Audio-Visual** | **MUStARD++ (Ray et al., 2022)** | TV Shows (YouTube) | 601 / 601 | Manually corrected | Emotion recognition in sarcasm detection | Ray et al. (2022) |
| **Audio-Visual** | **MUStARD++ Balanced (Bhosale et al., 2023)** | MUStARD++ & House MD | 691 / 674 | Balanced sarcasm-type labels | Addresses imbalance in sarcasm types | Bhosale et al. (2023) |
| **Audio-Visual** | **SE-MUStARD (Chauhan et al., 2020)** | MUStARD | 345 / 345 | Sentiment and emotion labels | Sentiment-assisted sarcasm detection | Chauhan et al. (2020) |
| **Audio-Visual** | **SEEmojiMUStARD (Chauhan et al., 2022)** | MUStARD++ | 691 / 601 | Augmented with emojis and sentiment labels | Extends MUStARD++ with emoji-based sentiment analysis | Chauhan et al. (2022) |
| **Audio-Visual** | **WITS** | TV Show Dialogues | 55 Episodes | Human-annotated | Multimodal sarcasm analysis using facial expressions | - |
| **Audio-Visual** | **MUStARD (Castro et al., 2019)** | TV Shows (Friends, The Big Bang Theory, etc.) | 345 / 345 | Human-annotated | Multimodal sarcasm detection (text + audio + video) | Castro et al. (2019) |

Table 1: Datasets for Sarcasm Detection

| **Dataset Category** | **Modality** | **Prosody** | **Accents / Diversity** |
|---|---|---|---|
| Text-Based (Reddit, Twitter, Headlines, etc.) | Text only | ✗ | ✗ |
| Visuo-Textual (MMSD, Gold-Standard, MORE, etc.) | Text + Visual | ✗ | ✗ |
| Audio-Visual (MUStARD, MUStARD++, WITS, etc.) | Text + Audio + Visual | ✓ | ✗ |
| Audio-Visual Multilingual (Spanish Multimodal, ArSarcasm, ArSarcasm-v2) | Text + Audio + Visual | ✓ | ✓ |

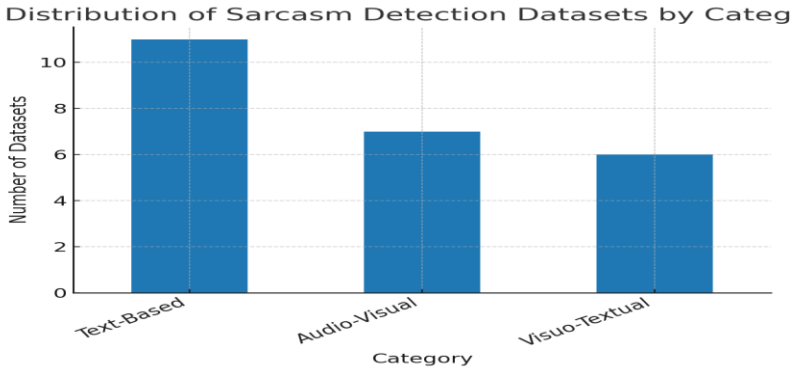



Figure 1: Distribution of Sarcasm Detection Datasets by Category

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VIII, August 2025

Figure 1. shows the number of available sarcasm detection datasets across three major categories: text-based, visuo-textual, and audio-visual. Text-based datasets dominate, while audio-visual datasets remain limited, highlighting the scarcity of natural conversational data.

Figure 2. shows that Text-based and visuo-textual datasets lack prosodic and accentual variation. Audio-visual datasets incorporate prosody but are predominantly English-only, with only ArSarcasm/ArSarcasm-v2 (Arabic) and Spanish Multimodal introducing linguistic diversity.

**Need for More Natural, Human-Like Datasets for Audio Sarcasm Detection**

Sarcasm in spoken language differs significantly from its textual counterpart because it relies heavily on prosody—intonation, pitch variation, stress, and rhythm—to convey meaning. Existing sarcasm detection models, particularly those trained on textual data, often struggle to generalize well in real-world conversational settings. This is because written sarcasm usually depends on wordplay or exaggerated expressions, whereas spoken sarcasm is often subtle, requiring additional auditory and contextual cues.

***Prosodic Cues & Emotional Tone*** – Sarcasm is conveyed through variations in intonation, stress, and rhythm, making prosody essential for detection. A diverse dataset capturing real-world speech can improve model robustness.

***Contextual Dependency*** – Sarcasm often depends on previous dialogue turns. Current datasets lack dynamic conversations, making real-time sarcasm recognition challenging.

***Speaker Variability*** – People express sarcasm differently based on accent, speech style, and linguistic patterns**.** A diverse dataset ensures better generalization across users.

***Multimodal Integration*** – Facial expressions and gestures complement sarcasm in speech. Including synchronized video data enhances sarcasm comprehension.

***Conversational AI & HCI Applications*** – AI assistants and chatbots struggle with sarcasm. More natural datasets will help develop models that interpret sarcasm accurately, improving human-AI interactions**.**

Current datasets are insufficient for capturing sarcasm's real-world complexity. A prosodic ally diverse, contextually rich dataset is essential for advancing AI's sarcasm understanding**,** making interactions more intuitive and human-like**.** These improvements will bridge the gap between artificial intelligence and real-world sarcasm comprehension, making conversational AI systems more intuitive and effective.

**Practical Implications of Sarcasm Misclassification**

While sarcasm detection is often studied in academic settings, its misclassification can have significant real-world consequences. A few notable use cases include:

**A. Healthcare Chatbots and Virtual Assistants**

Patients often use sarcasm to downplay pain, frustration, or dissatisfaction. For example, a patient saying "Oh sure, this medicine works wonders" sarcastically may actually be expressing that the treatment is ineffective. If a healthcare chatbot misinterprets this as positive feedback, it could compromise patient safety and reduce trust in AI-based care.

**B. E-Commerce and Product Reviews**

Customer reviews frequently employ sarcasm, such as "Great, another gadget that broke on day one." A sentiment analysis system that misclassifies this as positive feedback would mislead both potential buyers and retailers, impacting sales, reputation, and decision-making.

**C. Social Media Monitoring and Brand Reputation**

Brands often use AI to track customer sentiment. Misinterpreting sarcastic comments like "Best customer service ever—after waiting two hours on hold" as genuine praise could prevent companies from addressing critical service issues, damaging public perception.

**D. Human–AI Interaction (Voice Assistants, Customer Support)**

In natural conversations, sarcasm signals dissatisfaction or humor. If virtual assistants fail to recognize sarcastic intent, users may find interactions frustrating and unnatural, reducing adoption and satisfaction with AI-driven services.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VIII, August 2025

Misclassifying sarcasm is not just a technical error; it carries practical risks in healthcare, commerce, and customer engagement. These scenarios highlight the urgent need for natural, prosodically diverse, and context-aware sarcasm datasets that reflect real-world usage.

**Characteristics of a Natural Audio Sarcasm Dataset**

To make the dataset closer to real human speech, it should contain:

**Conversational Context:** Collect spontaneous conversations rather than scripted content.

**Speaker Diversity:** Include a wide range of accents, age groups, and speaking styles.

**Prosodic Features:** Capture variations in intonation, pitch, stress, and rhythm**,** as sarcasm often relies on these.

**Multimodal Elements:** If possible, include facial expressions and gestures.

**Future Research Suggestions**

To develop more human-like sarcasm detection models, future research should focus on real-world conversational data. One promising approach is leveraging audio clips, which naturally contain sarcasm due to frustration, exaggerated politeness, and contextual dependency.

Key Advantages of real-world conversational data

a. Spontaneous Sarcasm – Captures genuine sarcastic speech, unlike scripted datasets.

b. Diverse Speakers – Includes varied accents, emotions, and speaking styles.

c. Context-Rich Conversations – Enables sarcasm detection within real dialogue flows.

d. Emotional Variation – Covers sarcasm from mild humor to intense frustration.

**Implementation in Future Research**

a. Collect & anonymize real-world conversational data

b. Manually Annotate Sarcasm Instances based on tone, intonation, and speaker intent.

c. Develop AI Models trained for sarcasm detection.

By integrating, real-world conversational data future research can create more natural, context-aware sarcasm detection models, improving AI-human interactions in real-world applications.

**IV. Conclusion**

Sarcasm detection remains a complex challenge within Natural Language Processing and multimodal AI. While existing datasets (text-based, visuo-textual, and audio-visual) have contributed to the field, they often fall short in capturing the nuances of real-world conversational dynamics, speaker variability, and prosodic features essential for accurate sarcasm recognition. This review highlights the critical need for more natural, dynamic datasets that reflect the complexities of spoken and multimodal sarcasm. Moving forward, research should focus on creating diverse, contextually rich datasets, particularly those incorporating prosodic cues, emotional tone, and real conversational contexts. Such improvements will be pivotal in enhancing the capabilities of AI in understanding sarcasm, ultimately improving applications like conversational AI, chatbots, and sentiment analysis, making interactions more intuitive and human-like.

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