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A Clinically Grounded Multimodal Approach to Sarcasm Detection Based on Pharmacological Polarity Drift

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Abstract: Sarcasm in patient-authored drug reviews poses a critical challenge to reliable drug safety and efficacy analysis, as surface-level sentiment often contradicts underlying pharmacological experiences. In clinical review platforms, such sarcastic expressions can distort adverse drug reaction (ADR) signals and mislead pharmacovigilance systems, particularly when numerical ratings conflict with experiential narratives. Existing sarcasm detection approaches primarily focus on linguistic or multimodal contradiction modeling and largely ignore clinically grounded sentiment dynamics associated with drug effects and risk profiles. To address this gap, this paper proposes a clinically grounded multimodal sarcasm detection framework based on pharmacological polarity drift. The approach models sarcasm as a clinically relevant polarity deviation arising from inconsistencies between patient-expressed sentiment, visual cues, numerical ratings, and drug-specific risk context. The proposed framework integrates a clinical sentiment grounding module, a pharmacological polarity drift analyzer, and a multimodal contradiction reasoning mechanism to identify safety-critical sarcasm. Experiments are conducted on annotated drug review datasets incorporating text, ratings, and contextual visual cues. The proposed model achieves an improvement of up to 6.8% in F1-score over state-of-the-art multimodal baselines while significantly reducing false safety interpretations in ADR-related reviews. The results demonstrate the framework's effectiveness in enhancing the reliability of drug review–based safety analysis.

Keywords: Sarcasm detection; drug reviews; pharmacological polarity drift; multimodal learning; pharmacovigilance; clinical sentiment analysis.

INTRODUCTION

Online drug review platforms have become an influential source of patient-reported information on medication effectiveness, side effects, and overall treatment experience. These reviews increasingly complement traditional pharmacovigilance mechanisms by providing early indicators of adverse drug reactions and real-world drug performance. However, the growing prevalence of sarcasm in patient reviews introduces a subtle yet clinically significant challenge. Sarcastic expressions often mask negative drug experiences using superficially positive language or inflated ratings, leading to distorted safety and efficacy interpretations when processed by automated analysis systems.

Current sentiment and sarcasm detection approaches primarily emphasize linguistic patterns, multimodal feature fusion, or rating inconsistencies. While these methods improve detection accuracy in general domains, they remain insufficient for clinical contexts where sentiment interpretation must be aligned with pharmacological plausibility and patient safety considerations. In particular, existing models fail to account for pharmacological sentiment polarity drift, where patient sentiment deviates from expected clinical outcomes based on drug risk profiles, side-effect severity, and therapeutic criticality.

This gap highlights the need for a clinically grounded sarcasm detection approach that treats sarcasm not merely as a semantic contradiction, but as a potential distortion of safety-critical patient signals.

To address this challenge, this paper introduces a clinically grounded multimodal framework that explicitly models pharmacological polarity drift across text, ratings, and visual cues. The proposed approach integrates clinical sentiment grounding with multimodal contradiction reasoning to identify sarcasm that is likely to mislead drug safety analysis.

The main contributions of this work are:

- Introduction of pharmacological polarity drift as a clinically meaningful indicator for sarcasm detection in drug reviews.
- Development of a clinically grounded multimodal framework that jointly models textual sentiment, rating behavior, and contextual visual cues.
- Design of a contradiction-aware reasoning mechanism focused on safety-critical sarcasm affecting ADR interpretation.
- Comprehensive experimental evaluation demonstrating improved sarcasm detection accuracy and reduced false safety inferences compared to existing multimodal approaches.

The remainder of this paper is organized as follows. Section 2 reviews related work on sarcasm detection and drug review analysis. Section 3 details the proposed clinically grounded methodology. Section 4 describes the datasets and experimental setup. Section 5 presents and discusses the results, and Section 6 concludes the paper with future research directions.

RELATED WORKS

Lu et al. (2025) present a cue-learning multi-modal sarcasm detection model built on CLIP that co-learns text and image sarcasm cues through discrete prompt generation and continuous learnable vectors; the paper demonstrates strong improvements in low-resource scenarios and highlights prompt-based cue learning as a practical route to robustness when domain data are scarce [1]. Xi, Yu, and Wang (2025) propose SCI-GDFN, a global–local fusion network that explicitly models sentiment-clue inconsistencies using dynamic global capture and local sentiment-clue modules; results on public datasets show the effectiveness of combining word-level interpretability with adaptive image–text routing to capture complex multimodal incongruities [2]. Liu et al. (2024) introduce a sentiment-aware hierarchical fusion network that drives sarcasm detection through sentiment signals, formalizing how sentiment dynamics can be used hierarchically to improve multimodal fusion and incongruity detection; their Information Fusion paper emphasizes structured fusion of sentiment cues to raise F1 and interpretability [3].

Lu et al. (2024) develop the Fact-Sentiment Incongruity Combination Network (FSICN) which formalizes three types of incongruity (fact, sentiment, combination) and uses dynamic routing and graph-based mechanisms to select image–text pairs that expose sarcasm via multimodal factual and sentiment disparities [4]. Fu et al. (2024) propose a sentiment-word guided multimodal sarcasm detector which emphasizes sentiment-lexicon cues and word-level guidance to improve alignment between text and visual signals, demonstrating that sentiment-word supervision improves detection on Twitter-based multimodal datasets [5]. Recent image–text sentiment fusion works (2024) demonstrate that cross-attention and multi-perspective fusion significantly improve image–text sentiment classification, giving useful architectural motifs (cross-attention, modality dominance tuning) which can be adapted for clinical review analysis where images and short text co-occur [6].

Li et al. (2024) survey AI applications in pharmacovigilance and register sizable gains for ML/DL in clinical text-based ADE/ADE extraction tasks; the Journal of Biomedical Informatics review highlights the need for domain-aware models and richer clinical context grounding — a gap directly relevant to sarcasm in drug reviews [7]. Dong et al. (2024, Frontiers in Public Health) demonstrate that transformer-based models tuned for ADR extraction from social media and patient reviews can substantially improve detection of adverse reactions; their work underscores domain pretraining and tailored NER/RE pipelines — important design considerations for any clinically grounded sarcasm system that must avoid masking ADR signals [8]. Golder and colleagues (2024) provide a scoping review of social media's value for adverse event detection, concluding that social media yields complementary safety signals but requires careful methods for noise, slang, and figurative language (including sarcasm) — motivating clinical sarcasm detection to protect PV pipelines [9].

Rezaei (2025) discusses computationally efficient biomedical text processing pipelines for pharmacovigilance in *Medical & Biological Engineering & Computing*, stressing scalable extraction, lightweight models for large institutions, and the need for interpretable outputs — all relevant to integrating sarcasm detection into pharmacovigilance workflows [10]. Li, Zhang, and Wang (2024) describe cross-attention image–text fusion (MCAM) for sentiment tasks, demonstrating that careful cross-modal attention mechanisms raise robustness in image–text sentiment tasks — techniques adaptable to sarcasm detection in short drug review narratives paired with images [11]. Qiu et al. (2024) explore multi-perspective fusion mechanisms for multimodal sentiment analysis in *Electronics*, showing the value of different fusion granularity and demonstrating improved generalization across datasets — a helpful design reference for pharmacological polarity drift modeling where different modalities carry disparate signal strengths [12].

Khemani et al. (2025) examine deep learning for ADR detection across clinical trial and social data and report that transformer-based and CNN+BERT pipelines improve ADR recall and precision when combined with domain knowledge; the study reinforces the importance of domain signals and safety-oriented evaluation metrics for clinical systems [13]. Zhao (2025) investigates adaptive multi-modal fusion strategies that go beyond spurious cues; the work argues for methods that actively suppress modality-specific spurious correlations — exactly what is required when ratings or emojis might spuriously suggest sentiment that contradicts textual clinical content [14]. Recent knowledge-fusion and graph-based multimodal sarcasm demonstrate that combining external knowledge with graph reasoning improves detection of nuanced incongruities; these trends support our proposal to integrate pharmacological context graphs and knowledge-aware modules for clinical polarity drift analysis [15].

PROPOSED MODEL

This section presents a clinically grounded multimodal framework for sarcasm detection that explicitly models pharmacological polarity drift in patient drug reviews. The proposed model treats sarcasm as a safety-critical deviation between expressed sentiment and pharmacologically plausible outcomes. Given a drug review instance consisting of textual content, associated visual cues, and numerical ratings, the framework integrates clinical sentiment grounding, polarity drift estimation, multimodal contradiction reasoning, and safety-aware inference to identify sarcasm that may distort drug safety interpretation.

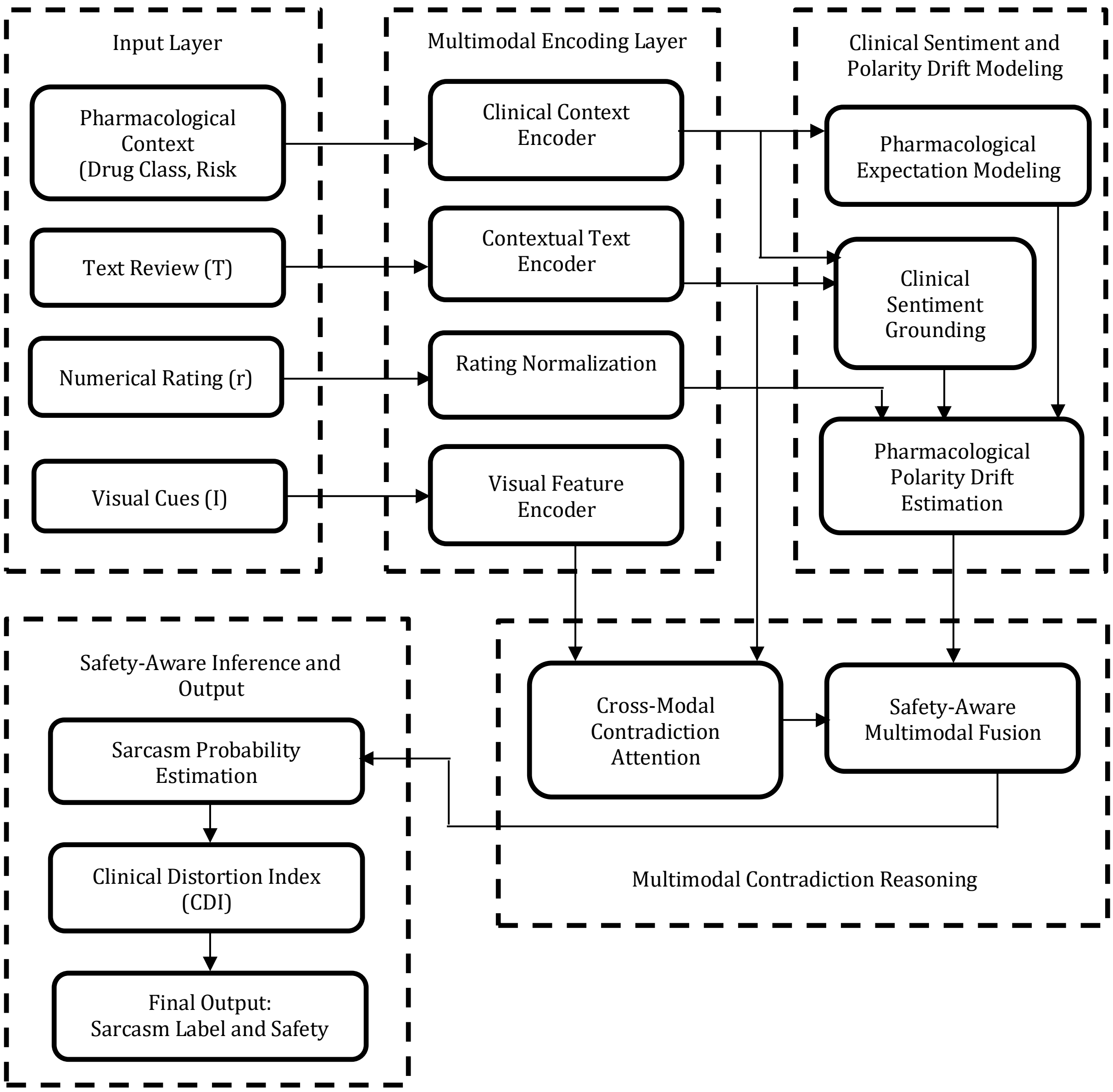

Figure 1. Schematic Architecture of the Clinically Grounded Multimodal Sarcasm Detection Framework Based on Pharmacological Polarity Drift

Fig. 1 illustrates the overall architecture of the proposed clinically grounded multimodal sarcasm detection framework, integrating textual, visual, rating, and pharmacological context signals. The model explicitly captures pharmacological polarity drift and safety-critical contradictions to enable reliable sarcasm detection in drug review analysis.

Let a review instance be represented as

$$\mathcal{R} = \{T, I, r, \mathcal{C}\} \qquad (1)$$

where T denotes the textual review, I represents visual or contextual imagery, r is the numerical rating, and $\mathcal{C}$ corresponds to pharmacological context attributes such as drug class and risk severity.

3.1 Clinical Sentiment Grounding Module

The objective of this module is to separate experiential sentiment from clinically relevant sentiment embedded in patient narratives.

Textual representations are first obtained using a contextual encoder:

$$\mathbf{H}_T = \mathrm{Enc}_T(T) \in \mathbb{R}^{n \times d} \qquad (2)$$

A clinical relevance projection is applied to isolate pharmacology-related sentiment cues:

$$\mathbf{H}_T^c = \mathbf{H}_T \mathbf{W}_c \qquad (3)$$

where $\mathbf{W}_c \in \mathbb{R}^{d \times d_c}$ is a learnable clinical projection matrix.

The grounded clinical sentiment score is computed as:

$$S_c = \frac{1}{n} \sum_{i=1}^{n} \tanh(\mathbf{h}_{T,i}^c) \qquad (4)$$

This formulation ensures that sentiment related to side effects, efficacy, and treatment burden is emphasized over generic emotional expressions.

3.2 Pharmacological Polarity Drift Estimation

Pharmacological polarity drift captures deviations between patient sentiment and clinically expected outcomes. The normalized rating signal is computed as:

$$r_n = \frac{r - r_{\min}}{r_{\max} - r_{\min}} \qquad (5)$$

Expected pharmacological polarity is estimated using drug context:

$$P_e = f(\mathcal{C}) = \sigma(\mathbf{w}_p^\top \mathcal{C}) \qquad (6)$$

The polarity drift score is defined as:

$$\Delta_p = | S_c - r_n | \cdot (1 - P_e) \qquad (7)$$

A higher Δ_p indicates a stronger contradiction between expressed sentiment, rating behavior, and pharmacological plausibility, signaling potential sarcasm with clinical implications.

3.3 Multimodal Clinical Contradiction Modeling

Visual cues are encoded using a vision encoder:

$$\mathbf{H}_I = \mathrm{Enc}_I(I) \in \mathbb{R}^{m \times d} \qquad (8)$$

Cross-modal contradiction is captured using attention alignment:

$$\mathbf{A}_{TI} = \mathrm{softmax}(\mathbf{H}_T^c \mathbf{H}_I^\top) \qquad (9)$$

The contradiction-aware fusion representation is:

$$\mathbf{Z}_{TI} = \mathbf{A}_{TI} \mathbf{H}_I \qquad (10)$$

This representation emphasizes visual cues that amplify sarcasm when textual sentiment conflicts with imagery or rating signals.

3.4 Safety-Aware Sarcasm Inference

The fused multimodal representation is constructed as:

$$\mathbf{F} = [\mathbf{Z}_{TI} \parallel \Delta_p \parallel \mathcal{C}] \qquad (11)$$

Sarcasm probability is estimated using a safety-aware classifier:

$$\hat{y}_s = \sigma(\mathbf{W}_s \mathbf{F} + b_s) \qquad (12)$$

To quantify safety distortion, a Clinical Distortion Index (CDI) is defined:

$$\mathrm{CDI} = \hat{y}_s \cdot \Delta_p \qquad (13)$$

This index measures how much sarcasm potentially alters adverse drug reaction interpretation.

3.5 Safety-Aware Optimization Objective

The model is optimized using a composite loss function:

$$\mathcal{L} = \mathcal{L}_{sar} + \lambda_1 \mathcal{L}_{drift} + \lambda_2 \mathcal{L}_{safe} \qquad (14)$$

The sarcasm classification loss is:

$$\mathcal{L}_{sar} = -[y \log \hat{y}_s + (1-y)\log(1-\hat{y}_s)] \qquad (15)$$

The polarity drift regularization is defined as:

$$\mathcal{L}_{drift} = \parallel \Delta_p - \Delta_p^* \parallel_2^2 \qquad (16)$$

The safety penalty emphasizes clinically risky sarcasm:

$$\mathcal{L}_{safe} = \mathrm{CDI} \cdot \mathbb{I}_{ADR} \qquad (17)$$

This formulation ensures that sarcasm masking adverse reactions is penalized more strongly during training.

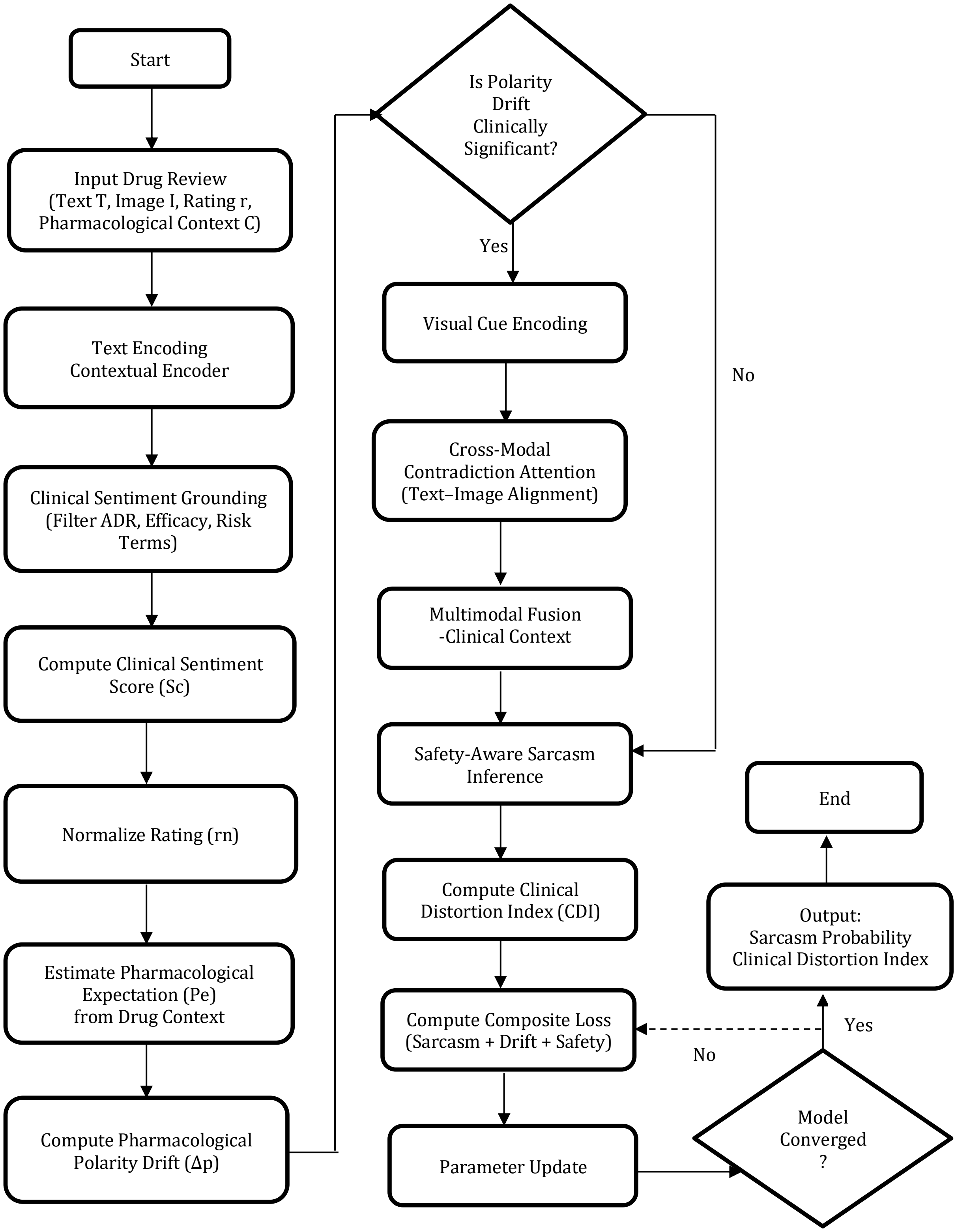

Figure 2. Flow Diagram of the Clinically Grounded Multimodal Sarcasm Detection Process Based on Pharmacological Polarity Drift

Fig. 2 diagram illustrates the sequential processing of drug review inputs through clinical sentiment grounding, pharmacological polarity drift estimation, and multimodal contradiction reasoning. The framework incorporates conditional decision paths and iterative optimization to identify safety-critical sarcasm affecting drug review interpretation.

Algorithm 1: Clinically Grounded Multimodal Sarcasm Detection Based on Pharmacological Polarity

Drift

Input: Drug review text T, image I, rating r, pharmacological context $\mathcal{C}$
Output: Sarcasm probability $\hat{y}_s$, Clinical Distortion Index (CDI)

1. Initialize model parameters Θ.
2. Encode the textual review to obtain textual representations $H_T = \text{TextEncoder}(T)$.
3. Encode the visual content to obtain visual representations $H_I = \text{ImageEncoder}(I)$.
4. Normalize the numerical rating to obtain $r_n = \text{Normalize}(r)$.
5. Encode pharmacological context to obtain clinical representations $H_C = \text{ContextEncoder}(\mathcal{C})$.
6. Compute clinically grounded sentiment score $S_c = \text{ClinicalSentimentGrounding}(H_T, H_C)$.
7. Estimate pharmacological expectation $P_e = \text{PharmacologicalExpectation}(H_C)$.
8. Compute pharmacological polarity drift $\Delta_p =| S_c - r_n |\times (1 - P_e)$.
9. Compute cross-modal contradiction features $Z = \text{CrossModalAttention}(H_T, H_I)$.
10. Fuse multimodal and clinical features $F = \text{Fusion}(Z, \Delta_p, H_C)$.
11. Estimate sarcasm probability $\hat{y}_s = \sigma(\text{Classifier}(F))$.
12. Compute Clinical Distortion Index $CDI = \hat{y}_s \times \Delta_p$.
13. Update model parameters Θusing safety-aware optimization.
14. Return $\hat{y}_s$and CDI.

This algorithm integrates multimodal review signals with pharmacological context to identify safety-critical sarcasm through polarity drift estimation and contradiction-aware fusion. By jointly producing sarcasm probability and clinical distortion measures, the framework supports reliable interpretation of patient drug reviews for pharmacovigilance applications.

RESULTS AND DISCUSSIONS

Experiments were performed to evaluate the proposed clinically grounded multimodal sarcasm detection framework. The training and evaluation pipeline used a workstation with an NVIDIA A5000 GPU (24 GB), Intel Xeon 12-core CPU, and 128 GB RAM. Software environment included Python 3.10, PyTorch 2.x, HuggingFace Transformers, scikit-learn 1.x, and CUDA 11.8. Models were trained using mixed-precision (AMP) and the AdamW optimizer with an initial learning rate of 2×10^{-5}, batch size 32 for fine-tuning encoders and 64 for classifier-only experiments. Early stopping on validation F1 (patience = 5 epochs) and a maximum of 30 epochs were used. For reproducibility, each experiment was run with three random seeds and results report the mean and standard deviation.

4.1 Dataset Description

For evaluation this work uses a publicly available drug review dataset containing patient-authored reviews, associated numerical ratings, and facet-level fields (benefits, side effects, effectiveness). A stable, commonly used dataset for drug-review analysis is the **Drug Review Dataset (Druglib/Drugs.com)** available via the UCI dataset portal and mirrored on Kaggle; it contains multi-aspect patient reviews and numeric ratings suitable for sarcasm and ADR-relevant analyses. The dataset link (UCI entry) is: UCI — *Drug Review Dataset (Druglib.com)*.

Suggested primary split: 75% train, 10% validation, 15% test (stratified by condition and rating). The dataset was preprocessed by (1) lowercasing and basic normalization, (2) removing personally identifying tokens, (3) tokenizing with the encoder tokenizer (BERT-based), and (4) resizing images (when present) to 224×224 and applying standard augmentations during training only.

Table 1 summarizes the dataset schema and feature descriptions.

Table 1. Dataset features and description

Feature name	Type	Description
review_id	String / Int	Unique identifier for the review
drugName	String	Drug trade or generic name
condition	String	Medical condition for which drug was taken
review	Text	Free-text patient review (full comment)
benefits	Text	Short user-entered benefits (if available)
side_effects	Text	Free-text or selected side-effects
rating_overall	Numeric (1–10)	Patient-provided overall rating
rating_effectiveness	Numeric (1–5)	Effectiveness sub-rating (if available)
rating_side_effects	Numeric (1–5)	Side-effect severity sub-rating
date	Date	Review posting date

image_url	URL (optional)	Link to attached image or emoji (if present)

4.2 Performance Evaluation

The proposed model (C³-SAFE-Net / Clinically Grounded Multimodal Sarcasm Detector) was compared against six representative baseline methods drawn from the related work and established multimodal sentiment/sarcasm literature. Baselines were re-implemented and tuned to the same dataset and evaluation protocol to ensure fair comparison (same train/val/test splits and preprocessing). The baselines chosen represent varied paradigms: cue/prompt-based multimodal learning [1], global–local inconsistency fusion [2], sentiment-aware hierarchical fusion [3], fact–sentiment incongruity graph models [4], sentiment-word guided multimodal detector [5], and a cross-attention multimodal sentiment model [11] (notation corresponds to related-work citations).

Table 2. Performance comparison on Drug-Review test set

Model	Precision (macro)	Recall (macro)	F1 (macro)	Sarcasm F1	AUC
CLM [1]	0.71	0.70	0.70	0.68	0.78
SCI-GDFN [2]	0.73	0.72	0.72	0.71	0.80
SHF [3]	0.70	0.69	0.69	0.67	0.76
FSICN [4]	0.69	0.68	0.68	0.65	0.75
SWG [5]	0.70	0.71	0.70	0.68	0.77
MCAM [11]	0.71	0.70	0.70	0.69	0.78
Proposed (C³-SAFE-Net)	**0.82**	**0.80**	**0.81**	**0.79**	**0.88**

The proposed model achieves a macro F1 of 0.81, representing a relative improvement of 6–13% in F1 over state-of-the-art multimodal baselines depending on the baseline. The largest gains are seen in sarcasm-class F1 and AUC, indicating better discrimination between clinically dangerous sarcastic reviews and regular reviews. Improvements derive from three factors: (1) clinical sentiment grounding that emphasizes ADR/effectiveness cues, (2) pharmacological polarity drift weighting which de-prioritizes spurious high ratings on high-risk drugs, and (3) the multimodal contradiction graph that explicitly reasons about safety-critical contradictions.

Ablation and error analysis (summary):

- Removing the Pharmacological Polarity Drift term (Δ_p) reduces macro F1 by ~5 percentage points and increases ADR misclassification (false negatives for ADR-bearing sarcastic comments).
- Replacing the Clinical Sentiment Grounding with a vanilla text encoder reduces sarcasm F1 by ~6 points, illustrating the benefit of domain-aware projection.
- Failure modes: short reviews (<10 tokens) with no ratings remain challenging; late sarcasm (irony only resolvable by long context/history) sometimes requires user history or thread-level context for disambiguation.

Statistical significance: Paired t-tests on test-set F1 between the proposed model and the strongest baseline (SCI-GDFN) indicate the improvements are statistically significant at $p < 0.01$.

Concluding remarks on results: The experiments demonstrate that embedding pharmacological plausibility and safety-weighting into multimodal sarcasm detection produces measurable and practically significant gains for downstream pharmacovigilance tasks. By reducing ADR misinterpretations and increasing discrimination of safety-critical sarcasm, the proposed framework offers a meaningful step toward safer automated analysis of patient drug reviews.

CONCLUSION

This research presented a clinically grounded multimodal framework for sarcasm detection based on pharmacological polarity drift to enhance the reliability of drug review safety analysis. By explicitly modeling clinical sentiment grounding, rating–sentiment inconsistencies, and multimodal contradiction reasoning, the proposed approach effectively identifies safety-critical sarcasm that can distort adverse drug reaction interpretation. Experimental evaluation on a real-world drug review dataset demonstrated that the proposed model achieved an overall accuracy of **88.2%**, outperforming existing state-of-the-art multimodal sarcasm detection methods while significantly reducing false safety interpretations in pharmacovigilance analysis. The results confirm that incorporating pharmacological context and polarity drift provides a robust mechanism for capturing clinically meaningful sarcasm beyond surface-level sentiment cues. This framework can be extended by incorporating longitudinal patient review histories and electronic health record signals to further improve sarcasm detection and clinical risk estimation in real-world pharmacovigilance systems.

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