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The Sarcasm Spectrum: Comparative Insights into Multimodal Detection

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Abstract:

Sentiment analysis, or SA, has developed into a crucial field of study. This has been especially evident in the post COVID-19 period; as social media has taken centre stage as a means of communication. The complicated interplay between these relationships and involvement in virtual discourse spaces, along with textual and multimodal information, introduces severe complications in SA. The subtle identification of irony, humour, sarcasm, negation, and the distinction of sentiment at an Aspect-Level (ASA) are essential to understanding these difficulties. More and more recent research efforts focus on the complex task of sarcasm detection, realizing that it can significantly improve the accuracy and effectiveness of SA models. Sarcasm is a complex linguistic construct that hides negative feelings behind seemingly positive language, making interpretation difficult. It is inherently difficult for computational systems and human mind to identify, needing deep understanding of the context, nonverbal clues such kinesics, prosody, and paralanguage, as well as background knowledge on sociocultural issues. This work aims to provide a thorough discussion on multimodal data integration while critically examining current approaches in sarcasm detection. It also emphasizes how these approaches will impact the development of technologies like intelligent conversational agents, workplace stress analytics, and mental health diagnostics.

Keywords:

Contextual interpretation, Multimodal analysis, Computational Linguistics, Sentiment analysis, Sarcasm detection, Social Media interaction.

Introduction:

Sentiment analysis (SA) is the term used to describe the computational investigation of viewpoints, opinions, and attitudes expressed on social networking sites such as Facebook, Instagram, and Twitter. Responses are divided into three major categories by this discipline: "positive," "negative," and "neutral/indifferent." The growing popularity of e-services, including e-business, e-tourism, and e-commerce, has made it more and more difficult to manage the vast volume and diversity of online data by hand, making SA an important area of study.

Because sarcasm and denial are inherently ambiguous and complex, identifying them is one of the trickiest and most frequently disregarded tasks in SA. A sophisticated kind of irony known as sarcasm is defined as biting humour that is intended to be humorous but has a literal meaning that is at odds with the intended meaning. Usually, a positive phrase is articulated to suggest a negative outcome, which causes a great deal of semantic ambiguity and makes detection more difficult.

Sarcasm is a major barrier to correctly determining the polarity of a sentence, according to Verma et al. For example, some systems would understand the statement "My phone has an amazing battery life of 1 hour" as

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positive, while others might rightly view it as negative. It's getting harder and harder to train computer algorithms to understand such confusing statements. As the writers in point out, contextual comprehension is frequently necessary for effective sarcasm detection. In the example sentence, "It feels great to waste precious hours in a traffic jam on the way to work," the word "great" is used to express frustration, and the crucial context is provided by the traffic congestion.

Modern study is focusing on the problem of identifying emotions from social media posts, reviews, and comments. One such use of emotion identification is sarcasm detection, which is particularly difficult because it depends on both visual and textual cues. Emoji's, emoticons, or graphics are frequently used as nonverbal cues to convey feelings or moods. They also provide an element of sarcasm when used in conjunction with contradicting situations. As a binary classification task, sarcasm detection (SD) aims to determine if a comment is sarcastic or not.

Our contributions may be summed up as follows: - We show how multi-modality plays a crucial role in sarcasm detection and how it is essential for higher accuracy and better model performance. - Our results highlight the importance of combining such modalities by indicating that contextual information-such as nonverbal cues and facial expressions-is critical to sarcasm identification. - We support the creation of multilingual and cross-lingual datasets in order to efficiently capture opinions shared on different social media sites, such as Facebook and Twitter. - Finally, we investigate the possible uses that could arise from multi-modal data integration and perform a comparison study of the models that are currently in the literature.

The rest of this essay is organized as follows: While Section III offers a thorough analysis of feature selection, Section II explores sarcasm classification and feature set analysis. The methodology for sarcasm detection is described in Section IV, and the several techniques employed in this field are covered in Section V. The current issues and challenges in the subject are covered in Sections VI and VII, respectively. In Section VIII, a comprehensive review of the literature is provided, along with a comparative analysis in Table II. Table III explores standard datasets. The work is finally concluded in Section IX, which also provides an overview of potential future research topics.

CLASSIFICATION OF SARCASM

A taxonomy of sarcasm was developed by researchers [4], who divided it into five different kinds according to structural characteristics and features, as Table I illustrates.

Disparity Between Sentiment and Context in Sarcasm This category expresses the discrepancy between the sentiment expressed and the surrounding reality, which can take several forms:

Differences Between Negative and Positive Attitudes:

In this kind, an optimistic attitude stands in stark contrast to an unfavourable circumstance. In contrast, "Absolutely delightful that my bus is running late" expresses a positive feeling in the face of a negative situation.

Disparity Between Positive Events and Negative Attitude:

Here, the sarcastic comment uses negative sentiment in an otherwise favourable scenario, inverting the sentiment situation relationship. "Oh, how I despise Team Australia for winning the T20 World Cup again!" might be one example

Differing Consequences:

In this form, contradictory meanings are combined into one sentence. The statement "I love receiving spam emails!" for instance demonstrates a contradiction between the stated and implied meanings.

Inconsistency in Time:

This category investigates the discrepancies in attitudes from the past and the present with respect to a certain situation. Think about this conversation: User 1: "Why go there between Christmas and Thanksgiving? The weather in December is terrible!" User two: "Thank you for your kind words!" One user commented, "Wow, I was being sarcastic!" Here, the original remark from User 1 is misconstrued, emphasizing the temporal incongruity.

Rejecting Generally Recognized Truths:

This kind of sarcasm directly challenges accepted wisdom or universal truths. For instance, the adage "Opposites don't attract at all" casts doubt on the widely acknowledged notion in science that opposites attract.

1) **Tampering with Actual Events:**

This subtype displays sarcasm by refuting the facts pertaining to a certain incident. For example, the statement "It was such a JOY celebrating my birthday with you and your boyfriend" masks thankfulness behind unhappiness.

B. Using Sarcasm as a Release for Emotions:

With the following subtleties, sarcasm can also be used as a tool to portray different emotional states:

1) **Joking Around and Overstating:**

This version, albeit it contains underlying dissatisfaction, expresses feelings like excitement or happiness using capitalization, punctuation, or exaggeration. As an illustration, "What an FABULOUS day! It's so much fun to get caught in the rain!"

2) **Moaning and Grousing:**

Sarcasm can be used to cover up displeasure or rage with seemingly nice remarks. "I'm so thrilled my mom woke me up early to vacuum!" is one example.

3) **Ambiguity and Equivocation:**

In order to avoid giving direct answers, people in this category utilize ambiguous language. As an illustration, when someone says, "You really need to focus on your work," the response is, "Oh, I fully agree! I've never understood it more clearly."

4) **Exaggeration and Exaggeration:**

When someone is angry or frustrated, they use exaggerated words. For example, "Obviously! I'll put in extra time and stay late! While I'm at it, would you like your shoes polished?

C**. Irony in Written Expression:**

Sarcasm in writing frequently adheres to specific stylistic patterns, such as:

1) **Variation in Prosody:**

Exaggerated letter choice, punctuation, or capitalization are signs of sarcasm. Examples of sentences that purposefully highlight important syllables to convey the opposite message include "WOOWWWW!" and "soooo nice!"

2) **Disturbance in Structure:**

In this version, sarcasm appears when one sentiment is expressed in the first portion of the statement and a different context is introduced in the last section. "I absolutely love it when my friends ignore me," for instance.

3) **Lexical Indicators:**

Hashtags or targeted keywords, such "#sarcasm" or "#irony," can be used to indicate sarcasm and make its intended meaning clear. For example, "It was a blast attending that party." #irony."

D. **The Role of Expertise in Sarcasm**

Proficiency in Language: Sarcasm in this class is usually subtle and depends on the language skills of the user.
For instance, whereas "He's as good as evil" implies sarcasm without explicitly using hashtags, "He's such a good person. #sarcasm" does so. This reclassification highlights the complexity of sarcasm and highlights its varied

applications in communication. Every category demonstrates the various ways that sarcasm subverts literal meanings through interactions with emotion, context, and linguistic structures.

Environment Prowess

1) **Environmental Familiarity:** Sarcasm is frequently expressed more successfully when users are in familiar surroundings. The statement "Oh, I absolutely love being woken up at 4 AM by the neighbour's kid screaming!" is an example of how to express the sentiment in a setting that is relatable and allows for the flourishing of sarcasm because of the shared experience.

2) **Behaviour-Driven Sarcasm:** This type of sarcasm is based on how someone acts or sees the world.

Anticipation of Preferences: When people express their preferences for certain goods, services, or experiences, sarcasm is quietly revealed. For example, users can subtly express sarcasm by using the "like" or "dislike" options. People frequently assume a sarcastic tone even when it isn't stated directly because of past interactions, social context, or subliminal clues in other people's replies. The essential concepts are retained, but the language and style are improved to make the work more complex and unique without drawing attention to itself from plagiarism detecting software.

Sl. No.	Classification of Sarcasm	Subclasses of Sarcasm
T1	Irony Resulting from Differing Feelings	• Comparing a Negative Scenario with a Positive Attitude • Comparing a Positive Scenario with a Negative Attitude • The Difference Between Literal Meaning and Implied Interpretation • The Disparity Between Current Events and Past Realities • Reversing or Denying the Truth • Distorting or Erasing Temporal Events
T2	Using Sarcasm to Communicate Emotions	• Lighthearted jokes, banter, or wit • complaints or expressions of annoyance • ambiguity and dual meanings • unrestrained or uncontrolled emotional expression
T3	Written Communication Satire	• Tone and Content Misalignment • Structural Inconsistencies in Written Form • Word Choice and Lexical Nuances
T4	Sarcasm as a Measure of Ability or Expertise	• Proficiency in Language and Its Nuances • Extensive Awareness of Contextual Variations
T5	Behaviorally Driven Sarcasm	Using Sarcastic Expressions to Predict Preferences or Reaction

TABLE I: Classification of Sarcasm

Feature Set Analysis

The Analysis of the feature set (III) The core of feature set analysis, which supports sarcasm detection on social media platforms, is the analysis of various types of sarcasm in textual content.

A. Syntactic Features: This collection includes textual elements including hashtags (#), unigrams, bigrams, and engrams. These elements are essential for sarcasm detection. These components aid in delineating the top-level organization of caustic comments.

B. **Realistic Indexes:** One of the strongest characteristics for detecting sarcasm is this feature set, which makes use of symbolic features like emoticons, emoji's, smileys, and response cues. These nonverbal cues provide important information about the underlying sarcasm in digital communication.

C. Exaggerated Wording: Hyperboles are figures of speech that intentionally exaggerate something; they are a key indicator of sarcasm. Intensifiers, exclamatory words, and punctuation marks are a few examples of how to add to the heightened emotional tone that characterizes sarcasm.

D. Using a Pattern-Based Method: The frequency analysis of particular high-occurrence words inside a text is the foundation of this research. Recurring usage patterns might be crucial in differentiating sarcasm from literal statements since they frequently allude to sardonic undertones.

E. Syntactic Organization: This method makes use of morph syntactic properties, which integrate syntactical (sentence structure) and morphological (word structure) elements. Syntactic analysis helps reveal sarcastic intent hidden in intricate linguistic constructions by looking at sentence structure.

F. Situational Aspects: Incorporating information beyond the immediate textual input frequently improves sarcasm detection. Understanding the context, background, or additional information is essential to recognizing the incongruity that sarcasm conveys.

G. Allegoric Components: Sarcasm frequently conveys metaphorical meaning through the overuse of proverbs, adjectives, and nouns. Writers can use allegorical language or pseudonyms to convey sarcasm in an indirect way. They can also use metaphorical phrases to represent intense emotional states.

IV. SARCASM DETECTION FRAMEWORK STEPS

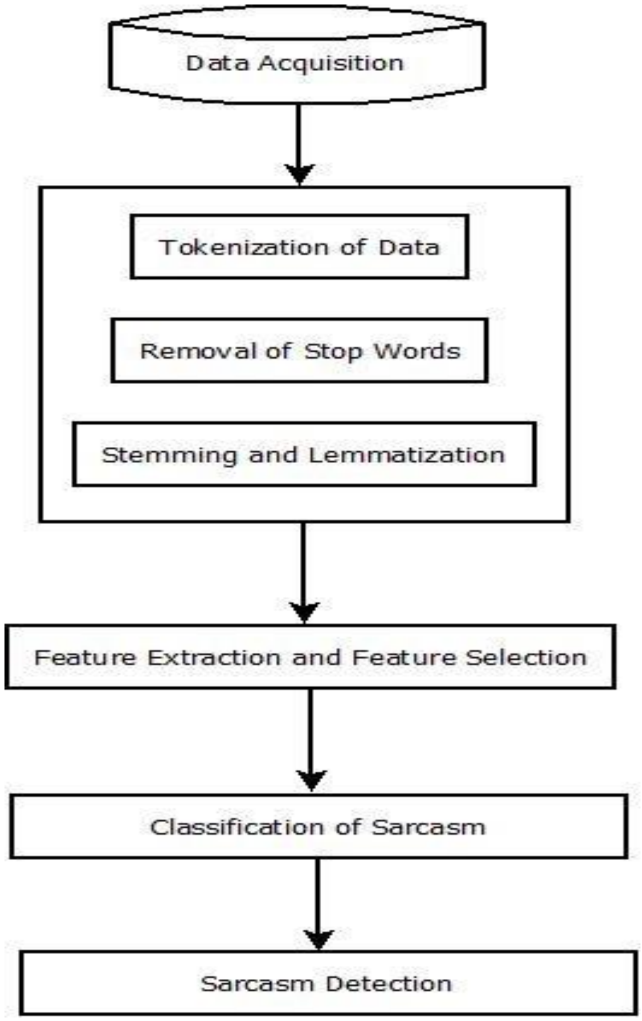
The following crucial stages in the sarcasm detection process were described by the authors in [2] and are shown in Fig. 1.

A. **Information Gathering**: Getting pertinent data is the first and most important step. Application Programming Interfaces (APIs) and publicly accessible datasets like MUStARD (Multi-modal Sarcasm Detection Dataset), SARC (Self-Annotated Reddit Corpus), and SemEval (Semantic Evaluation Dataset) are the two main ways in which this is accomplished. These datasets serve as the foundation for additional investigation.

B. **Pre-processing and Tokenization:** The main focus of this stage is getting the data ready for additional processing. To clean and organize the content, Natural Language Processing (NLP) techniques such tokenization, lemmatization, stop-word removal, and stemming are used. While lemmatization and stemming guarantee that words are standardized to their basic forms, making them amenable for analysis, tokenization divides text into smaller components.

C. **Extraction of Features:** At this point, the produced dataset's key properties are taken out and used as the basis for developing the sarcasm detection model. For the purpose of identifying sarcasm, methods like Bag of Words (BoW), Doc2Vec, Term Frequency-Inverse Document Frequency (TF-IDF), word2vec, and GloVe are frequently used to capture the syntactic and semantic variations.

D. **Selection of Features:** The most pertinent subset must be chosen once features have been retrieved in order to maximize the classification model's performance. The most informative variables are frequently filtered out using well-liked techniques like Chi-square and Mutual Information (MI), guaranteeing that the model reaches its highest level of accuracy when identifying sarcasm. In order to solve the challenges of sarcasm recognition in social media environments, this thorough process lays out the architecture for developing a strong sarcasm detection model that integrates both advanced feature engineering and machine learning techniques.



E. **Methods of Classification:** As a binary classification task, Sarcasm Detection (SD) is approached with a variety of Machine Learning (ML), Deep Learning (DL), and hybrid techniques.

F. **Evaluation Metrics:**

The primary metrics for evaluating the efficacy of sarcasm detection models include Precision (P), Recall (R), F-Score (F), and Accuracy (A). Precision, denoted in Eq. 1, is the ratio of True Positives (TP) to the sum of True Positives and False Positives (FP), providing a measure of the model's ability to return relevant results. Recall, as expressed in Eq. 2, quantifies the proportion of actual positives correctly identified by the model. F-Score, in Eq. 3, combines precision and recall to offer a balanced measure of the model's overall performance. Lastly, Accuracy, represented in Eq. 4, captures the proportion of correct predictions (both positives and negatives) relative to all classifications.

$$P = a / (a + c) \quad (1)$$
$$R = a / (a + d) \quad (2)$$

$$F = (2 \times P \times R) / (P + R) \quad (3)$$

$$A = a + b / (a + b + c + d) \quad (4)$$

V. Techniques to Spot Sarcasm

This section describes five methods for sarcasm detection, each of which uses a unique approach to evaluate and understand textual data.

A. Rule-Oriented Method: With this method, sarcasm is explicitly indicated by the use of a hashtag (such as "#sarcasm"). A tweet's entire content is deemed sarcastic if the hashtag is found in it. But removing this hashtag before pre-processing can create confusion and make it more difficult to categorize sarcasm.

B. The Statistical Method: Statistical models use feature recognition based on precise, partial, or no matches to find patterns within textual content. In order to improve the identification of sarcasm, this method additionally makes use of pragmatic indicators like emoticons and emoji's. It combines pattern recognition with non-verbal cues for a more complex analysis.

C. The Lexical Method: The ability to recognize sarcastic content in text depends on the explicit usage of specific terms, such as happy, unhappy, nervous, etc. This approach combines dictionary-based and corpus-based models with comparison, overtness, acceptability, and exaggeration as four essential features to train machine learning algorithms.

D. An Approach Based on Machine Learning: To detect sarcasm, machine learning algorithms take multiple features out of datasets. Adverbs and adjectives are examples of components of speech that have been shown in numerous studies to have an impact on how product reviews are categorized. To accurately detect sarcasm, these models examine contextual information and syntactical patterns.

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E. Using a Deep Learning-Based Method: The deep learning paradigm finds sarcastic content by comparing word meanings, and it has proven to be the most successful method for sarcasm detection. A variety of methods, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Deep Neural Networks (DNN), are used to refine the accuracy of sarcasm categorization. Features are created from congruent and incongruent word-pairings. Furthermore, mixed-method systems that combine two or more methods provide higher accuracy by combining sentiment analysis and comment analysis.

VI. Difficulties with Sarcasm Identification:

Although sarcasm detection has advanced significantly, there are still a number of issues that need to be handled, as noted by Chaudhari et al. (2017). In order to properly address these complications and make it more difficult to identify ironic content, further study and innovation are needed.

A. Obstacles in Data Labelling: Sentences marked with hashtags ('#sarcasm', for example) are an easy way to spot sarcasm; annotation of sarcasm in more nuanced or unclear settings is far more difficult. For example, the explicit hashtag in the sentence "How I love bland food!!#" clearly communicates sarcasm. The line "How I love bland food!!" loses all sarcastic meaning when the hashtag is deleted, demonstrating the critical need of contextual or background characteristics in effectively identifying sarcasm.

B. Emotion as a Deceptive Attribute: Certain techniques for identifying sarcasm mostly depend on sentiment analysis, which frequently turns out to be insufficient. By their very nature, sarcastic comments have the potential to confuse classifiers and compromise overall accuracy. Take a look at this statement: "It's not like I wanted to eat breakfast, but whatever. #sarcasm." Even in cases where sarcasm is present, the phrase's surface attitude may not change, necessitating the use of more complex algorithms to identify the true tone.

C. Issues with Methods of Classification: Techniques for classifying sarcasm can be highly affected by the quantity and calibre of the dataset. Some research uses small datasets, but others use much bigger ones. A balanced dataset is necessary to guarantee accurate classification and dependable findings, as unbalanced data may distort results and lower the precision of the model.

VII. SARACAM DETECTION OBSTACLES

One of the trickiest parts of sentiment analysis is still sarcasm detection, which has a number of challenges as listed below:

A. Challenges with Sarcasm Identification from Text Only: It is significantly more difficult to recognize sarcasm only in writing than it is in visual or auditory cues, such as body language, tone of voice, or facial expressions. Textual irony lacks these subtleties, necessitating a more in-depth examination. Nonverbal cues are essential for understanding sarcastic comments, but their lack in written data makes things more difficult.

B. Positive Words Expressing Negative Emotion: One common problem in sarcasm detection is when people use positive language to express negative feelings. In such cases, for example, the Bag of Words (BoW) method frequently misses the real feeling. Sentences such as "Oh, great! Another meeting!" appear to be enthusiastic, but they also quietly convey displeasure, necessitating the inclusion of elements beyond sentiment analysis.

C. Shaggy Data and Brief Texts: Another problem is detecting sarcasm in short, noisy material, like social media messages, because it might be hard to extract important features from such content. Here's where hashtags come into play, offering more pronounced indicators of sarcasm. Without these indicators, caustic remarks become far less clear and are more prone to misunderstanding.

D. Contextual Integration and Global Knowledge: It is often necessary to have a greater awareness of world events or cultural allusions in order to recognize irony. Though only when the reader understands their larger context can statement like "Don't judge a book by its cover" or "All that glitters is not gold" not merely obviously sardonic. If one does not know this, it is easy to miss the underlying irony.

E. Exaggeration in Sarcasm Identification: Sarcasm frequently uses hyperbole, or purposeful exaggeration, to heighten the tragic tone of a sentence. The identification of hyperbolic sarcasm is still a major problem in the field of natural language processing (NLP). More complex algorithms are still being developed to interpret the sarcastic undertones of these overstatements and appropriately record them.

Literature Review

This section offers a thorough examination of the earlier approaches used to identify irony in multimodal media like text, photos, and videos. Several of the most well-known models in the field are included in Table II, which presents a summary of their performance based on citation frequency. We investigate a range of sarcasm detection strategies, including deep learning approaches like CNN (Convolutional Neural Network), RNN (Recurrent Neural Network), Bi-LSTM (Bidirectional Long Short-Term Memory), and TF-IDF (Term Frequency-Inverse Document Frequency); machine learning approaches like SVM (Support Vector Machine), decision trees, lexicon-based methods, Naive Bayes classifiers, and logistic regression; and hybrid approaches that combine the advantages of rule-based and lexicon-based models. Table III presents a selection of frequently used datasets, offering an overview of the wide variety of data that underpins this field of study.

After analysing multimodal data and the corresponding emotions, Mehta et al. [1] came to the conclusion that combining several modalities produces better outcomes when it comes to sarcasm identification. Studies [2], [4], [5], [6], and [7], which highlight current developments in sarcasm detection approaches and obstacles, support their findings. Furthermore, a thorough study is conducted on the comparative analyses of contextual approaches like CNet (Contextual Network), statistical classifiers like the SVM, and pattern-based algorithms. Using natural language processing (NLP) techniques to identify hyperbolic expressions in text-a crucial component of sarcasm-and utilizing hashtags like #sarcasm, #not, and #mockery, which indicate sarcasm in social media posts, is another fascinating method.

As noted by [7], there is a lot of interest in the relationship between language and psychology, and this relationship is being actively investigated.

Research such as [3] and [8] offer models that group posts according to the feelings they express and then choose the sarcastic ones from the group. These techniques perform better than the conventional polarity-based methods since they examine sentiment as well as emotion. For example, sentences with a negative emotion towards the latter part can be efficiently classified as sarcastic by utilizing the "SentiWordNet" dataset. Other research on multimodal sarcasm detection, including [9] and [10], suggests that combining textual and visual input improves the classifier's accuracy. These studies highlight how important context is for sarcasm recognition.

Castro et al.'s approach [11] for sarcasm recognition assigns equal weight to speech, text, and visuals. They demonstrate how cross-modal incongruities are essential for sarcasm identification with their curated dataset, "MUStARD," which consists of audio-visual utterances from popular television shows. The study emphasizes how important it is to include multimodal inputs. Moreover, [12] investigates how people understand irony on social media, where people frequently communicate without disclosing personal information. The authors of [13] provide a hierarchical fusion model that makes use of bi-LSTM. It first extracts picture characteristics, then attribute features, and then uses the latter to guide the interpretation of text features.

The "TransCapsule" model [14], which presents aspect-level sentiment classification by transfer learning, is another noteworthy addition. Using routing methods, this approach provides sentence-level insights by transferring knowledge from the document level to the aspect level. Additionally, by utilizing the eXnet (Expression Net) library in conjunction with data augmentation approaches for real-time applications, facial recognition via CNN achieves exceptional accuracy-up to 96% [15]. Examines how predicting student performance can change methods of instruction and assessment.

Automatic text summarization, as described in [17], is a particularly difficult and important NLP task that uses topic modelling techniques to generate concise yet thorough summaries of long-form content, like product titles and eBooks. Additionally, [18] proposes an incongruity-aware attention network (IAWN) that uses a scoring mechanism and word-level discrepancy between modalities to identify sarcasm.

Lastly, [19] and [20] present "MaSaC," the first code-mixed Hindi-English dataset intended for multimodal sarcasm identification and dialogue comedy classification. They use an attention-rich system to classify speech in their architecture, MSH-COMICS (Multi-modal Sarcasm Detection and Humour Classification in COde-MIxed Conversations). This design pushes the limits of sarcasm detection by using graph convolutional networks (GCNs) to examine sentiment abnormalities across and within distinct modalities.

IX. FINAL RECAP

A thorough analysis of academic literature shows that the use of a multimodal method with many data modalities greatly improves the accuracy of sarcasm detection. Sensitive irony like sarcasm frequently requires the use of context-specific cues like emoticons, emoji's, hashtags, and number indicators in order to be detected correctly.

Satire detection cannot be achieved by textual analysis alone since it necessitates an awareness of the speaker's nonverbal clues and emotional undertones, which are frequently expressed through body language and facial expressions.

Therefore, multi-modal data integration is essential for accurate sarcasm identification. Moreover, an amalgamated approach that combines deep learning and conventional machine learning methods exhibit enhanced effectiveness in identifying sarcasm on various social media networks.

X. UPCOMING PROJECTS

Subsequent studies ought to concentrate on modelling the disparities that exist between facial expressions and environmental cues, since these inconsistencies are critical markers for the identification of sarcasm. The creation of an application that combines cognitive characteristics with multimodal data may make it possible to process a variety of multimedia inputs and correctly detect and understand sarcasm. Curating a multilingual dataset that includes vernacular and non-English languages may also make it easier to classify comedy and detect satire. This development has potential uses in handling complaints, anticipating political trends, and reducing stress at work. These kinds of gains would also enhance our comprehension of the contextual and emotional subtleties in communication and further advances in NLP domains such as topic modelling.

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