IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

SARCASM DETECTION FOR MENTAL HEALTH PREDICTION

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Abstract:

The ubiquity of online communication platforms has led to an increasing concern about the potential impact of sarcasm on mental health, as misinterpretation of sarcastic remarks can contribute to stress and emotional distress. This study explores the application of machine learning techniques to detect sarcasm in online text, aiming to contribute to mental health awareness and support. By analyzing linguistic features, sentiment patterns, and contextual cues, the proposed model demonstrates promising results in identifying sarcastic expressions. The research emphasizes the importance of accurate sarcasm detection in fostering a more positive online environment, reducing the risk of misunderstandings, and ultimately contributing to improved mental well-being. The findings have significant implications for the development of tools and interventions that prioritize mental health in the digital era, fostering a more supportive and empathetic online community.

***Index Terms* - Sarcasm Detection, Machine Learning, Online Communication, Mental Health, Sentiment Analysis, Linguistic Feature**

I.INTRODUCTION

In recent years, the pervasive nature of online communication has transformed the way individuals interact, share information, and express themselves. While the digital age has facilitated unprecedented connectivity, it has also introduced new challenges, particularly in the realm of mental health. One such challenge arises from the intricate dynamics of sarcasm, a linguistic phenomenon that, when misinterpreted, can have significant implications for individuals' emotional well-being. Recognizing the potential impact of sarcastic expressions on mental health, researchers and practitioners are increasingly turning to machine learning techniques to develop robust sarcasm detection models.

This survey paper delves into the burgeoning field of sarcasm detection for mental health within the domain of machine learning. The aim is to comprehensively review the existing literature, methodologies, and advancements in the development of algorithms designed to identify and understand sarcasm in online communication. By exploring the intricate interplay of linguistic features, sentiment patterns, and contextual cues, this survey aims to shed light on the evolving landscape of sarcasm detection and its potential applications in promoting mental health awareness.

As we navigate the intricate tapestry of online interactions, the ability to accurately detect and interpret sarcasm becomes paramount. Misunderstandings arising from sarcastic remarks can contribute to stress, emotional distress, and strained interpersonal relationships. The integration of machine learning models tailored for sarcasm detection holds promise in mitigating these challenges, fostering a more empathetic and supportive digital environment. This survey not only provides an overview of the current state-of-the-art sarcasm detection algorithms but also explores the broader implications for mental health advocacy and intervention in the digital era.

II. LITERATURE SURVEY

In the case of sentiment analysis, feature extraction in the presence of sarcasm is critical; it has been proposed that several feature categories, such as lexical, pragmatic, prosodic, and syntactic features, can be extracted using NLP techniques in this regard. Sarcasm detection for data in languages other than English has also been examined in depth, with examples available in, as well as other languages such as Italian, Dutch, Japanese, Spanish, and Greek, and bilanguages such as English-Hindi code mixed. Suhaimin et al. concluded that the three combinations of syntactic pragmatic and prosodic feature categories were the most successful in the context of Malay social media data detection.

a) Using Machine Learning Techniques

In addition to the word context, Lunando et al. employed negative information and the quantity of interjection words. For classification, supervised machine learning techniques such as Nave Bayes, Maximum Entropy, and Support Vector Machine are utilized because they provide high accuracy. Although much research has been done on uni-language sarcasm recognition, Suhaimin et al. proposed detecting sarcasm using multilingual texts. To recognize unusual phraseology in the corpus, a syntactic rule in the form of "NOUN-ADPOSITION-NOUN" was developed. SVM classifiers were employed in all tests on Weka knowledge flow to recognize sarcasm. They made a variety of combinations, the best of which were syntactic and prosodic. The rule they devised to identify idiosyncratic characteristics was not successful, and it performed poorly. Texts were classified using a non-linear SVM based on discovered attributes and the presence or absence of sarcastic content to assess the method's performance.

The researchers discovered that combining syntactic, pragmatic, and prosodic elements might result in an F-measure of 0.852.

E. Lunando et al. investigated sentiment analysis and sarcasm identification in Indonesian social media. Sarcasm is a particularly challenging topic in the realm of SA. The authors of this study presented two new parameters that may be used in conjunction with sentiment analysis to detect sarcasm more effectively. The prevalence of exclamation and other interjection marks was its most distinguishing feature. They also employed a regional edition of SentiWordNet for sentiment analysis. The process was automated using machine learning techniques.

F. B. Kader et al. discussed sarcasm extensively in internet forums. Recent breakthroughs in sarcasm detection based on a decade of research by allowing for the taking into account the context to identify sarcasm and permitting unsupervised pre-trained transformers to be used in multimodal situations. The study's purpose was to conduct a survey. the cutting-edge of computational techniques to sarcasm In written English, analysis and modelling. Sarcasm detection data, methods, trends, challenges, problems, and jobs are explored. This paper also provided summarized and compiled tables of sarcasm datasets, sarcastic qualities, and their extraction processes, as well as performance analyses of alternative methodologies, to assist researchers in related fields and fully comprehend current state-of-the-art practices in sarcasm recognition.

b) Using Deep Learning Techniques

M. Bouazizi et al. used Part-of-Speech (POS) tags to identify and extract patterns that characterize the intensity of sarcasm in tweets. The pattern they devised yielded positive results. They offered four sets of criteria to capture each of the four varieties of sarcasm described in their paper. They used them to determine whether a tweet had irony. The accuracy was 83.1%, and the precision was 91.1%; they also examined the value of each feature set recommendation and evaluated its effect on categorization.

Ren, Lu et al. presented an emotion-semantics-trained multi-layer neural network for parsing sarcasm. Their model used a two-layer memory network, with the first layer storing the emotional undercurrents of each phrase and the second layer storing the contrast between the emotional undercurrents of the phrase and the context of the sentence. Similarly, a modified CNN was used to boost the memory network's performance without requiring any more data about a particular area. Their technique had been validated by experimental findings on the Twitter dataset & Internet Argument Corpus (IAC-V1 and IAC-V2)

M. Shrivastava et al. investigated the identification of sarcasm in textual communications. To get over this obstacle, an innovative technique based on Google BERT was presented. This model is capable of handling enormous amounts of data. Several methodologies, both old and new, were utilised to compare the model's accuracy to their claims of being used for similar purposes. Models in their category included the LSTM and CNN, as well as the BiLSTM and attention-based models like the SVM and Linear Regression (LR). Many metrics were utilised to assess how well the suggested model performed, including recall, F1 score, precision, and accuracy.

Aside from the Twitter database, many additional datasets are used in research, including the Internet Argument Corpus (IAC) SARC , SemEval 2018 Task 3 , and SemEval 2015 Task 11. Similarly, Mandal et al. employed a news headline dataset with 26,709 headlines. 43.9% of these headlines were satire, while 56.1% were true. They stated that no other research had used that dataset to train neural networks before and that they had detailed the CNN-LSTM-based architecture and achieved 86.16% accuracy. Rhetoric irony was discovered in the corpus by Du et al.There were various types of sarcasm, one of which was Rhetoric. Rhetorical Sarcasm can be understood as follows: Do you wish to seem skinny without losing weight? As a result, the sentence did not have a literal sense in this case. Researchers have rarely found this type of irony.

III. PHASES IN SARCASM RECOGNITION MODEL

A) Data Collection

Twitter data sets or Twitter API (Application Programming Interface), News Headline Datasets, and other datasets such as MUStARD (Multi-modal Sarcasm Detection data set) , SARC (Self annotated Reddit Corpus) , Sem Eval (Semantic Evaluation Data set) , and others are the primary sources for sarcasm detection work. Other common datasets utilised for sarcasm recognition include Amazon and Facebook datasets. None of the informative datasets are currently standardised data sets for sarcasm recognition, which is one of the major challenges that new researchers confront in sarcasm detection. Many academics have produced their own annotated data set for use in sarcasm recognition.

B) Data preprocessing

Several techniques are used in data pre-processing, including tokenization, stop-word removal, stemming, and lemmatization.

• Tokenization breaks the corpus into words, punctuation marks, etc. To deal with words with the same root stemming and lemmatization are used.

• Stemming reduces a word to its root form irrespective of the meaning of the root word but lemmatization reduces a word to its meaningful root form. Porter stemmer, snowball stammer, and Lancaster stemmer are the common stemmers available in NLTK (Natural Language Toolkit) library The idea of stop word removal is to remove the articles and pronouns as stop words since they are typically found throughout the document in the corpus.

C) Feature selection

• POS (part-of-speech) tagging is also one of the data pre-processing techniques which are very crucial for sarcasm recognition. The words are separated into different parts of speech using POS tags, such as nouns, adjectives, etc. Another crucial data preprocessing step includes parsing and removal of URLs and other special symbols etc.

Several algorithms and strategies are available to extract features from textual and non-textual data sources in order to prepare the model. Bag of words, N-Grams, word2vec, Term Frequency - Inverse Document Frequency (TF-IDF), and other processes are examples. Some academics have also used emoticons, negation marks, and other symbols to recognize sarcasm.

Accuracy can be improved by selecting relevant features The feature can be lexical (the presence of hashtags and n-grams in sentences), pragmatic (the presence of emoticons and smileys in sentences as they are used to express feelings in text), hyperbolic (the presence of punctuation and interjections as they aid in understanding the importance of sentences), or sentimental (the polarity of emotions). Other characteristics include semantic, syntactic, context, and so on.

D) Sarcasm classification technique

Using sarcasm detection as a binary classification problem, various classifiers and rule-based approaches are applied.

Many academics use the following basic classification methods:

a) Support vector machine (SVM)

The hyperplane in an N-dimensional space can be obtained using this supervised machine learning technique for both regression and classification.

b) Naïve Bayes (NB):

Naive Bayes classifiers fall under the supervised category of learning algorithm, utilizing Bayes' Theorem. It handles both continuous and discrete data. Multinomial Naive Bayes is usually used in natural language processing as the frequency at which specific events were produced by a multinomial distribution are depicted by feature vectors.

c) RNN stands for Recurrent Neural Network. :

One of the deep learning approaches is RNN. RNN's actual potential has been discovered in recent years, however it is an old algorithm developed in the 1980s. It is effective with sequential data. The importance of RNN grows as a result of an internal memory contained in the hidden layer that remembers past input and uses current and previous inputs to make a decision. It behaves similarly to human brain activities. RNN is also used in Apple's Siri and Google's Voice Search.

d) Long-Term Memory (LSTM) is a type of short-term memory.

LSTM is one of the deep learning approaches. LSTM is a form of RNN that addresses the RNN fault. RNNs are unable to predict words retained in long-term memory, whereas LSTMs do better since they can store data for longer periods of time.The flow of information into and out of the cell is handled by three gates: forget gate, input gate, and output gate.

e) CNN

CNN is a popular deep-learning neural network. A CNN can include tens or even hundreds of layers, and each layer can be trained to recognise different characteristics of a picture . CNN captures all critical features. It extracts contextual local information from a sentence and converts those local features into a global feature vector using several convolutional calculations.

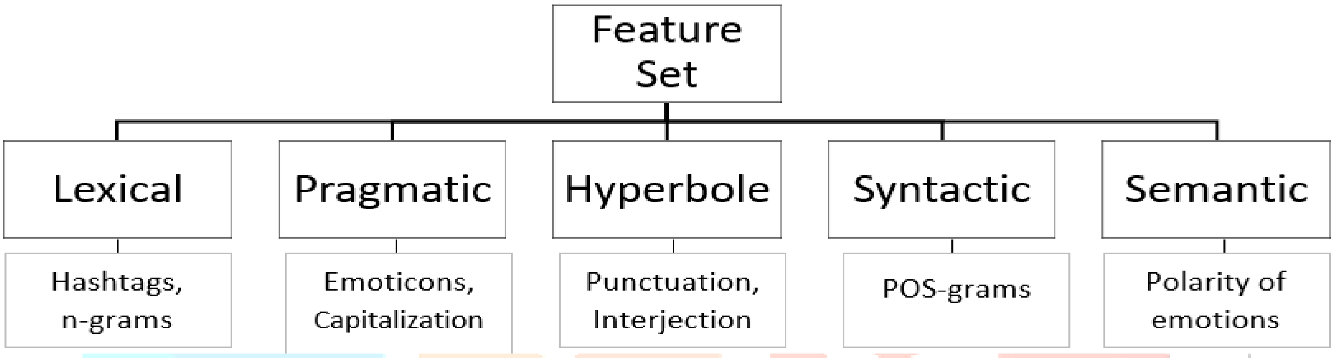

Figure.1. Different Feature Sets Considered in Recognition of Sarcasm to Improve the Accuracy of The Model

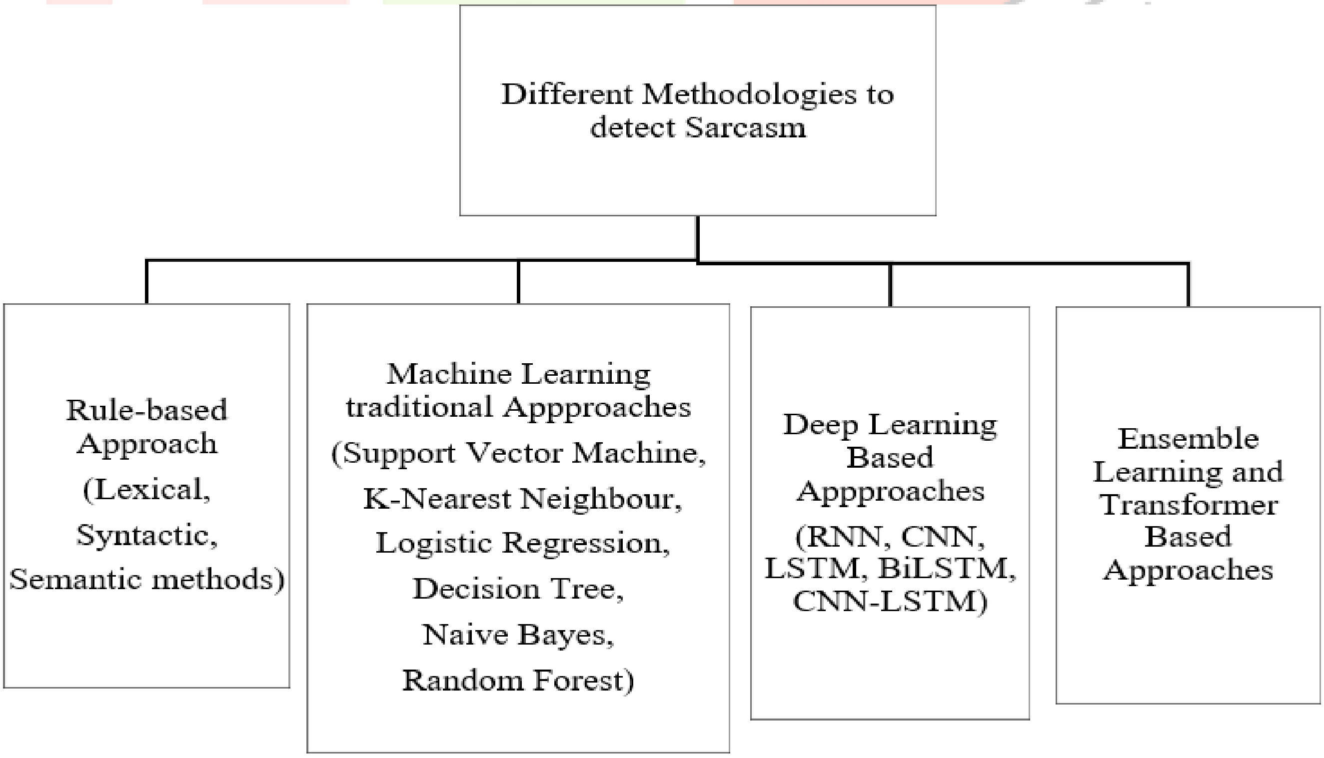

Figure 2: Different Methodologies to Detect Sarcasm

Evalution Metrics:
recall (r), Precision (p), accuracy (a), and F-score (f) are used to assess the model's performance.
Precision is the ratio of correctly predicted sarcastic data to total predicted sarcastic data. The proportion of successfully predicted sarcastic data to all actual sarcastic data is defined as recall.
The harmonic mean of 'p' and 'r' can be used to get the F-score.
The following formula can be used to calculate a model's accuracy, 'a.
accuracy = (Tp+Tn) / (Tp+Fp+Fn+Tn) where Tp denotes True Positive, Tn denotes True Negative, Fp denotes False Positive, and Fn denotes False Negative.

IV CHALLENGES IN SARCASM DETECTION:

Sarcasm detection has become difficult due to a variety of concerns and challenges, some of which are highlighted below while highlighting the dataset and various approaches:
a) Datasets are necessary for constructing a model for sarcasm identification because if there is a disparity in the dataset, it may be unclear what sarcastic sentences frequently consist of. This ambiguity can be overcome by employing hashtags, like in the Twitter dataset, but without them it gets problematic. However, datasets such as news headlines do not include hashtags.

b) In rule-based techniques, we leverage Twitter's hashtag as an inconsistent and unreliable means to detect sarcasm.
Because of the time-consuming manual rules, such procedures can only be utilised with certain types of data or in limited contexts.

c) While machine learning algorithms did well with text, detecting sarcasm by combining facial expression, body language, tone of voice, and other features is a difficult issue.

d) Although pre-trained language models such as BERT improved the accuracy of deep learning approaches, nuanced sarcastic phrases from texts are often too complex for these models to understand, especially when the phrase is tightly related to past information.
Existing techniques and algorithms are insufficient for identifying sarcasm directly through typographic pictures.

V. CONCLUSION AND FUTURE WORK:

One of the most difficult aspects of sentiment analysis is recognising sarcasm. In this paper, we aimed to present an overview of previous sarcasm recognition efforts utilising various versions of the dataset, as well as several approaches for sarcasm identification and certain sarcasm detection issues. The multimodal dataset yields better results than the textual dataset, although it is still not the best. The importance of detecting sarcasm has grown dramatically in recent years. It may be impossible to identify if a comment is sarcastic or not using only one way, and memes have grown increasingly popular for communicating sarcastic messages. It is difficult to detect if someone is being sarcastic or not without any background knowledge or awareness of the speaker's facial expression or body language. We also looked at non-English research because the majority of sarcasm detection research is done in English. Because memes have grown so popular on many social media platforms, we must also include those typographic and graphical pictures that carry sarcasm. Detecting sarcasm in typographic and infographic pictures with and without other feature sets offers hopes for future work.

REFERENCES

1) Dhawale, Apurva D., Sonali B. Kulkarni, and Vaishali M. Kumbhakarna. "A survey of distinctive prominence of automatic text summarization techniques using natural language processing." International Conference on Mobile Computing and Sustainable Informatics. Springer, Cham, 2020.

2) Adarsh, M. J., and Pushpa Ravikumar. "Sarcasm detection in text data to bring out genuine sentiments for sentimental analysis." 2019 1st international conference on advances in information technology (ICAIT). IEEE, 2019.

3) F. B. Kader, N. H. Nujat, T. B. Sogir, M. Kabir, H. Mahmud, and K. Hasan, “Computational Sarcasm Analysis on Social Media: A Systematic Review,” 2022,

4) Verma, Palak, Neha Shukla, and A. P. Shukla. "Techniques of sarcasm detection: A review." 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE). IEEE, 2022

5) Baruah, Arup, et al. "Context-aware sarcasm detection using bert." Proceedings of the Second Workshop on Figurative Language Processing. 2020.

6) Srivastava, Himani, et al. "A novel hierarchical BERT architecture for sarcasm detection." Proceedings of the Second Workshop on Figurative Language Processing. 2020